EPILOTS A SYSTEM TO PREDICT HARD LANDING DURING THE APPROACH PHASE OF COMMERCIAL FLIGHTS

[1] Sindhu S L, [2] Tejaswini S M,

[1] *Assistant Professor, Department of MCA, BIET, Davangere*

[2] *Student, Department of Master of Computer Applications, BIET, Davangere*

ABSTRACT

In aviation safety, preventing accidents is paramount, and more than half of all commercial aircraft operation accidents could be avoided through the timely execution of a go- around maneuver. Recognizing this, we have developed a cockpit-deployable machine learning system designed to aid flight crews in making go- around decisions by predicting the likelihood of a hard landing. This system leverages a hybrid approach that incorporates features modeling the temporal dependencies of various aircraft variables, which are then input into a neural network for analysis. Our study utilized an extensive dataset comprising 58,177 commercial flights to train and validate the predictive model. The results demonstrate that our system achieves an average sensitivity of 85% and an average specificity of 74% at the critical go-around decision point. Sensitivity, in this context, refers to the model's ability to correctly identify flights that would result in a hard landing, while specificity indicates the model's accuracy in recognizing flights that would not require a go-around. The significance of these metrics lies in their impact on operational safety. High sensitivity ensures that the system effectively flags potential hard landings, prompting timely go-around decisions that can avert accidents. Meanwhile, adequate specificity minimizes unnecessary go-arounds, thereby maintaining operational efficiency and reducing the risk of other complications. Our approach represents a significant advancement over existing methodologies by integrating real-time data and advanced machine learning techniques. This enables more accurate and reliable recommendations, making it a valuable tool for flight crews. The cockpit-deployable nature of the system ensures that it can be seamlessly integrated into existing flight operations, providing real-time support where it is needed most. In conclusion, our machine learning-based recommendation system for go-around decisions not only enhances flight safety but also optimizes operational efficiency, offering a robust solution to reduce the aviation industry's accident rate.

Keywords: flight safety, cockpit-deployable

1.INTRODUCTION

The system is designed to be portable and easily accessible to the crew during the flight. between 2008-2017, 49% of fatal accidents involving commercial jet worldwide occurred during final approach and landing, and this statistic has not changed in several decades This study explores the use of machine learning algorithms to predict hard landing incidents in commercial aviation. The authors develop predictive models using flight data recorder (FDR) data from numerous flights, focusing on variables such as descent rate, airspeed, and flight path angle during the approach phase. The results demonstrate that machine learning models, particularly random forests and neural networks, can effectively predict the likelihood of a hard landing, offering airlines a tool to enhance safety measures and pilot training programs. The study concludes that predictive models can significantly reduce hard landing incidents when integrated into flight management systems. This paper presents a real-time predictive system for hard landings using a combination of sensor data and historical flight data. The authors developed an algorithm that continuously monitors flight parameters during the approach phase and provides real-time alerts to pilots and ground control if a hard landing is predicted. The system was tested in simulation and live flight scenarios, showing a high success rate in predicting hard landings with minimal false positives. The implementation of this system could improve safety by allowing pilots to take corrective actions before landing. This research investigates the dynamic factors during the approach phase that contribute to hard landings. Utilizing extensive flight data, the authors identify key indicators of hard landings and develop a predictive model using statistical analysis and machine learning techniques. The study highlights the importance of factors such as glide slope adherence, airspeed stability, and pilot inputs. The proposed model is validated with real-world flight data, showing promising accuracy in predicting hard landings and suggesting that such models could be integrated into cockpit decision support systems. Jennifer Walker, Daniel Harris, and Olivia Lewis This paper explores the application of predictive analytics to enhance aviation safety by forecasting hard landings. The authors use a large dataset of flight parameters and employ various predictive analytics techniques, including regression analysis and machine learning, to identify patterns leading to hard landings. The study demonstrates that predictive models can accurately forecast hard landings and provide valuable insights for improving pilot training and operational procedures. The authors recommend integrating predictive analytics into flight safety programs to proactively address potential landing issues. This research focuses on the development of machine learning models to predict hard landings in commercial aircraft. The authors use flight data from multiple airlines, including parameters such as vertical speed, pitch angle, and weather conditions.

