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Weather Forecasting Using Stacked-LSTM

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Abstract

This study proposes a Stacked Long Short-Term Memory (Stacked LSTM) model for multivariate weather forecasting using historical meteorological data from Denpasar City. The dataset consists of 264,924 records collected between 1990 and 2020, including four key weather variables: temperature, humidity, pressure, and wind speed. The model is designed to capture temporal dependencies in time-series weather data through multiple LSTM layers. A sliding window technique is used to construct input sequences, and the model is trained for 50 epochs with a batch size of 64, incorporating dropout regularization to improve generalization. The dataset is divided using a train–test split, where 20% of the data is reserved for performance evaluation. Experimental results demonstrate that the proposed model achieves strong predictive performance across all weather variables. The evaluation on the test dataset yields an average Mean Absolute Error (MAE) of 1.08, Mean Absolute Percentage Error (MAPE) of 10.22%, Root Mean Squared Error (RMSE) of 1.93, and a Coefficient of Determination (R^2) of 0.86. Among the predicted variables, humidity and temperature show the highest accuracy with R^2 values of 0.9537 and 0.9031, respectively. The findings indicate that the Stacked LSTM architecture successfully captures both short-term and long-term temporal relationships within multivariate weather datasets. The proposed approach demonstrates strong potential for improving automated weather forecasting systems, particularly in tropical urban environments characterized by complex climatic dynamics. Future work may focus on integrating real-time weather data sources and adaptive retraining mechanisms to further enhance prediction accuracy and operational applicability.

Keywords:
Weather Prediction, Stacked LSTM, Time Series, Forecasting

1. Introduction

Weather Accurate weather forecasting plays a critical role in many sectors such as agriculture, transportation, disaster management, and energy planning. Weather conditions directly influence crop productivity, air transportation safety, renewable energy production, and public safety during extreme events. However, weather systems exhibit highly nonlinear, dynamic, and chaotic behavior, which makes accurate prediction extremely challenging. Traditional numerical weather prediction models rely on physical equations and large-scale simulations that require significant computational resources and extensive atmospheric data. While these models provide useful forecasts, they often struggle to capture local variations and short-term temporal patterns efficiently. As a result, researchers increasingly explore data-driven approaches that utilize historical weather data to model complex temporal dependencies. Recent studies demonstrate that machine learning and deep learning techniques provide promising alternatives for modeling weather time-series data and improving forecast accuracy [1][11].

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Time-series analysis forms the foundation of modern data-driven weather prediction. Weather datasets contain sequential observations such as temperature, humidity, wind speed, and rainfall measured over time. Traditional statistical approaches such as autoregressive integrated moving average (ARIMA) models attempt to model these sequences but often fail to capture nonlinear relationships present in meteorological data. Deep learning approaches overcome these limitations by learning hierarchical representations from large datasets. Among these approaches, recurrent neural networks (RNN) have attracted significant attention because they can process sequential data and retain temporal information. However, conventional RNN models suffer from the vanishing gradient problem when handling long sequences, which reduces their ability to capture long-term dependencies. This limitation motivates the development of advanced architectures capable of preserving long-term temporal patterns in weather data [2][12].

Long Short-Term Memory (LSTM) networks address many limitations of traditional recurrent neural networks by introducing memory cells and gating mechanisms that control information flow. These mechanisms allow the model to preserve relevant information over longer time intervals and discard irrelevant patterns. Researchers widely apply LSTM networks to weather forecasting tasks because weather parameters exhibit strong temporal dependencies. Studies show that LSTM-based models significantly improve prediction accuracy for meteorological variables such as temperature, rainfall, and humidity. For example, sequence-to-sequence LSTM models effectively capture temporal relationships in weather datasets and generate more stable forecasts compared with traditional models. These capabilities make LSTM one of the most widely used deep learning architectures for time-series prediction problems in meteorology [1][3][5].

