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Improving Accuracy of Daily Weather Forecast Model at Soekarno-Hatta Airport Using BILSTM with SMOTE and ADASYN

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Abstract: Bidirectional LSTM (BiLSTM) is an extension of LSTM which can improve model efficiency and accuracy in classification scenarios based on time series data or longer time series data repeatedly. This research uses the BiLSTM algorithm to build a daily weather forecast model at Soekarno-Hatta Airport. The model built will assist forecasters in making weather forecasts on a local scale. This research is expected to be implemented and able to increase the verification value of Soekarno-Hatta Airport weather forecasts to support flight safety in Indonesia. The dataset used is hourly surface air weather parameter data (synoptic data) of Soekarno-Hatta Meteorological Station for the period January 2018 - December 2022. There is an imbalance in the data set, so the SMOTE and ADASYN techniques are used to handle the problem. The output of this research is weather conditions categorised into sunny, sunny cloudy, cloudy, light rain, moderate rain, heavy rain, and thunder rain. The results obtained will go through model verification and evaluation by finding the accuracy value by comparing the weather forecast model output with actual weather data using a multi-category contingency table. The BiLSTM - ADASYN model obtained the highest average accuracy value compared to other models, which was 83.2%.

Keywords: ADASYN; BiLSTM; SMOTE; Weather forecast

Introduction

Meteorological information plays an important and integral role in the world of aviation . In a flight, meteorological information must be included in making a flight plan (ICAO, 2010; Wardani et al., 2018)). Daily weather forecast is one of the products of Soekarno-Hatta Meteorological Station which is a strategic step in the context of publishing the Soekarno-Hatta Airport Weather Forecast to concerning the preparation and dissemination of Aerodrome Forecast for Aviation Meteorological Information Services. Airport weather forecasts will be very useful in the implementation plan of Air Traffic Flow Management (ATFM) with Air Navigation, and Airport Collaborative Decision Making (A-CDM) by the Ministry of Transportation (Kemenhub) to develop airspace and airport capacity optimisation for more effective air transport flight operations in Indonesia.

Artificial Intelligence (AI) (Fente & Singh, 2018) is the study of giving computers the ability to work like humans using various algorithms, which include thinking and other functions (Akhila et al., 2022). In AI development, Deep Learning (DL) algorithms can be used to make weather forecasts by utilising BiLSTM which is a development of LSTM which can improve model efficiency and accuracy in classification scenarios (Bengio, 2009; Ravi et al., 2017; Vaidya et al., 2021). This increase in accuracy is mentioned because BiLSTM uses information from historical data in the past and future as input data for the model (Nizar et al., 2021).

BiLSTM is able to forecast weather parameters with time series data sets in an area, but no research has been found that uses Soekarno-Hatta Airport as a research

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location. Because of this, researchers will use the BiLSTM algorithm to build a daily weather forecast model at Soekarno-Hatta Airport. The model built will assist forecasters in making weather forecasts on a local scale, namely by using synoptic weather parameter data observed by Soekarno-Hatta Meteorological Station as a data set. The weather parameters in question are parameters that are closely related to determining daily weather conditions physically, namely air temperature, wind speed, air humidity, cloud coverage, air pressure (Anaxos, 2008).

Along with the development of technology, a new approach to processing large and complex data sets is known as Machine Learning (ML). According to (Goldberg & Holland, 1988). The use of ML on a computer can handle new situations through self-training, experience, analysis, and observation. However, ML algorithms tend to focus on learning only one or two layers of data representation, so for this condition further research is carried out so that DL or deep learning appears. Artificial Neural Network (ANN) is one of the effective techniques DL algorithm to build a computerised system capable of processing non-linear weather conditions in a particular domain and can also make forecasts (Fente & Singh, 2018; Jishan et al., 2015). ANN architecture or structure arrangement of layer components and neurons contained in the input, hidden and output connected with weights, activation functions and learning functions (Fente & Singh, 2018; Wica et al., 2019). One ANN model that can be used in making a weather forecast is BiLSTM (Sharma & Sharma, 2022). BiLSTM is able to capture the context of input data at previous and future times so that it is quite relevant in use for a forecast.

Method

Dataset

The input parameter dataset used in this study is the weather elements data from the observation of surface air every hour at Soekarno-Hatta Meteorological Station for the period 1 January 2018 - 31 December 2022 used to make daily weather forecasts at Soekarno-Hatta Airport, namely in the form of temperature, air humidity (Wardani et al., 2023), cloud coverage, wind speed, air pressure, and weather conditions.

Bidirectional Long-Short Term Memory (BiLSTM)

BiLSTM can improve the model performance of sequential classification problems (Verma et al., 2021). Long-Short Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997) itself is one of the models which is an extension of RNN (Akram & El, 2016; Salehin et al., 2020; Singh et al., 2019) LSTM is well used to classify, process and make forecasts based on time series data or longer time series data repeatedly (Hsu et al., 2021). In addition to the given h(t) at the next time step, LSTM uses linear dependence to connect the current memory cell and the given past memory cell from one unit time step to the next time step. With these memory cells, LSTM is able to remember information for a long time and use the information for current processing without forgetting important information from the previous time step (Hennayake et al., 2021).

The LSTM consists of memory blocks that allow it to store long-term memory well. The LSTM memory block consists of a memory cell and three gate units called forget gate, input gate, and output gate (Canar et al., 2020; Mimboro et al., 2021) three unit gates will control the flow of data that will enter and exit the memory cell. The LSTM memory block architecture is shown in Figure 1.

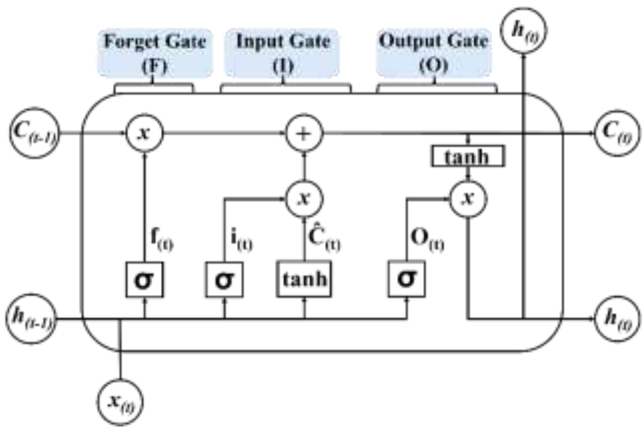

Figure 1. LSTM memory block architecture

The LSTM memory block receives three input signals, namely the input data at the current time step (x(t)), the hidden state of the previous unit (h(t-1)) and the cell state of the previous time step unit (C(t-1)). The LSTM memory block outputs two output signals, namely the hidden state of the current unit (h(t)) and the cell state at the current unit time step (C(t)). Forget gate (f(t)) determines how much information can be passed on. The input signals x(t) and h(t-1) are calculated with an output value between 0 and 1.

$$f_{(t)} = \sigma\,(W_f\,[h\,x_{(t-1)}\,,\,x_{(t)}] + b_f) \quad (1)$$

Input gate (i(t)) decides the value to be updated using the sigmoid layer (Eq. 2). Next, the hyperbolic tangent is used to generate a new context vector candidate value, C̃(t).

$$i_{(t)} = \sigma\,(W_i\,[h\,x_{(t-1)}\,,\,x_{(t)}] + b_i) \quad (2)$$

$$\tilde{C}(t) = \tanh\,(Wi\,[h\,x(t-1)\,,\,x(t)] + bi) \quad (3)$$

Next to update the previous cell state C(t-1), this stage the memory cell will eliminate information on past data and add new information.

$$C(t) = f(t)*C(t-1) + i(t)*\tilde{C}(t) \quad (4)$$

Output gate (o(t)) will decide the results that have been obtained. The first step uses a sigmoid layer to determine the information that has been generated from the cell state.

$$o(t) = \sigma\ (Wo\ [h(t-1)\ ,\ x(t)] + bo) \quad (5)$$

Then the calculation is done through the tanh layer to scale the value between -1 to +1 so as to produce (tanh(C(t))). In this process will only produce new subjects or parts that are decided to get the current hidden state unit (h(t)).

$$h_{(t)} = o_{(t)} * \tanh(C_{(t)}) \quad (6)$$

BiLSTM is referred to as an improvement over the LSTM model. In Figure 2 shows that BiLSTM runs information in both forward and backward directions at each time step (Verma et al., 2021), both forward and backward data sequences will be used to calculate the output value. This step can provide additional context for the network to understand the problem faster and more comprehensively.

