International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

A System to Predict Hard Landing during the Approach Phase of Commercial Flights

Mr.P.Vinay Kumar[1] and Dr.U.Srinivas [2]

[1]Assistant Professor, Department of Information Technology, MREC (A), Hyderabad-500100
[1] Assoc.Professor, Department of Information Technology, MREC (A), Hyderabad-500100

Abstract: By performing a go-around, more than half of all business aeroplane operation errors may have been avoided. Making a prompt choice to do a go-around manoeuvre may help to lower the overall accident rate in the aviation industry. In this paper, we define a cockpit-deployable equipment learning system to support flight staff decision-making for a go-around based on the forecast of a difficult touchdown event. In order to forecast challenging touchdowns, this work offers a hybrid approach that uses attributes that model the temporal dependencies of aircraft data as inputs to a semantic network. Based on a large dataset of 58177 commercial flights, the findings indicate that our technique has an average level of sensitivity and uniqueness at the go-around point of 85% and 74%, respectively. It follows that our strategy outperforms other approaches and can be deployed in the cockpit.

Key words: CNN, RCNN, SSD, dataset, weapon detection.

I. INTRODUCTION

Among different modes of transport air ways is opted by most people who want to travel larger distances in shorter period of time and also by people who want to travel across the seas. Even though airways are free from congestion and other parameters compared to other modes of transportation, they are not exempt from accidents. A record says that more than 70-90 flight crashes occur annually worldwide including both commercial and privately owned ones. Accidents may occur due to any reason such as weather conditions, aircraft maintenance and other issues. Can these accidents be prevented? The answer is yes in majority cases. It was found that most of the aircraft accidents are due to hardlanding and can be prevented if the pilot can stop go around instead of doing a hardlanding. To take a go around the aircraft should be above 38 meters from the land. Therfore it is important to predict the hardlanding above this range. In normal aircrafts where the pilots are human, it is taken care by them and sometimes it may be that they recognise this very lately. UAV (Unmanned Aerial Vehicles) are the aircrafts without any human pilot or passengers. Though they can fly with the help of sensors embedded in them calculating the speed and distances they can predict the hardlandings, they are small and cannot be suitable for passengers as these does not have any aviation like commercial flights. Therefore, the project we made proposes a system that detects the hardlanding and make pilotless aircraft but full of passengers to be achieved. In today’s world artificial intelligence and machine learning are playing an important role in making things automated. Therefore, we used machine learning algorithms like SVM, Logistic regression, AP2TD, AP2DH, DH2TD to make a system which predicts hard landing during the approach phase of the flights. This system takes the flight details like aviation of the flight, wind speed, flight speed, information regarding the actuators etc. These are the important information to detect the hard landing. Also, the above listed algorithms help the system to predict the hard landing above 38 meters itself so that the flight can be prevented from having a hard landing. These are the steps which we are going to follow: Step 1: Data collection where we collected the data of different flights. Step 2: Data pre-processing where we will be cleaning the data and also see that any missing data is available in the values are to be checked. Step 3: Feature extraction is done by the values where in the values we have encoded the values means the original data is encoded into unreadable format. Because so many people are hacking the information due to the hacking will lost all the information. Step 4: We have extracted the features by some of the algorithms are decision tree having root nodes and sub node, when we consider in my project the root node is the dataset further it is divided into sub-nodes as attributes, further the attributes divided into trained data and compare with threshold value, that value predicts whether it is hardlanding or not hardlanding. Step 5: The dataset is divided into training dataset and testing dataset, always the training dataset is more than the testing datasets. Step 6: Based on the trained value we will test the result as hardlanding or not hardlanding. When we consider the trained value, we have to compare with the threshold value based on these values we can predict and detect whether hardlanding occurs or not.

