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PREDICTION PERFORMANCE OF AIRPORT TRAFFIC USING BILSTM AND CNN-BI-LSTM MODELS

Willy Riyadi[1*]; Jasmir[2]

Sistem Komputer [1,2]
Universitas Dinamika Bangsa
https://unama.ac.id/
wriyadi5@gmail.com[1*], ijay_jasmir@yahoo.com[2]

(*) Corresponding Author

Abstract— *The COVID-19 pandemic has had a significant and enduring impact on the aviation industry, necessitating the accurate prediction of airport traffic. This study compares the predictive accuracy of biLSTM (Bidirectional Long Short-Term Memory) and CNN-biLSTM (Convolutional Neural Network-Bidirectional Long Short-Term Memory) models using various optimization techniques such as RMSProp, Stochastic Gradient Descent (SGD), Adam, Nadam, and Adamax. The evaluation is based on Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) indices. In the United States, the biLSTM model utilizing the Nadam optimizer achieved an MAPE score of 9.76%. On the other hand, the CNN-biLSTM model utilizing the Nadam optimizer demonstrated a slightly improved MAPE score of 9.62%. For Australia, the biLSTM model using the Nadam optimizer obtained an MAPE score of 31.52%. However, the CNN-biLSTM model employing the RMSprop optimizer had a marginally higher MAPE score of 33.33%. In Chile, the biLSTM model using the Adam optimizer obtained an MAPE score of 44.04%. Conversely, the CNN-biLSTM model using the RMSprop optimizer had a slightly higher MAPE score of 44.09%. Lastly, in Canada, the biLSTM model using the Nadam optimizer achieved a comparatively low MAPE score of 14.99%. Similarly, the CNN-biLSTM model utilizing the Adam optimizer demonstrated a slightly better MAPE score of 14.75%. These results highlight that the choice of optimization technique, model architecture, and balanced dataset can significantly influence the prediction accuracy of airport traffic.*

Keywords: *Airport Traffic, biLSTM, CNN-biLSTM, Covid19, Prediction.*

Intisari— *Pandemi COVID-19 telah memiliki dampak signifikan dan berkelanjutan pada industri penerbangan, yang membutuhkan prediksi yang akurat terhadap lalu lintas bandara. Penelitian ini membandingkan akurasi prediksi dari model biLSTM (Bidirectional Long Short-Term Memory) dan CNN-biLSTM (Convolutional Neural Network-Bidirectional Long Short-Term Memory) dengan menggunakan berbagai teknik optimasi seperti RMSProp, Stochastic Gradient Descent (SGD), Adam, Nadam, dan Adamax. Evaluasi dilakukan berdasarkan indeks Mean Absolute Error (MAE) dan Mean Absolute Percentage Error (MAPE). Di Amerika Serikat, model biLSTM yang menggunakan optimasi Nadam berhasil mencapai skor MAPE sebesar 9,76%. Di sisi lain, model CNN-biLSTM yang menggunakan optimasi Nadam menunjukkan peningkatan skor MAPE yang sedikit lebih baik yaitu 9,62%. Untuk Australia, model biLSTM yang menggunakan optimasi Nadam memperoleh skor MAPE sebesar 31,52%. Namun, model CNN-biLSTM yang menggunakan optimasi RMSProp memiliki skor MAPE yang sedikit lebih tinggi yaitu 33,33%. Di Chili, model biLSTM yang menggunakan optimasi Adam memperoleh skor MAPE sebesar 44,04%. Sebaliknya, model CNN-biLSTM yang menggunakan optimasi RMSProp memiliki skor MAPE yang sedikit lebih tinggi yaitu 44,09%. Terakhir, di Kanada, model biLSTM yang menggunakan optimasi Nadam mencapai skor MAPE yang relatif rendah yaitu 14,99%. Demikian pula, model CNN-biLSTM yang menggunakan optimasi Adam menunjukkan skor MAPE yang sedikit lebih baik yaitu 14,75%. Hasil-hasil ini menyoroti bahwa pilihan teknik optimasi, arsitektur model, dan dataset yang seimbang dapat secara signifikan mempengaruhi akurasi prediksi terhadap lalu lintas bandara.*

