Design of an Intelligent Model for Predicting Flight Safety Risk in the Approach Phase Using the BI.M-LSTM Algorithm

Mansour Yahyavi
Ph.D. .Student, Department of Information Technology Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran .

Abbas Toloie Eshlaghi
Professor, Department of Information Technology Management, Science and Research Branch, Islamic Azad University, Tehran, Iran.
Corresponding Author toloie@gmail.com

Mohammad Ali Afshar Kazemi
professor ,Department Information Technology Management, Central Tehran Branch, Islamic Azad University, Tehran

Reza Radfa
professor, Department of Information Technology Management, Science and Research Branch, Islamic Azad University, Tehran, Iran

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ABSTRACT
The present article introduces a novel model, BI.M-LSTM, which integrates the BI algorithm with the Long Short-Term Memory (LSTM) neural network to predict flight safety risks during the approach phase. Although this phase comprises only 3% of the total flight process, it is considered the most perilous stage. The proposed method involves training supervised neural networks to estimate target parameters. A standardized dataset from 2019 to 2020 was utilized, consisting of 28,813 records related to safety risk parameters such as weather conditions, aircraft configuration, flight information, speed, altitude, and air traffic. The data was summarized, cleaned, and normalized before use. Given the sequential nature of flight data and the necessity for memory retention, training was conducted using the LSTM algorithm within a Python environment. The model's mean squared error for deviations was approximately 6.38%, indicating a negligible error rate and high credibility compared to similar models. This model, enhanced with advanced tools including ETL (Extract, Transform, Load), metadata, and real-time monitoring, effectively addressed the challenges of analyzing and cleaning large-scale flight data. It successfully identified the most critical safety factor during the approach phase: control of speed and altitude during landing. This robust approach aids flight crews in managing vital safety parameters, such as preventing loss of control, maintaining appropriate aircraft speed, determining the touch-down position, and avoiding runway excursions.

Keywords: Flight Safety Risk, Aviation, BI.M-LSTM Model

1. Introduction

The control, monitoring, and evaluation of safety in the aviation industry are crucial and vital concerns. Most aviation accidents result from a decline in flight safety levels, including factors such as human error, technical failures, loss of control, and adverse weather conditions (Haber et al., 2021). Although the likelihood of accidents due to flight safety issues is relatively low, they can result in significant human and financial losses (Jury et al., 2020). Globally, approximately 24.9 million flights are conducted annually, with the approach phase—representing only 3% of the total flight process—being the most hazardous, accounting for 67% of fatal accidents (ICAO, 2022). Emphasizing flight safety is a risk reduction strategy aimed at saving lives, protecting assets, and preventing unfortunate incidents (Rey et al., 2021).

Analyzing historical accident data to prevent future incidents has proven to be an effective strategy (Li et al., 2023). For successful prevention programs, it is crucial to identify both the primary and contributing factors of accidents. Structured data encompasses raw flight data from sources such as quick access recorders and flight data recorders, as well as processed safety data. Unstructured data includes national transportation safety accident reports (Bitins et al., 2022). Traditional flight safety management systems (FSMs) that rely on physical, fuzzy, and statistical methods for analyzing flight data often struggle to assess flight safety risks accurately and promptly due to computational complexity, errors, and processing delays. The extensive volume of black box data necessitates rapid and efficient processing (Zhi Lu et al., 2018).

Conversely, the cost of flight safety reviews escalates with the increasing volume of accident reports and the expansion of commercial aviation industries (Gallo et al., 2022). Numerous studies have been conducted to enhance aviation safety and establish precise criteria for reducing accidents, particularly through the use of

machine learning techniques (Aysha et al., 2024). For instance, Aysha and colleagues (2024) employed deep learning methods to predict risks associated with the approach and landing phases of flights. Similarly, T. Jas J. and team (2020) developed a global predictive model for landing performance criteria using supervised machine learning to forecast safety criteria in aviation (Puranik et al., 2023).

