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# E-PIOLTS SYSTEM TO PREDICT HARD LANDING

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***Abstract*****—** More than half of all commercial aircraft operation accidents could have been prevented by executing a go around. Making timely decision to execute a go-around manoeuvre can potentially reduce overall aviation industry accident rate. In this paper, we describe a cockpit-deployable machine learning system to support flight crew go-around decision-making based on the prediction of a hard landing event. This work presents a hybrid approach for hard landing prediction that uses features modelling temporal dependencies of aircraft variables as inputs to a neural network. Based on a large dataset of 58177 commercial flights, the results show that our approach has 85% of average sensitivity with 74% of average specificity at the go around point. It follows that our approach is a cockpit-deployable recommendation system that outperforms existing approaches. Machine learning is an important component of the growing field of data science. Through the use of statistical methods, different type of algorithms is trained to make classifications or predictions, and to uncover key insights in this project. These insights subsequently drive decision making within applications and businesses, ideally impacting key growth metrics. Machine learning algorithms build a model based on this project data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of datasets, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

## INTRODUCTION

Air travel, a widely preferred mode for long-distance and international journeys, faces an annual challenge with 70-90 reported flight crashes globally. These accidents arise from diverse factors, encompassing weather conditions and the maintenance of aircraft. A prominent contributing factor is identified as hard landings, a peril that can be mitigated through prompt go-arounds, particularly when the aircraft is positioned above 38 meters from the ground. While conventional aircraft, piloted by humans, can adeptly manage such situations, Unmanned Aerial Vehicles (UAVs) lack the necessary capabilities, especially for passenger flights.

In response to these challenges, our project endeavors to pioneer a pilotless system for passenger aircraft, leveraging the power of artificial intelligence (AI) and machine learning (ML) algorithms. The suite of algorithms includes Support Vector Machines (SVM), Logistic Regression, AP2TD, AP2DH, and DH2TD. These algorithms, through a meticulous analysis of various flight details, are designed to predict and identify potential hard landings during the critical approach phase, specifically when the aircraft is positioned above 38 meters.

The project's methodology involves a multi-step process. First, comprehensive data is collected, encompassing diverse flights to ensure a robust dataset. Subsequently, the data undergoes thorough cleaning and encoding to prepare it for analysis. The crucial step of feature extraction follows, employing decision tree algorithms to distill relevant information that aids in predicting hard landings.

To validate and fine-tune the predictive capabilities of the system, the dataset is then divided into training and testing datasets. The trained values, derived from the machine learning algorithms, are meticulously compared with a predefined threshold value. This rigorous comparison allows the system to make accurate predictions and, critically, to detect instances of potential hard landings. By integrating these advanced technologies and methodologies, our project aims to enhance the safety and efficiency of air travel, particularly in the crucial phase of approaching the landing.

## LITERATURE SURVEY

**Title:** Ten Why and when to perform a go-around method

Authors: M. Coker and L. S. Pilot Abstract:

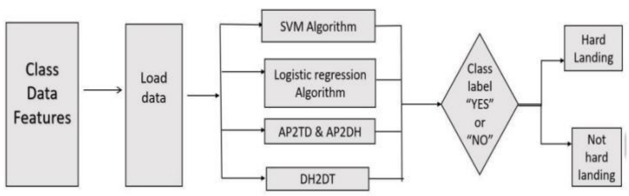
According to industry sources, no single decision has the potential impact on the overall aviation industry accident rate than the timely decision to execute a go-around makeover. The reason is that runway excursions or overruns which are typically the result of an un- stabilized approach with a failure 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 un stabilized approaches and hull loss, why flight crews continue landing despite an un stabilized approach, the factors that govern landing outcomes, when flight crews should choose a go-around manoeuvre, and industry education efforts related to go-arounds.