Kata Kunci: *Lalu lintas Bandara, biLSTM, CNN-biLSTM, Covid19, Prediksi.*

INTRODUCTION

Airports play a vital role in the transportation industry by serving as crucial terminals for aircraft takeoff, landing, and passenger transfer [1]. However, the COVID-19 pandemic in 2020 had a profound impact on the aviation sector. During the peak period from March to June, there was a significant decrease in passenger numbers, and approximately 17,000 aircraft fleets were non-operational [2]. Fluctuations in air traffic are a common occurrence in the aviation industry [3], and these fluctuations vary over time, making them suitable for analysis as Time Series data [4].

Over the past few decades, the air transport industry has been focusing on traffic forecasting methodologies. While formal studies and academic research on this topic have emerged relatively recently (around three decades ago) [5], various forecasting techniques have been developed to analyze Time Series data. These techniques include statistical methods, computational intelligence, or a combination of both [6],[7]. The primary objective of Time Series data analysis is to utilize historical observations to develop accurate models that reflect the underlying structure of the series [8]. These models enable the prediction and classification of future events [9].

In recent years, deep learning methods and techniques, particularly bidirectional Long short-term memory (biLSTM) and Convolutional Neural Network (CNN), have gained significant attention in academic research [10]. These methods have been successfully applied to real-world prediction problems, including the analysis of Time Series data. In particular, biLSTM and CNN models have emerged as popular and effective approaches for predicting traffic flow [11].

To utilize these models, the data undergoes preprocessing before being inputted into the CNN model to extract spatial features. However, CNNs alone lack the ability to capture sequential correlations in the data. To address this limitation, the biLSTM model, which propagates signals both forward and backward in time, is employed. This allows the biLSTM model to excel in tasks that require sequential modeling, outperforming traditional LSTM models to extract temporal features that contribute to predicting performance [12].

Several previous studies have focused on analyzing and predicting various aspects of airports. For instance, [13] conducted a study on aircraft track anomaly detection using the Multidimensional Outlier Descriptor (MOD) and the Bidirectional Long-Short Time Memory network (Bi-LSTM). This research demonstrated improved accuracy and recall in anomaly detection. In another study by [14], a multi-time window convolutional neural network-Bidirectional Long Short-Term Memory (CNN-BiLSTM) neural network was proposed for active hazard identification of APU in civil aircraft. This model exhibited the best identification accuracy and F1 values, as well as effective identification performance for imbalanced data samples.

Furthermore, [15] combined the CNN-BiLSTM model to forecast short-term traffic flow on highways, demonstrating enhanced prediction accuracy compared to other models. Another study by [16], focused on traffic states prediction in air transportation systems. By utilizing auto-regressive integrated moving average (ARIMA) and Bidirectional long short-term memory (LSTM), this approach achieved the best accuracy measurement for long-term prediction of ETA given departure time, with an accuracy rate of 92% and a mean absolute error (MAE) of 6.09 minutes.

This paper presents our primary contributions, which involve a comparative analysis of the performance of biLSTM and CNN-biLSTM models for predicting airport traffic. We explore the use of different optimizers, including RMSProp, Stochastic Gradient Descent (SGD), Adam, Nadam, and Adamax, to assess their impact on the models' predictive capabilities. The analysis focuses on airport traffic Time Series data obtained from various regions, namely the USA, Canada, Chile, and Australia.

To evaluate the performance of the models, we employ a range of evaluation indices. These indices serve to compare our models with previous approaches, specifically autoregressive moving average (ARMA), LSTM and CNN-LSTM models. The evaluation indices used include Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Through these evaluations, we aim to determine the effectiveness and accuracy of the biLSTM and CNN-biLSTM models in predicting airport traffic, providing valuable insights for future studies in this field.