Based on the information provided, deep learning proves to be a powerful method for analyzing and interpreting complex data across various fields. One such application is in analyzing aircraft movement patterns during flight to mitigate potential risks. This approach is valuable for evaluating flight crew performance, detecting risk factors and incidents, enhancing flight safety and efficiency, and supporting simulation training. Utilizing recurrent neural networks to identify effective data change rules is particularly beneficial. This paper introduces, for the first time, the BI.M-LSTM platform—a suitable and efficient tool for analyzing safety data during the approach phase and predicting risks. The BI.M-LSTM platform combines the BI model, which includes advanced control tools for handling large-scale flight data, an intelligent database, and monitoring tools, with the LSTM recurrent network.

2- Literature Review

Jury et al. (2020) found that estimating parameters such as fuel flow, flap settings, and landing gear can significantly reduce safety risk errors. Wang et al. (2023) introduced a deep learning-based approach for calculating aircraft load weight. Additionally, Goyendarjan et al. (2015) proposed an optimal control framework for evaluating flight control laws. When detecting and analyzing unstable approaches, both weather factors—such as low visibility and crosswinds—and human factors contribute significantly to the risk (Sun et al., 2023).

Yay et al. (2023) aimed to understand the flexibility limitations of a pilot’s mental model during aircraft landing using machine learning. Their study highlighted that delayed control by air traffic controllers in inappropriate landing situations is a significant factor in identifying human performance errors and anomalies in the flight environment (Yay et al., 2023).

AI-based methods, including artificial neural networks (Singh et al., 2012) and support vector machines (SVM) (Zhou et al., 2011), have revolutionized the prediction of flight safety risks (Zhe et al., 2022). Alexanders et al. (2020) demonstrated that integrating multiple advanced algorithms enhances the extraction of incident data for aviation safety assessment. The AIRSAFE conceptual architecture aids in preventing flight control loss, improving safety assessment, and ensuring flexible control in risky situations (Eleksanderz et al., 2020). Machine learning algorithms, such as random forests (RF), SVM, and logistic regression, are employed to analyze the relationships between excessive risk indices and flight parameter data. The SVM model specifically identifies risks within the aircraft's electrical system by evaluating the status of its components. With advancements in machine learning, deep learning models like LSTM and AE have shown excellent performance in risk assessment (Zhe et al., 2020). Hang Sun et al. (2022) introduced an innovative model, PS-LE-LSTM, which combines time series data analysis with LSTM networks to mitigate flight risks.

During the safety phases of the approach, when the aircraft enters a Standard Terminal Arrival Route (STAR), the system status is updated based on the final assessments by the pilot and crew. As the aircraft nears the runway, both speed and altitude are gradually reduced. If, by the end of the landing phase (STAR 5), the aircraft does not meet the stable approach criteria, the landing is categorized as an unstable near-miss event. Conversely, in subsequent STARs, the flight crew adheres to the guidelines of each respective STAR. If landing conditions are unfavorable, the pilot and crew work to minimize landing instability, and landing is only carried out after reducing speed. The pilot also adjusts the flaps to facilitate a quicker landing. However, if the airspeed or altitude is controlled excessively beyond the STAR parameters, the pilot may struggle to stabilize the aircraft promptly. Deviations from STARs can occur for various reasons, such as failure to comply with STAR regulations. For instance, in the MMD3 scenario, speeds are executed at 20 knots above the STAR limit, and in MMD4, the pilot maintains a higher altitude to conserve fuel (Hush-Li, 2023).

In this phase, the pilot's responsibilities include deciding whether to land or execute a go-around, as well as adjusting the aircraft's angle and power settings from those used during the final approach to those suitable for landing. If equipped, the radio altimeter assists the pilot in determining the optimal point to begin the flare by providing the precise height above the runway. When executed correctly, the flare enables the aircraft to achieve the proper landing angle with the power set to idle or near-idle, a reduced descent rate, and decreased airspeed, typically a few inches to a few feet above the

landing surface, depending on the aircraft type. Incorrect execution of the flare can lead to a hard landing, gear collapse, tail strike, or, in severe cases, a runway excursion. Another common approach to risk assessment involves calculating or predicting operational distances based on aircraft performance analysis. Accurate representation of the takeoff dynamics system is essential for calculating these distances. The takeoff and landing distances of an aircraft, derived from performance analysis, are critical parameters for risk assessment (Hush et al., 2023).