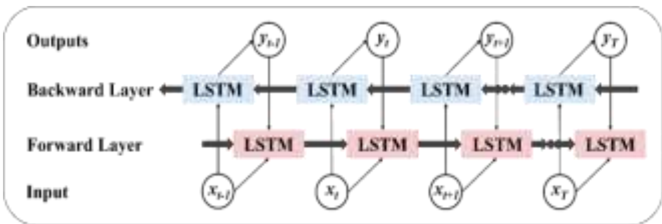

Figure 2. BiLSTM Architecture

Preprocessing Data

Data normalisation is done because of the difference in values or units in the input data used and the output obtained (Abhishek et al., 2012). Equation 7 is a data normalisation min-max equation used to produce new values in the 0-1 value range.

$$Xnorm = \frac{Xi - Xmin}{Xmax - Xmin} \quad (7)$$

where Xi is the value of a feature in the dataset

Training data uses the initial part up to 70% of the data set used, while the remaining 30% of the data set is used as validation or testing data. The output of this research is weather conditions categorised into sunny, sunny cloudy, cloudy, light rain, moderate rain, heavy rain, and thunder rain. The results obtained will go through model verification and evaluation by finding the accuracy value by comparing the weather forecast model output with actual weather data using a multi-category contingency table. The best model will be used to built the daily weather forecasts are displayed with a web-based viewer system. The experimental design of the model in this study is generally presented in the flow chart in Figure 3.

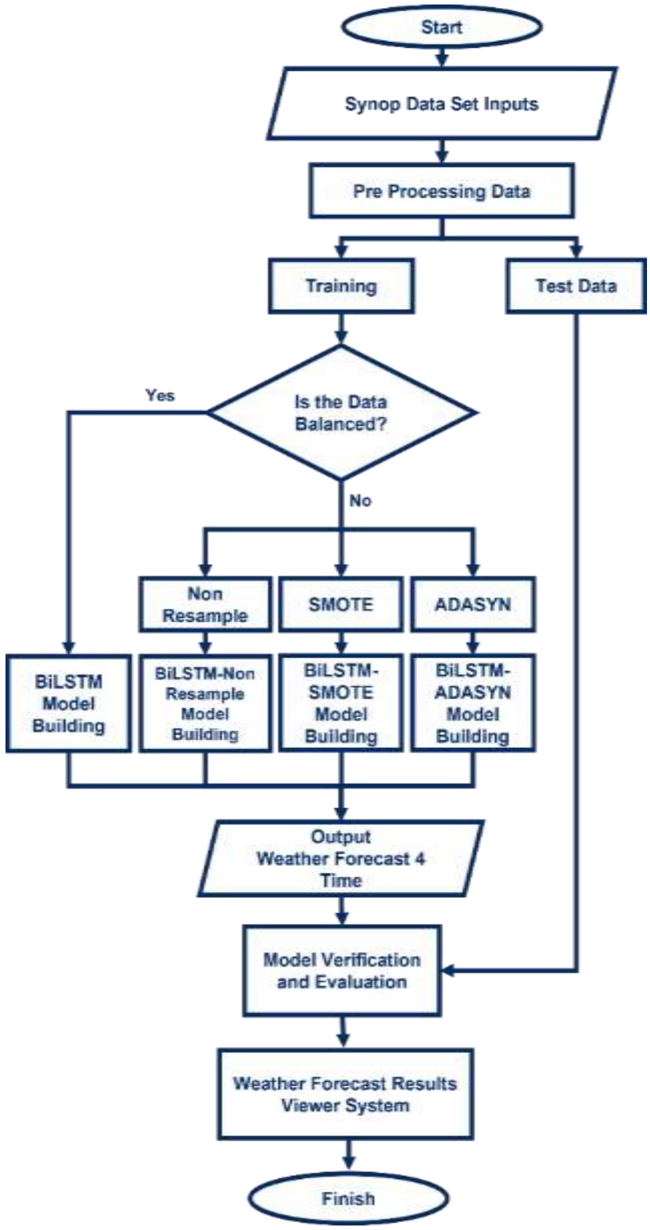

Figure 3. Flowchart of research experiment design

Model Algorithm Design

The BiLSTM model was built using the Python3 programming language. The BiLSTM structure used in this research can be seen in Figure 4. The BiLSTM model used in this study consists of BiLSTM as encoder, BiLSTM as decoder, and forward layer. The input data set is 6 time series data from the selected input parameters using a time range scheme of 1 day, 3 days, and 7 days. This is done to get the best modelling scheme. The entire data set is normalised using equation 13 which is then divided into training data and testing data. The training data is pre-processed with selected over-sampling techniques which will then be processed by the model. The output data of the model will produce daily weather forecasts based on 4 time conditions of morning, afternoon, evening, and early morning in the form of JavaScript Object Notation (JSON) data format.

Figure 4. BiLSTM Model processing algorithm block

Sampling Methods on Imbalanced Data

In general, there are several approaches to overcome imbalanced data, one of which is by using the original data sampling metho (Rahayu et al., 2017; Yakshit et al., 2022; Chen et al., 2019). In this study, we will use the over-sampling technique to overcome the problem of imbalance in the data set used. Over-sampling will duplicate instances exactly so that it can increase the weight on the minority class by repeating instances of the minority class (Rahayu et al., 2017; Yakshit et al., 2022). Examples of over-sampling techniques include:

Adaptive Synthetic (ADASYN)

The ADASYN approach can produce adaptive samples in synthetic data against minority classes formed by data distributions, with the objective of reducing bias due to unequal data distribution on other labels with majority classes (He et al., 2008).

Synthetic Minority Oversampling Technique (SMOTE)

Over-sampling in SMOTE takes samples from the minority class and then finds the k-nearest neighbour of each sample, then produces synthetic samples derived from replication in the minority class (Chawla et al., 2002; Sutoyo & Fadlurrahman, 2020). In SMOTE algorithm the number of synthetic samples generated for each minority class is the same whereas in ADASYN the required number of synthetic samples is generated for each minority class sample according to its distribution (Gosain & Sardana, 2017).

Model Verification and Evaluation

At this stage, verification of model performance is carried out by comparing output and real data (observations). In this study using multicategory verification (Brooks & Doswell, 1996) which is verification for outputs consisting of several categories with the help of the following multicategory contingency table 1.

Table 1. Multicategory Contingency Table

		Observation category (O)			
	i	1	...	K	Total
Forecast category (F)	1	$n(F_1.O_1)$	...	$n(F_1.O_K)$	$N(O_1)$
	...	...	...	...	...
	K	$n(F_K.O_1)$	...	$n(F_K.O_K)$	$N(O_K)$
	Total	$N(F_1)$	...	$N(F_K)$	N

Where i (1, ..., K) is the category in each forecast (F) and observation (O) and N is the total of all categories in each forecast (F) and observation (O). After obtaining the N value, calculations are then carried out to obtain the accuracy value of the model in forecasting the weather at each time condition. This is done by multiplying the N value by 100%.

System Design of Daily Weather Forecast Result Viewer

Daily weather forecasts are displayed with a web-based viewer system. The webpage is built using the Gin Gonic web framework with the Go Language (Golang) programming language. In the model output viewer system for weather forecasts, an Application Programming Interface (API) is built. The viewer application is placed on the localhost network so that the prediction model does not need to send data in JSON format because it is on the same localhost network. By using the Asynchronous JavaScript and XMLHTTP (AJAX) technique, the web page can update its own display without updating the page on the forecaster's browser.

Result and Discussion

At this stage, training is carried out on each of the three BiLSTM Model schemes. The ready training data is then processed by 3 hidden layers with 15 neurons for each layer. Training is done using the Pytorch framework. The training process is carried out using the following hyperparameter configuration: learning rate = 0.0001, epoch = 100, batch size = 64, and the process will be completed when it reaches the last epoch value. This hyperparameter configuration is obtained through a trial and error process so that the optimal value is obtained.

```
Epoch: 14, Loss: 0.659892490368611
Epoch: 15, Loss: 0.6598985459692853
Epoch: 16, Loss: 0.6598468802356392
Epoch: 17, Loss: 0.6598784528348671
Epoch: 18, Loss: 0.6598272901534267
Epoch: 19, Loss: 0.659850976865433
Epoch: 20, Loss: 0.6598582247940196
Epoch: 21, Loss: 0.6598490057964942
```

Figure 5. BiLSTM training process history

Figure 5 shows the training process of the BiLSTM Model for forecasting weather forecasts in the morning time conditions with a 1 day data input scheme as an example to represent the entire model training process where the higher the epoch value, the lower the loss value.

The three modelling schemes utilise a backpropagation algorithm to learn the patterns given in the training phase. When using backpropagation, the weight and bias values in the BiLSTM will be updated continuously in one epoch. Figure 6 shows the training convergence graph for each model with the 1 day input data scheme taken as an example to represent all scheme.

