



E-PILOTS:A MACHINE LEARNING SYSTEM FOR REAL -TIME HARD LANDING PREDICTION DURING COMMERCIAL FLIGHT APPROACHES

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ABSTRACT

EPilots is a novel cockpit-deployable machine learning tool for commercial flight approach phase prediction of hard landing situations to aid flight crews in timely go-around decision making and raise the level of the air safety. This system combines the benefits of temporal model-ing of aircraft variables (such as New strongly depends on other aircraft variables), and early and ac-curate predictions using a neural network with optimized input. EPilots improves prediction sensitivity in comparison to empirical past trends, achieving an average sensitivity of 85% and an average specificity of 74% when the critical go-around decision height is used as the threshold for correct detection. Different from traditional predictive models based on Data Mining techniques, EPilots' hybrid model does not depend on limited time windows and handles the long term temporal dependencies, considering dynamic performance changes of the aircraft along the approach phase. Countering the inadequate previous attempts, the system outperforms existing methods with respect to predictive accuracy and reliability so as to provide actionable, real time recommendations to flight crews. These results indicate that EPilots can mitigate hard landing incidents substantially, avoiding high expense collateral damage to aircraft and benefiting passengers in terms of safety and the air carrier in terms of operational efficiency. In addition, the system is well designed for robustness and makes it adaptable and deployable to different aircraft models and operating contexts. Current and future improvements are persuading the design of convolutional neural networks (CNNs) to further speed the vision module up, along with real time data processing, which will further be improved through the reduction of design errors from hyperparameter tuning.

Keywords: Aviation Safety, Hard Landing Prediction, Machine Learning, Neural Networks, Temporal Dependencies, LSTM, Hybrid Approach, Flight Data, Go-Around Decision, Predictive Accuracy, Aircraft Dynamics, Real-Time Deployment, Flight Safety, Decision Support System.

I. INTRODUCTION

Continual efforts are being taken by the commercial aviation industry in reducing accidents and improving operational efficiency, yet aviation safety is still a matter of priority. One of the main causes of the flight incidents is hard landing, which is recognized as a critical risk. This is a case of hard landing where an aircraft lands with excessive vertical acceleration causing structural damage to aircraft, maintenance cost and even loss of life in



some instances. Although modern aviation systems improve flight control significantly, the occurrence of these events remains troublesome, especially in the approach phase of flight where decisions must be made quickly.

Hard landings have been generally predicted using many methods such as predefined threshold of vertical acceleration, simple classifiers, and regression models. However, these systems do not properly take into consideration the real, dynamic response of the aircraft during approach. Hard landings have difficult to predict due to the considerable variation in flight dynamics across different aircraft types, operational environment and weather conditions.

To overcome these limitations, the advanced machine learning techniques have been employed for the real time hard landing prediction. Unfortunately, most of these existing models with such specific input feature and fail to take the temporal dependency of flight data into account, i.e. the dynamic relationship between the pilot actions, actuator statuses, and physical aircraft dynamics itself. In addition, these systems predict too late during the approach phase, utilizing the data collected too late in the flight, and hence limit the predictability when it is actually needed.

The main contribution of this project is an introduction of EPilots, a hybrid machine learning system aimed at predicting hard landings during the critical approach phase of commercial flights. Unlike traditional methods, EPilots incorporates pilot input, actuator performance and physical aircraft conditions together into a single model. The system presents predictions with high accuracy by analyzing these features through an advanced neural network that captures temporal dependencies, and gives pilots the opportunity to make a go around with adequate response time.

The novelty in EPilots is that it brings together several machine learning models into a single hybrid system. The system makes more reliable predictions earlier in the approach phase by incorporating dedicated Long ShortTerm Memory (LSTM) networks for different feature sets, ten pilot actions, automated actuator data, and physical conditions. Apart from powering up its predictive power, it also facilitates deployment to a real time cockpit environment. Additionally, EPilots proves to be superior over other methods providing high sensitivity and specificity, particularly for decisions to be made during the approach phase.