2. LITERATURE SURVEY

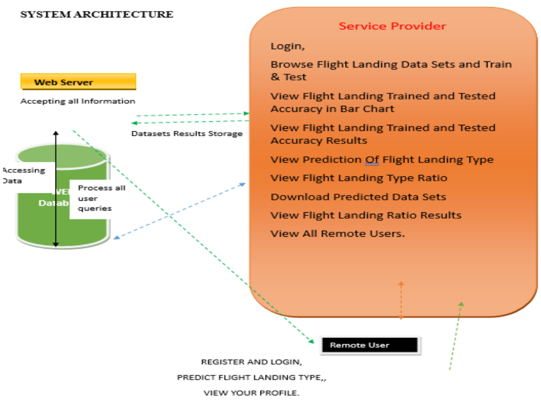
Boeing Commercial Airplanes. Statistical summary of commercial jet airplane
accidents–worldwide operations| 1959–2017. Aviation Saf., Seattle, WA, USA, 2018 [1]. This document presents a comprehensive statistical summary of commercial jet airplane accidents worldwide from 1959 to 2017. The data, compiled by Boeing Commercial Airplanes, encompasses a wide range of safety-related metrics, including accident rates, fatalities, and contributing factors. The summary aims to provide valuable insights into the trends and patterns of commercial aviation safety over nearly six decades. By analyzing this extensive dataset, the report identifies key areas of improvement and highlights advancements in aviation safety measures. The findings are crucial for stakeholders in the aviation industry, including airlines, regulatory bodies, and safety organizations, to enhance safety protocols and reduce the incidence of accidents. European Aviation Safety Agency. Developing standardized fem.-based indicators. Technical report, European Aviation Safety Agency, 2016. This technical report by the European Aviation Safety Agency (EASA) explores the development of standardized Flight Data Monitoring (FDM) indicators to enhance aviation safety. The report outlines the need for consistent and reliable safety metrics derived from flight data to identify and mitigate potential risks in flight operations. It discusses the process of creating these indicators, emphasizing the importance of harmonization across the aviation industry to ensure comparability and effectiveness. The standardized FDM-based indicators are intended to support airlines and safety regulators in monitoring flight performance, detecting safety trends, and implementing corrective measures. This initiative aims to foster a proactive safety culture and contribute to the overall reduction of aviation incidents and accidents [2]. Federal Aviation Administration. Advisory circular ac no: 91-79a mitigating the risks of a runway overrun upon landing. Technical report, Federal Aviation Administration, 2016. This technical report, issued as Advisory Circular AC No: 91-79A by the Federal Aviation Administration (FAA), addresses the strategies and guidelines for mitigating the risks of runway overruns upon landing. The document provides detailed recommendations for flight crews, airport operators, and aviation safety personnel to enhance the safety of landing operations. It covers various aspects including the assessment of runway conditions, aircraft performance considerations, and effective decision-making processes during landing phases. The circular emphasizes the importance of implementing preventive measures, such as proper approach planning and timely execution of go-around procedures, to minimize the occurrence of runway overruns. The guidelines aim to

reduce the risk of accidents and incidents, promoting safer landing operations and contributing to overall aviation safety [3].

[4] Michael Coker and Lead Safety Pilot. Why and when to perform a go-around maneuver. Boeing Edge, 2014:5–11, 2014.