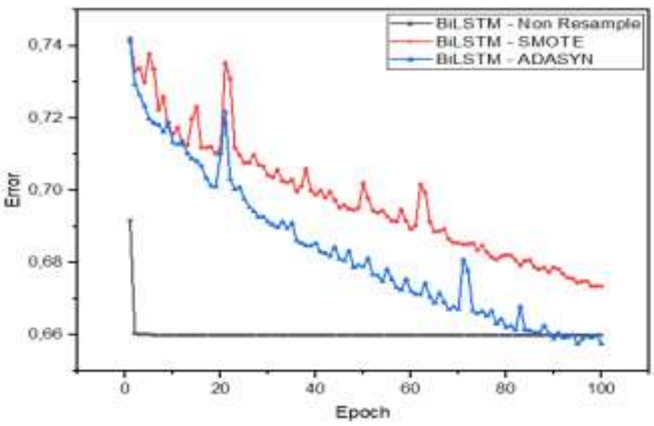

Figure 6. Training convergence chart

Figure 6 shows the comparison of loss convergence in BiLSTM - Non Resample, BiLSTM - SMOTE, and BiLSTM - ADASYN models. The BiLSTM - Non Resample model shows a drastic loss value convergence in the initial training phase but looks constant afterwards. The BiLSTM - ADASYN model is more significant in reducing the loss value during the initial training phase than the BiLSTM - SMOTE model. In general, the loss value graphs on all models appear to decrease where the error value decreases, indicating that the model is able to learn the given data pattern.

Model performance is carried out as an indicator of model performance in each weather category in each forecast time condition presented in the form of a contingency table. Furthermore, the accuracy value is calculated based on the accuracy of the model in making weather forecasts.

Morning Weather Forecast Model Performance

The performance of the BiLSTM Model calculation results is shown in Figure 7. The BiLSTM - Non Resample model has a high accuracy value in predicting cloudy weather conditions of 81%, but in other weather conditions the forecast accuracy is 0%.

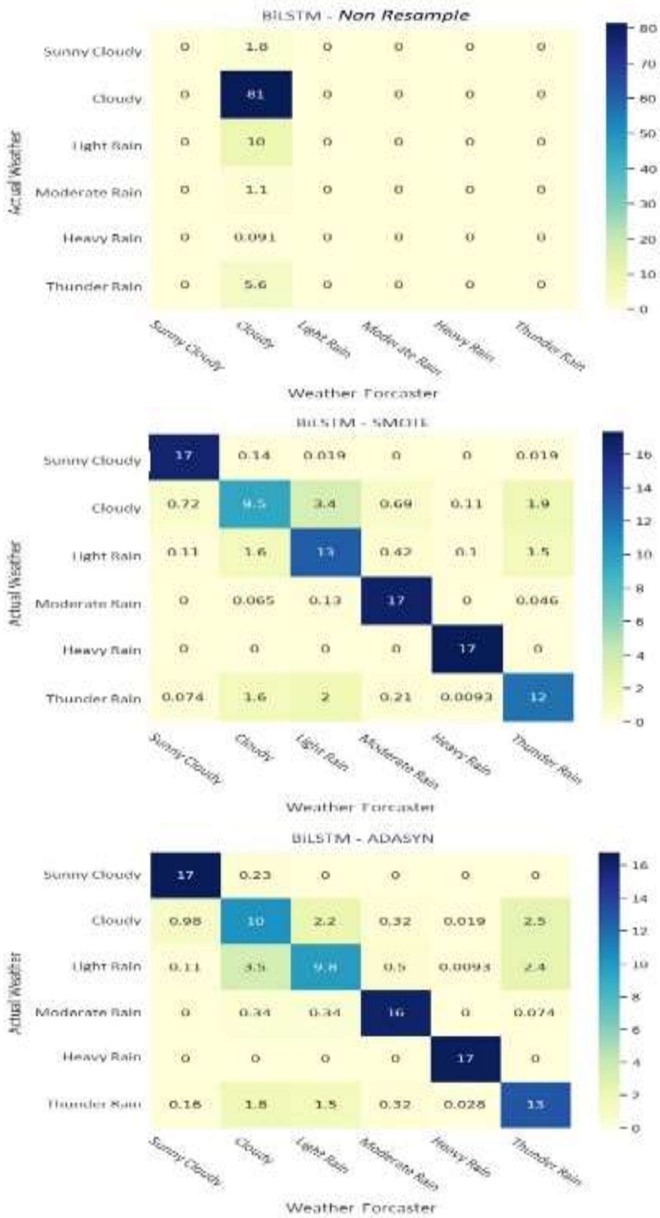

Figure 7. Contingency table display of morning weather forecasts in each modelling scheme with 1 day data input

In the BiLSTM-SMOTE Model, there is a distribution of accuracy values in each weather forecast with actual weather. Accuracy in predicting moderate rain and heavy rain weather conditions gets the highest value of 17%, while the lowest accuracy value in light rain weather conditions is 9.5%. Just like the BiLSTM-SMOTE Model, the BiLSTM - ADASYN Model produces a spread of accuracy values in forecasting weather conditions at Soekarno-Hatta Airport. The highest value of 17% occurred during cloudy and heavy rain weather conditions, while the lowest accuracy value was 9.8% during light rain weather conditions.

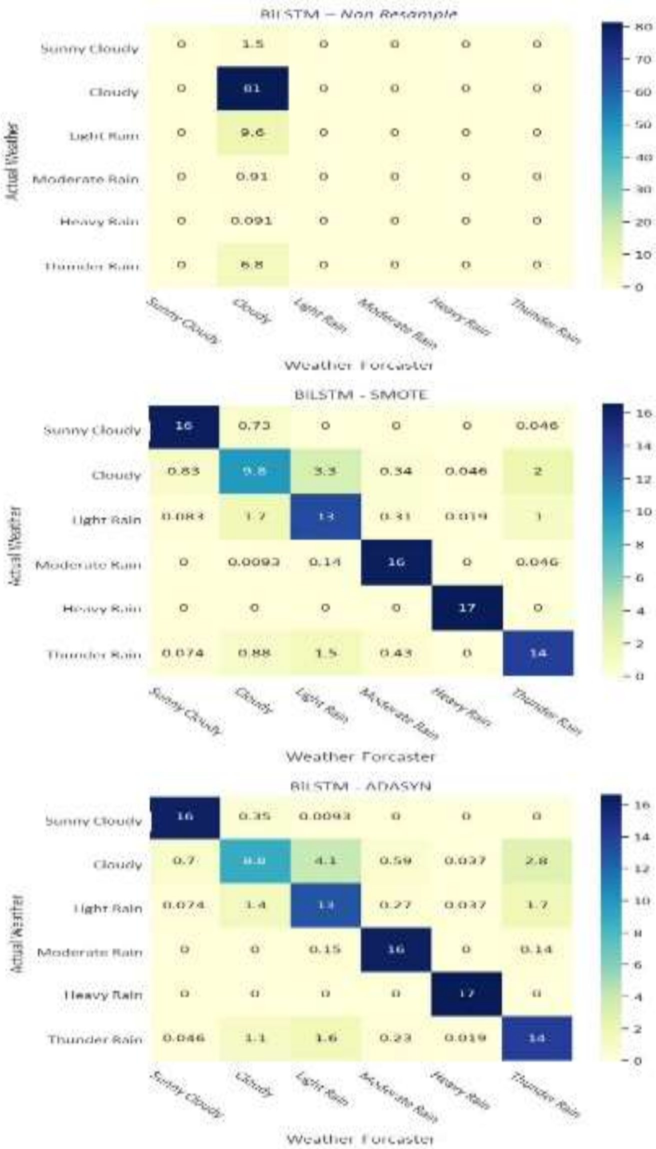

Figure 8. Contingency table display of morning weather forecasts in each modelling scheme with 3 days of data input

Figure 8 displays the morning weather forecast contingency table in each model scheme with 3 days of data input. The results of the BiLSTM - Non Resample Model calculation have a high accuracy value in predicting cloudy weather conditions, which is 81%, but in other weather conditions the forecast accuracy is 0%. The BiLSTM - SMOTE and BiLSTM-ADASYN models get the highest accuracy value in predicting heavy rain conditions, which is 17%.

