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Enhancing Flight Delay Prediction and Classification Using a Hybrid Bi-LSTM: Machine Learning

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Abstract:
The flight delay prediction system plays a vital role in the airlines which helps to predict the delay of flight in real time. Airlines must estimate flight delays accurately because the findings can be used to boost customer satisfaction and airline agency profits. This research introduces a flight delay prediction framework employing the Bidirectional Long Short-Time Memory (Bi-LSTM) model. To capture the long-term dependencies in the sequential data LSTM works as a hybrid component. Overcoming the difficulties faced by the airline industries mainly focusing on flight on-time performance and the weather data through the confusion Matrix The results show that the BiLSTM model improves the LSTM model and achieves the maximum accuracy. The BiLSTM model effectively utilizes both forward and backward hidden sequences. The outcomes demonstrate the Hybrid BiLSTM approach's potential as a useful instrument for enhancing flight delay management in the aviation sector.

Keywords: flight delay prediction system, Bi-LSTM, LSTM, Deep graph embedded LSTM (DGLSTM), LSTM-AM

1. Introduction

Air Traffic surveillance system is a tremendous technology that plays a vital role in predicting flight delays due to natural occurrences and operations malfunctioning in the airlines. not only these, but weather and air traffic conditions also affect the flight delay. the present traditional surveillance technology cannot meet the requirements of the future to control air traffic. the most important challenge of the airline is to predict the flight delay. flight delay can affect both the passengers and the airline agencies negatively. not only these the airline agencies have to pay the compensation to the passengers, depending upon the delay airlines must provide refreshments and arrange alternative flights. all these effects the airline's economy goes down.to avoid all these constraints it is necessary to predict the delay of flight. In the conceptual models, there are still issues with conventional algorithms in the aircraft trajectory prediction field today, which were mostly created for land traffic. one major challenge is the sparseness of waypoints in flight trajectories [15].

current models, which rely on points of interest are not well-suited to deal with dynamic flying situations. furthermore, the difficulty of making precise trajectory predictions is further complicated by external factors that impact flight envelopes. On the flight delays issue, numerous scholars have examined and proposed many solutions. Flight delays predicted by CNN are to be designed for the tasks which are involving in spatial relationships, collecting the relevant information like previous data like weather, airport traffic, and other factors causing delays which were used to test the metrics mean absolute error or the mean squared error [11]. CNNs may find it difficult to accurately model the temporal features and also, they don't naturally capture complex connections between various kinds of features like weather data and airport traffic delays. In the LSTM-based flight prediction model LSTM networks are used as the recurrent neural networks designed to address the challenges of capturing the long-term problems in the sequential data. The neural networks have an issue to identify the particular cause of the flight delay by external factors [12].

As part of the proposed system, flight delay prediction is built to address all these challenges by using the hybrid BiLSTM mechanism. It is also highlighted that this BiLSTM technique utilizes both forward and backward hidden sequences which is superior [14]. This system is designed to deal with the challenges that are generated by the airline's delays and to provide important information on who is involved in the airline industries for improving flight delay prediction through a hybrid Bidirectional Long Short-Term Memory [16].

2. Literature Survey

Jingyi Quetal et al [1] introduced the Att-Conv-LSTM system to predict flight delay prediction. This system obtained more accuracy to predict the flight delay prediction. It addressed the challenges in the actual flight delay prediction and it enhanced prediction capabilities. This system fills the gap between the temporal and spatial dimensions for the effective efficiency of flight delay prediction by considering the meteorological data for a particular delay time. Methods used in this system were Att-conv-LSTM-based deep learning, Linear regression, Decision tree regression, and Random Forest regression for predicting flight delays. The Att-Conv-LSTM model improved the flight delay prediction accuracy the prediction error of this system was reduced by 11.41%.

A method of reducing flight delay prediction by exploring the internal mechanism of flight delays by Yakun Cao et al [2, 17] utilized statistical analysis and also mathematical modeling to examine the internal mechanism of flight delays especially the departure delays for Delta Air Lines for this in this system the power law and the shifted power law is used. A particular metric for creating flight schedules is generated from the mathematical statics approach. This system seeks to cut the flight delays without raising the operating costs.