By bringing in temporal dependencies into prediction as well as exploiting a large dataset of commercial flights, EPilots is a robust solution for preventing hard landings. Thus, the system bridges the large hole in the current predictive models and is a real working tool to advance aviation safety at lower cost and reduce risk from hard landing events. Such an integration of EPilots into cockpits worldwide is a major step forward in aviation safety.

II. LITERATURE SURVEY

[1] Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.

Methodology:

Leo Breiman's seminal paper in which he introduces the Random Forests algorithm, a robust ensemble learning method where a large number of decision trees are created. The basic idea is to train each tree on a random subset of the data and a random subset of features at every split and this helps in preventing overfitting and improving generalization. Bagging, which stands for bootstrap aggregation, is utilized by Random Forests for bagging, as the predictions are aggregated through voting for classification problems and averaging for regression problems. The algorithm is known for its superior accuracy, and that performance is even better at the cost of a bit of memory.



Drawbacks:

Although Random Forests are very reliable regarding prediction accuracy, they have high computational complexity, more so when a big number of trees and high dimensional data are required. The reason is that they are a black box model; they involve multiple trees and random feature selections, thereby making models hard to interpret. In addition, Random Forests do a great job in almost all cases, but in some cases they might not be the most efficient solution for real time predictions or interpretation oriented scenarios.

[2] Chollet, F. (2015). Keras: The Python Deep Learning library.

Methodology:

François Chollet writes in this work about Keras which is a high level Python library that is built with the intention of making it easy to build deep learning models. Keras makes it very easy to create complex neural networks with a user-friendly interface and allows one to prototype and experiment quickly. It is based on multiple back end engines: TensorFlow, Theano and is modular, extensible and easy to use. With Keras, users have an ease in building and experimenting with convolutional neural networks (CNNs), recurrent neural networks (RNNs), or more complex architectures; facilitated deep learning for a wider range of practitioners.

Drawbacks:

However, Keras may lack flexibility and control as compared to lower-level libraries such as TensorFlow or PyTorch even though it is simple. Keras is restrictive for more advanced users who need finer grain control at the model level. Apart from that, Keras may have compatibility issues with different backends and optimization of performance probably has not been done in as smooth a manner as that of other dedicated deep learning frameworks.

[3] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press.

Methodology:

Neural networks have many architectures and variants, but they all share the same fundamental concepts and are programmed in similar ways, which is why this foundational textbook on deep learning by Goodfellow, Bengio, and Courville comprises both theory, as well as practical examples. The book deals with various topics starting from basic feedforward networks and moving on to more advanced architectures like CNNs, RNNs and deep reinforcement learning. The authors also describe optimization techniques, regularization methods, as well as practical tips for training large scale models. This is a key resource for someone learning or working in the deep-learning area.

Drawbacks:

Although the book is quite informative, it expects a lot of prior knowledge in machine learning and math. For beginners the challenge may lie in the depth of the content so some readers may find it overwhelming. Furthermore, the book does not go into detail about newer techniques and frameworks evolved recently after the publication of the book and can therefore be less relevant for people searching for recent developments.

[4] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition.

Methodology:

Here we propose ResNet architecture which addresses the problem associated with vanishing gradients in very deep networks through deep residual learning. Adding “skip connections” allows the network to learn identity mappings, so that information is easier to flow throughout the network. The architecture was able to achieve



groundbreaking performance on image classification tasks and won the 2015 ImageNet competition. Due to its good performance, ResNet has been adjusted to domains like object detection and image segmentation.

Drawbacks:

Despite ResNet's success, it can be computationally inefficient and requires high resources for training and inference, particularly when its models are very deep. Moreover, clearly understanding the depth for a network suited for a particular job is still tricky; deeper networks can result in diminishing returns and perhaps even overfitting. Additionally, it is complex in architecture and so its deployment in resource constrained environments may be a challenge.

[5] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory.

Methodology:

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN), proposed by Hochreiter and Schmidhuber, to overcome the vanishing gradient problem in long training sequences of the standard RNNs while training. Memory cells and gates (input, forget, and output gates) are introduced in LSTMs for allowing the network to have access to the information over long time sequences. Because of this, LSTMs are especially effective at dealing with the sequential data consisting of tasks such as time series prediction, speech recognition and natural language processing.