MATERIALS AND METHODS

This research involved a series of systematic stages, encompassing data collection, data preprocessing, data partitioning into train and test sets, data modeling using biLSTM and CNN-biLSTM, parameter tuning, prediction results, and performance evaluation using metrics such as Mean Absolute Error (MAE) and Mean Absolute

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Percentage Error (MAPE). The process and outcomes of these stages are illustrated in Figure 1.

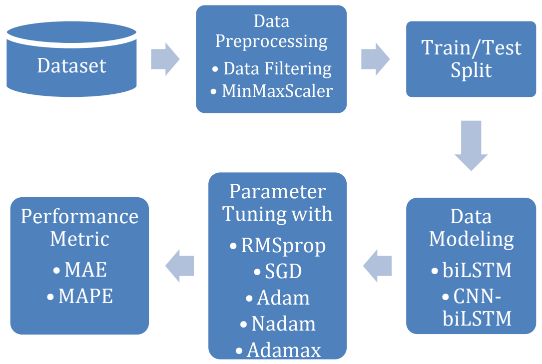

Figure 1. Research Stages

A. Dataset

In this research, we make use of a collection of data that covers a period from March 16, 2020, to December 12, 2020. This dataset is easily available on Kaggle [17]. The dataset consists of a single numerical characteristic that can be rearranged or modified in its arrangement. The dataset consisted of a single numerical attribute that could be transposed, comprising a total of 7247 data points for 'PercentOfBaseline' with daily aggregation. These data points were collected from various airports in the United States, Canada, Chile, and Australia refer to Table 1 for a detailed information.

Table 1. Airport name and location

Airport Name	City, Country
Boston Logan International	Boston, USA
Calgary International	Calgary, Canada
Charlotte Douglas International	Charlotte, USA
Chicago O'Hare International	Chicago, USA
Dallas/Fort Worth International	Grapevine, USA
Daniel K. Inouye International	Honolulu, USA
Denver International	Denver, USA
Detroit Metropolitan Wayne County	Romulus, USA
Edmonton International	Leduc County, Canada
Halifax International	Halifax, Canada
Hamilton International	Hamilton, Canada
Hartsfield-Jackson Atlanta International	College Park, USA
John F. Kennedy International	New York, USA
Kingsford Smith	Sydney, Australia
LaGuardia	New York, USA
Los Angeles International	Los Angeles, USA
McCarran International	Paradise, USA
Miami International	Miami Springs, USA
Montreal Mirabel	Mirabel, Canada
Montreal Trudeau	Quebec, Canada
Newark Liberty International	Newark, USA
San Francisco International	South San Francisco, USA
Santiago International Airport	Santiago, Chile
Seattle-Tacoma International	SeaTac, USA
Toronto Pearson	Mississauga, Canada
Vancouver International	Richmond, Canada
Washington Dulles International	Floris, USA
Winnipeg International	Winnipeg, Canada

B. Data Preprocessing

To ensure the relevance and accuracy of the analysis, we employed a filtering process to eliminate irrelevant data. This process allowed us to focus solely on the relevant parameters, including 'Date,' 'AirportName,' 'PercentOfBaseline,' 'City,' 'State,' and 'Country.'

In order to standardize the data and maintain the relative relationships between different features, we applied the MinMaxScaler to rescale the 'PercentOfBaseline' data. This scaling process transforms the attribute values or variables into a specified range, typically between 0 and 1. By doing so, we ensure that the data values for each attribute are standardized and consistent across the dataset [18]. This scaling process is represented by equation (1), where the MinMaxScaler adjusts the values accordingly:

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

C. Train/Test Split

To facilitate calculations and address the issue of imbalanced distribution of airport data across different countries, we devised a solution. We created an average airport baseline for each country on a daily basis. This was achieved by utilizing the Pandas dataframe.groupby().mean() function. By applying this function, we were able to group the dataset based on countries and calculate the mean value of the airport data for each day.

