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PM2.5 Concentration Estimation Using Bi-LSTM with Osprey Optimization Method

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ABSTRACT

Outdoor air pollution causes a lot of health problems for humans. Particulate Matter 2.5 (PM2.5), due to its small size, can enter the human respiratory system with ease and cause significant health effects on humans. This makes PM2.5 significant among the various air pollutants. Hence, it is important to measure the value of PM2.5 accurately for better management of air quality. Algorithms for deep learning and machine learning can be used to forecast air quality data. A model that minimizes the prediction error of the PM2.5 forecast is needed. In this paper, a PM2.5 concentration estimation model using Bi-LSTM (Bidirectional Long Short-Term Memory) with meteorological data as predictor variables is proposed. For a better estimation of PM2.5 values, the hyperparameters of the Bi-LSTM model used are tuned using the Osprey Optimization Algorithm (OOA), a recent meta-heuristic algorithm. The model that works with the optimal values of hyperparameters identified by OOA performed better than the other models when they are compared based on evaluation metrics like Mean-Squared Error and R^2.

INTRODUCTION

Air pollution is the process of any material contaminating an interior or outdoor environment and changing the inherent characteristics of the atmosphere. This includes chemical, physical, and biological contaminants (World Health Organization 2023). Recent research by the World Health Organization (World Health Organization 2018) estimates that 4.2 million fatalities globally in 2016 were attributable to outdoor air pollution. The research outlines statistics on the total deaths attributable to ambient air pollution in 2016 under various categories like by region, by disease, and by age and sex. According to WHO data (WHO 2023), nearly all people on the planet (99 %) breathe air that is higher than recommended and contains significant quantities of pollutants. Air Quality Index (AQI) is a measure to identify the level of air pollution in a place. The eight pollutants used in India's AQI computation are particulate matter 10, carbon monoxide, particulate matter 2.5, nitrogen dioxide, ozone, sulphur dioxide, ammonia, and lead (CPCB 2015). There are six AQI categories available (Good to Severe).

Table 1 Displays the AQI breakpoints that relate to each of the eight pollutant characteristics (CPCB 2015).

Air quality is an important issue with broad consequences for both environmental and public health, particularly when it involves PM2.5. Particulate matter (PM10, PM2.5, SPM) is the result of the exhaust of diesel automobiles, building activities, road dust, and domestic wood (Swarna Priya & Sathya 2019). They have a serious health impact on humans. Among other air pollutants, PM2.5 is considered noteworthy because of its detrimental impacts on human health. The following section outlines the main ideas emphasizing the importance of PM2.5.

Based on statistics from the Global Burden of Disease Project WHO, the pollutant PM2.5 is associated with the highest amount of harmful health consequences as a result of air pollution, both nationally and globally (Thangavel et al. 2022).

The incidence and mortality of several diseases, such as lung cancer, stroke, and other breathing disorders, have been related to exposure to ambient PM2.5. Because PM2.5 particles are light and small, they can readily pass through nasal and throat filters in humans and remain in the atmosphere for extended periods (Xing et al. 2016).

Black carbon, polycyclic aromatic hydrocarbons, aryl hydrocarbons, volatile organic hydrocarbons, heavy metals, organic molecules, minerals, inorganic ions, and other hazardous materials are the main constituents of PM2.5. PM2.5 is a typical air quality meter that is frequently released

Table 1: Pollutant parameters and their corresponding AQI breakpoints.