Utilizing the Stacking algorithm which is a group learning method that enhances predictive performance through the combination of several basic models, Jia Yi et al[3, 18l predicted the flight delays by employing the second-level learner logistic regression and the first five levels which are supervised machine learning algorithms like KNN, Random Forest, Logistic Regression, Decision Tree and the Gaussian Naïve Bayes are engaged to create a classification model for the flight delay prediction.

Fujun Wang et al [4] Flight delay forecasting and analysis of direct and indirect factors mainly concerned with creating a model to forecast flight delays by utilizing an attention mechanism in a long short–term memory network attention mechanism (LSTM-AM). This system emerged with all direct and indirect fight delay variables taken into account. While indirect variables provide human action before delays, direct factors which associated with the flight characteristics and arrival time frames. Numerous contributing factors linked to airport delays have distributive features, according to the system the dimensionality of the incoming data was decreased and it looked only at the historical data from Beijing International Airport and interactions between airports in a cluster [26].

The study Deep graph embedded LSTM (DGLSTM) for airport delay prediction presents a new method for forecasting the delays in airports networks, for precise and reliable delay predictions, Weili Zeng et al [5] suggest a deep learning model that blends graph neural networks with the sequence-to-sequence LSTM network. By considering the airports as nodes in a directed graph network the system expands the use of graph neural networks for the delay prediction. The methodology takes into account the interdependence of the airports and the forecasts and delays by taking these linkages into account. This system depicts the airport network using a weighted adjacency matrix. The number of flight pairs and the spherical distances are the two examples of the parameters that affect the weights for the edges between airports. The operational and geographical features of the airport's links are acknowledged by the particular method. To represent the features of the delay’s propagation across airports. The diffusion convolution kernel is introduced in the article and implemented within the graph network. The goal of this novel approach is to improve the model's comprehension and the forecasting of the distribution of delays throughout the airport system. To capture the time domain properties this system includes a sequence-to-sequence LSTM network [15]. The LSTM's encoding and decoding modules are employed to extract temporal patterns from the delay data and offer a thorough framework for recording and forecasting delays over time [23][25].

Tsegai O.Yhdego et al [6] introduced Hybrid Recurrent Network Model for Estimating and Projecting Flight Delays which explains the hybrid approach which combines a gated recurrent unit (GRU) model to capture the historical trends and a dense layer to handle short-term dependencies. This system expands on the application of the RNNs for delay prediction.RNNs have been used for a variety of time series prediction problems due to their capacity to capture sequential dependencies by using the hybrid design and it also seeks to improve on the conventional RNN architectures to better understand model delays and their effects. To capture past patterns in the delays this system includes a GRU model Recurrent neural networks such as GRUs have demonstrated efficacy in the learning of long-term dependencies. A deep layer to capture short-term relationships between arrival and departure delays in addition to the historical patterns recognizes that flight operations are dynamic and that it is important to take into account any current issues that might cause the delays. By utilizing all the component's capabilities this system seeks to give an in-depth understanding of the delay patterns[21][22][24].

Flight delay prediction using deep learning with stack denoting autoencoder and the Levenberg Marquardt Algorithm by Maryam Farshchiian Yazdi et al [7, 19] addressed the challenges of accurately predicting flight delays which considering the significant impact on the airlines. This system used deep learning and machine learning techniques to forecast aircraft delays. It involves an understanding of the difficulties in obtaining precise forecasts presented by the enormous delta quantities dependencies and a multitude of factors to calculate the precise value of the flight delay of airlines. The significance of the precise flight delay estimate on customer happiness and the total revenue creation is highlighted in the introduction underscoring its vital role for the airlines. This system is consistent with the larger field research environment where precise forecasts enhance operational effectiveness [27][28].

