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PREDICTIVE SYSTEM FOR HARDLANDING OF COMMERCIAL FLIGHTS

LAGADAPATI SRILATHA, MR.B.SURESH M Tech

[1] PG Scholar in the department of MCA at QIS College of Engineering & Technology (AUTONOMOUS), Vengamukkapalem, Ongole- 523272, Prakasam Dt., AP., India.

[2]Professor in the department of CSE/MCA at QIS Collegeof Engineering & Technology (AUTONOMOUS), Vengamukkapalem, Ongole- 523272, Prakasam Dt., AP., India.

ABSTRACT:

Hard landings in commercial aviation pose significant safety risks and can lead to injuries, aircraft damage, and operational disruptions. In response to this challenge this paper proposes a predictive system for detecting and forecasting hard landings in commercial flights. Leveraging advanced machine learning algorithms and real-time flight data, the predictive system analyzes a comprehensive set of flight parameters including aircraft altitude, airspeed, vertical acceleration, and landing gear status, to identify patterns indicative of hard landing events. Through extensive experimentation and validation on historical flight data, the predictive system demonstrates high accuracy in detecting hard landings and provides timely alerts to flight crews and ground personnel, enabling proactive measures to prevent accidents and enhance flight safety. By integrating predictive analytics into commercial aviation operations, this system offers a proactive approach to mitigating hard landing risks and improving overall flight safety standards.

INDEX: Hard landings, aircraft altitude, airspeed, vertical acceleration, and landing gear status, overall flight safety

I. INTRODUCTION

Commercial aviation safety is of mount importance, and the prevention of hard landings is a critical aspect of ensuring passenger and crew safety. Hard landings, characterized by excessive vertical acceleration upon touchdown, pose significant risks including aircraft damage, passenger injuries, and operational

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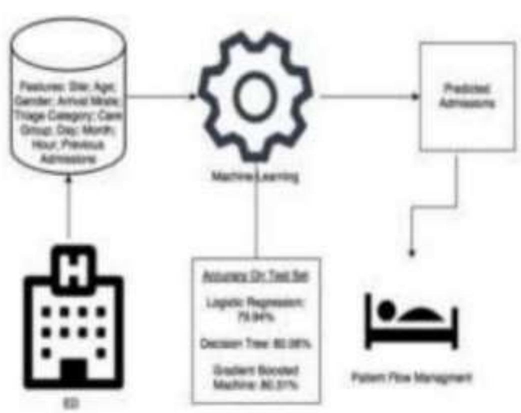
disruptions. Despite advancements in aviation technology and safety protocols, hard landings continue to occur, highlighting the need for proactive measures to detect and prevent these events. In response to this challenge, this paper proposes the development of a predictive system for hard landing detection and forecastingincommercialflights.Byleveragin gadvancedmachinelearningalgorithmsand real- time flight data analysis, the predictive system aims to provide early warnings of potential hard mitigate the occurrence of hard landings.

SYSTEMARCHITECTURE



METHODOLOGY

Altitude Sampling

AP2TD range: This includes all sampling altitudes , from the beginning of the approach phase to touchdown .models trained with this set of altitudes set the maximum accuracy that the system can achieve.

AP2DH range : This includes altitudes from the beginning of the approach phase to the decision height :[1500,1000,500,400,300,200,150,100].models trained with this set of altitudes set the actual capability for HL early detection and the usefulness of the system for a go-around recommendation.

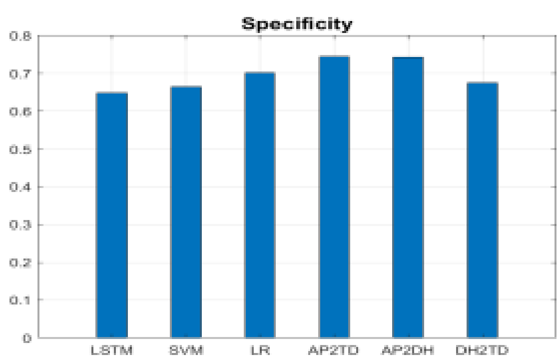
DH2TD range : This set includes altitudes from the decision height to 30 feet before touchdown:[50,40,30].models trained with this altitude with this altitude range will assess the capability to predict HL just in time to safely avoid it.

