Machine Learning-based Live Predictive Warnings for Unstabilized Approaches in Aircraft

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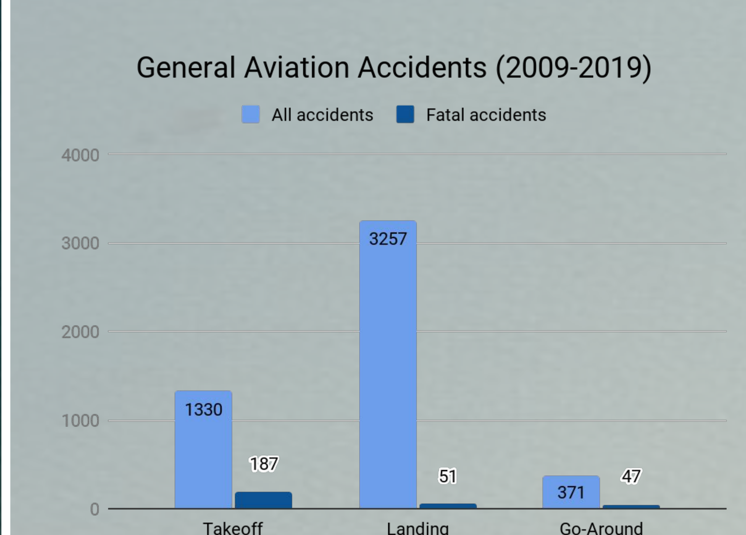
Introduction

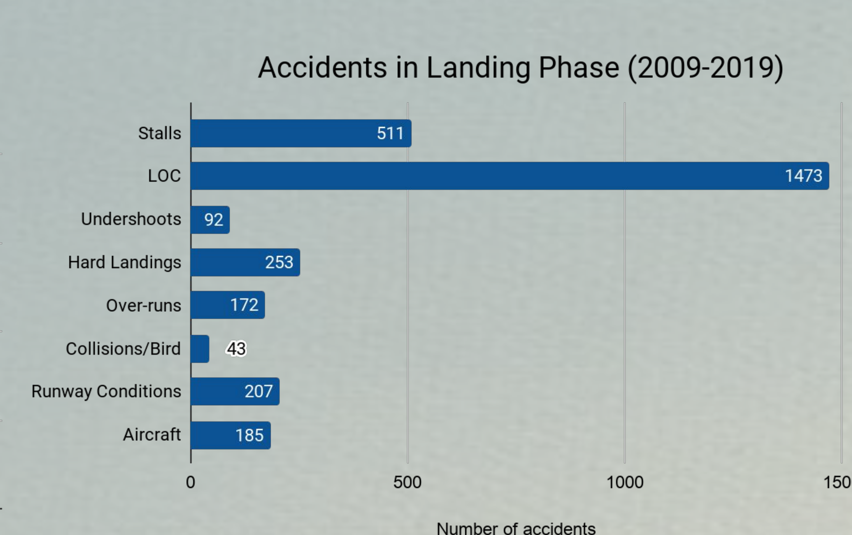
Unstabilized approaches are a major hazard for general aviation aircraft. An unstabilized approach can lead to runway excursions, structural damage on touchdown, or even Controlled Flight into Terrain (CFIT). Machine Learning-based predictive warnings can be used to create objective 'call-outs' to aid decision making, which has been emphasized in research by Flight Safety Foundation (2017) and International Air Transportation Association (2016)

Background

The Aircraft Owners and Pilots Association reported that 3,257 general aviation accidents from 2009-2019 occurred during the landing phase of a flight. The FAA determined that Landing Expectancy is a major cognitive bias that prevents pilots from executing a go-around maneuver when needed. There is a need for decision-making aids for general aviation pilots to decide what constitutes an unstabilized approach and execute a go-around. A lack of objectivity increases the risk of physiological illusions affecting perception and cognitive bias such as confirmation bias and expectation bias influencing pilot decision-making.

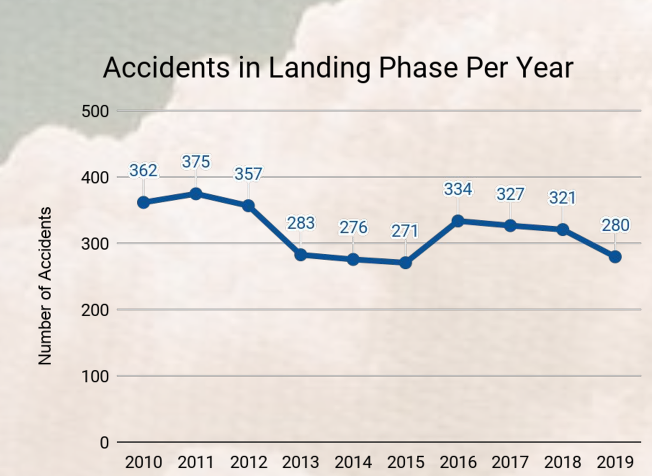


(Aircraft Owners and Pilots Association, 2020)



(Aircraft Owners and Pilots Association, 2020)

The advancement of machine learning technology offers the opportunity to develop low-cost, flexible technology that can improve flight safety. This research is aimed at developing machine learning-based predictive warnings for pilots to abort an unstabilized approach and execute a go-around maneuver.



(Aircraft Owners and Pilots Association, 2020)

Research Methods

The research will be based on the following research questions:

- RQ 1: How well can a deep neural network predict an unstabilized approach of a general aviation aircraft using real-time flight data?
- RQ 2: What flight data variables are the most important predictors of an unstabilized approach in a general aviation aircraft?