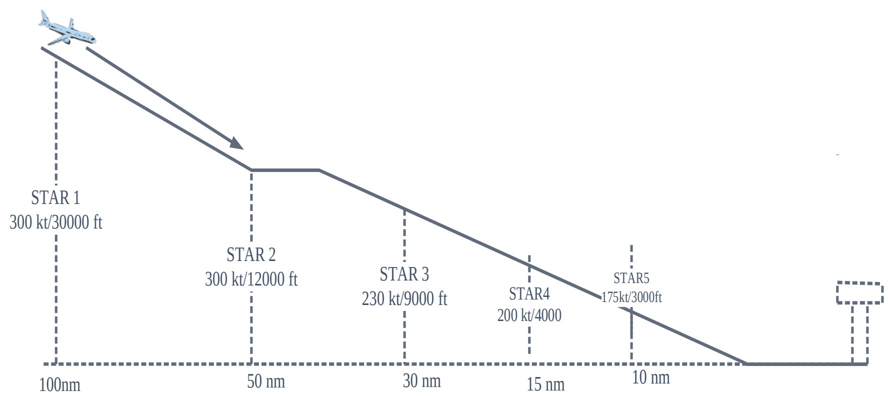

Figure 1 - Flight Process of the Approach and Landing Phase (Based on the Hush-Li Model, 2023)

3- Research Method

Data visualization is crucial for interpreting complex datasets, as it helps uncover patterns, trends, and correlations. Integrating high-quality data sources with effective feature engineering can greatly enhance machine learning research outcomes and lead to more accurate and insightful predictions (Singe et al., 2012).

3.1- Data

The dataset was collected and processed through a multi-step procedure in compliance with ICAO Annex 19. Seventeen common factors, accounting for approximately 95% of all incidents, were identified. Therefore, selecting the most influential parameters is essential for developing a robust and scalable model. Feature selection was performed to

exclude irrelevant data or parameters, enhancing accuracy and reducing computational costs during the prediction phase. The dataset, sourced from Kaggle and Zenodo, consisted of raw flight data from 2019 to 2020 related to past flight incidents leading to accidents. This data included six high-frequency categories: human factors, aircraft, company policy, procedures, weather, and airport (incidents caused by rare factors were not considered in this study). After data cleaning and summarization, resulting in 28,818 records, 20,072 records (70% of the total time-series data) were used for training the BI.M-LSTM supervised model, while the remaining 30% were reserved for model validation, as detailed in Table 1.

Table 1 - Features of Flight Data in the Approach and Landing Phase

	Feature	Description	Source
1	Approach Unstable	The approach phase to the runway begins some time before touchdown. It acts as the first line of defense in preventing runway excursions.	Tswing China (2023)
2	Landing / Height	High landing height leads to high airspeed and ground speed on the runway.	Hushu Yay Li (2023)
3	Landing / Airspeed	Airspeed during the approach to the runway and landing airspeed (VREF) stops the airspeed.	Aysha (2024)
4	Weight Calculation Error	Gross weight on landing distance is one of the main determinants of landing distance.	Chang Fen (2023)
5	Landing / Touchdown	AFM/POH distances based on a touchdown point.	Mirzon Lori (2023)
6	Runway / Slope	Runway slope (gradient) has a direct impact on landing distance.	Aysha (2024)
7	Reverser	Engine reverse thrust.	Chang Feng (2023)
8	Height Over the Runway	Excessive height over the runway threshold above 50 feet.	Jing Li (2022)
9	Flaps Control	Flaps during approach provide low altitude and steep landing.	Jang Feng (2023)
11	Wind Blow	Wind speed.	Jing Li (2022)
12	Runway	Runway condition during aircraft landing.	Aysha (2024)
13	Tire Failure	Visual condition and deployment of the tire.	Tswing China (2023)
14	Temperature	Airport temperature in degrees Celsius.	Jing Li (2022)
15	Engine	Engine power during landing.	Jang Feng (2023)
16	Trophic	Flight time calculation to reach the destination.	Yi Lin (2020)
17	Pilot-in-Command Supervision	Improper use of the checklist by the pilot.	Koul Paul (2024)