This approach provided us with a more representative and balanced measure for the airport data of each country, enabling easier analysis and comparison across different locations. To create this average baseline, we divided the dataset into an 80/20 ratio. Then, we specifically applied the mean function to the countries of the USA, Canada, Chile, and Australia. As a result, we calculated the average baseline values for these countries, which are presented in Table 2:

Table 2. Train/Test Split

Country	Training (80%)	Testing (20%)	Total (100%)
United States of America	210	52	262
Chile	191	47	238
Canada	210	52	262
Australia	206	51	257

D. Data Modeling

The Bi-directional LSTM (BiLSTM) is a type of neural network that has been used for solving classification or regression problems. It is designed to handle long-term dependencies in data by incorporating LSTM (Long Short-Term Memory) units. Our BiLSTM Model Parameter settings are presented in Table 3.

Table 3. CNN-BiLSTM Model Parameter Settings

Model Parameter	Value
biLSTM unit	64
biLSTM activation function	ReLu
biLSTM return_sequences	True
Dropout	0.2
biLSTM unit	32
biLSTM activation function	ReLu
biLSTM return_sequences	False
Dense units	1

BiLSTM network takes advantage of future information by including two sets of LSTM layers: one that processes the data in a forward direction and another that processes it in a backward direction [19]. To prevent the model from overfitting, a dropout layer is employed. In the final stage of the network, a fully connected layer is used to leverage the spatial correlation patterns that have been extracted from the previous layers. These patterns capture relationships between the input data and are used to predict future values. This enables the model to make accurate estimations about upcoming outcomes. Figure 2, illustrates the architecture of our biLSTM network used in this research based on our model parameter settings:

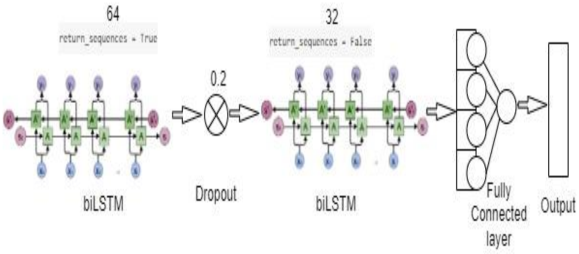

Figure 2. Our Flow Diagram LSTM Model

The CNN-biLSTM model combines the strengths of a Conv1d block and a biLSTM block to effectively process input data [20]. Our CNN-BiLSTM Model Parameter settings are presented in Table 4:

Table 4. CNN-BiLSTM Model Parameter Settings

Model Parameter	Value
Conv1d filters	64
Conv1d kernel_size	3
Conv1d activation function	ReLu
Conv1d padding	casual
MaxPooling1d pool_size	3
MaxPooling1d strides	1
MaxPooling1d padding	Same
Dropout	0.2
biLSTM unit	64
biLSTM activation function	ReLu
biLSTM return_sequences	True
biLSTM unit	32
biLSTM activation function	ReLu
biLSTM return_sequences	False
Dense units	1

The Conv1d block is utilized to extract complex characteristics from the input matrix by applying a one-dimensional convolutional operation. The MaxPooling1D layer is employed to reduce the size of the one-dimensional input data. It does this by selecting the maximum value within a window of data as a representative value.

The biLSTM block plays a crucial role in understanding the temporal dependencies between variables. It processes the input data in both the forward and backward directions, enabling it to comprehend the context from both past and future perspectives. This bidirectional approach helps the model capture and learn the relationships and dependencies within the data more effectively. To address the issue of overfitting, a Dropout layer is utilized. In the final stage, a fully connected layer is used to make predictions based on the spatial correlation patterns that have been extracted by the preceding layers.

This layer takes advantage of the relationships between different parts of the input data to predict future values accurately. Figure 3 represents the architecture of our CNN-biLSTM model based on our model parameter settings to process the data and make informed estimations about the future values in a time series.