AQI Category	Range	PM10 24-h	PM2.5 24-h	NO_2 24-h	O_3 8-h	CO 8-h [$mg.m^{-3}$]	SO_2 24-h	NH_3 24-h	Pb 24-h
Good	0-50	0-50	0-30	0-40	0-50	0-1.0	0-40	0-200	0-0.5
Satisfactory	51-100	51-100	31-60	41-80	51-100	1.1-2.0	41-80	201-400	0.6 - 1.0
Moderate	101-200	101-250	61-90	81-180	101-168	2.1-10	81-380	401-800	1.1-2.0
Poor	201-300	251-350	91-120	181-280	169-208	10.1-17	381-800	801-1200	2.1-3.0
Very poor	301-400	351-430	121-250	281-400	209-748*	17.1-34	801-1600	1201-1800	3.1-3.5
Severe	401-500	430 +	250+	400+	748+*	34+	1600+	1800+	3.5+

Units are in $mg.m^{-3}$ except if stated otherwise. *One hourly monitoring (exclusively for use in mathematical computations)

from a variety of sources, including home heating, motor vehicles, industrial sources, and the combustion of fuels like gasoline, oil, diesel, or wood (Thangavel et al. 2022).

Because PM2.5 is so tiny, it can irritate and erode the alveolar wall in the lung, causing lung function to be compromised (Xing et al. 2016). For the management of air quality and the preservation of public health, accurate PM2.5 concentration forecasting is essential. Numerous studies have developed original methods for predicting PM2.5, including empirical models (like deep learning models) and physical models like CMAQ4 (Xiao et al. 2020). These models are useful for estimating PM2.5 concentrations for air quality forecasts and for the early diagnosis of air pollution events.

The authors (Ameer et al. 2019, Senthivel & Chidambaranathan 2022, Saminathan & Malathy 2023) have elaborated upon the recent state-of-the-art works carried out in Air quality research using machine learning methods. Besides doing an exhaustive literature survey related to this topic, the authors (Ameer et al. 2019) presented their findings with a prediction method that found Random Forest as the most efficient one among different methods tested on the dataset that includes PM2.5 data along with meteorological data for 5 cities of China.

As the world's population and economy rise, so does its energy consumption, which raises air pollution levels. Many places have had their PM2.5 concentrations predicted using machine learning approaches such as random forests. An example of South African cities has been given in (Morapedi & Obagbuwa 2023).

The key objective of this paper is to develop a model that accurately predicts PM2.5 levels. Precise PM2.5 concentration prediction is essential to human existence and forms the basis of pollution prevention and control. The significance of this research lies in its commitment to developing a model that transcends the limitations of existing approaches. By placing a specific focus on minimizing the prediction error of PM2.5 forecasting, the proposed model seeks to enhance the precision and reliability of air quality predictions. This, in turn, empowers decision-makers with more accurate information for prompt and targeted interventions to mitigate the adverse effects of air pollution.

LSTM and Bi-LSTM have been used in recent PM2.5 prediction systems, and some optimization techniques are also used with them that help in processes like hyperparameter tuning. The following section is an introduction to LSTM, Bi-LSTM, and a recent metaheuristic optimization method called the Osprey optimization technique, along with their applications in recent literature.

LSTM (Long Short-Term Memory) can capture temporal dependencies, making them suitable for sequential data. Input data is organized into sequences with multiple features at each time step, reflecting the multivariate nature of the regression task. Each sequence consists of a series of time steps, and the LSTM processes these steps sequentially to capture temporal patterns.

Bi-LSTMs include two sets of hidden states, forward and backward, concatenated to enhance the model's ability to capture bidirectional dependencies. Like unidirectional LSTMs, input data for Bi-LSTM is organized into sequences with multiple features at each time step. Each sequence comprises a series of time steps, and Bi-LSTMs process these steps bi-directionally, considering information from both earlier and later time steps. The model typically includes one or more Bi-LSTM layers to capture bidirectional temporal dependencies in the sequential input. The final output layer predicts multiple continuous values corresponding to the target variables, integrating information from both forward and backward passes. Mean Squared Error (MSE) is commonly used as the loss function for regression tasks, measuring the difference between predicted and actual values. Training involves adjusting model parameters using backpropagation through time considering bidirectional information flow.