3 .2- Data Analysis

This section examines various flight parameters during the approach and landing phases. The pitch angle and angle of attack, which are critical for specific landing operations, are analyzed and their distribution is illustrated using a histogram.

Figure 2 illustrates the distribution of flight event data during the approach and landing phases. Notable changes are observed in the time intervals before and after the approach, highlighting the potential of deep learning for analyzing flight parameters. Among these parameters, the change in sch_dep is identified as a key indicator for detecting a stable approach.

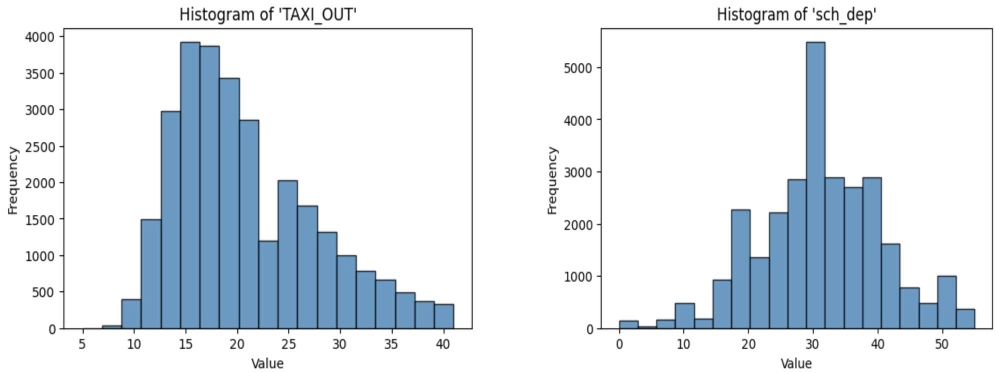

Figure 2 - Distribution of Events Affecting Unstable Approach

3.3 -LSTM Model

The LSTM network is a specialized type of RNN designed to learn long-term dependencies, making it well-suited for classification, processing, and predicting time series data (Gers, 1999). These models can train multiple layers of high-performance hidden computational units. LSTMs utilize a cell state to retain past information and incorporate three gates to update, predict, and compute the cell state. The 5-layer BI model, used for business prediction and analysis, enhances performance (Jaary et al., 2022; Ng Aries et al., 2023). In supervised learning, whether for classification or regression, targets are utilized during the model training phase. In regression problems, the target represents the actual predicted output value (Zho et al., 2020).

3.4 -ETL

This layer, built on the BI architecture, comprises three key stages in the data preparation process. Data preprocessing involves data cleaning, transformation, normalization, and standardization. In the initial stage, 17 features were used as input to the LSTM network to reduce the dimensions of the input signal. Consequently, the input data can be represented as a flight data matrix, as illustrated below:

$$X=\begin{bmatrix} p_{t-n}^{1} & p_{t-n+1}^{1} \ldots\ldots & p_{t-1}^{1} & p_{t}^{1} \\ p_{t-n}^{2} & p_{t-n+1}^{2} & p_{t-1}^{2} & p_{t}^{2} \\ p_{t-n}^{3} & p_{t-n+1}^{3} \cdots \cdots \ldots \cdots & p_{t-1}^{3} & p_{t}^{3} \\ . & . & & \\ . & . & & \\ p_{t-n}^{17} & p_{t-n+1}^{17} \cdots \cdots & p_{t-1}^{17} & p_{t}^{17} \end{bmatrix}$$

In this matrix, the element p_{t-n}^{17} represents the value of the flight parameter (flight altitude) at time step (t-n) . This matrix is expressed as an input vector, where each element represents a vector of flight parameters. In the next time step, a multivariate sequence of flight parameters is dependent on the past (n) time steps.