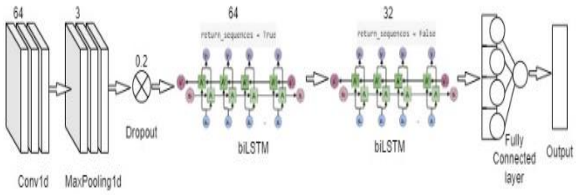

Figure 3. Our Flow Diagram CNN-biLSTM Model

E. Performance Metric

In order to evaluate and compare the performances of the implemented methods, Equation (2) is used to calculate Mean Absolute Error (MAE) from a sample of N data points. It provides a measure of the average magnitude of the prediction errors, regardless of their direction. Assume y_i and are $\hat{y}_i$ variables of paired observations that express the same phenomenon.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}| \quad (2)$$

Equation (3) is used to calculate the Mean Absolute Percentage Error (MAPE). This metric takes into account the relative magnitude of the errors and provides an indication of the accuracy in percentage terms. Where y_i is the actual airport baseline value and $\hat{y}_i$ is the predicted value N.

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

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RESULTS AND DISCUSSION

In this study, we performed an analysis utilizing biLSTM (Bidirectional Long Short-Term Memory) and CNN-biLSTM (Convolutional Neural Network-Bidirectional Long Short-Term Memory) models to predict the airport's percentage of baseline. We applied the model parameter settings, as described earlier, along with a fixed number of epochs set to 60 and a batch size of 64. To evaluate the performance of the models, we employed two metrics: Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

In the CNN-biLSTM model, we introduced a specific modification by adding extra Conv1d and MaxPooling layers to the existing biLSTM model. Figure 4 provides a visual representation of the CNN-biLSTM model structure for USA.

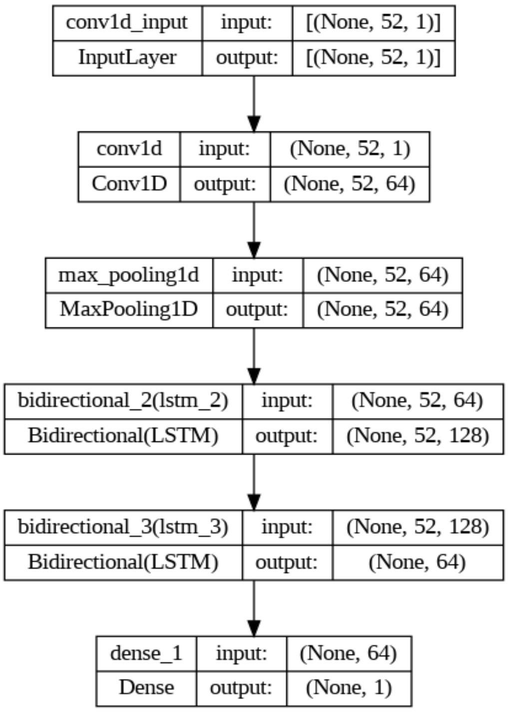

Figure 4. CNN-BiLSTM model structure

Table 5 presents a comprehensive summary of the performance metric scores obtained for different countries, specifically the USA, Canada, Chile, and Australia. Throughout the analysis, we employed various optimization techniques, namely RMSProp, Stochastic Gradient Descent (SGD), Adam, Nadam, and Adamax, to train the biLSTM and CNN-biLSTM models. The models were trained using Google Colaboratory, a cloud-based development platform. By comparing the scores achieved with these optimization techniques, we can assess the effectiveness of the models in predicting the airport percentage of baseline for each country.