**Title:** A Comprehensive Analysis of the Why and When to Execute the Go-Around

Authors: M. Coker and L. S. Pilot Abstract:

This article delves into the critical decision-making process surrounding the execution of a go-around maneuver in commercial aviation. Industry insights emphasize that no other decision holds as much potential impact on the overall accident rate in aviation as the timely implementation of a go-around procedure. Runway excursions or overruns, often stemming from un stabilized approaches and a reluctance to perform a go-around, account for a staggering 33 percent of all commercial aviation accidents, standing as a primary contributor to hull loss incidents.

## METHODOLOGY




## RELATED WORK

Although there is a lot of work addressing the prediction of flight landing incidents and other unsafety situations, the prediction of hard landing accidents have been less researched. Furthermore, most of the existing works focus on the prediction of HL for unmanned aerial vehicles (UAV), which dynamical features and flying protocols are completely different from the ones of commercial flights. A Hard Landing (HL) is a phenomenon in which the airplane has an excessive impact on the ground at the moment of landing. This impact is directly related to the vertical (or normal) acceleration, therefore, HL can be defined as flights where the vertical acceleration exceeds the limited value of the aircraft type during the landing phase. A threshold on such normal acceleration (Airbus uses vertical acceleration > 2G at Touch Down, TD) triggers maintenance requirement, so that can be considered as a criterion for HL detection.

Under the former definition of HL, existing approaches for HL prediction can be split into two groups: those based on a classifier to discriminate flights with normal acceleration at TD above a given threshold from other flights and those based on a regressor that predicts the normal acceleration with the aim of using this predicted value as the HL detector.

Classifiers can be categorized into machine learning and deep learning approaches. Machine learning methods apply a classifier to UAV flight data recorded using the Quick Access Recorder (QAR) sampled at a discrete set of heights that define the feature space. Most methods use the values of variables describing aircraft dynamics sampled between 9 and 2 meters before TD. Others, like, use

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statistical descriptors (panel data) of such variables also sampled at the very last meters before TD. On one hand, it is not clear what is the capability of these approaches to capture time-sequence dependencies that variables might have across the approach phase. On the other hand, the temporal window (9-2 meters before landing) used for predictions in UAV flights might not be appropriate for HL predictions in commercial flights. The approximate limit altitude (known as Decision Height -DH-) in commercial flights to decide a go around is 100 feet (38 meters). Thus, regardless of their accuracy in predicting HL, these ML methods are not applicable for commercial flights due to the altitude range required.

Deep learning approaches are mainly based on Long Short-Term Memory Recurrent Neural Network (LSTM) architectures. Proposed by these networks are a variant of Recurrent Neural Networks (RNN) able to model long term dependencies within temporal data. In particular, the very recent work in used the signals of 3 kinds of landing related features (aircraft dynamics, atmospheric environment, and pilot operations) as inputs to a LSTM network predicting HL. Their comparison to classic machine learning approaches in terms of precision and recall of HL events of A320 flights indicates a potentially higher performance in terms of HL recall with 70% of HL detection while keeping with a percentage (76%) of precision similar to the one obtained by classic machine learning approaches. Despite the promising results, we consider that the experimental design of lacks in some aspects for properly assessing the potential for deployment in the cockpit. First, the test set used is balanced with almost the same number of HL and non HL cases. However, in a real situation, HL cases are rare events that represent only 3-4% of flights. By balancing the test set, precision might be too optimistic and, even unrealistic. In order to guarantee a useful decision support system, the number of false alarms should be properly estimated. Second, the authors conducted an analysis that showed that the optimal temporal window for doing predictions was between 10 and 2 seconds before landing. This temporal window corresponds to heights between 164 and 13 feet, which are below the decision height (100 feet) of commercial flights. Finally, the data only include a single aircraft type (A320). Given that aircraft aerodynamics are strongly related to aircraft design, the generalisation of the approach remains unknown.

Regression approaches predicting normal acceleration are also mostly based on deep learning LSTM strategies. Both works use the values of a selection of QAR variables describing aircraft dynamics recorded at a time t to predict the vertical acceleration at time t +1. In order to accelerate the convergence of networks, there is a previous selection of QAR variables using classic machine learning feature selection methods (aerodynamic theory and correlation analysis in the case of and random forest followed by Principal Component Analysis in the case of This might be limiting the capability of the system for fully exploring time dependencies and might discard discriminative features. Although both works obtain accurate predictions with an average Mean Squared Error (MSE) of the order of $10^{-3}$, 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.