It also recognizes that the complexity of the dealings with the large amounts of data and the dependencies of the many factors limits the ability of the current approaches to achieve adequate accuracy. This acknowledgment lays the foundation for the deep learning-based approach that is suggested. To handle noisy flight delay data the system presents a unique approach based on the stack denoising auto encoder and is a significant improvement over the current model highlighting the delay prediction accuracy.

Bin YU et al [8, 20] work on the Flight delay prediction for commercial air transport: A deep learning approach was introduced as a multifactor methodology including a unique deep belief network technique to identify underlying trends in flight delays. This system incorporates support vector regression for the supervised fine-tuning and the ultimate goal is to develop a predictive architecture that can work with the big datasets and to identify important variables causing delays that linked airports may work together to reduce the spread of the flight delays. Exploring the system on the many models and the approaches that have been developed to forecast flight delays to analyze deep learning methods machine learning strategies and the conventional statistical models used to forecast flight delays. The deep belief networks in the predicative modeling particularly when dealing with complicated systems like airport operations and the time series of the data. The support vector regression is used in the predicative modeling in this system by paying particular attention to its advantages and also disadvantages while executing the regression tasks. Multiple factor techniques in flight delay prediction emphasize the value of taking several aspects into account at the same time.

Flight delay prediction using a deep convolution neural network based on the fusion of meteorological data by Jingyi Qu et al [9] introduced precise flight delay forecasting in the commercial aviation sector. On the ResNet and its uses in several fields emphasizing both its advantages and the disadvantages it suggests enhancing the conventional CNN algorithms particularly those that tackle the decline in the performance as the networks get more complex. It also highlights adaptive weight calibration and overall network performance improvement while combining all the advantages of the Dense Net and the SEnet. Analyzing this system on the three phases of the features extraction classification prediction and the data prediction in the flight delay grade prediction framework where all the grades are to be substituted for the delay time and converting prediction issue into a classification challenge. It also emphasizes how important meteorological information is for aviation forecasts to demonstrate the value of the meteorological data in the models for predicting flight delays that contrast conventional methods with the suggested deep convolution neural network models to draw attention to the research that highlights how deep learning models may extract hidden values without reducing the dimensionality of the features.

Ehsan Esmaeilzadeh et al [10] introduced a Machine learning approach for flight departure delay prediction and analysis by utilizing the support vector machine techniques to analyze factors contributing to flight delay and to enhance delay prediction. The seminal works on the difficulties and the importance of flight delay prediction. The current techniques for predicting flight delays such as statistical and machine learning methods address the use of the support vector machines in the aviation industry. The benefits and drawbacks of using the SVM to analyze the forecast delays in the national airspace system on the application of the multi-class SVM to flight delay prediction. It affects the explanatory variables on the flight delays taking into account elements like flow management features, ground operations, demand capacity, and weather information. The connection between these factors and the delay using the machine learning techniques especially the Support vector machine to improve the predictive time during the interruptions. This system also used the highlights of predictive analytics in the planning of traffic flow management. The system also applied machine learning methods to enhance TFM decision-making procedures and cut down on the overall time. The pinpoint and the measures that particularly affect different variables on the departure delay show that traffic management initiatives, weather activities, and departure demand capacity levels contribute to flight delays.

3. Proposed Technology And Features

One of the effective techniques that analyzes and extracts the critical data features that are needed for the prediction is a Bi-Directional Long Short-Term Memory. The proposed system, the hybrid machine learning technique LSTM used along with the Bidirectional long short-term memory to develop a framework for predicting flight delays. Complicated relationships in the flight delays are efficiently found by using both forward and backward hidden sequences. It shows the difficulties caused by aircraft delays and significantly enhances the disruptions in the airline sector.

A. Methodology

To predict the flight delay here we are going to take a dataset DS as input then it should be pre-processed and then the min-max feature scaling normalization takes place and the given Data Set DS is split into two sets as DS train and DS test data set. After completing this process the data set is sent into the proposed system architecture which consists of the Dense layer, and embedded layer then it should be sent to the BILSTM mechanism further classified and the output layer should release the expected data. Finally, the predicted expected data should be shown Fig.1 by the Model Accuracy Indicator.