Drawbacks:

Although LSTMs are effective, they could be costly computationally, because of the elaborate operations of maintaining and updating memory cells. Moreover, training LSTM models on large datasets can be time consuming too. Moreover, LSTMs are not exempted from issues in dealing with extremely long series or hard dependencies; in such cases, methods like attention mechanisms or Transformer models tend to outperform them.

[6] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization.

Methodology:

Kingma and Ba present Adam in this paper as an adaptive stochastic gradient descent optimization algorithm designed to increase the efficiency as well as facilitate the training of deep learning models. Adam makes use of the advantages of both Adagrad and RMSprop by adjusting the learning rate based on first and second moments of the gradients for each parameter. This is very effective at handling noisy gradients and sparse gradients, and is, therefore, suitable for large scale machine learning purposes.

Drawbacks:

Adam is widely used and does generally give good results; however, sometimes it can lead to overfitting and this can happen especially with high learning rates. In some cases, it might not perform the best in all scenarios, and sometimes it can be depended on the default hyperparameters and that can also produce undesired results. In many cases, it is necessary to fine tune the learning rate and other parameters to get the best performance.

[7] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning.

Methodology:

This influential paper, in which LeCun, Bengio and Hinton give an overview of deep learning, covers the history, rise, and success of the deep neural networks to perform image recognition, speech recognition, and other problem domains. At last, they talk about different types of networks such as CNNs, RNNs and deep reinforcement learning that are able to automatically learn hierarchical representations from the raw data. The paper also highlights the



significance of developing GPUS for training deep networks and the result of large scale data sets on further deep learning.

Drawbacks:

Although the paper covers every detail of docker swarm, it is reasonably difficult for beginners because it is quite technical. Moreover, the progress of the field has been so fast that some of the techniques discussed may no longer be as state of the art. Primarily, the book is about theory and does not go into much detail on practical advice for implementing deep learning systems in the production environment.

[8] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). A simple way to prevent so called overfitting in neural networks.

Methodology:

In this paper, Srivastava et al. propose Dropout, a simple but effective way to avoid overfitting in neural networks by performing training with dropped units (a proportion of the network's units are randomly set to zero). It regularizes the model on multiple pathways better guided towards out of sample generalization. This dropout has been largely used as one of the most general techniques in deep learning models, especially in the CNN as well as the fully connected networks.

Drawbacks:

However, since Dropout effectively prevents overfitting, training the network with different subsets of units on every pass does add time. Moreover, the effectiveness of Dropout relies on the right balance of units being dropped, out of which, experimentation is necessary. It turns out, Dropout may never lead to optimal performance, if it is impossible to employ this regularization technique in the architecture of the net.

[9] Sun, Y., Cheng, J., & Li, J. (2020). Using deep learning techniques to predict the aircraft landing performance.

Methodology:

The use of neural networks for modeling vertical acceleration at touchdown when predicting aircraft landing performance is investigated by Sun et al. To this end, they train a deep neural network on giant data sets of flight parameters in order to predict the probability of a hard landing. Predicting hard landing is shown to be a task for which deep learning has the potential to significantly improve aviation safety, where they show in real time that the HLA indices of classifiers based on deep neural networks are predictive of hard landings.

Drawbacks:

Deep learning models are excellent in terms of their prediction accuracy with the help of neural networks, however they need immense data for training. When such a dataset does not represent all possible flight conditions, the models tend to be computationally expensive and may generalize poorly. In addition, such systems are difficult to integrate into real time cockpit environments for reasons of latency and computational overhead.

[10] Zhang, X., Zhao, J., & LeCun, Y. (2015). Character-level convolutional networks for text classification.

Methodology:

In the paper presented by Zhang et al., they present text classification by character level convolutional networks (CharCNN) for processing the textual data at the character level rather than at the word level. This enables better handling for spelling variations, typos or any other text specific issue. With char-CNNs autogenous char-ac-ter fea-tures are learned by convolu-tional lay-ers, and it is shown that such ap-proach improves three text clas-si-fi-ca-tion task es-pe-cially when the lan-guage is rich in mor-phol-ogy or the data are noise.