Table 5. Performance in different optimizer

Country	Model	Optimizer	MAE	MAPE
United States of America	biLSTM	RMSprop	0.0564	0.1014
		SGD	0.0691	0.1229
		Adam	0.0562	0.1017
		Nadam	0.0535	0.0976
		Adamax	0.0554	0.0992
	CNN-biLSTM	RMSprop	0.0541	0.0971
		SGD	0.0678	0.1199
		Adam	0.0532	0.0976
		Nadam	0.0521	0.0962
		Adamax	0.0546	0.0989
Australia	biLSTM	RMSprop	0.0722	0.3252
		SGD	0.1400	0.4721
		Adam	0.0699	0.3154
		Nadam	0.0721	0.3152
		Adamax	0.0725	0.3224
	CNN-biLSTM	RMSprop	0.0786	0.3330
		SGD	0.1253	0.4547
		Adam	0.0780	0.3358
		Nadam	0.0804	0.3371
		Adamax	0.0796	0.3411
Chile	biLSTM	RMSprop	0.0890	0.4371
		SGD	0.1113	0.5223
		Adam	0.0869	0.4404
		Nadam	0.0886	0.4421
		Adamax	0.0872	0.4473
	CNN-biLSTM	RMSprop	0.0872	0.4409
		SGD	0.1188	0.5496
		Adam	0.0884	0.4469
		Nadam	0.0895	0.4455
		Adamax	0.0879	0.4495
Canada	biLSTM	RMSprop	0.0978	0.1506
		SGD	0.0991	0.1539
		Adam	0.0998	0.1529
		Nadam	0.0970	0.1499
		Adamax	0.0993	0.1506
	CNN-biLSTM	RMSprop	0.0977	0.1480
		SGD	0.0996	0.1552
		Adam	0.0976	0.1475
		Nadam	0.1022	0.1505
		Adamax	0.1017	0.1512

Table 5 illustrates the performance of different optimization techniques for biLSTM and CNN-biLSTM models across various countries. In the United States, both the biLSTM and CNN-biLSTM models exhibited superior performance when trained with the Nadam optimizer, surpassing the results achieved with other optimizers. For Australia, the biLSTM model yielded better predictions using the Nadam optimizer, while the CNN-biLSTM model showed improved performance with the RMSprop optimizer. In Chile, after parameter tuning, the biLSTM model coupled with the Adam optimizer, and the CNN-biLSTM model utilizing the RMSprop optimizer, delivered the best results. In Canada, the biLSTM model demonstrated better performance with the Nadam optimizer, while the CNN-biLSTM model showed enhanced results with the Adam optimizer.

To provide a visual representation of these results, figures 5 until figure 8 present the prediction outcomes of the best optimizers for the biLSTM and CNN-biLSTM models in estimating the airport percentage of baseline. The red line represents the actual airport percentage of baseline, while the blue line depicts the predictions generated by the biLSTM model. The green line illustrates the predictions made by the CNN-biLSTM model. By examining these graphical representations, we can evaluate the accuracy and effectiveness of the chosen optimizers in predicting the airport percentages of baseline.