The aim of data cleaning is to eliminate outliers to ensure accurate measurements and relevant data features. For machine learning algorithms, data preparation involved two key transformation methods: data encoding and data normalization. Data encoding converted categorical features into numerical representations, while data normalization scaled numerical data, such as aircraft speed, to a range between 0 and 1 based on their dynamic range. This process ensures that numerical features from different flights are on compatible scales and have a similar influence on the prediction model.

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

All flight data (28,813 records) were split into training and testing datasets. The training set, consisting of 20,169 records (70% of the total data), was used for the training process to compute gradients and optimize parameters. The remaining 8,644 records (30%) were randomly allocated to the testing dataset.

2.5 -LSTM Layer Architecture

Recurrent Neural Networks (RNNs) are designed for modeling sequence data in machine learning. These networks transmit information through a chain of interconnected nodes, processing input sequences to evolve over time. Among various learning models, the deep learning model, Long Short-Term Memory (LSTM), was selected for optimization due to its capability to handle dependencies between flight data points and maintain memory of previous inputs. The LSTM neural network incorporates several gates and variables. It was implemented using Python and TensorFlow. The architecture is described as follows:

Table 2 - Multi-Layer LSTM Network Architecture

Layer	Output	Parameters
1	LSTM_1	(128, 1)
2	LSTM_2	(64, 1)
3	Dense	1
Total		132,939
Trainable Parameters		132,929

In this study, two LSTM layers were used: the input layer with 34 neurons, the first layer with 128 neurons, the second layer with 64 neurons, and an output layer with 65 neurons. This algorithm can learn long-term dependencies, whereas a simple RNN only learns short-term dependencies. The LSTM neurons use a forget gate f_t to determine how much information from the previous cell state should be retained, calculated as follows:

$$f_t = \sigma \left(w_t \times [h_{t-1}, x_t] + b_f\right) \quad (2)$$

Here, w_t is the weight matrix of the forget gate, b_f is the bias term of the forget gate, and σ is the sigmoid function.

Next, the input gate, along with a tanh layer, selects the new information to be stored in the cell state. The input gate i_t regulates the amount added to the cell state at each time step, calculated as follows:

$$i_t = \sigma \left(w_i \times [h_{t-1}, x_t] + b_i\right) \quad (3)$$

$$\tilde{C}_t = tanh \left(w_c \times [h_{t-1}, x_t] + b_c\right) \quad (4)$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \quad (5)$$

Here, w_i is the weight matrix of the input gate w_c represents the memory weight, and b_i is the bias term of the input gate. The control of the forget and output gates allows the LSTM model to use past information for current predictions. The final output of the model is the result of the output gate multiplied by the tanh layer, calculated as follows:

$$O_t = \sigma \left(w_o [h_{t-1}, x_t] + b_c\right)$$
$$h_t = O_t \times tanh\, (C_t)$$

Here, w_o is the weight matrix of the output gate, and b_c is the bias term of the memory cell. Features are extracted from these parameters. The LSTM neural network consists of three layers and one regression output layer. The first layer is a batch normalization layer with 50 units and a tanh activation function. The output layer is a single neuron, and learning is performed using the Adam optimizer (Kingma, 2014).Figure 3 illustrates the structure of the proposed BI.M-LSTM model for predicting flight safety risks during the approach and landing phases. Data flows into the model from the first layer to the second layer, where the initial bulk of flight data is processed. This includes identification, cleaning, summarization, removal of redundant data, and integration (Baars et al., 2008). During this stage, data exploration is conducted to analyze the incoming data, which is then categorized for use in the deep learning model. The processed output is stored in the analytical data warehouse layer. Metadata plays a crucial role by providing information about all data and, importantly, updating and maintaining data changes and rule modifications to support and categorize safety cases.