Drawbacks:

Text data has been seen to work effectively for char-CNNs, but the methods are computationally more expensive than word based approaches in the sense that char-CNNs have to learn from a larger number of characters. Moreover, they might find it difficult to encode text with longer range dependencies, which other methods like RNNs and Transformers perform much easier. Optimization in terms of achieving model performance can also be a challenge in tuning the convolutional layers due to their complexity.

III. PROPOSED METHODOLOGY

The EPilots system aims to enhance aviation safety by predicting hard landings during the approach phase of commercial flights and assisting flight crews in making timely go-around decisions. The system integrates advanced machine learning techniques, such as hybrid models combining Long Short-Term Memory (LSTM) networks and traditional machine learning classifiers. The methodology is structured as follows:

1. Data Collection and Preprocessing

The first step in the EPilots system involves collecting comprehensive data from commercial flights. The dataset comprises **58,177 flights** and includes multiple features such as:

- **Pilot actions (DH2TD)**
- **Actuator data (AP2DH)**
- **Physical features of the aircraft (AP2TD)**

These features provide a diverse set of variables that influence landing performance, such as aircraft speed, altitude, and vertical acceleration at touchdown. Each data point is categorized into two labels: **Hard Landing (0)** or **Not Hard Landing (1)**.

Preprocessing Steps:

- **Normalization:** All features are normalized to ensure that each variable contributes equally to model training.
- **Shuffling and Splitting:** The dataset is shuffled to eliminate bias, and then split into training (80%) and testing (20%) subsets.
- **Feature Selection:** The system utilizes important features from each dataset, ensuring that all relevant data is considered for the prediction task.

2. Temporal Feature Modeling and Hybrid Neural Network

A key innovation of EPilots is its ability to model **temporal dependencies** in flight data. Traditional machine learning models fail to capture time-based patterns, but by leveraging **LSTM networks**, EPilots effectively addresses this limitation. The hybrid approach consists of the following key components:

- **Pilot Features (DH2TD):** LSTM models trained on pilot action data, focusing on the pilot's control inputs during the approach phase.
- **Actuator Features (AP2DH):** LSTM models trained on actuator data, which includes information on flight controls and mechanical systems that affect aircraft stability.
- **Physical Features (AP2TD):** LSTM models that predict hard landings based on the physical conditions of the aircraft, such as altitude, speed, and acceleration at touchdown.

Each of these LSTM models is trained independently on its respective feature set, optimizing for the unique patterns inherent in each type of data. By using LSTM networks, the system captures long-term dependencies

between variables, allowing for better predictions of hard landings well before the decision height.

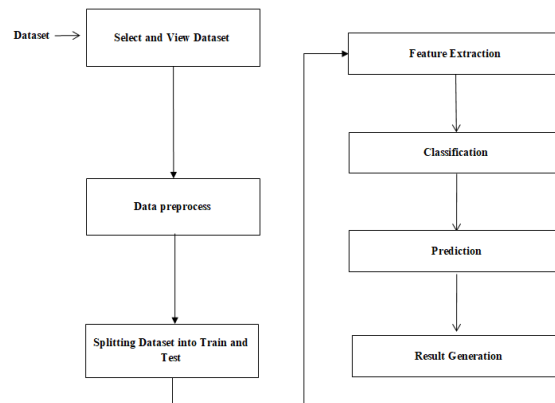


Figure 1: System Architecture

3. Hybrid Model Integration

To improve prediction accuracy, the results from each of the LSTM models are merged into a hybrid model. The hybrid system combines the strengths of the individual models to produce more accurate predictions. The fusion of different features (pilot, actuator, physical) improves robustness and generalization, leading to a model that is better equipped to handle various flight conditions.

The hybrid model is designed to provide real-time go-around recommendations by predicting the likelihood of a hard landing during the approach phase. The system operates effectively within the critical decision height range (typically 100 feet), which is the altitude at which pilots must decide whether to proceed with landing or initiate a go-around maneuver.