II. LITERATURE SURVEY

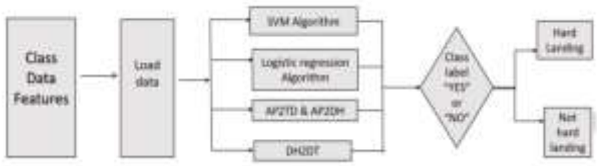
Many of the flight accidents can be prevented by predicting the hard landing in time. Hardlanding is a phenomenon where the flight lands with more pressure than it actually needs to be which may also damage the aviation of the flight. A classifier is used to predict the hardlanding. The classifier determines the flight with normal accerleration at the touchdown above a given threshold collected from other flights. With a sharp increment in AI advancement, there has been an exertion in applying machine learning and deep learning strategies to recommender frameworks. These days, recommender frameworks are very regular in the travel industry. Hardlanding predictions for commercial flights is quite different from predictions of hardlanding in UAV flights. The hardlanding prediction should be done above 38 meters from land which is nearly 100feet so that the required measures like a go round can take place. The dataset consists the details of various flights that had hardlanding and also flights that have soft landing. These details include actuators data, air speed, flight speed, direction and may more. The data set consists hardlanding and non hardlanding conditions so that result calculated can be accurate. The given collected data after being cleaned and preprocessed is divided in train and test data. The data is well trained under the algorithms specified. The test data is used to check whether the system predicts the hardlanding and non-hardlanding accurately or not. The accurate and fast predictions are the goals that are achieved. Algorithm like logistic regression makes the output more accurate as it also calculates the dependencies between the attributes in a dataset. Dependencies are important to calculate in systems like these as even a single mistake can cost lives of many people. SVM helps to segregate the given category in correct decision boundary. When all these algorithms are together used it gives the best accurate output of whether a hardlanding is going to take place or a soft-landing is taking place.

We have compared our method when all variables are considered to the LSTM model of and two typical models (Support Vector Machine (SVM) and Logistic Regression (LR)) also reported in . We have re-trained from scratch LSTM, SVM and LR in our data set using the variables and metrics proposed in our study. Following the same procedure as in, we build a LSTM network with one fully connected layer for classification, and train it using 9 sampled seconds of data from second 2 to 10 before TD. As there is no indication for the values of hyperparameters in the aforementioned work, we manually tuned the batch size and learning rates to 8 and 0.0001, respectively. We used an Adam optimizer and train for 55 epochs. To be able to handle overfitting, at each fold we divided the training set into training and validation using 5% of training data, and saved the model only when the validation loss decreases. As in the original study the authors do not use any regularization term, we also avoided using one. We fine-tuned the number of neurons of the LSTM by performing a 15-fold grid search over the same values as in the mentioned study, [20, 30, 40, 50, 60], and obtain metric values over the validation set. Finally, once we have selected the best performing value, we perform 15-fold training for the specific value and test it on the test set, obtaining the definitive results. The SVM kernel was also optimized using grid search. LR has not any hyperparameters. Bagplots in graphically compare average specificity and sensitivity achieved by our method at the 3 ranges of altitudes, the LSTM model of, SVM and LR. For the AP2TD, AP2DH altitude ranges our method has a sensitivity 5% higher than the best performer LSTM. Regarding specificity, AP2TD, AP2DH have average precision 7.7% higher than LSTM.

III.PROPOSED SYSTEM

In this paper 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 instructs pilot to avoid landing or divert landing route. 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.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362



IV. IMPLEMENTATION

Upload Flight Landing Dataset : This module accepts the data from the user.

Preprocess Dataset : This module preprocesses the provided dataset.

Run SVM Algorithm : This module runs the SVM model for the given dataset.

Run Logistic Regression Algorithm : This module runs the Logistic regression for the given dataset.

Run AP2TD Algorithm : This module runs AP2TD model for the given physical dataset.

Run AP2DH Algorithm : This module runs AP2DH model for the given actuators dataset.

Run DH2TD Algorithm : This module runs DH2TD model for the given pilot dataset.

Comparision Graph : This module is used to compare the accuracy of all the graphs.

The results procured from each of the four methods are good, yet that doesn't show that the recommender framework is ready for real-life applications. It still needs improvements. Predicted results show that the difference between the positive and negative class metrics indicates that the training data should be appropriately balanced using algorithms like Smote, Adasyn, Smote Tomek , etc. Proper hyperparameter optimization is also required for classification algorithms to improve the accuracy of the model. In the recommendation framework, we simply just added the bestpredicted result of each method. For better results and understanding, require a proper ensembling of different predicted results. This paper intends to show only the methodology that one can use to extract sentiment from the data and perform classification to build a recommender system.We will predict the condition type of landing with the dataset. Select the required data set of the required E-pilot and the run the required algorithm.

