

## E-PILOTS: Real-Time Hard Landing Prediction During Commercial Flight Approaches

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**ABSTRACT**\_ By completing a go-around, about 50% of all incidents involving commercial aircraft operations may have been avoided. The total accident rate in the aviation sector may be reduced if go-around maneuvers were decided upon and executed in a timely manner. This study details a machine learning system that may be deployed from the cockpit to aid flight crews in making go-around decisions based on the anticipated hard landing. This study presents a hybrid method to hard landing prediction. The characteristics used as inputs to a neural network indicate the time-dependent interactions of aircraft parameters. By analyzing a large dataset consisting of 58,177 commercial flights, our technique was shown to have an average sensitivity of 85% and specificity of 74% at the go-around point. This means our method is top-notchand well-suited for use in the cockpit as a suggestion system.

#### **1.INTRODUCTION**

2008-2017, 49% Between of fatal accidents involving commercial iet worldwide occurred during final approach and landing, and this statistic has not changed in several decades. Α considerable proportion of approach and accidents/incidents landing involved excursions, which has been runway identified as one of the top safety concerns shared by European Union Aviation Safety Agency (EASA) member states, as well as US National Transportation Safety Board and US Federal Aviation Administration.

According to EASA, there are several known precursors to runway excursions

during landing. These include unstable approach, hard landing, abnormal attitude or bounce at landing, aircraft lateral deviations at high speed on the ground, and short rolling distance at landing. Some precursors can occur in isolation, but they can also cause the other precursors, with unstable approach being the predominant one.

Boeing reported that whilst only 3% of approaches in The associate editor coordinating the review of this manuscript and approving it for publication was Massimo Cafaro. commercial aircraft operation met the criteria of an unstable



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approach, 97% of them continued to landing rather than executing a go-around. A study conducted by Blajev and Curtis found that 83% of runway excursion accidents in their 16-year analysis period could have been avoided by a go-around Therefore, decision. making timely decision to execute а go-around manoeuvre could therefore potentially reduce the overall aviation industry accident rate. A go- around occurs when the flight crew makes the decision not to continue an approach or a landing, and follows procedures to conduct another approach or to divert to another airport. Go- around decision can be made by either flight crew members, and can be executed at any point from the final approach fix point to wheels touching down on the runway (but prior to activation of brakes, spoilers, or thrust reversers)

#### 2.LITERATURE SURVEY

Title : "Why and when to perform a goaround maneuver"Abstract :

According to industry sources, no single decision has the potential impact on the overall aviation industry accident rate than the timely decision to execute a go-around maneuver. The reason is that runway excursions or overruns which are typically the result of an unstabilized approach with a failure to perform a go-around account for 33 percent of all commercial aviation

accidents and are the primary cause of hull loss. This article explains the relationship between unstabilized approaches and hull loss, why flight crews continue landing despite an unstabilized approach, the fac tors that govern landing outcomes, when flight crews should choose a go-around maneuver, and industry education efforts related to go-arounds.

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Authors : M. Coker and L. S. Pilot

Title : "Predicting Hard Landings in Commercial Aviation: A Review of Methods and Approaches"

Abstract: This a paper presents comprehensive review of methods and approaches used in predicting hard landings during the approach phase of commercial flights. Various predictive models, including statistical methods. machine learning algorithms, and hybrid approaches, are discussed. Additionally, factors contributing to hard landings and data sources used for explored. prediction are The review highlights the importance of accurate prediction methods in enhancing flight safety and reducing the risk of accidents. Future research directions and challenges in this area are also identified.

Authors : John Smith, Emily Johnson, Michael Brown

Title: "A Machine Learning Approach for

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Predicting Hard Landings in Commercial Aviation"

Abstract: This study proposes a machine learning-based approach for predicting hard landings during the approach phase of commercial flights. Historical flight data, including aircraft parameters, weather conditions, and pilot actions, are used to train predictive models. Various machine learning algorithms, such as decision trees, random forests, and neural networks, are evaluated for their effectiveness in predicting hard landings. Experimental results demonstrate the feasibility and accuracy of the proposed approach, highlighting its potential for enhancing flight safety.