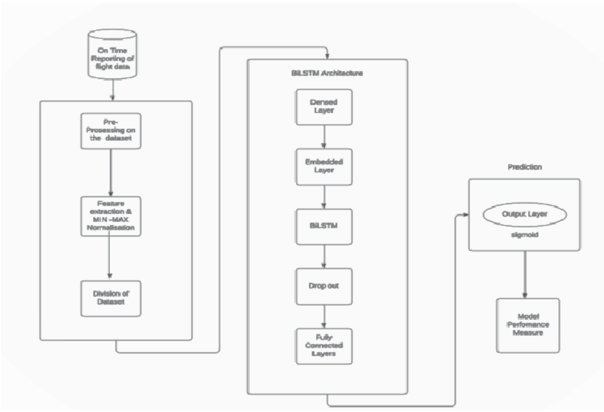

Figure 1: Architecture of the Accuracy

Proposed Algorithm Approach for the BiLSTM:

INPUT: Dataset DS, DStrain and DStest

OUTPUT: Classification and the prediction of the flight results in the RS of the test data.

1. Loading Input Dataset DS
2. Division of Dataset into DStrain and DStest
3. Division of DStrain into the train and the validation set for the training algorithm.
4. Preprocessiing on the DStrain and DStest: Min and max normalization
5. By using the BiLSTM layers to improve feature extraction of the significant prediction.
6. Dropout layer is used to overfitting.
7. Normalization of the batches
8. Dense layers
9. fully connected layer
10. final layer sigmoid layer
11. For each training epoch train the proposed model: Train (PM)
12. End for DStrain, DStest evaluation of the model using the model performance measure.

B. *Layer of batch normalization*

Here the training data set is collected batch after batch as a result the distributions are irregular and unstable requiring the fitting of the network parameters throughout each training cycle to demonstrate the significant convergence. Here reparameterization is done by batch normalization. The mean αDS and the variance ∝2DS are obtained from the normalization of the batch mechanism for every training dataset batch with the real dataset scaling to zero mean and the unity variance.

$$\alpha_{DS} = \frac{1}{N} \sum_{j=1}^{n} a_j \qquad (1)$$

$$\propto_{DS}^{2} = \frac{1}{n}\sum_{ij=1}^{n}(a_{ij} - \propto_{DS})^2 \quad (2)$$

$$\hat{a}_{ij} = \frac{a_{ij} - \propto_{DS}}{\sqrt{\propto^2 + F}} \quad (3)$$

$$b_{ij} = \gamma\widehat{a_1} + \beta \quad (4)$$

Where bij, γ, and β are the final normalized values and the parameters.

The Bidirectional long short-term memory resulted in the various neural network-based models that are utilized to solve the problems in this modern world. The flight delays are predicted by using the BiLSTM approach which is efficient due to OTS memory-oriented abilities. Two values that are stored in the BiLSTM hidden layer are utilized in both forward and backward calculations.

C. *Design of Bidirectional Long Short-Term Memory*

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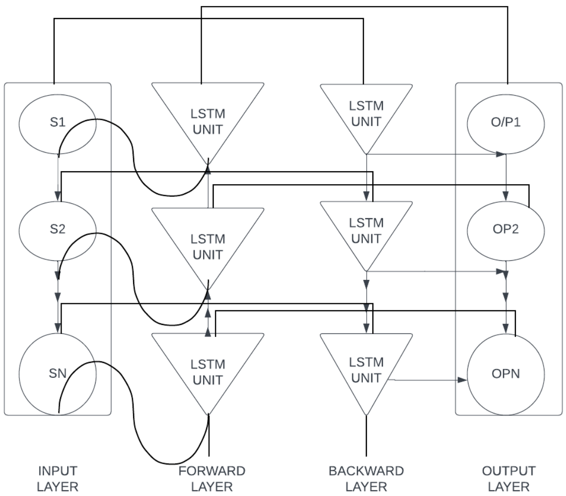

Figure 2: Forward and Backward layers present in the Bi-LSTM Architecture.