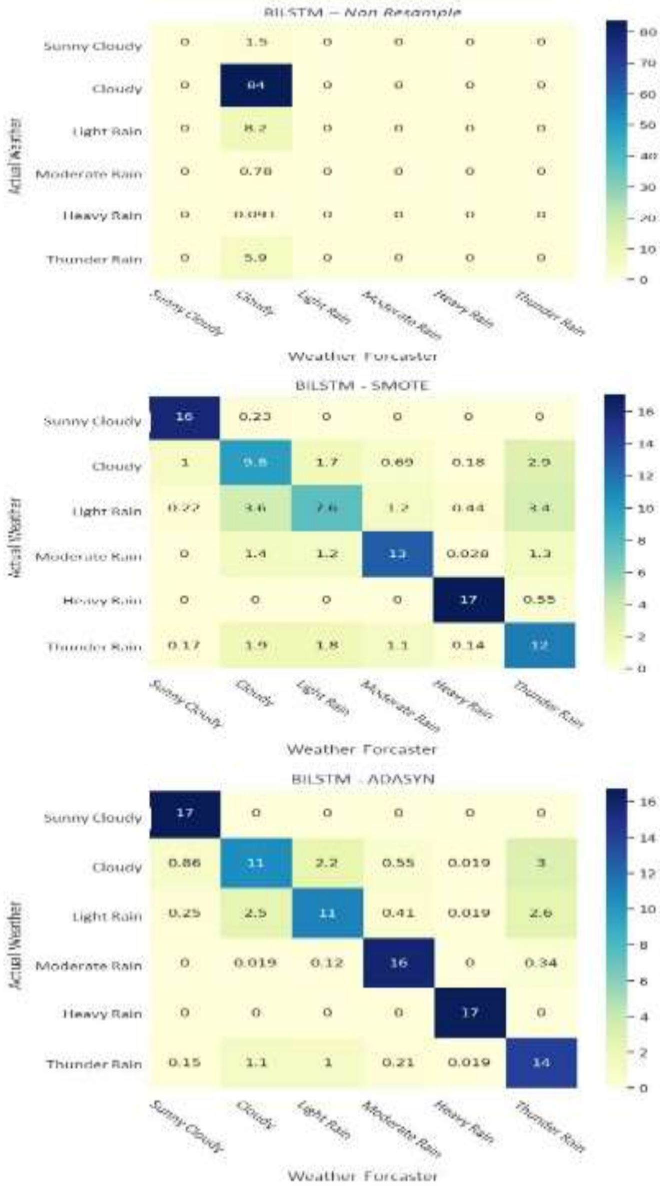

Figure 9. Contingency table display of morning weather forecasts in each modelling scheme with 7 days of data input

It can be seen in Figure 9 that the results of the BiLSTM - Non Resample Model calculation with 7 days of input data have a high accuracy value in predicting cloudy weather conditions, which is 84%. In the BiLSTM - SMOTE Model, the accuracy in predicting heavy rain weather conditions gets the highest value of 17%, while the lowest accuracy value in light rain weather conditions is 7.6%. The highest accuracy value on the BiLSTM-ADASYN Model of 17% occurred during cloudy and heavy rain weather conditions, while the lowest accuracy value was 11% during cloudy and light rain weather conditions.

After obtaining the accuracy value of each weather condition with the contingency table, calculations are then carried out to obtain the accuracy value of each model in predicting the weather in the morning with each data input scheme. Figure 10 shows a comparison of model accuracy results. In the 1 day and 3 days data input schemes, the BiLSTM - SMOTE model gets the highest accuracy value of the other two models, which is 85.5% and 85.8%. While the BiLSTM - ADASYN model excels in the 7 days data input scheme with an accuracy value of 86%.

Daytime Weather Forecast Model Performance

The contingency table display of daytime weather forecasts in each model scheme with 1 day of data input can be seen in Figure 11. The BiLSTM - Non Resample model has a high accuracy value in predicting cloudy weather conditions of 83%, but in other weather conditions the forecast accuracy is 0%.

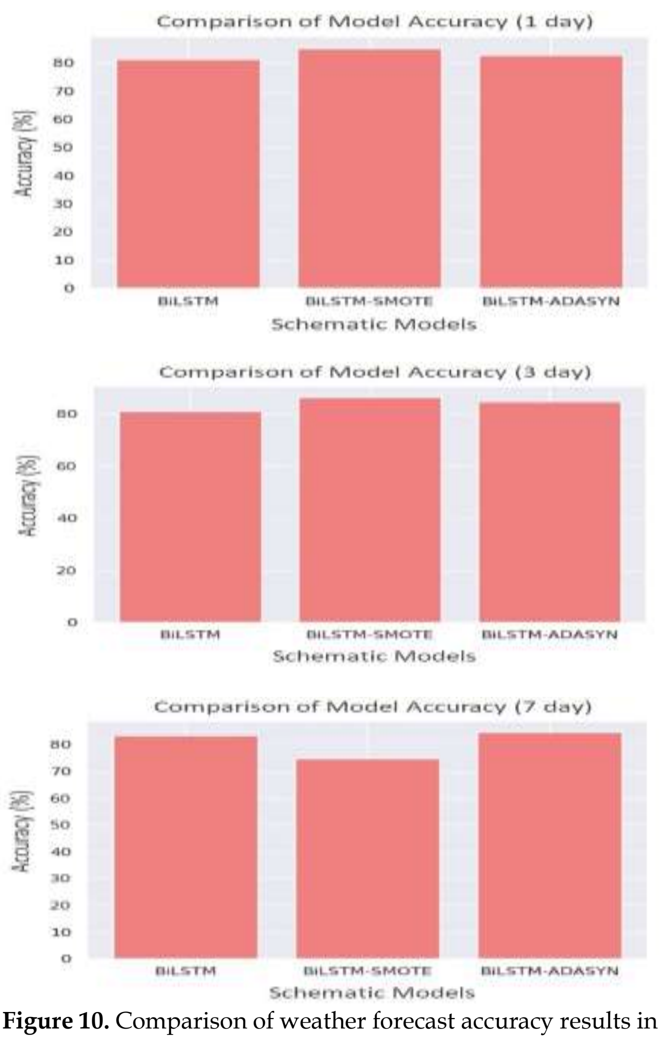

Figure 10. Comparison of weather forecast accuracy results in the morning time

In the BiLSTM - SMOTE and BiLSTM - ADASYN models, there is a distribution of accuracy values between weather forecasts and actual weather. Both models have the highest accuracy value in predicting heavy rain weather conditions, which is 17%, while the lowest accuracy value is in cloudy weather conditions.

Figure 12 shows the results of the BiLSTM - Non Resample Model calculation with 3 days of input data has a high accuracy value in predicting cloudy weather conditions of 83%. In the BiLSTM - SMOTE Model, the accuracy in predicting cloudy weather conditions, moderate rain, and heavy rain gets the highest value of 16%, while the lowest accuracy value in cloudy weather conditions is 7.9%. The highest accuracy value on the BiLSTM-ADASYN Model of 17% occurred during heavy rain weather conditions.

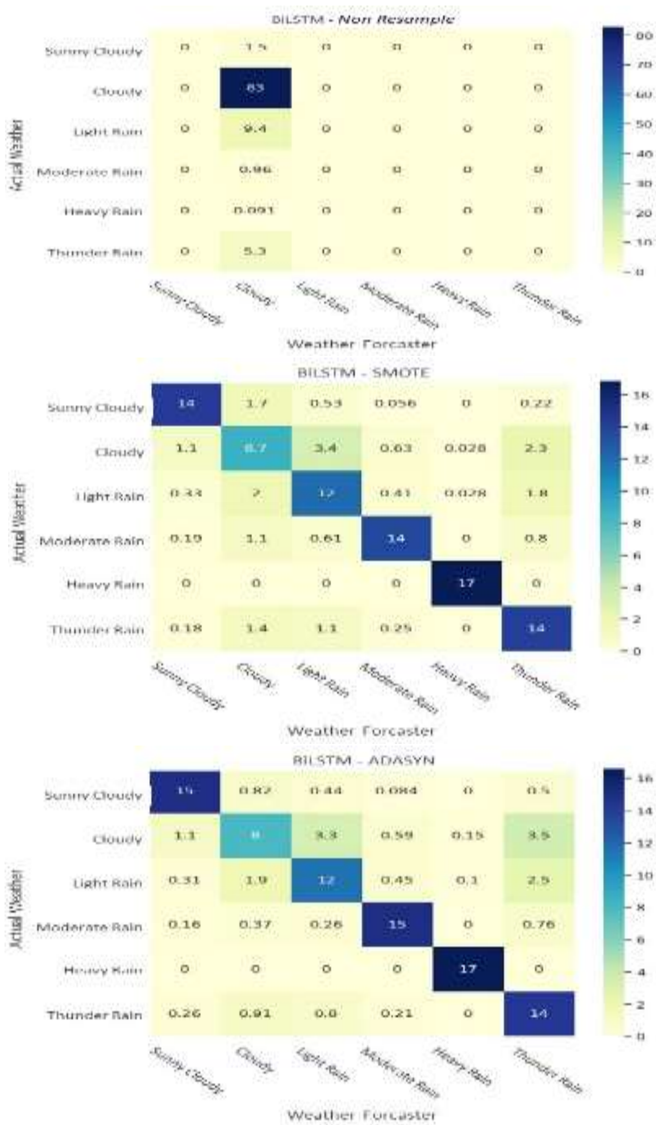

Figure 11. Contingency table display of daytime weather forecasts in each modelling scheme with 1 day data input

Figure 13 displays the contingency table of daytime weather forecasts in each model scheme with 7 days of data input. The results of the BiLSTM - Non Resample Model calculation have a high accuracy value in predicting cloudy weather conditions, namely 82%, in the BiLSTM - SMOTE and BiLSTM-ADASYN Models get the highest accuracy value in predicting heavy rain weather conditions, namely 17%, while the lowest accuracy value in cloudy weather conditions.