As shown in Figure 3, the final layer provides a powerful OLAP tool that quickly and accurately presents information in various formats to flight crew and airport staff.

Table 3 - Definition of Layers and Inputs of the B.I.M-LSTM Model

Layer	Layer Name	Input	Process	Strengths
1	Data Layer	Model input data	Data from internal and external databases enter the model	Utilizes vast existing flight data
2	ETL	Data Layer	Data extraction, integration, cleaning, summarization, and output to the LSTM model	Organized data extraction, classification, storage, and processing
3	LSTM	ETL	Time-series aviation data dependent on past data, suitable for LSTM networks for time-series prediction, used for training	Strong deep neural network algorithm (LSTM) for discovering new safety risk prediction patterns
4	Analytical Database	LSTM	Data storage for modeling	Updated dataset for learning
5	Metadata Layer	All layers	Metadata provides information about all data and, most importantly, updates and maintains data changes and rule changes to support and categorize safety cases	Powerful updating tool
6	Monitoring Layer	Analytical Database	Real-time monitoring of network output, available to managers and flight crew	Real-time reporting

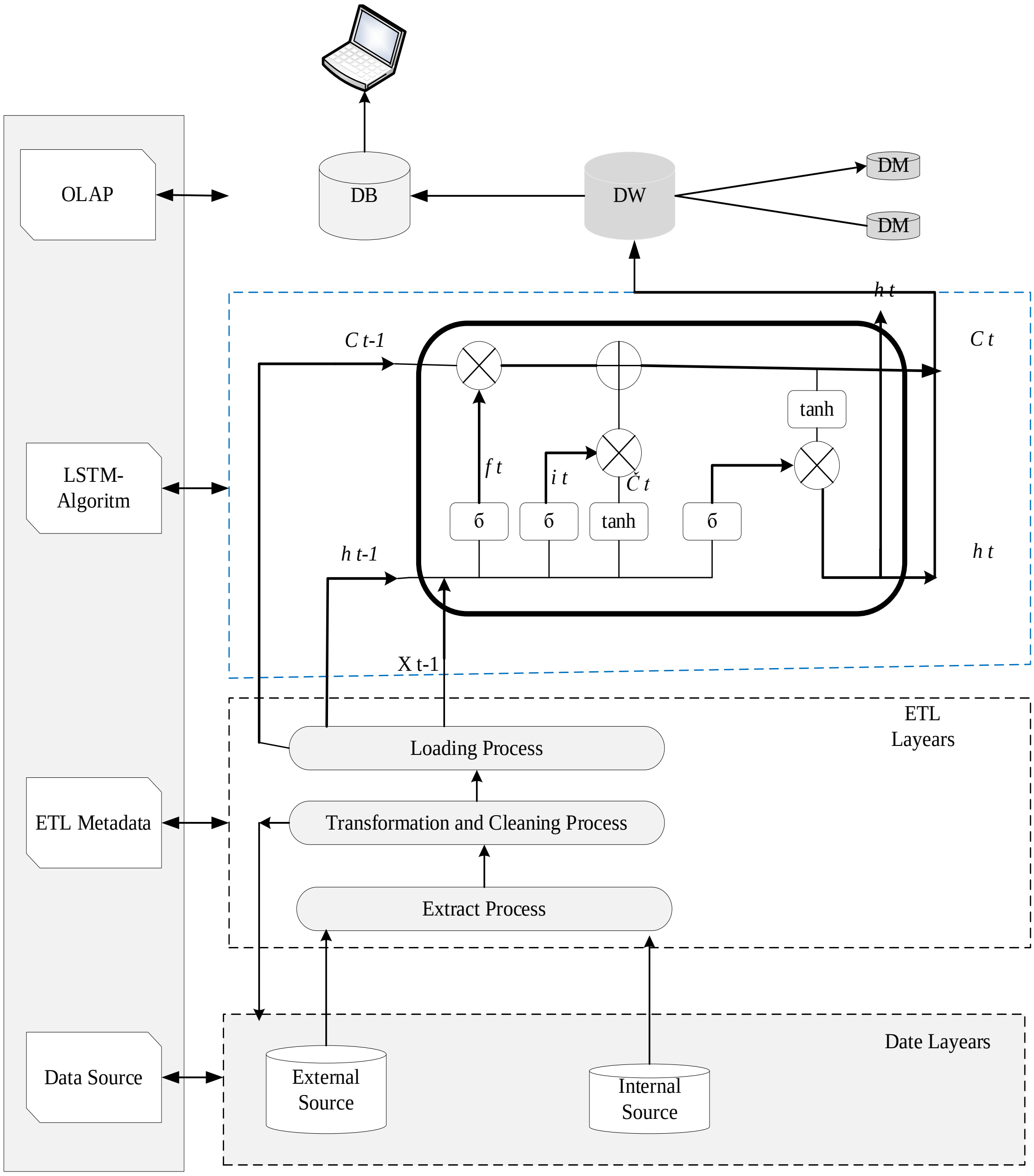

Figure 3 - Proposed BI.M-LSTM Model for Approach and Landing Optimization

To assess the network's performance, the Root Mean Square Error (RMSE) was employed as a metric to evaluate the accuracy of the proposed model's results.

$$RMSE \quad \frac{1}{n}\sqrt{\sum_{i=1}^{n}(y - \bar{y})^{2}} \tag{8}$$

In the above equation, (n) represents the number of observations, (y) represents the measured values, and (\bar{y}) represents the predicted values. This relationship calculates the relative error deviation between the

redicted values and the measured data, optimizing the network’s free parameters (weights and biases) through training algorithms based on training data (including input and target vectors) to minimize the error between the network output and the target parameter.