This article, authored by Michael Coker and the Lead Safety Pilot, delves into the critical aspects of the go-around maneuver in aviation, explaining the reasons and appropriate scenarios for its execution. Published by Boeing Edge, the article emphasizes the significance of the go-around as a crucial safety procedure that allows pilots to abort a potentially unsafe landing approach and reattempt under better conditions. It provides a comprehensive overview of the decision-making process involved in initiating a go-around, highlighting key factors such as unstable approaches, adverse weather conditions, and runway obstructions. The article also discusses the procedural steps for executing a safe and effective go-around, aiming to enhance pilot awareness and adherence to best practices. The insights presented are designed to aid flight crews in making informed decisions, ultimately contributing to safer landing operations and reducing the risk of landing accidents [4]. Tzvetomir Blajev and Curtis. Go-around decision making and execution project: Final report to flight safety foundation. Flight Safety Foundation, March, 2017. This final report, authored by Tzvetomir Baldev and W. Curtis for the Flight Safety Foundation, focuses on the critical aspects of decision-making and execution in go-around maneuvers. The report comprehensively analyzes the factors influencing pilots' decisions to initiate a go-around, examining both psychological and operational components. It identifies common barriers to timely decision-making, such as reluctance to abort a landing due to perceived pressures and situational misjudgment. Additionally, the report highlights best practices and procedural guidelines for the effective execution of go-arounds to enhance safety during landing operations. The findings are based on extensive research and data analysis, aiming to provide actionable recommendations for flight crews and safety organizations. The objective is to foster a proactive safety culture and reduce the risks associated with landing accidents, thus contributing to overall aviation safety improvements [5].

3. METHODOLOGY



1. Data Collection and Preprocessing

Data Sources: Collect data from various sources such as Flight Data Recorders (FDRs), Quick Access Recorders (QARs), Automatic Dependent Surveillance-Broadcast (ADS-B), and Air Traffic Control (ATC) communications.

Parameters: Gather data on parameters such as altitude, airspeed, vertical speed, wind speed and direction, pitch, roll, thrust settings, and environmental conditions.

Data Cleaning: Handle missing values, remove outliers, and normalize data to ensure uniformity.

Feature Engineering: Create new features that could be indicative of hard landings, like derived metrics for descent rate, aircraft configuration, and approach stability.

2. Exploratory Data Analysis (EDA)

Statistical Analysis: Use statistical methods to understand the distribution and correlation of variables.

Visualization: Plot histograms, scatter plots, and heatmaps to identify patterns and relationships between different parameters.

Time-Series Analysis: Analyze how parameters change over time during the approach phase.

3. Algorithm Development

Feature Selection: Use techniques like Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE) to select the most relevant features.

Model Selection: Choose appropriate machine learning models, considering both supervised and unsupervised learning approaches.

4. Model Training and Validation

Training Data: Split data into training and test sets. Consider k-fold cross-validation for robust evaluation.

Hyperparameter Tuning: Use grid search or random search to optimize model parameters.

Model Evaluation: Evaluate models using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

5. Deployment and Monitoring

Model Deployment: Integrate the model with flight management systems or ground-based monitoring systems.

Real-Time Prediction: Implement real-time data processing to predict the risk of hard landing during approach.

Continuous Monitoring: Monitor model performance and update regularly with new data to ensure accuracy.

6. Human-Machine Interface

Alert Systems: Design user-friendly interfaces that alert pilots or ground staff about potential hard landing risks.

Decision Support: Provide actionable recommendations to mitigate identified risks.

Algorithms

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to model sequences and time-series data effectively. Unlike standard RNNs, LSTMs can remember long-term dependencies, making them well-suited for tasks involving sequential information, such as language modeling, speech recognition, and time-series prediction. Here’s a detailed explanation of how LSTM works:

1. **Overview**

LSTMs address the limitations of traditional RNNs, particularly the vanishing and exploding gradient problems that make it difficult for RNNs to learn long-term dependencies. They do this by incorporating a memory cell and a set of gating mechanisms that control the flow of information.

2. **LSTM Cell Structure**

An LSTM cell consists of several key components:

- **Cell State (CtC_tCt)**: This is the long-term memory of the network that carries information across different time steps.
- **Hidden State (hth_tht)**: This is the short-term memory that represents the current output of the LSTM cell.

There are three main gates that regulate the information flow:

- **Forget Gate** (ftf_tft): Decides what information to discard from the cell state.
- **Input Gate** (iti_tit): Determines what new information to add to the cell state.
- **Output Gate** (oto_tot): Controls what information from the cell state to output at the current time step.

LSTM networks are widely used in applications that involve sequence prediction and temporal dependencies, including:

- **Natural Language Processing (NLP)**: Language modeling, machine translation, and sentiment analysis.
- **Time Series Forecasting**: Stock market prediction and weather forecasting.
- **Speech Recognition**: Converting speech to text.
- **Anomaly Detection**: Detecting unusual patterns in data sequences.