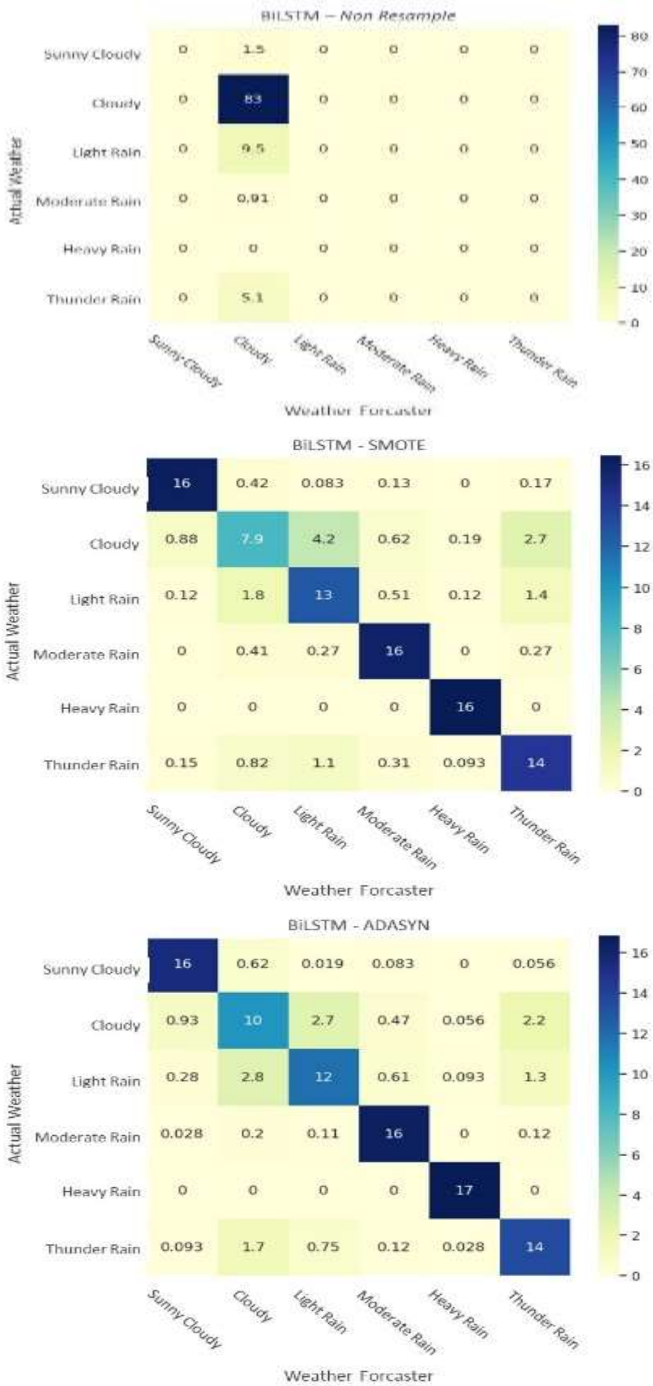

Figure 12. Contingency table display of daytime weather forecasts in each modelling scheme with 3 days of data input

Nighttime Weather Forecast Model Performance

Figure 15 shows the calculation results of the BiLSTM - Non Resample Model has a high accuracy value in predicting cloudy weather conditions, which is 82% in the 1 day data input scheme, but in other weather conditions the forecast accuracy is 0%. The BiLSTM - SMOTE and BiLSTM-ADASYN models get the highest accuracy value in predicting heavy rain weather conditions, which is 17%, while the lowest accuracy value in forecasting cloudy weather conditions.

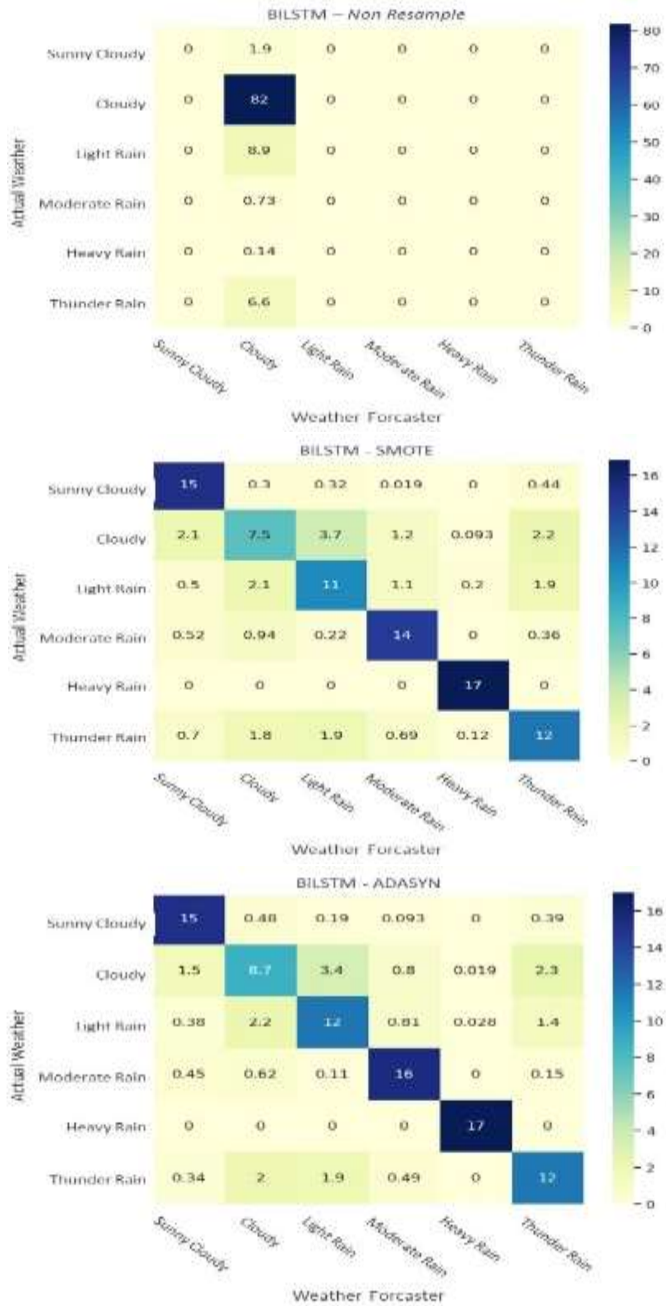

Figure 13. Contingency table display of daytime weather forecasts in each modelling scheme with 7 days of data input

Furthermore, Figure 14 shows a comparison of the accuracy results of weather condition forecast models during the day. It can be seen that the overall highest accuracy value is the BiLSTM - ADASYN Model in the 3 days data input scheme with an accuracy value of 85%.

Figure 16 displays the contingency table of weather forecasts at night time in each model scheme with 3 days of data input. The results of the BiLSTM - Non Resample Model calculation have a high accuracy value in predicting cloudy weather conditions, which is 82%. In the BiLSTM - SMOTE Model, the accuracy in predicting heavy rain weather conditions gets the highest value of 17%, while the lowest accuracy value in cloudy weather conditions is 8.9%. The highest accuracy value on the BiLSTM - ADASYN Model of 16% occurred during cloudy and heavy rain weather conditions.

Seen in Figure 17 shows the results of the BiLSTM - Non Resample Model calculation with 7 days of input data has a high accuracy value in predicting cloudy weather conditions, which is 83%. In the BiLSTM - SMOTE Model, the accuracy in predicting heavy rain weather conditions gets the highest value of 17%. The highest accuracy value in the BiLSTM - ADASYN Model of 16% occurred during heavy rain weather conditions, while the lowest forecast accuracy value in cloudy weather conditions was 5.4%.

The accuracy of weather forecasts at night time in each model is shown in Figure 18. In the overall data input scheme of 1 day, 3 days and 7 days, the BiLSTM - Non Resample model gets the highest accuracy value, which is 82%, 82%, and 83% respectively.