$$MAPE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\frac{y-\bar{y}}{y}} \tag{9}$$

4- Finding

To learn from a supervised deep learning model (RNN-LSTM), the output data for continuous risk prediction is determined using the following linear regression function:

$$f(x) = w^{t}\ (xi) + b$$

The performance of the proposed LSTM model was optimized during the training process by adjusting several parameters, including batch size, activation function, number of hidden units, optimizer type, and number of epochs (50). The optimizer was selected to minimize the loss function. Additionally, the Mean Absolute Error (MAE) was used as a metric to evaluate the error of the estimator relative to the actual values. MAE represents the average of the absolute differences between the predicted and actual values, providing a measure of the estimator's accuracy.

Table 4 shows the learning error rate (MSE) for each of the training and testing data groups. Since the values of this index are closer to zero, it indicates a lower error rate for the data group and an acceptable confidence level for the model.

According to Figure 4, the lower Mean Absolute Percentage Error (MAPE) index indicates higher accuracy of the estimator, with an error value of 5.256. The chart shows that the network’s mean squared error starts from a certain value and progressively decreases, reflecting improvement in the network's learning process.

Figure 5 displays two lines representing the input and target vectors, which were randomly divided into training (70%) and testing (30%) sets. The evaluation set is used to monitor the network’s performance. Training continues until the network error on the evaluation set decreases, thereby preventing overfitting to the training data. The RMSE values of the model indicate that the minimum mean squared error, calculated from equation (9), is 6.384 at epoch 50, marking the model's optimal performance.