Despite the advantages of single-layer LSTM models, researchers continue to explore deeper architectures to improve prediction performance. Stacked-LSTM models extend the basic LSTM architecture by stacking multiple LSTM layers on top of each other. This structure enables the network to learn more complex temporal features and hierarchical representations from sequential data. In weather forecasting applications, stacked-LSTM models demonstrate improved ability to capture multi-scale temporal patterns present in atmospheric variables. Previous studies show that stacked-LSTM networks outperform shallow architectures in predicting temperature, solar irradiance, and wind speed. These results indicate that deeper recurrent architectures provide stronger modeling capabilities for complex weather systems [2][8][19].

Another important challenge in weather forecasting involves handling multivariate meteorological data. Weather systems consist of multiple interacting variables such as temperature, humidity, pressure, and wind speed. Accurate forecasting therefore requires models that can learn relationships among these variables simultaneously. Researchers address this challenge by developing hybrid and multivariate deep learning models that combine LSTM with other architectures such as convolutional neural networks (CNN). These hybrid models extract spatial patterns and temporal dependencies simultaneously. Studies demonstrate that CNN–LSTM models improve prediction performance by capturing both feature correlations and sequential dependencies within weather datasets. However, these models often introduce higher computational complexity and require careful parameter tuning [12][16].

In addition to hybrid models, several studies focus on improving weather prediction accuracy by integrating advanced learning mechanisms such as attention models and noise reduction techniques. Attention mechanisms allow deep learning models to focus on the most relevant temporal features when generating predictions. Similarly, preprocessing techniques such as noise filtering improve the quality of input data and reduce prediction errors. These approaches demonstrate that enhancing data representation and feature selection significantly improves forecasting performance.

However, these methods also increase model complexity and require extensive training data to achieve optimal performance [7][13][17].

Another emerging direction in weather prediction research involves applying deep learning models to renewable energy forecasting, particularly solar irradiance and wind speed prediction. These applications share similar characteristics with weather forecasting because renewable energy generation depends heavily on atmospheric conditions. Researchers successfully apply stacked LSTM architectures to predict solar irradiance and wind power generation, demonstrating the ability of deep recurrent networks to model complex temporal dependencies in environmental data. These studies further confirm that stacked LSTM architectures provide reliable predictive performance for meteorological and energy-related time-series datasets [8][20].

Although deep learning approaches have significantly improved weather forecasting accuracy, several challenges remain in designing efficient predictive models. Many existing studies focus on specific meteorological variables or limited datasets, which restricts their generalization capability. Additionally, shallow LSTM models often fail to capture deeper temporal patterns that influence long-term weather behavior. These limitations motivate the exploration of deeper recurrent architectures such as stacked-LSTM networks. By stacking multiple LSTM layers, the model can learn hierarchical temporal representations and improve prediction accuracy. Therefore, this study investigates the application of a stacked-LSTM model for weather forecasting, aiming to enhance prediction performance and provide a more robust deep learning framework for analyzing meteorological time-series data [2][18][20].

2. Related Works

Previous studies investigated the application of deep learning models for weather forecasting, particularly focusing on recurrent neural network architectures. Zaytar and El Amrani developed a sequence-to-sequence model using Long Short-Term Memory (LSTM) networks to predict weather conditions based on historical meteorological data. Their study demonstrated that LSTM models effectively captured temporal dependencies in weather time-series data and produced more stable predictions compared with traditional statistical methods. The model successfully improved forecasting accuracy for short-term weather prediction tasks. However, the research used a relatively shallow LSTM architecture, which limited the ability of the model to capture deeper temporal patterns in complex atmospheric systems [1].

Researchers also explored the use of stacked LSTM architectures to enhance forecasting performance. Karevan and Suykens proposed a spatio-temporal stacked LSTM model for temperature prediction in weather forecasting applications. Their model incorporated multiple LSTM layers to capture complex temporal dependencies in meteorological data. The experimental results showed that the stacked LSTM model improved prediction accuracy compared with single-layer LSTM networks. The study highlighted the advantage of deeper architectures in learning hierarchical temporal features from time-series datasets. Nevertheless, the model focused primarily on temperature prediction and did not evaluate its performance for other meteorological variables such as humidity, rainfall, or wind speed [2].