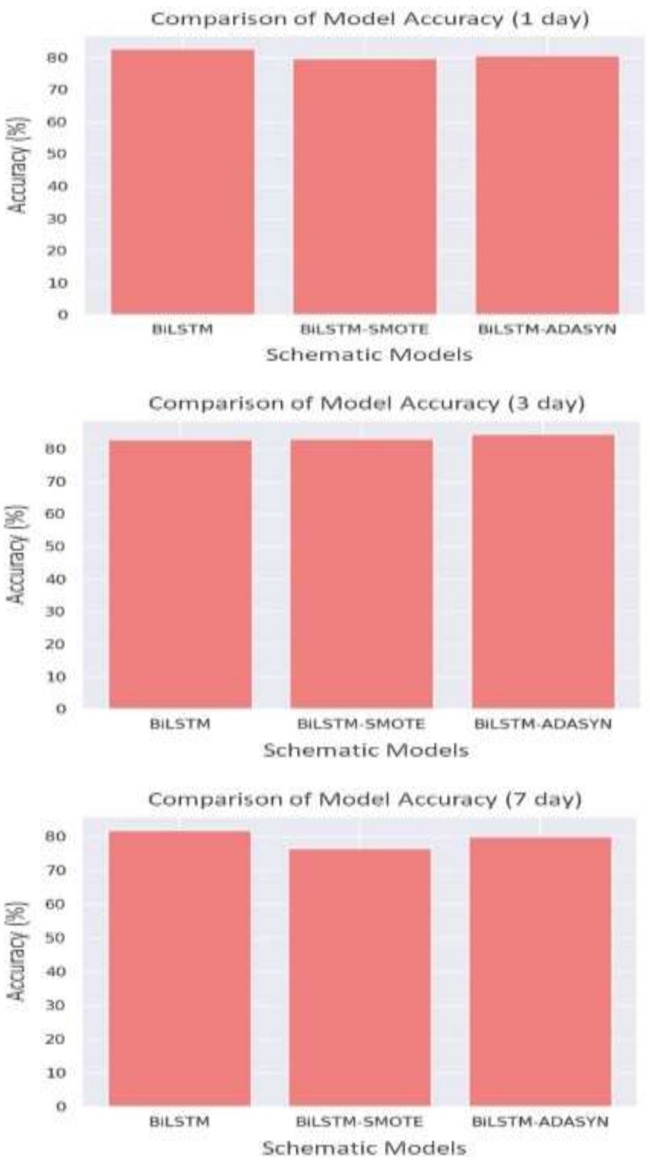

Figure 14. Comparison of weather forecast accuracy results at noon time

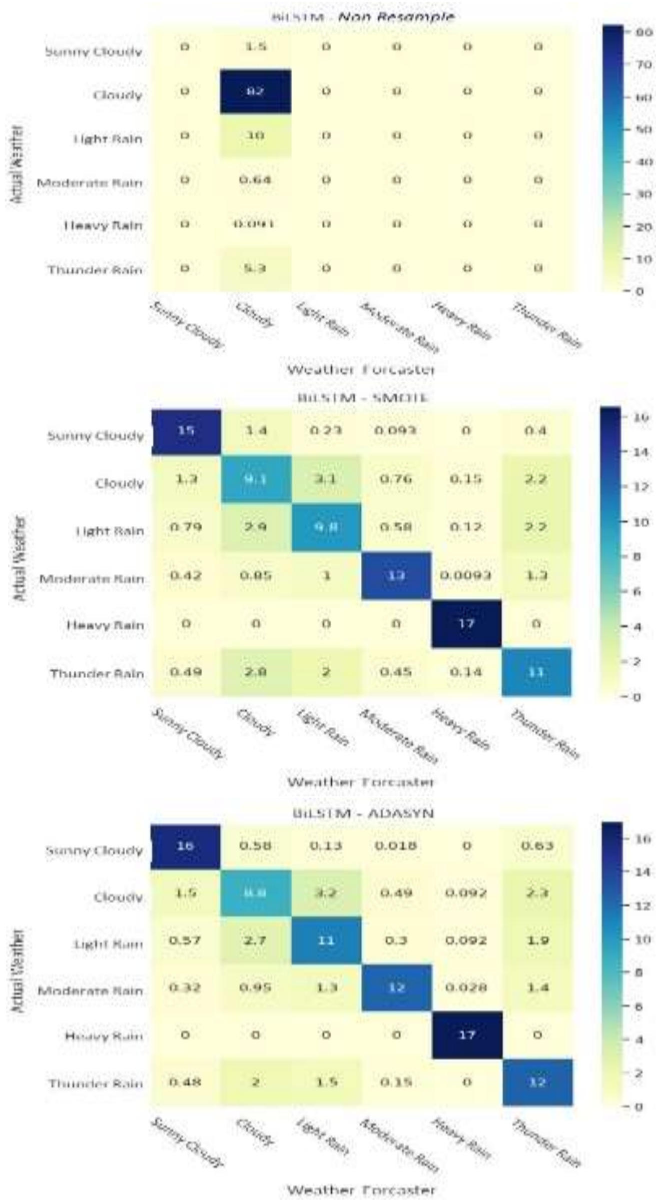

Figure 15. Contingency table display of night weather forecasts in each modelling scheme with 1 day data input

Early Morning Weather Forecast Model Performance

The performance of early morning weather forecasts in each model scheme with 1 day data input is shown in Figure 19. The BiLSTM - Non Resample model has a high accuracy value in predicting cloudy weather conditions, which is 81%. In the BiLSTM - SMOTE and BiLSTM - ADASYN models, there is a distribution of accuracy values between weather forecasts and actual weather. Both models have the highest accuracy value in predicting heavy rain weather conditions, namely 16% and 17% respectively, while the lowest accuracy value in cloudy weather conditions.

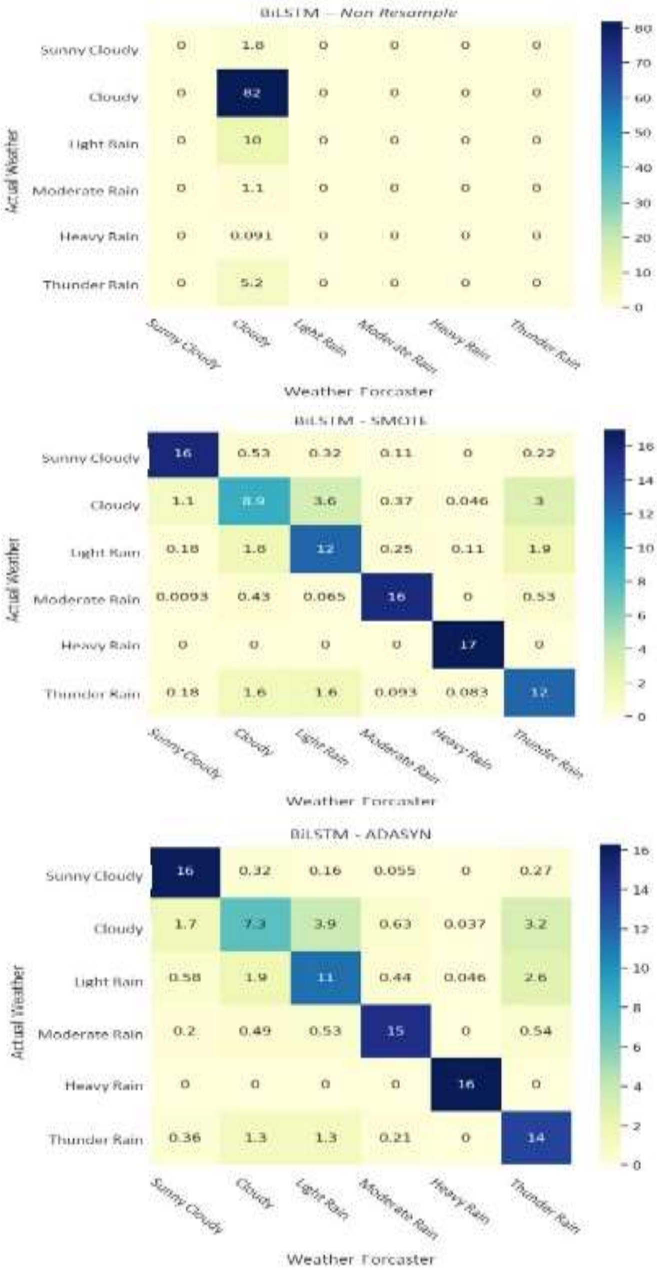

Figure 16. Contingency table display of night weather forecasts in each modelling scheme with 3 days of data input

Based on Figure 20 the results of the BiLSTM - Non Resample Model calculation with 3 days of input data have a high accuracy value in predicting cloudy weather conditions, which is 84%. In the BiLSTM - SMOTE Model, the accuracy in predicting cloudy and heavy rainy weather conditions gets the highest value of 16%. The highest accuracy value on the BiLSTM - ADASYN Model of 17% occurs during moderate rain and heavy rain weather conditions, while the lowest accuracy value in cloudy weather conditions, which is 8.7%.