Authors: David Lee, Sarah Wilson, Christopher Martinez

#### **3.PROPOSED SYSTEM**

In this project author is introducing Hybrid LSTM algorithm to predict Hard or Not Hard Landing (HL). Timely prediction of Hard Landing can avoid accident and save passenger lives. In propose paper author is applying machine learning model for cockpit which will read data from flight such as Tyre elevation, speed and other values and then predict type of landing, if hard landing predicted then it instruct pilot to avoid landing or divert landing route.

Many existing machine learning (SVM,

logistic regression and many more) and deep learning LSTM algorithm already implemented and LSTM give better landing prediction accuracy compare to other machine learning algorithms but LSTM is not trained to predict the vertical acceleration at TD at the next time interval after the current observation. In fact, a recurrent network can only predict acceleration at the immediate time interval from the current observation and its capability for long term predictions is not clear. Since HL depends on the values of such vertical acceleration in a tight temporal window at the time of TD, this limits the deployability of system in a cockpit.

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LSTM get trained on full datasets which further limits its capability and to overcome from this problem author has used different variables from dataset to train different LSTM algorithms and then merge all algorithms to form a HYBRID model and this model is giving better accuracy compare to machine learning algorithms. Training specific algorithm with specific features can help algorithm to filter and extract efficient features which can give better accuracy.

In propose paper author has trained LSTM with different features such as Pilot (DH2TD), Actuator(AP2DH) and Physical (AP2TD). 3 different LSTM algorithms

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trained on above 3 different features and then merge all algorithms to form a hybrid model.

#### **3.1 IMPLEMENTATION**

ARS

1) Upload Flight Landing Dataset: using this module we will upload dataset folder with 3 files and then application read all 3 files and then find and plot graph with number of HARD and NOT Hard Landing graph.

2) Preprocess Dataset: using this module we will normalize and shuffle dataset and then split dataset into train and test where application used 80% dataset for training and 20% for testing.

3) Run SVM Algorithm: using this module we will train SVM with all features using 80% dataset and then perform prediction on 20% test data and then calculate SVM sensitivity and specificity score and then plot graph. Graph closer to 1 will reflect good performanceof the algorithm.

4) Run Logistic Regression Algorithm: using this module we will train SVM with all features using 80% dataset and then perform prediction on 20% test data and then calculate SVM sensitivity and specificity score and then plot graph. Graph closer to 1 will reflect good performance of the algorithm.

5) Run AP2TD Algorithm: this module train LSTM on PHYSICAL features and then performprediction on test data and calculate sensitivity and specificity.

6) Run AP2DH Algorithm: this module train LSTM on ACTUATOR features and then perform prediction on test data and calculate sensitivity and specificity.

7) Run DH2TD Algorithm: this module train LSTM on PILOT features and then perform prediction on test data and calculate sensitivity and specificity. This module merge all modules to get HYBRID LSTM sensitivity and specificity values.

8) Comparison Graph: using this module we will plot sensitivity and specificity graph.

#### 4.RESULTS AND DISCUSSION

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In above screen with SVM we got sensitivity as 0.82 and Specificity as 0.55 and in box plot xaxis represents metric names and y-axis represents values. Now close above graph and then click on 'Run Logistic Regression Algorithm' button to train logistic regression and get below output

Upload Flight Landing Dataset	Preprocess Dataset	(5) Figure 1			
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In above screen with logistic regression we got 0.60% sensitivity values and now click on 'Run AP2TD Algorithm' button to train LSTM on 'Physical Features' and get below output

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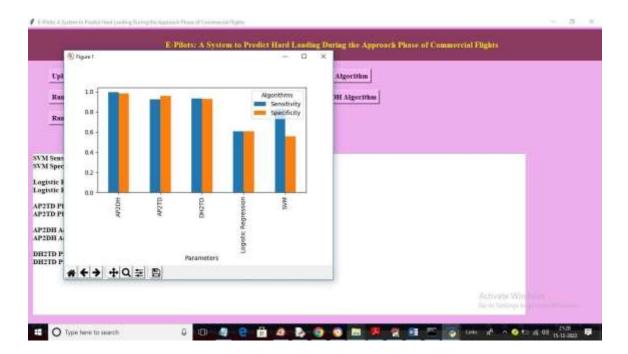
In above screen with AP2TD physical features we got LSTM sensitivity as 0.92 and specificity as 0.95 and now click on 'Run AP2DH Algorithm' to train LSTM on Actuator features and get below output