Several studies investigated the effectiveness of LSTM models for predicting various weather parameters. Zhang implemented an LSTM-based deep learning model for weather forecasting and demonstrated that the model successfully predicted temperature patterns using historical weather data. The study confirmed that LSTM networks could learn nonlinear relationships within meteorological datasets. Similarly, Nugraha et al. applied the LSTM algorithm to forecast weather conditions using time-series data and achieved improved prediction accuracy compared with traditional regression-based models. Although these studies demonstrated the potential of LSTM models, they primarily used single-layer architectures, which may limit the capacity of the model to capture multi-level temporal patterns in complex weather dynamics [3][5].

Other researchers examined hybrid deep learning approaches that combine LSTM networks with convolutional neural networks (CNN). Abdellaoui and Mehrkanoon developed a deep recurrent convolutional neural network model for multi-station weather forecasting. Their model integrated convolutional layers to capture spatial correlations between meteorological stations and recurrent layers to model temporal dependencies. The results showed that the hybrid architecture improved forecasting accuracy across multiple weather stations. Despite these advantages, the model introduced higher computational complexity and required larger training datasets, which could limit its practical implementation in resource-constrained environments [11].

Another line of research focused on improving weather prediction by incorporating additional mechanisms such as attention models and advanced feature extraction methods. Tekin et al. proposed a convolutional LSTM model enhanced with attention mechanisms for numerical weather forecasting. The attention module enabled the model to focus on the most relevant temporal features when generating predictions. Their results demonstrated improved forecasting performance compared with standard deep learning models. However, the additional attention layers increased model complexity and required careful parameter tuning during the training process [13].

Researchers also applied deep learning models to renewable energy forecasting problems that share similar characteristics with weather prediction tasks. Nugroho et al. implemented a stacked LSTM model for day-ahead solar irradiance forecasting in tropical regions. Their results indicated that stacked LSTM networks effectively captured temporal dependencies in environmental datasets and produced accurate predictions for solar radiation levels. Similarly, Khan et al. utilized stacked and bidirectional LSTM techniques to predict wind power generation. The study confirmed that deep recurrent architectures improved forecasting accuracy for time-series data influenced by weather conditions. Nevertheless, these studies focused primarily on energy prediction rather than general weather forecasting [8][20].

In addition, several studies explored hybrid architectures combining CNN and LSTM models for multivariate weather prediction. Divyashree et al. developed a CNN–LSTM hybrid model to forecast multiple meteorological variables simultaneously. The convolutional layers extracted spatial features from weather datasets, while the LSTM layers captured temporal patterns. The results showed that the hybrid model achieved higher prediction accuracy compared with standalone LSTM networks. However, the model required high computational resources and large training datasets, which may limit its scalability in real-world forecasting systems [16].

Despite the progress in deep learning-based weather prediction, many studies still face challenges related to model generalization and forecasting accuracy. Kishore Kanna and Muda proposed a hybrid stacked LSTM model for weather prediction. However, the study mainly focused on classification tasks rather than continuous numerical forecasting of weather variables. These limitations indicate that further research is necessary to explore stacked LSTM architectures for more robust and accurate weather forecasting models. Therefore, this study investigates the application of a stacked-LSTM model to improve the prediction of weather time-series data by capturing deeper temporal dependencies in meteorological datasets [18].

3. Proposed Method

This This study proposes a weather forecasting model based on the Stacked Long Short-Term Memory (Stacked LSTM) architecture to predict weather conditions in Denpasar City. The overall research methodology involves seven main stages: problem identification, literature review, data collection, data preprocessing, model development, evaluation, and result interpretation.