Figure 17. Contingency table display of night weather forecasts in each modelling scheme with 7 days of data input

Figure 21 displays the contingency table of each weather forecast model scheme at dawn with 7 days of data input. The results of the BiLSTM - Non Resample

Model calculation have a high accuracy value in predicting cloudy weather conditions.In the BiLSTM - SMOTE Model and the BiLSTM - ADASYN Model, the accuracy in predicting heavy rain weather conditions gets the highest value of 17%, while the lowest accuracy value in cloudy weather.

Figure 22 shows a comparison of model accuracy results in early morning weather conditions. The highest overall accuracy value is 84%, namely the BiLSTM - Non Resample Model in the 3 days data input scheme.

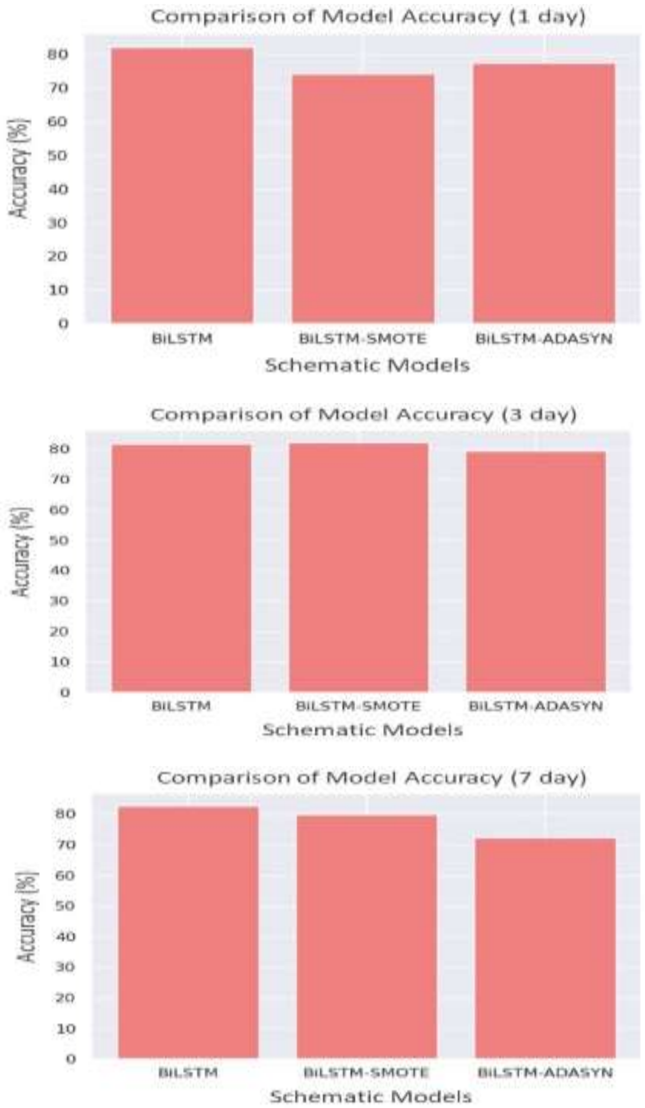

Figure 18. Comparison of weather forecast accuracy results at night time

Based on the overall description of the model verification results that can be seen in each display of the weather forecast contingency table, the BiLSTM - Non Resample Model scheme shows no precise weather forecasts with actual weather except in cloudy weather conditions, so the accuracy value in other weather conditions is 0%. In contrast to the BiLSTM - SMOTE Model and the BiLSTM - ADASYN Model which show a spread of accuracy values in each forecast of weather conditions at Soekarno-Hatta Airport. This proves that the over-sampling technique is able to overcome the imbalance of the data set used.

Model Comparison Evaluation Results

After knowing the performance of each model at each weather forecast time condition with different input data, then an overall comparison evaluation is carried out to find the best model. This is done by finding the average accuracy value of each model across all weather conditions (a combination of morning, afternoon, night, and early morning) against the input data scheme used.

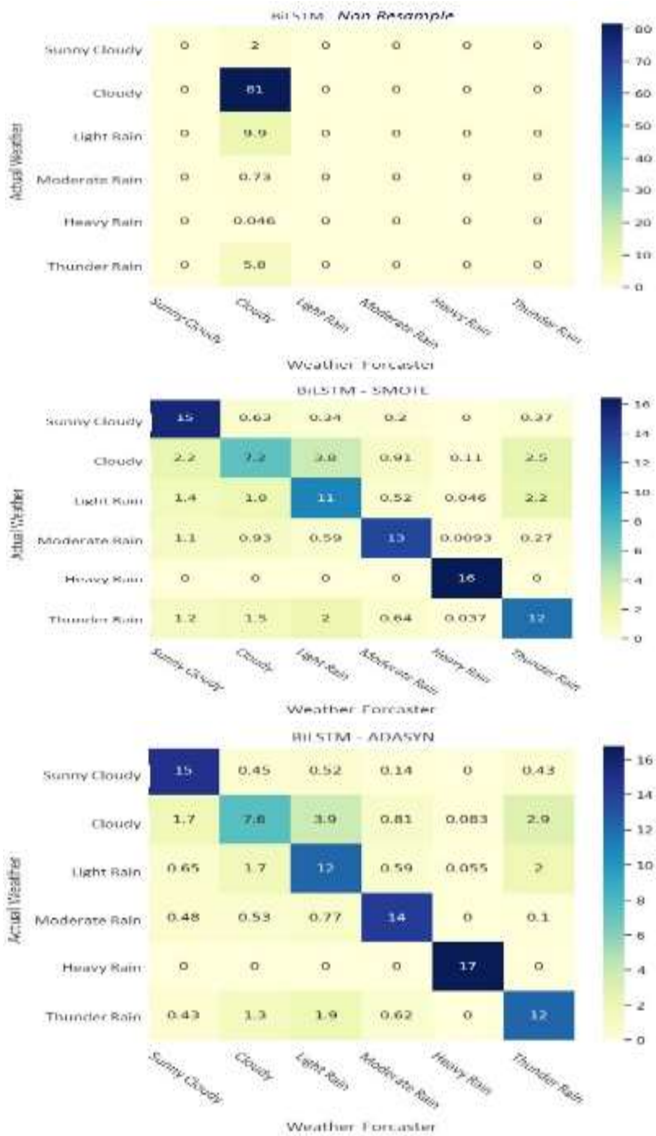

Figure 19. Contingency table display of early morning weather forecasts in each model scheme with 1 day data input

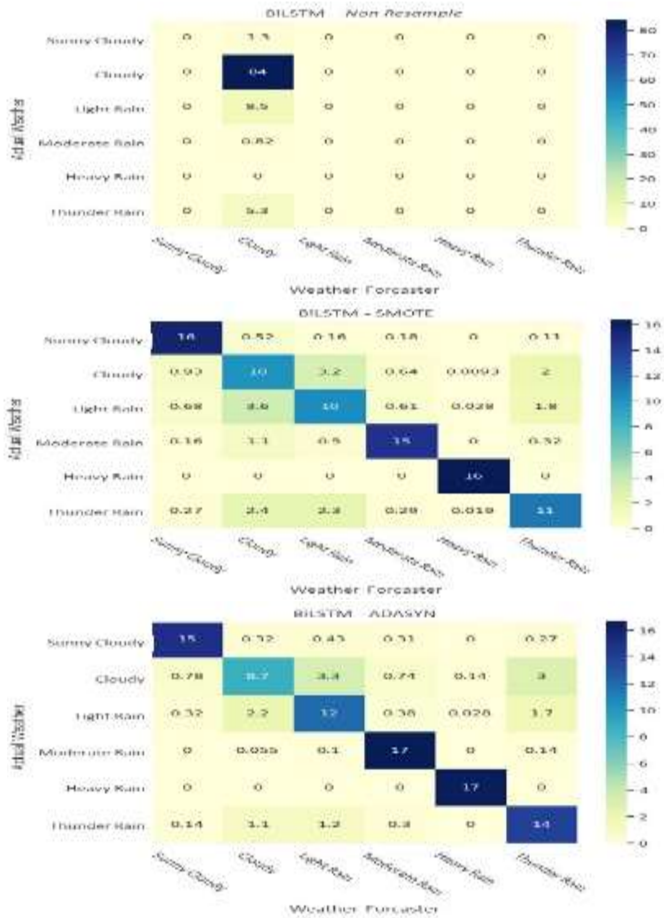

Figure 20. Contingency table display of early morning weather forecasts in each model scheme with 3 days of data input

Based on Figure 23, it is known that overall the BiLSTM - Non Resample Model gets an average accuracy value above 80% in all data input schemes, but it has been stated in the previous description, that the BiLSTM - Non Resample Model is only able to accurately predict cloudy weather conditions. This is certainly a mistake if the BiLSTM - Non Resample Model is used. Unlike the other two models, the BiLSTM - SMOTE Model and the BiLSTM - ADASYN Model appear to experience the same graphical shape. Both models get a fairly low average accuracy value in the 1 day and 7 days data input schemes but there is an increase in value in the 3 days data input scheme. This is due to the large number of weather parameters (features) processed in the 7 days data input scheme so as to get a lot of feature patterns, but the distribution of the amount of data from each feature used is relatively small, especially in the number of weather condition features (WW). In the 1 day data input scheme, the information provided is too little so that the model is less optimal in making weather forecasts. In contrast to the previous two data input schemes, the 3 days data input scheme obtained a higher accuracy value because many features used get a pattern that is in accordance with the model built, thus getting optimal results shown by the acquisition of high accuracy values. Along with the above description, it can also be mentioned that Figure 23 shows that the BiLSTM - ADASYN Model with a 3 days data input scheme is the best model with the highest average accuracy value of 83.2%.