Forecasting PM2.5 concentrations is a crucial issue, and using cutting-edge methods like Bi-LSTM has produced encouraging results. In a study by (Kim et al. 2023), the authors proposed a method in which a weighted Bi-LSTM model is used to forecast the PM2.5 concentration after input variables are chosen based on the feature importance determined by random forest. In a different study (Zhang et al. 2021), the efficacy of a hybrid model known as CNN-Bi-LSTM-Attention was demonstrated in both short-and long-term forecasts by predicting the PM2.5 concentration over the following two days.

Furthermore, studies (Yang et al. 2021, Masood et al. 2023, Chen et al. 2023) have demonstrated that deep learning models, like LSTM, can efficiently use historical PM2.5 concentrations, air quality indices, and other pertinent data for precise predictions. The promise of Bi-LSTM and other sophisticated models in PM2.5 forecasting is demonstrated by these studies, which also emphasize the models' capacity to manage the intricate and erratic nature of PM2.5 data.

To estimate PM2.5 concentrations, this paper by (Zhang et al. 2023) suggested a weighted complementary ensemble empirical mode decomposition with adaptive noise and an improved long and short-term memory neural network. The adaptive mutation particle swarm optimization technique was established to identify the key hyperparameters of LSTM. This helped to increase the prediction accuracy of PM2.5 values. Correctly setting the hyperparameters of the prediction methods was aided by the application of the AMPSO approach.

Bi-LSTMs are applied in various domains, such as financial forecasting, weather prediction, and healthcare, where capturing bidirectional dependencies in sequential data improves prediction accuracy. Hyperparameters of Bi-LSTM include the following parameters: The number of LSTM units or neurons in each LSTM layer, the number of LSTM layers stacked, dropout that is applied between LSTM layers and after the bidirectional layer to prevent overfitting, learning rate (the rate of update of the weights of the model during training), batch size (the number of samples used in each training iteration), optimizer (the algorithm used during training like Adam), activation functions for LSTM units and output layer, the length of input sequences.

More and more metaheuristic methods are being utilized to optimize hyperparameters for deep neural networks and other machine learning models to improve the accuracy and dependability of predictions. Optimization techniques such as metaheuristics can be applied to find the best hyperparameters in a high-dimensional space. When dealing with complicated optimization issues, where more conventional optimization techniques might not be helpful, these algorithms come in handy. As an example, a study explored the benefits of using metaheuristics in the hyperparameter tuning of deep learning models for energy load forecasting (Bacanin et al. 2023).

A novel metaheuristic algorithm called the Osprey Optimization Algorithm (OOA) mimics the actions of Ospreys. The primary source of inspiration for OOA is the tactic used by Ospreys to catch fish in the ocean. Using this hunting tactic, the osprey locates its prey, hunts it, and then transports it to a suitable location where it will eat it. Osprey's behavior during hunting is simulated to create a mathematical model for the proposed OOA technique, which consists of two phases: exploration and exploitation (Dehghani & Trojovský 2023).

A simplified version of the Osprey Optimization Algorithm is given here. The algorithm is inspired by the hunting behavior of osprey birds and aims to find the best solution to a problem.

Initialization	:	Start with a group of potential solutions called the population.
Exploration and Hunting	:	For each solution in the population, simulate the hunting behavior of osprey birds. This involves updating the positions of the solutions based on certain calculations.
Boundary Checks	:	Make sure the updated positions stay within certain limits (boundaries).
Improvement	:	Improve the solutions by adjusting their positions based on a second set of calculations.
Boundary Checks Again	:	Ensure the adjusted positions still fall within the specified boundaries.
Update Population	:	Keep the best solutions found so far and discard the rest.
Repeat	:	Repeat the process for a set number of iterations.

The overall goal is to guide the solutions through a series of adjustments inspired by osprey hunting behaviors, with the hope that this process leads to finding the best solution to the given problem.

In (Ismaeel et al. 2023), the OOA is used to address one of the primary problems in a power system known as economic load dispatch (ELD). To assess the dependability of the OOA, its performance is contrasted with several methodologies. The OOA is contrasted with various methods found in the literature, including the monarch butterfly optimization (MBO), the chimp optimization algorithm (ChOA), the moth search algorithm (MSA), the sine cosine algorithm (SCA), and artificial bee colonies (ABO). Based on the findings obtained, the OOA is found to be superior to all competing algorithms. Table 2 gives a summary of recent and significant literature on PM2.5 prediction systems.