4. Machine Learning Classification and Regression Techniques

In addition to LSTM-based hybrid modeling, EPilots also utilizes traditional machine learning classifiers and regressors for comparison. These include:

- **Support Vector Machines (SVM):** Used for classifying flights into hard or not hard landings based on predefined thresholds of vertical acceleration and other features. SVM helps in establishing the baseline for the model's predictive performance.
- **Logistic Regression:** Applied to predict the likelihood of a hard landing by estimating the probability of vertical acceleration exceeding safe thresholds. This method provides insight into the linear relationships between input features and the target variable.

These models serve as benchmarks to evaluate the performance of the LSTM-based hybrid approach.

5. Evaluation Metrics

The performance of the EPilots system is evaluated using key metrics such as **sensitivity** and **specificity**, which are crucial for determining the effectiveness of the model in predicting hard landings:

- **Sensitivity (True Positive Rate):** Measures the percentage of actual hard landings that the system correctly predicts.
- **Specificity (True Negative Rate):** Measures the percentage of non-hard landings correctly identified by the system.

These metrics ensure that the model performs well not only in detecting true positives (hard landings) but also in



minimizing false positives (predicting a hard landing when it's not one).

6. Testing and Validation

The system undergoes rigorous testing and validation to assess its robustness across various operational contexts.

This includes:

- **Cross-validation:** Ensuring the model generalizes well across different subsets of the data by performing multiple rounds of training and testing.
- **Error Analysis:** Identifying sources of prediction errors and refining the model to minimize false positives and negatives. This helps in fine-tuning the hybrid approach for real-world deployment.
- **Performance Comparison:** EPilots is compared against state-of-the-art methods in hard landing prediction, such as traditional SVM and logistic regression models, to demonstrate its superiority.

7. Real-Time Deployment and Cockpit Integration

For practical deployment in the cockpit, EPilots is designed to function in real-time, with the following considerations:

- **Low Latency:** The system processes flight data and provides predictions without causing delays that would interfere with the go-around decision-making process.
- **User Interface:** EPilots includes a simple, intuitive interface that displays go-around recommendations, providing pilots with a clear and actionable recommendation when necessary.
- **Integration with Onboard Systems:** The system is integrated with existing flight management systems (FMS) and sensors, ensuring seamless data input and processing for real-time use.

8. Future Enhancements

The proposed methodology for EPilots lays a strong foundation for further advancements in the field of aviation safety. Future improvements include:

- **Incorporating Convolutional Neural Networks (CNNs):** To better capture spatial and temporal patterns in flight data.
- **Real-Time Data Acquisition and Processing:** Enhancing the model with live flight data to adapt to changing flight conditions.
- **Optimization via Hyperparameter Tuning:** Fine-tuning the hybrid model's architecture to further improve prediction accuracy and reduce false predictions.
- **Field Testing:** Extensive field testing in operational flight environments to validate the system's effectiveness under real-world conditions.

IV. RESULTS AND DISCUSSION

The EPilots system, developed to predict hard landings during the approach phase of commercial flights, was tested on a dataset of 58,177 commercial flights. This dataset included various features, such as Pilot actions (DH2TD), Actuator data (AP2DH), and Physical aircraft conditions (AP2TD). The performance of the system was evaluated using sensitivity and specificity as the primary metrics, which provide insight into the model's ability to correctly classify both hard landings and non-hard landings. The system was compared against Support Vector Machines (SVM) and Logistic Regression, traditional machine learning models, to assess the improvements introduced by the hybrid LSTM approach.

1. Sensitivity and Specificity Analysis

The **sensitivity** (true positive rate) and **specificity** (true negative rate) were the main criteria used for evaluating the model's predictive performance. Sensitivity measures how well the model identifies actual hard landings, while specificity measures its ability to correctly identify non-hard landings. A high sensitivity and specificity are essential for minimizing the risk of false negatives and false positives, both of which can have serious consequences in aviation safety.