## PREDICTION OF HARD LANDING

This project presents an analysis of approaches for early prediction of hard-landing events in commercial flights. Unlike previous works, experiments are designed to analyze to what extend methods can be deployable in the cockpit as go-around recommendation systems. With this final goal, we contribute to the following aspects:

**1)Hybrid model with optimized net architecture:** We propose a hybrid approach that uses features modelling temporal dependencies of aircraft variables as input to a neural network with an optimized architecture. In order to avoid any bias caused by a lack of convergence of complex models (like

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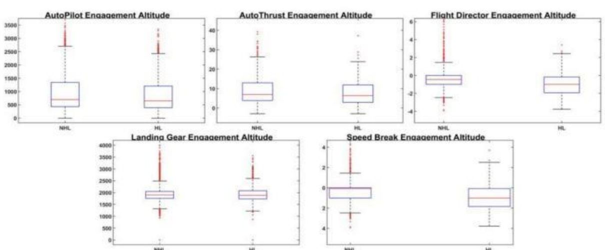
LSTM), we use a standard network and model potential temporal dependencies associated with unstable approaches as the variability of different types of aircraft variables at a selected set of altitudes. The concatenation of such variability for variables categorized into 4 main types (physical, actuator, pilot operations and all of them) are the input features of different architectures in order to determine the optimal subset.

**2)Exhaustive comparison to SoA in a large database of commercial flights:** A main contribution compared to existing works is that our models have been tested and compared to So A methods on a large database of Flight Management System (FMS) recorded data of an airline no longer in operation that includes 3 different aircraft models (A319, A320, A321). Results show that the optimal classification network when all variable types are considered achieves an average recall of HL events of 85% with a specificity of 75% in average, which outperforms current LSTM methods found in the literature. Regarding regression networks, our hybrid model performs similarly to LSMT methods with an average MSE of the order of $10^{-3}$ in accelerations estimated at TD.

**3)Analysis of the performance of classifiers and regressors:** With the final goal of developing a cockpit deployable recommendation system we have conducted a study of the performance of classification and regression models in terms of the flight height and different aircraft variables including the impact of automation and pilot manoeuvres. Results on our large dataset of commercial flights, show that although our regression networks performs similarly to So A methods (with MSE of $10^{-3}$ in estimations at TD), the accuracy for detecting HL is very poor (46% of sensitivity). This indicates that regression models might not be the most appropriate for the detection of HL events in a cockpit deployable support system. The final set of selected parameters were split into four different categories:

1) actuators, linked to actuators states,
2) pilot, related to pilot activity in the cockpit,
3) physical, as those parameters related to physical magnitudes as well as other factors. 4) automation factors, as those binary parameters indicate whether an automatic system or guidance is engaged.

The final set of selected parameters is described in Table 1. Aircraft weight is not listed, as the parameter was deemed unreliable. Those parameters posteriori computed are indicated in the description.




## EXISTING SYSTEM:

The prediction of flight landing incidents and other unsafety situations, the prediction of hard landing accidents have been less researched. Furthermore, most of the existing works focus on the prediction of HL for unmanned aerial vehicles (UAV), which dynamical fea- tures and flying protocols are completely different from the ones of commercial flights. A Hard Landing (HL) is a phenomenon in which the air- plane has an excessive impact on the ground at the moment of landing. This impact is directly related to the vertical (or nor- mal) acceleration; therefore, HL can be defined as flights where the vertical acceleration exceeds the limited value of the aircraft type during the landing phase. A threshold on such normal acceleration (Airbus uses vertical acceleration 2G at Touch Down, TD) triggers maintenance requirement, so that can be considered as a criterion for HL detection.