A different network was trained for each variable category (Physical, Actuator, Pilot) and range of altitudes (AP2TD, AP2DH and DH2TD). We also trained a model having as input the concatenation of the 3 categories. This model was labelled as AllÂ˙I. Table 2 reports the dimensionality of each of the networks input features for the 9 models considered, as well as the concatenation of all of them.

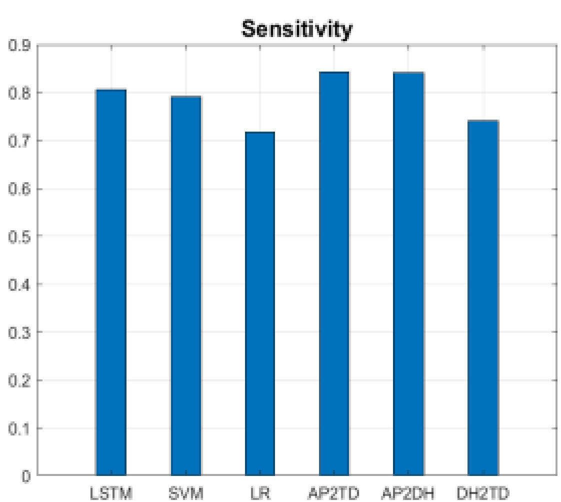
Network models

	AP2TD	AP2DH	DH2TD
Physical	187	136	51
Actuator	88	64	24
Pilot	44	32	12
All	341	248	93