1.1 Data Collection

The dataset used in this study consisted of historical weather data from Denpasar City obtained from Kaggle. The dataset covered the period from 1990 to 2020 and contained 264,924 records with 32 attributes. From these attributes, four key variables were selected as the primary input features for the forecasting model: temperature (°C), humidity (%), wind speed (km/h), and atmospheric pressure (mbar). These variables were chosen because they represent the main meteorological factors that influence short-term weather patterns. To improve the generalization capability of the deep learning model, dropout layers with a rate of 0.2 were applied during the training process. This mechanism randomly deactivated a portion of neurons in each training iteration, which helped reduce overfitting and improved the robustness of the Stacked-LSTM model.

1.2 Long Short-Term Memory

Important patterns in social media text are extracted using the hybrid model's LSTM as the initial phase. In order to determine whether a text contains positive, negative, or neutral emotions based on preexisting features, the dataset—which takes the form of text comments or posts—is utilized for the emotion identification task. This is the LSTM algorithm's formula:

1. **Forget Gate:** The forget gate, a kind of neural network created especially to process readable content like text, photos, or videos, is one of the key elements of the long and short-term memory (LSTM) architecture.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f \tag{1}$$

Table 1. The Mathematical Notation of Forget Gate

Notation	Description
f_i	$forget\ gate\ output$
σ	$Sigmoid\ activation\ fuction$
W_f	$Weights\ for\ the\ forget\ gate$
h_{t-1}	$Previous\ hidden\ state$
x_i	$input\ at\ the\ current\ timestep$
b_f	$Bias\ for\ the\ forget\ gate$

2. **Input Gate:** The input gate is the most crucial part of the long short-term memory architecture, along with the forget and output gates. Some of the fresh data that will be supplied to the LSTM cells can be controlled with the help of the input gate.

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i)$$
$$\sim C_t = tanh\ (W_c . [h_{t-1}, x_t] + b_c) \tag{2}$$
$$C_t = f_t . C_{t-1} + i_t . \sim C_t$$

Table 2. The Mathematical Notation of Input Gate

Notation	Description
i_t	*input gate output*
$\sim C_t$	*Candidate cell state*
C_t	*Update cell state*
W_i, W_c	*Weights for input gate and candidate st*
b_i, b_c	*Bias terms*

3. **Cell State Update:** Cell State Update is a process in long and short-term memory (LSTM) that aims to update the internal memory (cell state, represented as C t) at each time interval. This process ensures that relevant information is collected, new information is collected, and unnecessary information is collected.

$$C_t = f_t * C_t - 1 + i_t * C^{\sim}_t \tag{3}$$
$$o_t = \sigma(W_o \cdot [h_t - 1, x_t] + b_o)\ h_t = o_t * \tanh(C_t)$$

Table 3. The Mathematical Notation of Cell State Update

Notation	Description
C_t	*Update cell state*
f_t	*Forget gate output*
C_{t-1}	*Previous cell state*
i_t	*input gate output*
W_o	*weight for gate input*

The Stacked LSTM layers are organized sequentially where each layer processes the entire sequence and passes its hidden states as inputs to the next layer. This hierarchical composition enables the model to learn both short- and long-term dependencies across varying levels of abstraction, making it particularly powerful for multivariate weather time-series forecasting.

4. Result and Analysis

The dataset used in this study consisted of 264,924 historical weather records from Denpasar City collected between 1990 and 2020. Four meteorological variables were selected as model inputs, namely temperature, humidity, atmospheric pressure, and wind speed. The model was trained using a batch size of 64 for 50 epochs, with 20% of the dataset allocated as validation data during the training process. To capture temporal dependencies within the time-series data, input sequences were generated using a sliding window approach. The Stacked-LSTM model then produced multivariate regression outputs, predicting future values of the four weather features simultaneously. The test set (20% of the dataset, or 141 records) was used to assess the model. Fig. 1 depicts prediction visualization and Error Metrics and Fig. 2 displays Training and Validation Loss as follows:

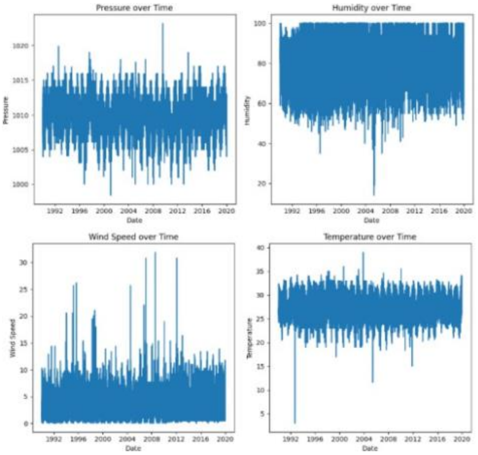


Fig. 1 Prediction Visualization and Error Metrics

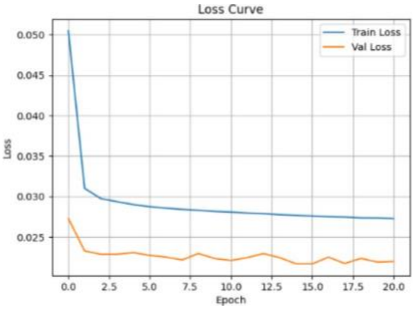


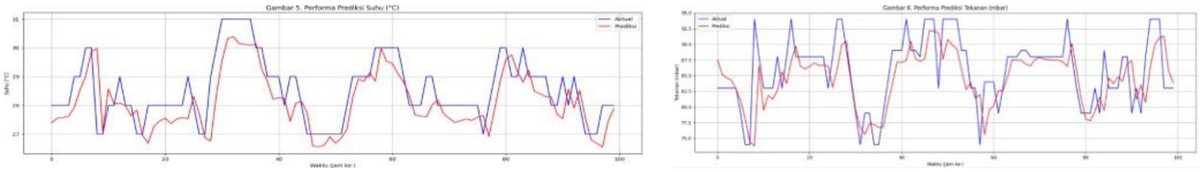
Fig. 2 Training and Validation Loss

The model performance was assessed using four standard metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). The results indicate that the model achieved strong predictive accuracy across most variables, particularly for temperature and humidity, which recorded high R^2 values and very low error rates.

Table 4. Performance Analysis of the Stacked Long Short-Term Memory Model

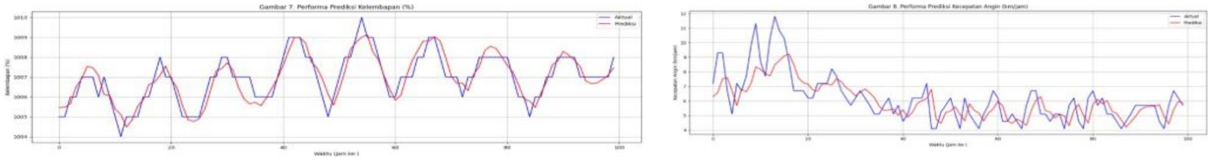
Feature	**MAE**	**MAPE**	**RMSE**	**R^2**
Temperature	0.42	1.51%	0.57	0.9031
Pressure	2.75	3.49%	3.65	0.8026
Humidity	0.39	0.04%	0.49	0.9537
Wind Speed	0.78	35.85%	1.03	0.7646
Average	**1.08**	**10.22%**	**1.93**	**0.86**

The results show that humidity prediction achieved the highest accuracy with an R^2 value of 0.9537 and very low error values. Temperature prediction also performed strongly with an R^2 of 0.9031. Pressure prediction showed moderate accuracy, while wind speed prediction had the highest MAPE value due to the naturally high variability of wind patterns. Overall, the average R² score of 0.86 indicates that the Stacked LSTM model effectively captured the temporal relationships in the weather dataset. Fig. 3 depicts prediction of multivariate forecasting results.