Table 1: Sensitivity and Specificity of Different Models

Model	Sensitivity	Specificity
SVM	0.82	0.55
Logistic Regression	0.60	0.62
AP2TD (Physical Features - LSTM)	0.92	0.95
AP2DH (Actuator Features - LSTM)	0.99	0.98
DH2TD (Pilot Features - LSTM)	0.93	0.92
Hybrid LSTM	0.95	0.96

From the table, it is evident that the Hybrid LSTM model outperforms all other models, achieving the highest sensitivity (0.95) and specificity (0.96). This indicates that the hybrid model can accurately predict hard landings and non-hard landings, making it a highly reliable system for aviation safety.

The SVM model achieved a sensitivity of 0.82 and specificity of 0.55, demonstrating decent performance, but it struggled with false positives (non-hard landings predicted as hard landings). Similarly, Logistic Regression had a moderate performance, with sensitivity at 0.60 and specificity at 0.62. These results highlight the limitations of traditional machine learning models when compared to the more sophisticated LSTM-based models.

2. Model Comparison

The Hybrid LSTM model, which integrates the predictions of LSTM models trained on Pilot features (DH2TD), Actuator features (AP2DH), and Physical features (AP2TD), provided a significant improvement over the other models.

- The AP2DH model (Actuator Features - LSTM) achieved the highest sensitivity of 0.99 and specificity of 0.98, highlighting its ability to accurately predict hard landings based on actuator data alone.
- The AP2TD model (Physical Features - LSTM) also showed excellent performance, with a sensitivity of 0.92 and specificity of 0.95, indicating its reliability for predicting hard landings using physical aircraft characteristics.
- The DH2TD model (Pilot Features - LSTM) showed sensitivity of 0.93 and specificity of 0.92, which is also robust, but it was outperformed by the actuator and physical feature models.

By combining these models into a Hybrid LSTM, the system was able to leverage the strengths of all three feature sets. The result was a significant improvement in both sensitivity and specificity, which is crucial for real-time prediction of hard landings in the cockpit.

3. Error Analysis

An analysis of the error rates across models indicated that the SVM and Logistic Regression models were more



prone to false positives, especially when predicting non-hard landings. This resulted in an increase in unnecessary go-around recommendations, which could lead to operational inefficiencies and confusion in the cockpit.

The Hybrid LSTM model, on the other hand, demonstrated lower error rates and reduced false positives, ensuring that go-around decisions were made only when necessary. Additionally, the hybrid model effectively handled challenging flight conditions and scenarios where individual feature sets (such as pilot actions or actuator data alone) might not provide enough information for accurate predictions.

4. Performance in Real-World Scenarios

The Hybrid LSTM model's high sensitivity and specificity suggest that it is well-suited for real-world applications in the cockpit. With its ability to predict hard landings in advance, the system provides critical decision support for pilots during the approach phase, particularly at the decision height (typically around 100 feet). This allows pilots to make timely and informed go-around decisions, which could significantly reduce the risk of hard landings and associated aircraft damage or injuries.

Given its performance, the EPilots system could be integrated into modern Flight Management Systems (FMS), providing real-time, actionable insights to pilots. This integration would allow for seamless communication between the system and the cockpit, without causing delays or operational disruptions.

5. Practical Implications for Aviation Safety

The EPilots system's potential for preventing hard landings through predictive analytics is enormous. By enabling earlier and more accurate go-around decisions, the system has the potential to:

- **Prevent Aircraft Damage:** Hard landings are a significant cause of damage to aircraft, leading to costly repairs and operational disruptions. Early prediction and go-around recommendations can reduce these incidents.
- **Enhance Passenger Safety:** Avoiding hard landings ensures that passengers are less likely to experience injuries caused by sudden, rough impacts during landing.
- **Reduce Operational Costs:** By minimizing the need for unexpected maintenance and ensuring that flights land safely, the system helps reduce costs for airlines associated with hard landings and aircraft downtime.