Daily Weather Forecast Viewer System Results

The simulation results of the weather forecast system in this study can be seen in Figure 24. The system created uses the best model algorithm, namely the BiLSTM - ADASYN Model with a 3 days data input scheme. In the web application, the system will display forecasts of weather conditions at 4 different time conditions for the next day or within 24 hours, namely in the morning, afternoon, evening, and early morning time conditions. Figure 26 is an example of a weather forecast system display on Friday, 2 June 2023. It can be seen that the model predicts weather conditions in the morning to be cloudy, in the afternoon light rain is predicted, and at night and early morning it is predicted to be cloudy.

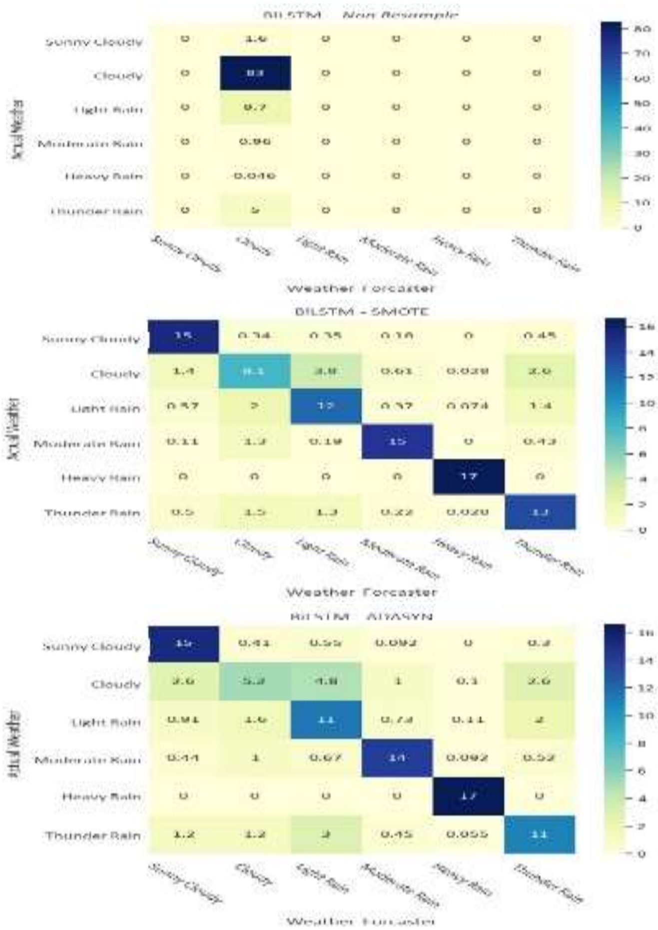

Figure 21. Contingency table display of early morning weather forecasts in each model scheme with 7 days of data input

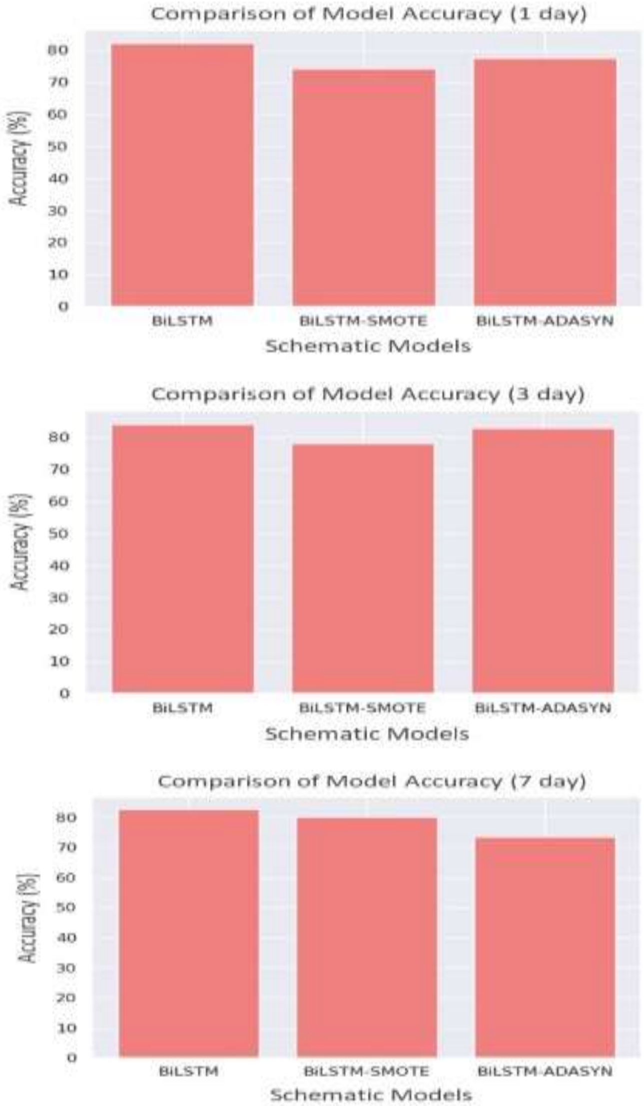

Figure 22. Contingency table display of early morning weather forecasts in each model scheme with 3 days of data input

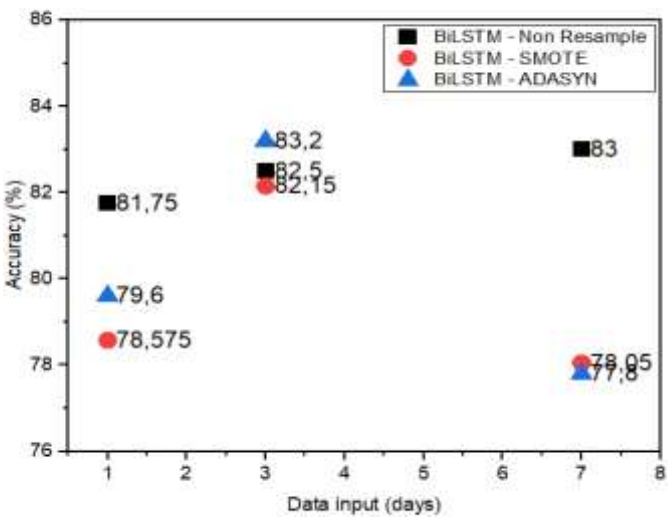

Figure 23. Comparison graph of the average accuracy value of the model

Figure 24. Daily weather forecast viewer system

Conclusion

The BiLSTM - ADASYN Model with a 3 days data input scheme in this study has a better performance than the two comparison models, which is 83.2%. Data on weather elements from hourly observations of surface air Soekarno-Hatta Meteorological Station can be used to build a daily weather forecast model at Soekarno-Hatta Airport using the BiLSTM algorithm. Data imbalance in the data set used can be overcome with SMOTE and ADASYN over-sampling techniques. This is evidenced by the results of verification using a multicategory contingency table which shows the distribution of accuracy values in each forecast weather condition on the results of the BiLSTM - SMOTE Model and the BiLSTM - ADASYN Model weather forecasts where before the data is over-sampled it is only able to accurately make weather forecasts in cloudy weather conditions, while the rest is obtained 0% accuracy value shown by the BiLSTM - Non Resample Model weather forecast results. After comparing the accuracy value of each model against the data input scheme. The best model algorithm is then used in the weather forecast system. The simulation results of the system display the forecast of weather conditions at 4 time conditions well. The model produced in this study just be used to make weather forecasts in Soekarno-Hatta Airport. If the research location is changed to another location, it is necessary to replace the data set used in building the model. This is done because different locations have different surface air observation data, and the location will also be influenced by the geographical location and disturbances at that location so that it is necessary to build a suitable model.

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Author Contributions

Conceptualization: F. D, D. H.; supervision: D. H, I. P.; data curation: F. D.; funding acquisition: D. H, F. D.; methodology: F. D, D. H, M. R.; visualization: F. D.; writing-original draft: F. D.; writing–review : D. H, I. P.; editing: F. D.

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Conflicts of Interest

No Conflicts of interest.

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