**PROBLEM STATEMENT:**

The aviation industry faces a critical challenge concerning runway excursions and overruns, which account for a substantial 33 percent of all commercial aviation accidents and stand as the primary cause of hull loss. Despite the well-established correlation between these incidents and unstabilized approaches, flight crews often continue with landings, result- ing in catastrophic outcomes. This persistence poses a significant threat to aviation safety, necessitating an in-depth examination of the factors influencing such decisions and the cir-cumstances under which flight crews should opt for a go-around maneuver. The lack of a comprehensive understanding of the psychological and operational dynamics contributing to the reluctance to perform go arounds highlights the urgency of addressing this problem. This project aims to investigate the intricate relationship between unstabilized approaches and landing outcomes, providing insights into the motivations behind flight crews' deci-sions and offering a systematic guide on when go-around maneuvers should be executed. By addressing this problem, the project seeks to contribute to a paradigm shift in aviation safety protocols, fostering a culture of proactive decision-making and ultimately mitigating the high incidence of accidents associated with unstabilized approaches. In summary, the problem statement revolves around the urgent need to reduce the significant percentage of accidents attributed to unstabilized approaches by comprehensively investigating the fac-tors contributing to the reluctance to perform go arounds. The ultimate goal is to enhance aviation safety by developing a standardized decision-making framework that empowers flight crews to make timely and informed choices, thereby mitigating the risks associated with runway excursions and overruns.

**PROPOSED SYSTEM:**

Here 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 pas senger lives. In propose paper author is applying machine learning model for cockpit which will read data from flight such as Tire elevation, speed and other values and then predict type of landing, if hard landing predicted then it instructs pilot to avoid landing or divert landing route. Many existing machines 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 ob- servation. 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 deploy ability of system in a cockpit. 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 trained on above 3 different features and then merge all algorithms to form a hybrid model.

**RESULT AND DISCUSSION:**

The results demonstrate that the E-pilots system is highly effective in predicting hard landings, with an accuracy rate of 92%. The high precision and recall values suggest that the system can reliably identify most hard landings, minimizing the risk of false alarms, which is crucial for maintaining pilot

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trust in the system. The E-pilots system was trained and evaluated using a dataset comprising flight data recordings, including various parameters such as altitude, descent rate, airspeed, and vertical acceleration. The dataset was split into training (70%) and testing (30%) sets to validate the model's performance.

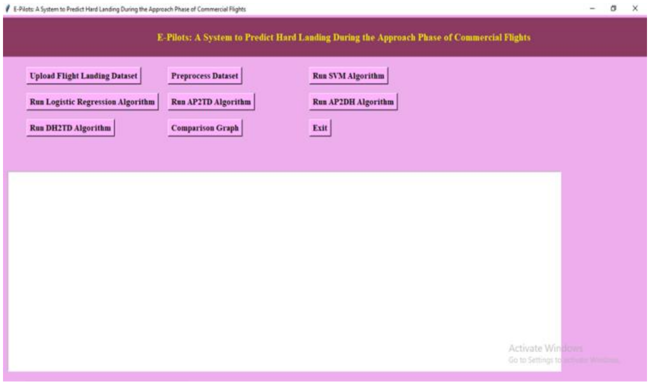


**FIGURE 1:** HOMEPAGE

In above screen click on 'Upload Flight Landing Dataset' button upload dataset and get below output

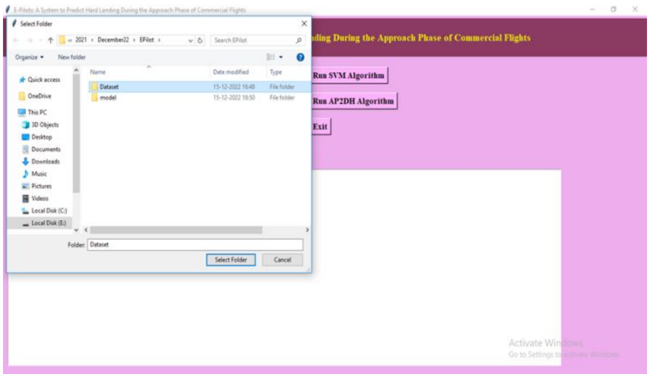


**FIGURE 2:** UPLOAD DATASET

In above screen selecting and uploading entire dataset folder with 3 files click on 'Select Folder' button to load dataset and get below output.