Table 3 gives a summary of recent and significant literature on metaheuristic algorithms and OOA optimization techniques.

Table 2: Summary of existing literature on PM2.5 prediction systems.

Sl. No.	Author	Datasets	Pollutants and other factors used	Methodology	Remarks
1.	Ameer et al. (2019)	5 cities, China	PM2.5 data, along with meteorological data	Decision Tree, Random Forest, Multilayer Perceptron, Gradient Boosting	Random Forest was efficient
2.	Kim et al. (2023)	4 monitoring stations, Republic of Korea	Air pollution data, meteorological data	Weighted Bi-LSTM	It can predict PM2.5 values even when the data in the high-concentration area is not enough
3.	Zhang J. et al. (2021)	Shunyi District, Beijing	PM2.5, Air pollution data, meteorological data	CNN-Bi-LSTM-Attention	Predictions of the next 144 h with this model are superior to those of the next 48 h with other models.
4.	Yang et al. (2021)	Multiple stations, Beijing	PM2.5, Wind Speed	Bi-LSTM	Deep learning outperformed shallow learning models in hourly PM 2.5 prediction.
5.	Masood et al. (2023)	New Delhi	PM2.5	Extreme Learning Machine - Snake Optimization	This method is a valuable tool for accurately predicting PM2.5 values
6.	Chen et al. (2023)	Kaohsiung, Taiwan	PM2.5	CNN–RF	The ensemble framework can produce better results compared with the single CNN and RF techniques.
7.	Zhang L. et al. (2023)	Three monitoring stations, Xinyang City	PM2.5	Weighted complementary ensemble empirical mode decomposition with adaptive noise, an improved LSTM neural network	The experimental results demonstrate the superiority of the proposed model.

MATERIALS AND METHODS

In this section, the proposed PM2.5 concentration estimation model using Bi-LSTM (Bidirectional Long Short-Term Memory) with meteorological data as predictor variables is explained. For a better estimation of PM2.5 values, the hyperparameters of the Bi-LSTM model used are tuned using the Osprey Optimization Algorithm (OOA).

The proposed Bi-LSTM+OOA algorithm for PM2.5 prediction is outlined in Fig. 1.

Fig. 2 outlines the Work-Flow Diagram of the PM2.5 Concentration Estimation system with Bi-LSTM+OOA. The steps are explained here. The first step is preprocessing the dataset. This work has made use of data from the Air Quality dataset given in Chen (2019). There are 17 attributes in the data set. The time-related attributes are year, month, day, and hour. The pollution concentration-related ones are PM2.5, SO_2, PM10, NO_2, CO, and O_3. The meteorological attributes are temperature, wind speed, pressure, dew Point, and wind direction. They act as the predictor variables, with PM2.5 being the dependent variable in this study. The dataset includes hourly data on air pollutants collected between March 1, 2013, and February 28, 2017, for 12 air-quality monitoring sites in the People's Republic of China, spanning from Aotizhongxin to Wanshouxigong.

The following factors were considered while choosing the above dataset. There are around 4 lakh records, which is enough to create a machine-learning model that can be built accurately. It incorporates pollutant data and weather-related

Table 3: Summary of existing literature on Metaheuristic OOA optimization techniques.

Sl. No.	Author	Data used	Methodology	Remarks
1.	Bacanin et al. (2023)	Energy, Weather data, Europe	Six metaheuristics algorithms are used to optimize the LSTM model	Better results are obtained when parameters are tuned with metaheuristics
2.	Dehghani et al. (2023)	CEC 2017 test suite	Implementation of OOA	The proposed OOA has provided superior performance compared to other algorithms by maintaining the balance between exploration and exploitation.
3.	Ismaeel et al. (2023)	Cost of fuel for ELD and the cost of fuel and emissions for CEED	Application of OOA for economic load dispatch	The superiority of the OOA is achieved as per the obtained results compared with other algorithms.