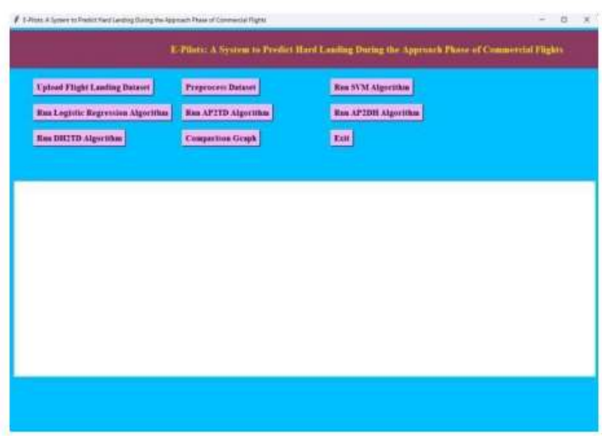


Fig.1. Output screen.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362
IJARST

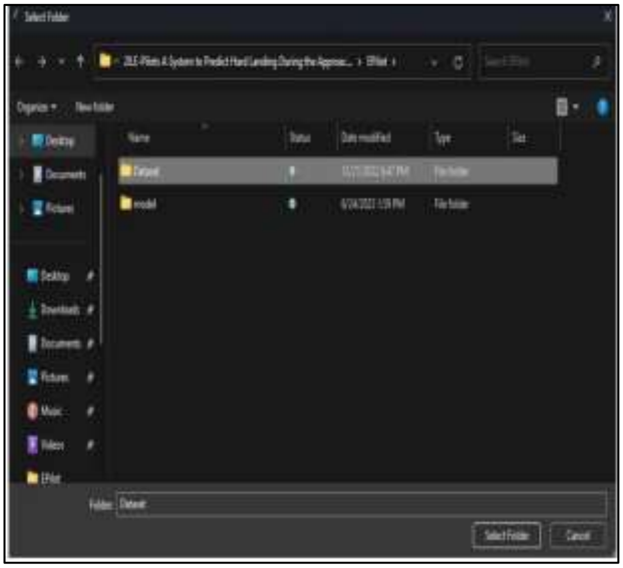


Fig.2. Loading Dataset.

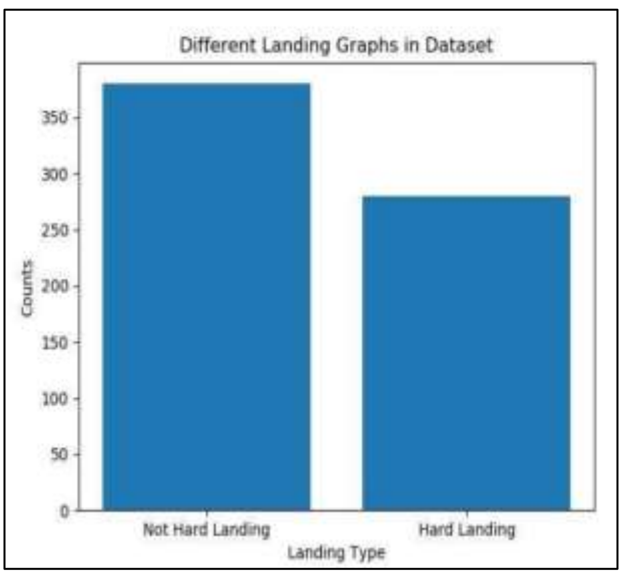


Fig.3. Landing Type.

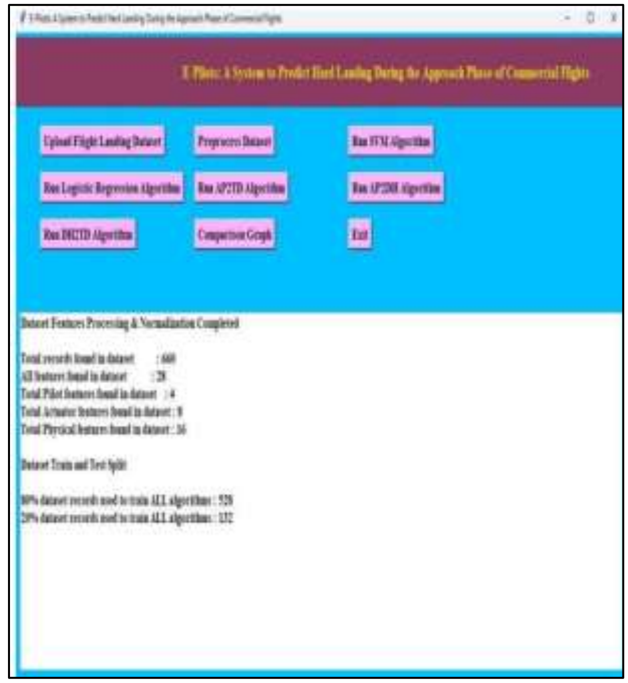


Fig.4. Prepossesing data.