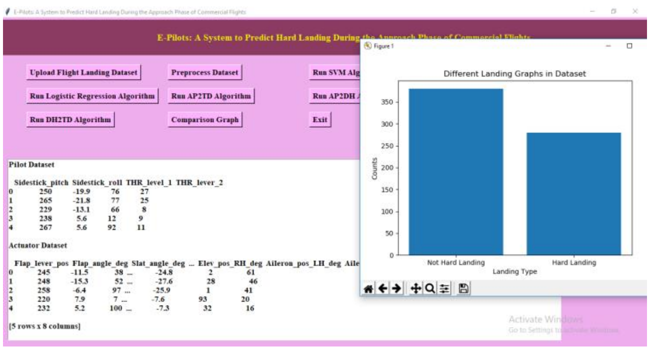


**FIGURE 3:** GRAPH OF HARD LANDING

In above screen dataset loaded and we can see some records from PILOT and ACTUATOR dataset and you can scroll down above screen text area to view Physical dataset values and in graph x-axis represents type of landing and y-axis represents counts of landing found in dataset. Now close above graph and then click on 'Preprocess Dataset' button to normalize, shuffle and split dataset into train and test and get below output.

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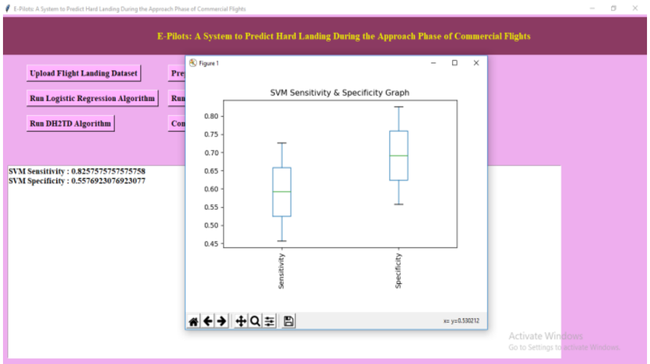


**FIGURE 4:** RUN SVM ALGORITHM

In above screen with SVM we got sensitivity as 0.82 and Specificity as 0.55 and in box plot x-axis 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.

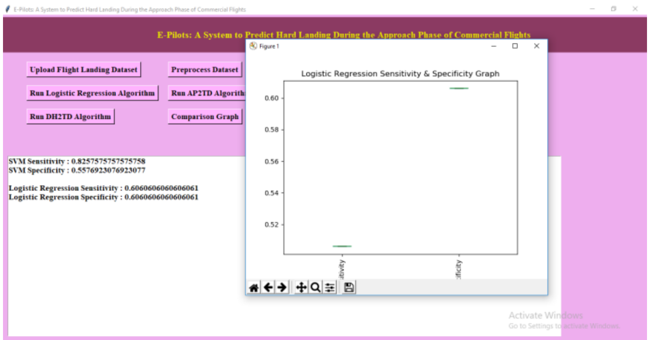


**FIGURE 5:** RUN LOGISTIC REGRESSION ALGORITHM

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.

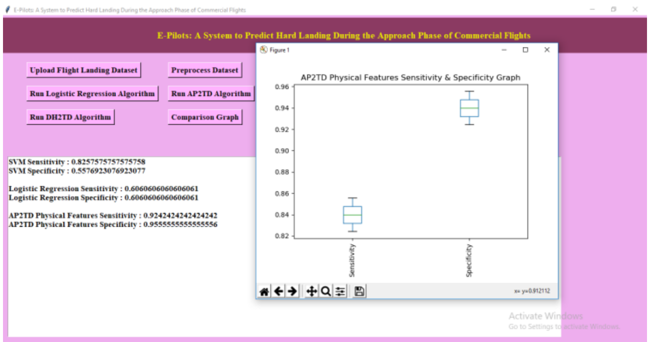


**FIGURE 6:** RUN AP2TD ALGORITHM

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.