Step 1: Get the dataset as input.
Step 2: Perform the necessary data preprocessing steps like handling missing values, etc.
Step 3: Apply OOA to find the optimal hyperparameter values for the number of Units drop for the Bi-LSTM model.
Step 4: Apply the LSTM, and Bi-LSTM models on the dataset and build the Bi-LSTM model with the hyperparameter values found in Step 3.
Step 5: Plot the graphs for the chosen metrics for comparing the models used in Step 4.

Fig. 1: PM2.5 prediction using Bi-LSTM+OOA algorithm.

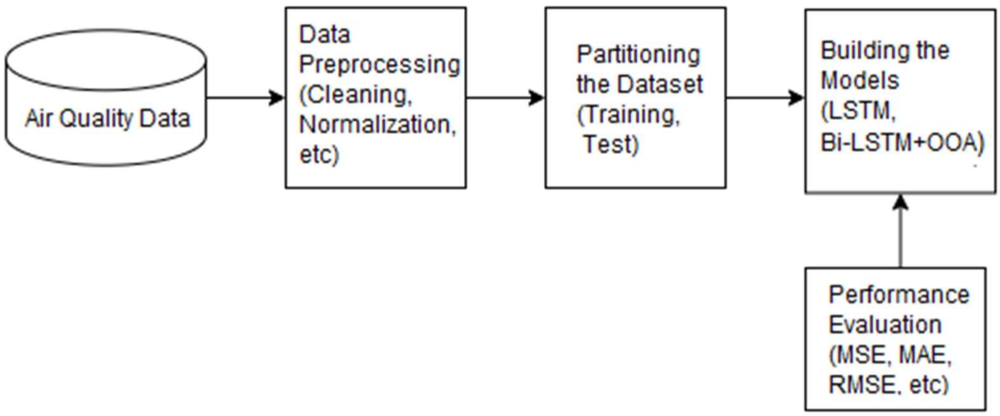

Fig. 2: Work-flow diagram of the PM2.5 concentration estimation system with Bi-LSTM+OOA.

data. In the proposed approach, meteorological data is used as a predictor variable.

The following data preprocessing steps were done:

1. Removal of the Null values.
2. The Wind direction variable is of the type of categorical data. It can be processed with 1-0 encoding or by converting the directions to their equivalent degree values. The second option is followed here.
3. It has been discovered that normalization improves accuracy. Normalization is therefore applied.

Then the dataset is partitioned into training that is used for building the model and test data, which is used for checking the accuracy of the model. The dataset is divided into the 70:30 ratio for training and testing data. The training and testing data size do not change during each iteration.

OOA is applied to find the optimal hyperparameter values for a number of units and the dropout rate for the Bi-LSTM model. hen, LSTM and Bi-LSTM models are applied to the dataset with some arbitrary values for the number of units and dropout. Then Bi-LSTM model is applied with the hyperparameter values found using OOA. Then the graphs are plotted for the chosen metrics for comparing the models.

RESULTS AND DISCUSSION

The following section discusses the results obtained by running the proposed model. The metrics that can be used for comparing the regression models are MSE, RMSE, MAE, and R^2. Table 4 outlines the performance metrics used for the evaluation of the methods used in PM2.5 estimation.

Out of the four metrics here graphs are given for two: RMSE and R^2. The reasons are that MSE and RMSE are similar metrics; MSE is a better metric for regression compared to MAE. The OOA gave 74.27 and 0.3394 as the number of units and dropout rate, respectively, as the ideal values for the hyperparameters. Table 5 gives the values of the RMSE values obtained on the dataset for different numbers of units and two dropout rates, 0.5 and 0.33. The values are plotted as a line graph in Fig. 3 and Fig. 4.