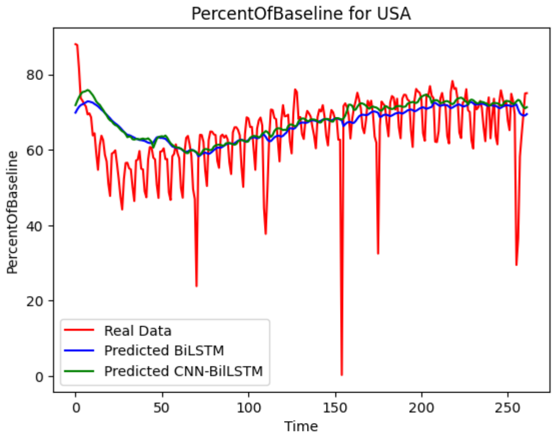

Figure 5. Best Prediction result in USA

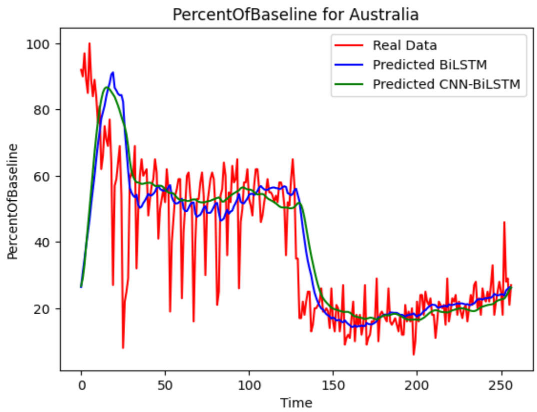

Figure 6. Best Prediction result in Australia

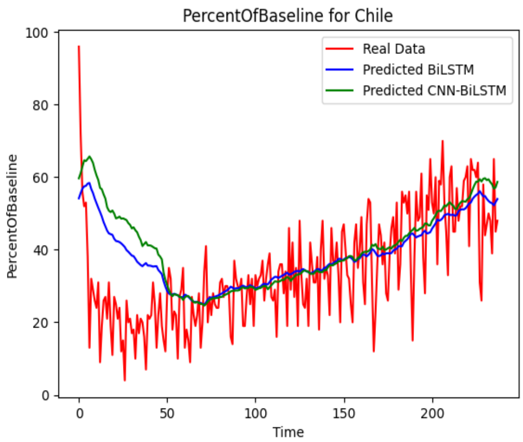

Figure 7. Best Prediction result in Chile

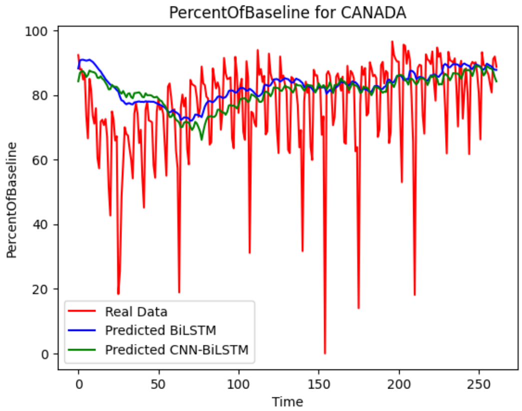

Figure 8. Best Prediction result in Canada

CONCLUSION

Due to the imbalanced dataset and the limited availability of data spanning only about 10 months, the prediction performance varied across different countries, namely the USA, Canada, Chile, and Australia. In the United States, the biLSTM model utilizing the Nadam optimizer achieved a Mean Absolute Error (MAE) score of 0.0535 and a Mean Absolute Percentage Error (MAPE) score of 0.0976 (9.76%). Conversely, the CNN-biLSTM model utilizing the Nadam optimizer achieved a slightly higher MAE score of 0.0521 and a slightly improved MAPE score of 0.0962 (9.62%).

For Australia, the biLSTM model employing the Nadam optimizer obtained a MAE score of 0.0721 and an MAPE score of 0.3152 (31.52%). In contrast, the CNN-biLSTM model utilizing the RMSprop optimizer exhibited a slightly higher MAE score of 0.0786 and a marginally higher MAPE score of 0.3330 (33.33%).

In the case of Chile, the biLSTM model using the Adam optimizer achieved a MAE score of 0.0869 and an MAPE score of 0.4404 (44.04%). Conversely, the CNN-biLSTM model employing the RMSprop optimizer showed a slightly higher MAE score of 0.0872 and a slightly higher MAPE score of 0.4409 (44.09%).

In Canada, the biLSTM model trained with the Nadam optimizer obtained a MAE score of 0.0970 and an impressively low MAPE score of 0.1499 (14.99%). Similarly, the CNN-biLSTM model utilizing the Adam optimizer demonstrated a slightly higher MAE score of 0.0976 and a slightly better MAPE score of 0.1475 (14.75%).

To enhance the accuracy of future predictions, it is recommended to conduct further research by incorporating a balanced dataset specific to each country. This approach can help address the issue of data imbalance and potentially lead to improved prediction results.

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