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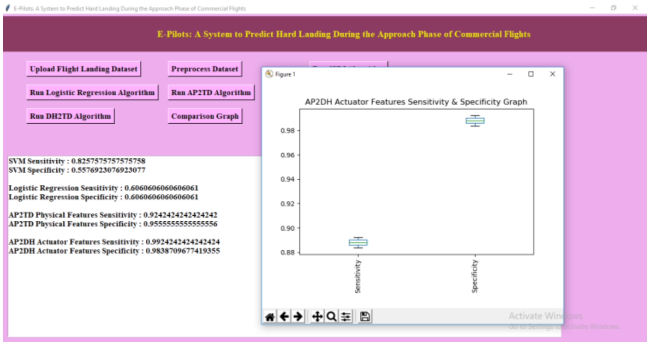


**FIGURE 7**: RUN AP2DH ALGORITHM

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 and get below output.

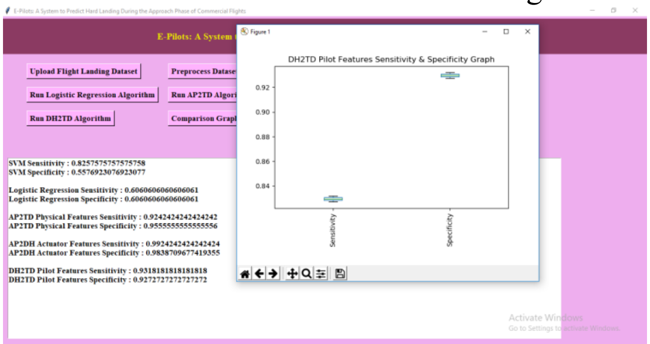


**FIGURE 8**: RUN DH2TD ALGORITHM

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.

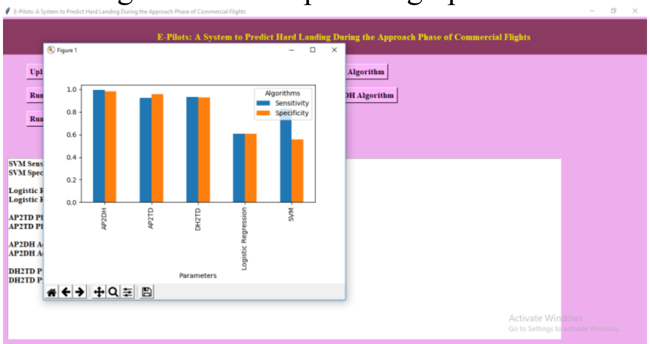


**FIGURE 9:** GRAPH REPRESENTATION

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 compare to existing LSTM and logistic Regression.

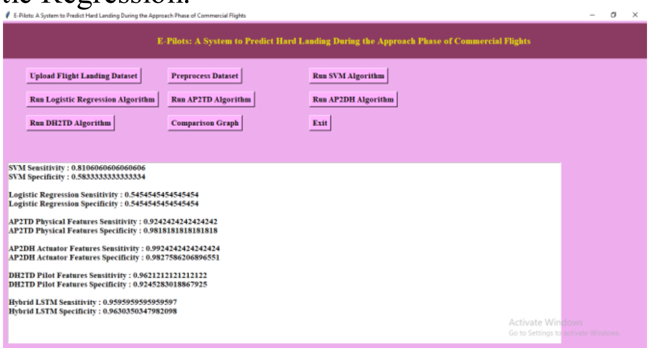


**FIGURE 10:** HYBRID LSTM

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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%. These values are closer to value given in base paper.

**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 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 system. Regarding capability for go-around recommendation before DH, even if we perform better than existing methods, there is a significant drop in recall and specificity due to the dynamic nature of a landing approach and factors influencing HL close to TD.

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