In Fig. 3, the RMSE values for Bi-LSTM are always less than the RMSE values for LSTM. In Fig. 4, the same pattern is followed except for the Number of Units=90 and 100. The lowest value for RMSE value obtained, i.e., 68.63 for Number of Units=74 and Dropout rate 0.34, are plotted as a red square with legend Bi-LSTM+OOA. This proves the ability of OOA to identify the optimal values for the hyperparameters: Number of Units and Dropout rate.

Table 4: Performance Metrics for PM2.5 estimation.

Sl. No.	Metric	Definition	Formula
1	Mean Absolute Error (MAE)	The mean absolute difference (MAE) between expected and actual values is calculated.	$MAE = \sum_{i=1}^{N} \lvert Ypred - Yactual \rvert / N$
2	Mean Squared Error (MSE)	MSE is commonly used as the loss function for regression tasks, quantifying the difference between predicted and actual values.	$\text{MSE} = \sum_{i=1}^{N} (Ypred - Yactual)^2 / N$
3	Root Mean Squared Error (RMSE)	By taking the square root of the mean square error (MSE), the average error magnitude (RMSE) can be determined.	$RMSE = \sqrt{\sum_{i=1}^{N} (Ypred - Yactual)^2 / N}$
4	R-squared (R2)	R2 is a statistical measure that indicates the percentage of the dependent variable's variation that can be predicted from the independent variable.	$R^2 = 1 - \frac{\sum_{i=1}^{N} (Yactual - Ypred)^2}{\sum_{i=1}^{N} (Yactual - Ymean)^2}$

Table 5: RMSE values for the models used.

Algorithm	Units/ Dropout Rate	RMSE						
		50	60	70	**74**	80	90	100
LSTM	0.5	70.01	69.40	69.23	69.26	69.21	69.08	69.02
Bi-LSTM	0.5	68.63	68.63	68.67	69.02	68.78	68.65	68.61
LSTM	0.34	69.26	69.03	68.96	68.91	68.83	68.79	68.72
Bi-LSTM	**0.34**	68.76	68.68	68.64	**68.63**	68.64	68.80	68.74

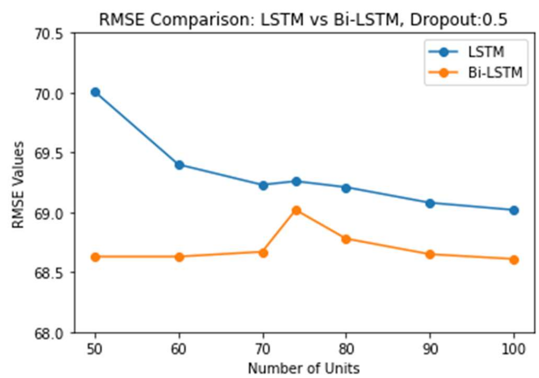

Fig. 3: Root Mean Squared Error comparison chart for different models for Dropout=0.5.

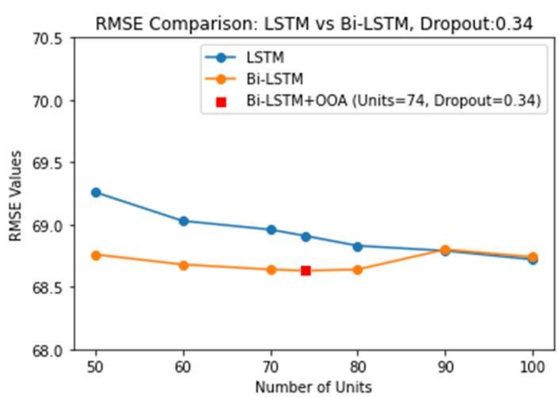

Fig. 4: Root Mean Squared Error comparison chart for different models for dropout = 0.34.

Table 6: R^2 values for the models used.