$$Specificity = \frac{TN}{TN + FP}$$



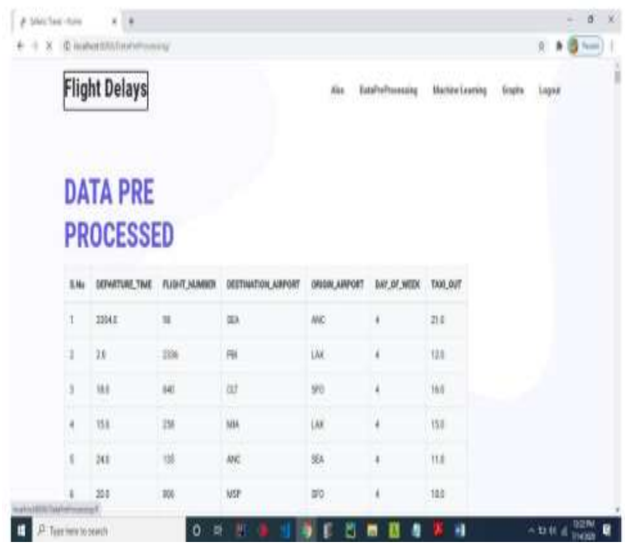
Accuracy results model-1

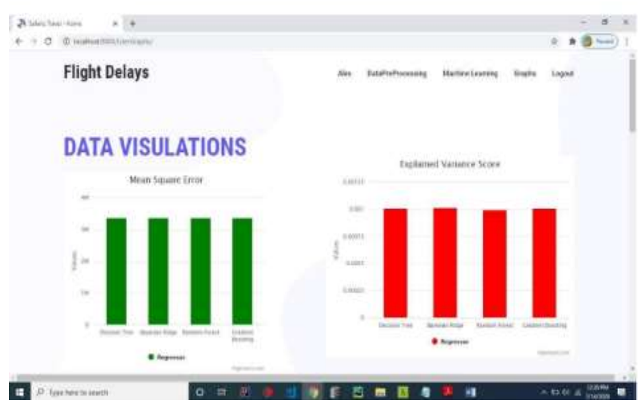


$$Sensitivity = \frac{TP}{TP + FN}$$

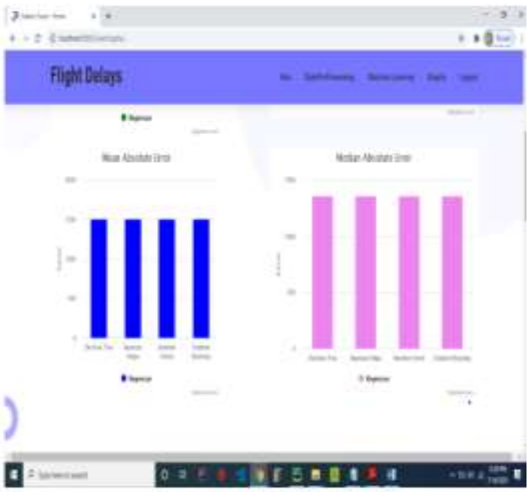
Accuracy results model-2

RESULT ANALYSIS

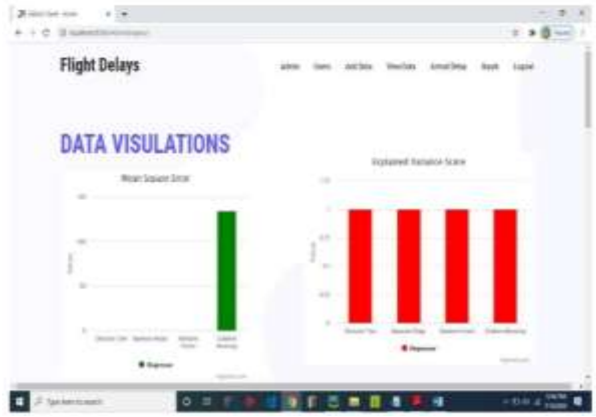




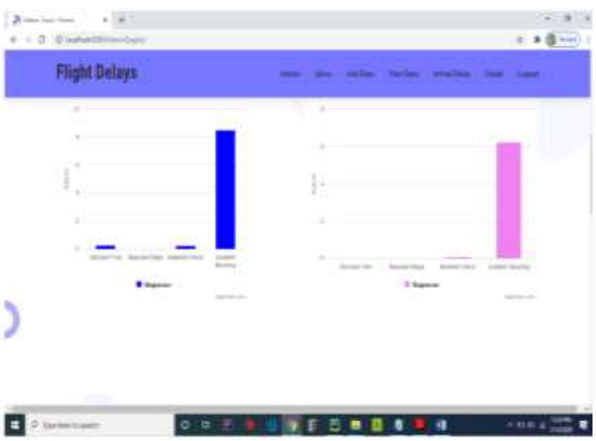
Graph:



ArrivalGraph



ArrivalGraph:



CONCLUSION

Machine learning algorithms were applied progressively and successively topredict flight arrival & delay. We built five models out of this. We saw for eachevaluation metric considered the values of the models and compared them. We foundout that: - In Departure Delay, Random Forest Regressor was observed as the bestmodel with Mean Squared Error2261.8 and Mean Absolute Error 24.1,which are theminimum value found in these respective metrics. In Arrival Delay, Random ForestRegressor was the best model observed with Mean Squared Error 3019.3 and MeanAbsolute Error 30.8, which are the minimum value found in these respective metrics.In the rest of the metrics, the value of the error of Random Forest Regressor althoughis not minimum but still gives a low value comparatively. In maximum metrics, we found out that Random Forest Regressor gives us the best value and thus should be the model selected.

Further Enhancement

The future scope of this paper can include the application of more advanced, modern and innovative pre processing techniques, automated hybrid learning and sampling algorithms, and deep learning models adjusted to achieve better performance. Toevolve a predictive model, additional variables can beintroduced. e.g., amodel wheremeteorological statistics are utilized in developing error-free models for flight delays.In this paper we used data from the US only, therefore in future,the model can betrained with data from other countries as well. With the use of models that arecomplex and hybrid of many other models provided with appropriate processingpower and with the use of larger detailed datasets, more accurate predictive modelscan be developed. Additionally, the model can be configured for other airports topredict their flight delays as well and for that data from these airports would berequired to incorporate .

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