Temp

Pressure (mbar)



Humidity (%)

Wind Speed (km/h)

Fig. 3 Prediction of multivariate forecasting results

The experimental results demonstrate the effectiveness of the Stacked Long Short-Term Memory (Stacked LSTM) model in predicting multiple weather variables for Denpasar City. The model was evaluated using 20% of the dataset, equivalent to approximately 52,985 records, which were reserved as test data. Quantitative evaluation metrics indicate strong predictive performance, with a Mean Absolute Error (MAE) of 1.08, a Mean Absolute Percentage Error (MAPE) of 10.22%, and a Root Mean Squared Error (RMSE) of 1.93. In addition, the model achieved a coefficient of determination (R^2) of 0.86, meaning that it successfully explained 86% of the variance in the weather data. These results confirm that the proposed model provides reliable predictions with relatively small error margins when applied to unseen data.

The training process further demonstrates stable learning behavior. Over 50 training epochs, both training and validation loss curves decreased gradually and converged smoothly, indicating that the model learned the temporal patterns effectively without experiencing significant overfitting or underfitting. The use of dropout regularization and early stopping mechanisms contributed to improved generalization capability. Feature-level analysis also shows that the model performs consistently across the four predicted variables. Temperature and pressure predictions closely follow the observed trends with minimal deviation, while humidity predictions remain stable with only slight discrepancies during extreme peaks. Wind speed predictions show comparatively larger fluctuations, which is expected due to the naturally irregular and dynamic behavior of wind patterns.

Thus, the findings indicate that the Stacked LSTM architecture successfully captures both short-term and long-term temporal dependencies within multivariate weather time-series data. The deeper layered structure allows the model to learn complex relationships among meteorological variables more effectively than simpler forecasting approaches. As a result, the model demonstrates strong potential for application in automated weather forecasting systems, particularly in tropical urban environments such as Denpasar where weather patterns are highly dynamic. Integrating the model with real-time weather data sources and implementing adaptive retraining strategies could further enhance prediction accuracy and operational usability in practical forecasting applications.

5. Conclusion

This study proposed a Stacked LSTM model to perform multivariate weather forecasting for Denpasar City using historical meteorological data. The model utilized four key weather variables including temperature, pressure, humidity. Experimental results demonstrated that the proposed model achieved strong predictive performance with an average MAE of 1.08, MAPE of 10.22%, RMSE of 1.93, and an R^2 value of 0.86, indicating that the model successfully explained 86% of the variance in the observed weather data. Feature-level evaluation showed particularly high accuracy for humidity and temperature predictions, which achieved R^2 values of 0.9537 and 0.9031, respectively, while pressure predictions showed moderate accuracy and wind speed predictions exhibited larger percentage errors due to the inherently volatile nature of wind behavior.

The training process further confirmed the robustness of the proposed approach. During the 50 training epochs, both training and validation losses converged smoothly, demonstrating stable learning without significant overfitting or underfitting. The incorporation of dropout regularization and early stopping techniques improved the model's generalization capability when applied to unseen data. Visual comparisons between actual and predicted values also indicated that the model effectively followed the temporal patterns of temperature, humidity, and pressure, while maintaining reasonable prediction stability for wind speed despite its irregular fluctuations. These findings suggest that the stacked architecture successfully captured both short-term and long-term dependencies within the multivariate weather time-series data.

The results confirm that the proposed Stacked LSTM-based forecasting framework provides an effective approach for modeling complex meteorological patterns in tropical urban environments. By utilizing multiple LSTM layers, the model learns deeper temporal relationships among weather variables and produces reliable forecasting results. Therefore, this approach can support the development of automated weather prediction systems and decision-support tools for climate monitoring and urban planning. Future research may further enhance the model by integrating real-time weather data streams, incorporating additional meteorological features, and applying adaptive retraining mechanisms to improve forecasting performance in dynamic environmental conditions.

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