Algorithm	Units/ Dropout Rate	R^2						
		50	60	70	74	80	90	100
LSTM	0.5	0.2626	0.2756	0.2790	0.2784	0.2794	0.2821	0.2835
Bi-LSTM	0.5	0.2834	0.2831	0.2863	0.2834	0.2864	0.2879	0.2873
LSTM	0.34	0.2784	0.2832	0.2847	0.2857	0.2874	0.2881	0.2897
Bi-LSTM	0.34	0.2888	0.2905	0.2912	0.2914	0.2913	0.2879	0.2892

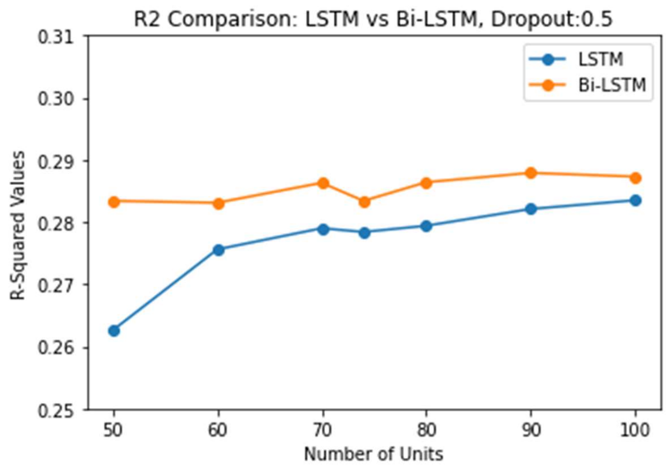

Fig. 5: R-squared error comparison chart for different models for Dropout=0.5.

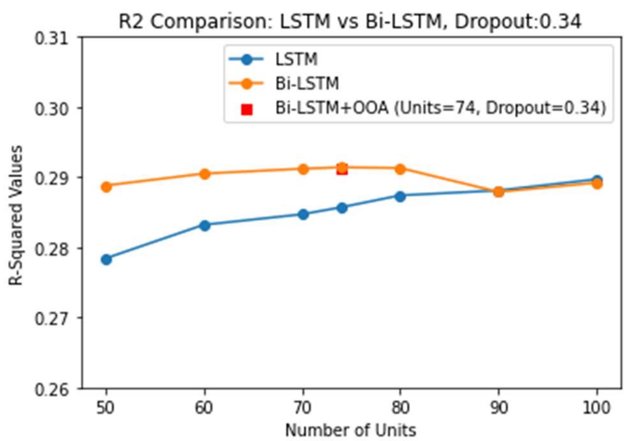

Fig. 6: R-squared error comparison chart for different models for Dropout=0.34.

Table 6 gives the values of the R^2 values obtained on the dataset for different numbers of units and two dropout rates, 0.5 and 0.33. The values are plotted as a line graph in Fig. 5 and Fig. 6.

In Fig. 5, the R^2 values for Bi-LSTM are always more than the R^2 values for LSTM. In Fig. 6, the same pattern is followed except for the Number of Units=90 and 100. The highest value for R^2 value obtained i.e., 0.2914 for Number of Units=74 and Dropout rate 0.34, are plotted as a square with legend Bi-LSTM+OOA. This proves the ability of OOA to identify the optimal values for the hyperparameters: Number of Units and Dropout rate.

CONCLUSION

This work introduces a Bi-LSTM model incorporating meteorological data for accurate PM2.5 concentration estimation. LSTM and Bi-LSTM-based models were used on a dataset involving meteorological data like temperature as a predictor variable. The use of the Osprey Optimization Algorithm for tuning hyperparameters enhances the model's predictive capabilities. Comparative analysis based on metrics such as Mean-Squared Error and R^2 highlights the advantage of the proposed Bi-LSTM+OOA model over the other model. The inclusion of additional relevant data sources to enhance model robustness and reliability can be done as further work. Recommendations for policy interventions include the implementation of the proposed model in air quality monitoring systems and incorporating its insights into decision-making processes. Continuous research and technological advancements in air quality monitoring are crucial for developing effective strategies to control and improve air quality. Research on air pollution, data analysis, model estimation, and machine learning will all be significantly impacted by this work.

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