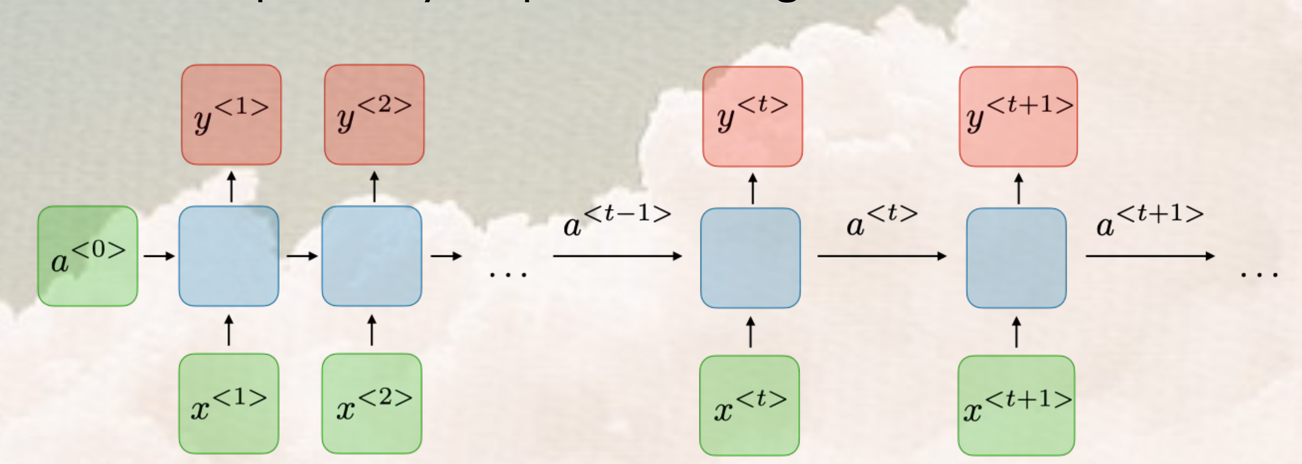
Methods

As the first step, we needed to collect feature-rich flight data which could be useful for making predictions of unstabilized approaches. The data utilized for the model preparation was derived from the Flight Data Monitoring (FDM) program of a Part-141 Flight Training Organization. The aircraft utilized was a Diamond DA42 NG VI. The FDM data for a period of 3.5 years was collected that included more than 42,000 flights.

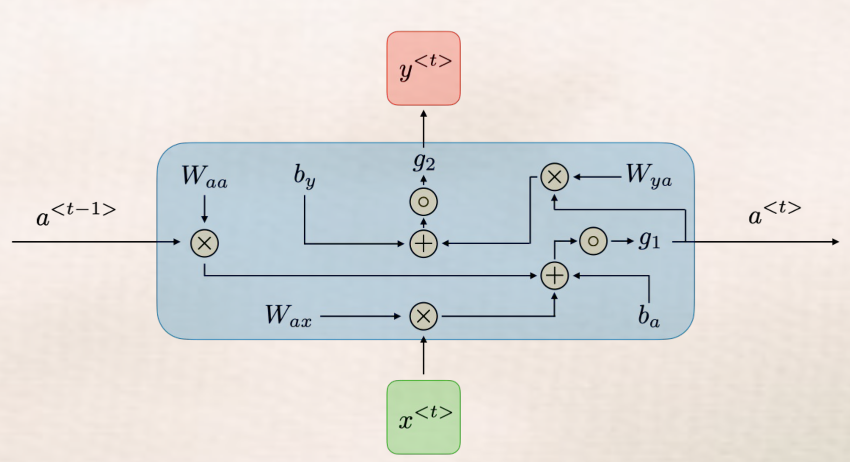
The unstabilized approach criteria was developed utilizing the resources provided by the FAA such as the Airplane Flying Handbook and Advisory Circular 120-71A. Additionally, the Airplane Flying Manual of the DA42 NG VI and Standard Operating Procedures (SOPs) of the Part 141 Flight Training Organization were referred for the criteria. Finally, to develop a model that suited that best fit the operations, a focus group with safety experts and experienced instructors from the Part 141 Flight Training Organization were interviewed.

Next, we needed to preprocess the data in order to avoid using an end-to-end deep-learning approach which would be computationally expensive and slow at the training stage. First, we decided to extract only the variables that would be determining factors when predicting approach stability, based on the developed criteria. Next, the data was structured into matrices corresponding to exactly on flight, which was done programmatically using a Python 3 script and the Pandas 1.1 library.

Next, we will use deep neural networks to train our machine learning model to predict unstabilized approaches. Since the data is structured with data points corresponding to every second of the flight, we will use a Recurrent Neural Network which is specifically adept at modeling time-series data.



The model architecture is shown below, where $a^{<t>}$ represents the activation function, $y^{<t>}$ represents the output of a layer, & W_{ij} represents the weights of a layer.



(Amidi & Shervine, 2018)

To develop our model, we will use an 85% training set, a 5% development set, and a 10% testing set split for our complete dataset comprising approximately 42,000 flights. The deep neural network architecture will be designed using the Tensorflow 2 framework.

Expected Results

We expect to achieve or exceed the following thresholds for our model on the testing set, based on evaluation metrics of existing RNN models on structured flight data (Nanduri & Sherry, 2016).

Metric	Threshold
Accuracy	0.95
Precision	0.95
Recall	0.98
F1 Score	0.96

Additionally, we expect to extract the most important predictors of an unstabilized approach and develop this model to be compatible with the Garmin G1000® flight instrument system.

Conclusion

The model developed in this project will be a low-cost, objective decision-making aid for pilots that will improve general aviation safety. The model will be integrable into general aviation avionics systems such as the Garmin G1000®. In the future, the model could be expanded to include additional aircraft models. The use of machine learning algorithms ensures that the model is flexible and can be continually improved with feedback and response.

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