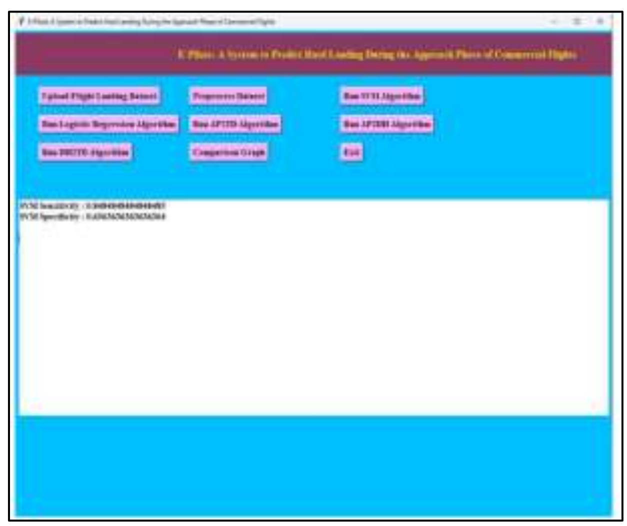


Fig.5. output of SVM.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
IJARST
www.ijarst.in
ISSN: 2457-0362

Fig.6. Output of Logistic Regression.

Fig.7. Output of AP2TD

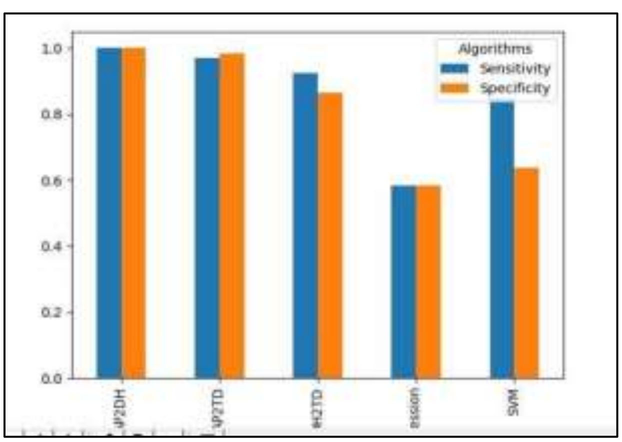


Fig.8. Output Graphs.

V. CONCLUSION

The evaluation carried out in this research can yield the following results. The analysis of automation features (autopilot, trip manager, and auto-thrust) indicates that these features have little bearing on the likelihood of an HL event and may not even be required to be included in models. The configurations that produce the highest level of sensitivity are those with the most accessible diversity of neurons, according to experiments for design optimization. Increasing the number of layers and nerve cells does not improve the performance of classifiers or regressors, according to the literature . Designs with only physical variables outperform advanced LSTM methods with a mean recall of 94% and an average uniqueness of 86%. This gives the version for early HL prediction in a cabin deployable system confidence. Even while we perform better than current ways in terms of ability for go-around recommendation before DH, the dynamic nature of a touchdown strategy and factors affecting HL close to TD cause a significant loss in memory and uniqueness. Experiments demonstrate that a low MSE error in the evaluation of maxG does not ensure accurate HL forecasts when comparing classifiers and regression techniques. Classifiers can accurately predict HL before DH, according to experiments evaluating the capacity of versions for early HL detection. This is not a situation where aggressors would anticipate maxG more accurately if data close to TD were taken into account. According to the study, classifiers are a better tool for predicting difficult landings very early on. One-dimensional convolutional networks and various architectures for a better blending of the three sets of variables might be used to eliminate deep understanding functions from continuous signals, which could improve the performance of semantic networks. Moreover, models should take into account additional details like aircraft mass and centre of gravity placement, which are known to affect car characteristics. Eventually, there are several issues that have not been addressed in this work, which require additional research and future work. The classifier's (regressor's) resistance to hidden conditions and its tendencies in a situation with roving information stand out among these instances. It would be necessary to examine such issues, as we foresee doing in future occupations, in an industry as safety-sensitive as aviation. In the future, this system might be expanded to include air traffic administration, in which the information is provided to the air traffic controller in order to maximise the use of the route and prepare for the most likely situation.

REFERENCES

[1] Statistical Summary of Commercial Jet Airplane Accidents–Worldwide Operations| 1959–2017, Boeing Commercial Airplanes, Aviation Saf., Seattle, WA, USA, 2018.

[2] ''Developing standardised FDM-based indicators,'' Eur. Aviation Saf. Plan 20122015, 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. [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, ''Go-around 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,'' Eurocontrol, 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] 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.

[10]L. Li, J. Hansman, R. Palacios, and R. Welsch, ''Anomaly detection via a Gaussian mixture model for flight operation and safety monitoring,'' Transp. Res. C, Emerg. Technol., vol. 64, pp. 45–57, Mar. 2016.