The above Bi LSTM architecture consists of the input layer, BiLSTM layers, as well as output layer. The flight data is the input to the networks which includes relevant features like departure time weather conditions etc., The main architecture of the BiLSTM consists of two LSTM sub-layers in these two layers one-layer processes the input sequences in the forward direction where whereas another layer processes in the backward direction. the LSTM units consist of memory cells and various gates to control the flow of the data. The last layer in the architecture is the Output layer which produces the final flight delay prediction. based on the specific task there should consist of one or more neurons.

$$f_m = \sigma(w[x_m, h_{m-1}, C_{m-1}] + n_u)$$

Where the x_m denotes the sequence of the inputs, h_{m-1} is the output of previous block, C_{m-1} indicates the block memory of the previous LSTM and the bias vector is denoted by the n_u.The individual vectors for every input is denoted by the wwhere the logistic sigmoid activation function is denoted by the σ.

D. Design of the One-way Long Short-Term Memory Network

The LSTM encoder uses the time series sequence as input and creates the input sequence for every LSTM cell result in a vector with hidden and cell states also the additional decoder inputs produced for the predictions are sent to the LSTM decoder to train against the expected result for the target output sequence as the decoder output during the model training process.

E. Evaluation Metrics Model

Accuracy is calculated by

$$\text{accuracy} = \frac{\sum_{m=0}^{Z}(TP_m + TN_m}{\sum_{m=0}^{z}(TP_m + FP_m + FN_m)}$$

4. Results and Discussion

In this Research, Flight delays is significantly affecting airline schedules, resource management, and passenger satisfaction, posing considerable challenges for blended the aviation sector and its customers. Address this issue helps to build a predictive system based on Bidirectional Long Short-Term Memory (BiLSTM) using historical flight data. To predict flight delay achieved by using Bi-Lstm and it's related to the Machine learning techniques.

Through the analysis of historical data and various factors pertinent to the aviation industry, our model demonstrated effectiveness in learning intricate patterns and making precise predictions. By integrating multiple parameters such as airport congestion, carrier information, and weather conditions, we achieved accurate predictions of flight delays. Recurrent Neural Networks (RNNs), specifically LSTMs, were utilized to process sequential data, crucial in capturing temporal dependencies inherent in-flight delays.

The BiLSTM architecture enabled flight delay system to incorporate both past and future information, thereby enhancing its predictive capabilities. Upon reading flight data from historical datasets, our system underwent a data cleaning phase to filter out canceled flights. We then normalized various delay metrics by the total number of arriving flights to ensure standardization. Subsequently, after preprocessing and normalization, plotted different types of delays against time for further analysis dedicates in the figure 3.

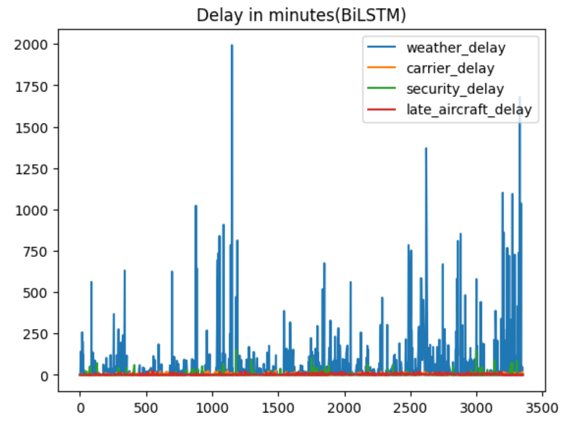

Figure 3: Different types of flight delay timings

The dataset underwent preprocessing, which involved filtering out canceled flights as a primary step. This preprocessing step aimed to enhance the robustness of predictions across diverse scenarios. Following this, the dataset was divided into training and testing subsets, with a significant portion reserved for testing purposes. To mitigate overfitting during the training phase, an early stopping method was employed.