Table 4 - Learning Error Rate (MSE)

Parameter	Training	Testing
Learning Error	17.01	17.10
RMSE	6.548	6.384
MEPA	5.249	-
Total Flight Data (28813)	20169	8644

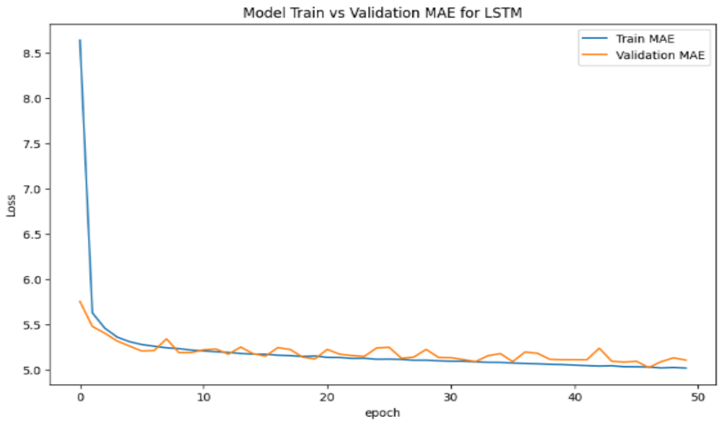

Figure 4 - Mean Absolute Error (MAE) Chart

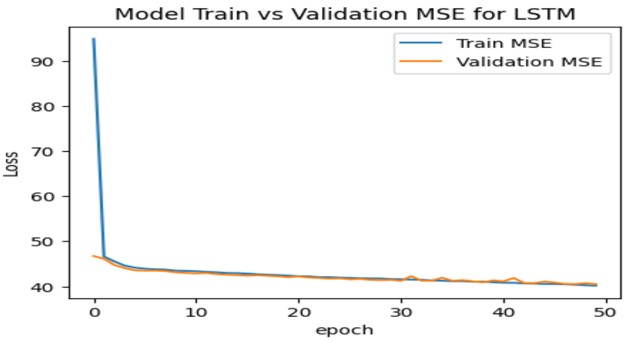

Figure 5 - Mean Squared Error (MSE) Chart

Table 5 - Comparison of the Present Model with Other Models

Study	Research Objective	Dataset	Algorithms	Performance
Robinson (2020)	Information from event reports	Aviation Safety Report	7,484	Discovering conceptual relationships
Shi (2020)	Using machine learning to identify key factors	Aviation Safety Event Report	168,227	Deep Learning
Dong (2021)	Main and secondary influencing factors	Aviation Safety Event Report	181,651	Recurrent Deep Neural Networks
Hong (2022)	Data analysis	Flight data analysis	PS-AE-LSTM	Innovative model
Present Study (2024)	Optimizing flight safety processes	Flight data analysis	28,813	Innovative model B.I.M-LSTM

5- Discussion and Conclusion

This article introduces the BI.M-LSTM model for predicting flight safety risks, utilizing the innovative BI.M-LSTM algorithm for the first time. The BI.M-LSTM model addresses the challenge of extracting, exploring, and categorizing extensive flight data with its advanced optimization tools, including the ETL layer, significantly reducing the high costs associated with data analysis. The problem statement emphasizes the ongoing need for risk identification to enhance flight safety data analysis. The model's metadata layer facilitates data storage and processing in flight safety analysis, continuously updating and reflecting changes in real time.

The results of the BI.M-LSTM metaheuristic algorithm in addressing the FSM problem demonstrate superior performance compared to similar algorithms, such as PS-AE-LSTM, after 50 repetitions under identical conditions. This improvement is evident both in terms of average results and objective function optimization. The BI.M-LSTM model utilizes the LSTM neural network to estimate parameters related to flight monitoring and safety systems, such as aircraft speed and flight altitude up to the touchdown point. The high correlation between the estimated curves and the actual curves indicates negligible error, with a flight safety risk error of 6.586%, which is an improvement over the FSM model known for its inefficiency in emergency situations (Blanchandran, 2015; Yu Ha and Ji, 2022). For comparison, the method proposed by Pi Wang (2023) has an average relative error of 8%, and the Hong model (2022) has a relative error of 13.51%. Thus, the BI.M-LSTM model, with an accuracy of 93.41%, shows better performance than other deep learning models. This model reliably supports flight crews at both ground and air stations in managing critical flight safety parameters, including aircraft speed, flight altitude, brake control, and, most importantly, preventing flight loss. Future research is needed to further investigate and enhance the BI.M-LSTM model.

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