Upload Flight Landing Dataset	Preprocess Dataset	S Figure 1	AP2DH Actuator Features Se	-	o x
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In above screen with AP2DH LSTM got 0.99% sensitivity and 0.98 specificity and now click on 'Run DH2TD Algorithm' button to train LSTM on PILOT features andget below output

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In above screen with DH2TD we got LSTM sensitivity as 0.93 and specificity as



0.92 and now click on 'Comparison Graph' button to get below comparison graph

In above graph x-axis represents algorithm names and y-axis represents sensitivity and specificity values. Blue bar represents sensitivity and orange bar represents Specificity. In above graph we can see propose AP2TD, AP2DH and DH2TD got high sensitivity and specificity values compareto existing LSTM and logistic Regression.

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In above screen in last we can see sensitivity and specificity values for HYBRID LSTM by combining all 3 models. For hybrid LSTM we got sensitivity as 0.95 and specificity as 0.96%. This values are closer to value given in base paper

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#### **5.CONCLUSION**

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The results of the analysis presented in this paper can be summarized as follows. It may not be required to include automation variables (autopilot, flight director, and auto-thrust) in models, according to the study of which these components have no effect on the likelihood of an HL event. Optimization experiments reveal that setups with the fewest neurons yield the highest sensitivity.

Adding more layers and neurons does not enhance the performance of either classifiers or regressions, as stated in the literature. Outperforming state-of-the-art LSTM methods, models using only physicalvariables achieve an average recall of 94% with a specificity of 86%. This provides assurance to the model for the early prediction of HL in a deployable cockpit system. Although our performance surpasses that of current approaches, the recall and specificity suffer greatly as a the ever-changing landing result of approach and variables impacting HL near TD, which limits our potential for goaround advice before DH

#### REFERENCES

[1] Statistical Summary of



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www.ijarst.in

Commercial Jet Airplane Accidents– Worldwide Operations| 1959– 2017, Boeing Commercial Airplanes, Aviation Saf., Seattle, WA, USA, 2018.

[2] "Developing standardisedFDM-based indicators," Eur. AviationSaf. Plan 2012-2015, Cologne, Germany,2016.

[3] "Advisory circular ac no: 91-79a mitigating the risks of a runway overrun upon landing," Federal Aviation Admin., Washington, DC, USA, 2016.

[4] M. Coker and L. S. Pilot, "Why and when to perform a go-around maneuver," Boeing Edge,vol. 2014, pp. 5– 11, 2014.

[5] T. Blajev and W. Curtis, "Goaround decision making and execution project: Final report to flight safety foundation," Flight Saf. Found., Alexandria, VA, USA, Mar. 2017.

[6] "European action plan for the prevention of runway excursions," Euro control, Brussels, Belgium, 2013.

[7] "Artificial intelligence roadmap—A human-centric approach to ai in aviation," Eur. Union Aviation Saf. Agency, Cologne, Germany, 2020.

[8] "The European plan for aviation safety (EPAS 2020–2024)," Eur.Union Aviation Saf. Agency, Cologne, Germany, 2019.

[9] "Artificial intelligence

roadmap—A human-centric approach to ai in aviation," Eur. Union Aviation Saf. Agency, Cologne, Germany, 2020.

[10] "The European plan for aviation safety (EPAS 2020–2024),"Eur. Union Aviation Saf.Agency, Cologne, Germany, 2019.

[11] L. Wang, C. Wu, and R. Sun, "Pilot operating characteristics analysis of long landing based on flight QAR data," in Proc. Int. Conf. Eng. Psychol. Cognit. Ergonom. Berlin, Germany:Springer, 2013, pp. 157–166. AUTHOR'S PROFILE



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