Training the dataset involved 200 epochs utilizing the Adam optimizer and binary cross-entropy loss function. The model's performance was evaluated using various metrics, including loss and accuracy depicts figure 4 & 5.

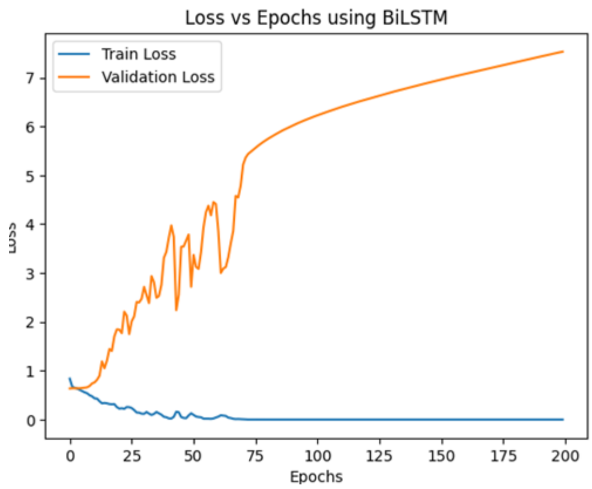

Figure 4: Different types of flight delay timings

The loss curve serves as an indicator of the system's proficiency in accurately categorizing flight delays. To evaluate the model's ability to generalize, both training and validation datasets were utilized. Upon reviewing the outcomes, we noted that the algorithm demonstrated effectiveness in predicting flight delays. The gradual decrease in loss across epochs suggests successful learning.

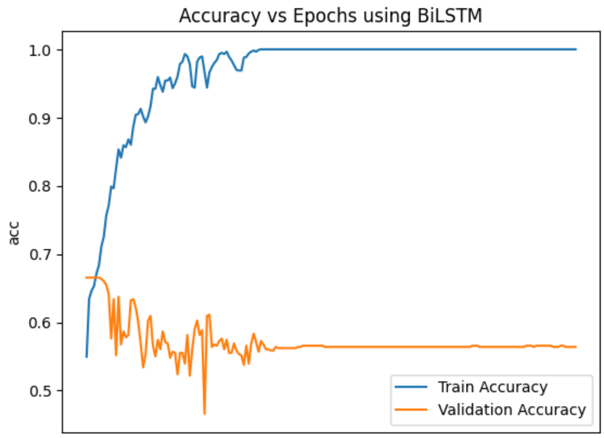

Figure 5: flight delay prediction system evaluated accuracy using various metrics

Likewise, the accuracy curve exhibited a steady rise, signifying the system's adeptness in classifying flight delays. Notably, the accuracy curve displayed a continuous ascent, peaking at the 150th epoch for both training and validation datasets. The final accuracy attained by the system on the validation set stood at 85%, denoting that the model accurately classified 85% of the flights in the test dataset.

5. Conclusion

As the air transport industry experiences rapid growth, the demand for travel, coupled with the limited capacity of airports and increasing aviation traffic, has amplified the impact of flight delays on both air transport efficiency and passenger experiences. Predicting flight delays plays a pivotal role in aiding decision-making for airline systems and improving the overall travel experience. In this regard, we have developed a flight delay prediction model leveraging the BiLSTM machine learning technique, considering a comprehensive range of factors influencing flight delays.

This model utilizes the BiLSTM architecture to accurately predict delay times by accounting for spatio-temporal dependencies within the data. Through the incorporation of batch normalization and dropout techniques during training, the model effectively captures sequential dependencies, crucial for precise predictions. The BiLSTM, a recurrent neural network, excels in learning dependencies within sequential data in both forward and backward directions. This bidirectional approach enables the system to glean insights from past and future information, thereby enhancing prediction tasks. Through meticulous parameter optimization, flight delay system achieved an accuracy of 84.1%, underscoring its effectiveness in accurately predicting flight delays and aiding decision-making processes within the aviation industry.

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