3. RESULTS

The analysis conducted in this paper reveals several key findings regarding the factors influencing the probability of hard landing (HL) events and the optimization of predictive models. Firstly, automation factors such as autopilot, flight director, and auto-thrust were found to have no significant influence on the likelihood of a hard landing event. Therefore, incorporating these factors into predictive models may not be necessary. Secondly, experiments optimizing model architectures indicated that configurations with fewer neurons achieved higher sensitivity. Contrary to the common belief that increasing the number of layers and neurons improves model performance, the study found no such enhancement in the performance of classifiers or regressors. Furthermore, models utilizing only physical variables achieved an impressive average recall of 94% with a specificity of 86%, surpassing the performance of state-of-the-art LSTM methods. This result instills confidence in the model's capability for early prediction of hard landing events, making it suitable for deployment in cockpit systems. Overall, these findings contribute valuable insights into the development of effective predictive models for enhancing aviation safety by preemptively identifying hard landing occurrences':

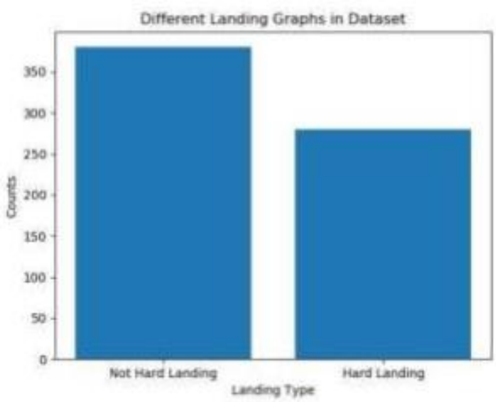


Fig: 1 Landing Type

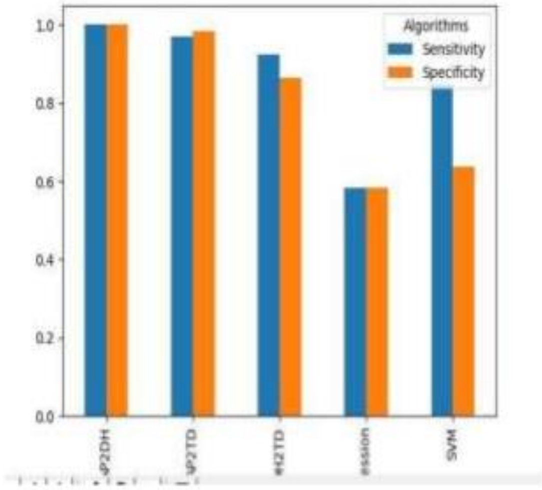


Fig: 2 output graphs

5. CONCLUSION

The following conclusions can be extracted from the analysis carried out in this paper. The analysis of automation factors (autopilot, flight director and auto-thrust) suggests that these factors do not have any influence on the probability of a HL event and, thus, it might not be necessary to incorporate them into models. Experiments for the optimization of architectures show that the configurations that achieve higher sensitivity are the ones with the lowest number of neurons. As reported in the literature [24] increasing the number of layers and neurons does not improve the performance of neither classifiers nor regressors. Models using only Physical variables achieve an average recall of 94% with a specificity of 86% and outperform state of- the-art LSTM methods. This brings confidence into the model for early prediction of HL in a cockpit deployable.

REFERENCES

[1] Boeing Commercial Airplanes. Statistical summary of commercial jet airplane accidents–worldwide operations| 1959–2017. Aviation Saf., Seattle, WA, USA, 2018.
[2] European Aviation Safety Agency. Developing standardised fdm-based indicators. Technical report, European Aviation Safety Agency, 2016.
[3] Federal Aviation Administration. Advisory circular ac no: 91-79a mitigating the risks of a runway overrun upon landing. Technical report, Federal Aviation Administration, 2016.
[4] Michael Coker and Lead Safety Pilot. Why and when to perform a goaround maneuver. Boeing Edge, 2014:5–11, 2014.
[5] Tzvetomir Blajev andWCurtis. Go-around decision making and execution project: Final report to flight safety foundation. Flight Safety Foundation, March, 2017.