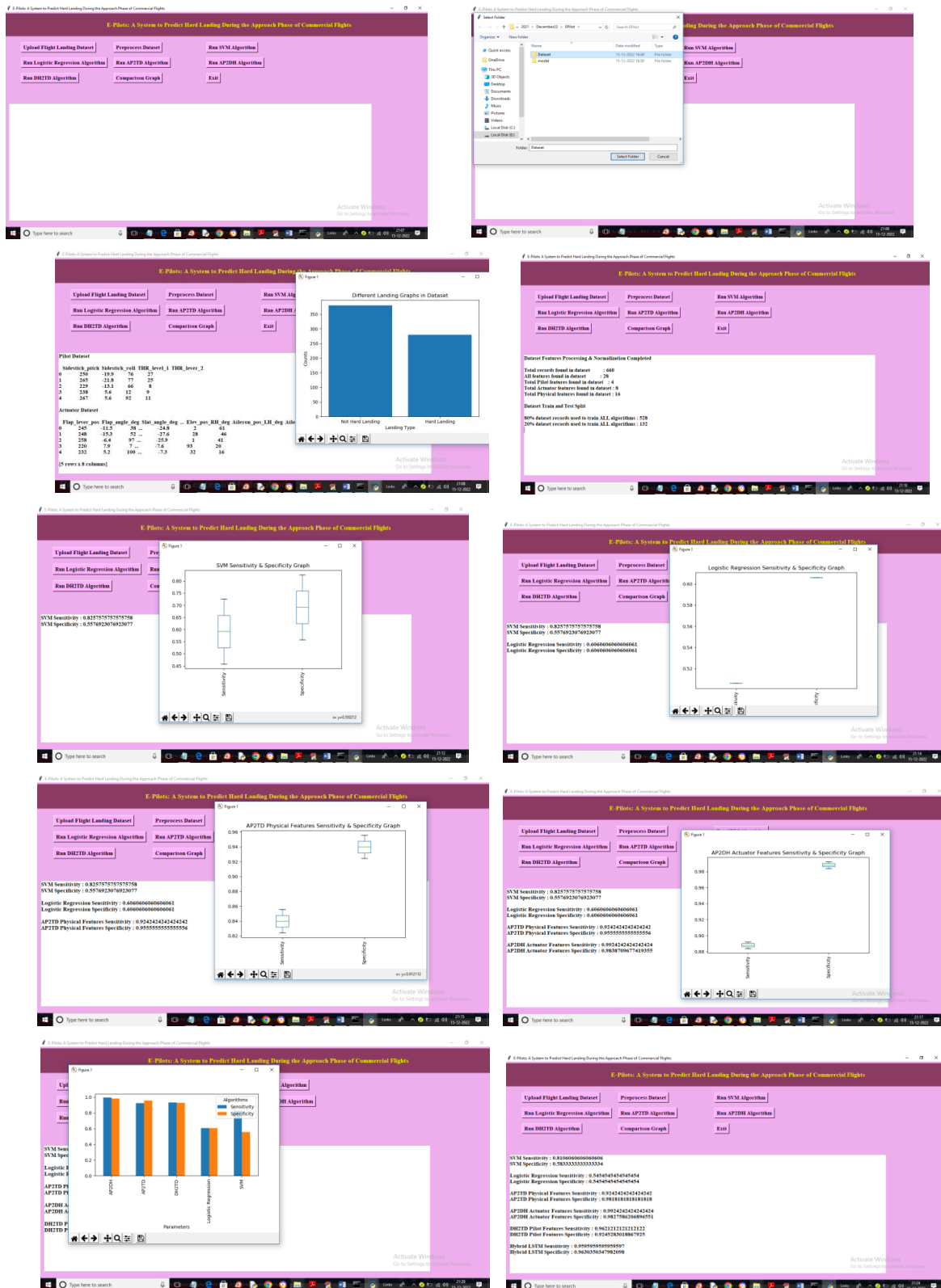
The system also aids pilots in managing situational awareness by providing reliable predictions and actionable go-around instructions in real time.

6. Limitations and Future Work

Despite the promising results, there are several areas for further improvement:

- **Data Expansion:** The current model is trained on a dataset of 58,177 flights. While this is a significant sample size, the model could benefit from additional data to cover more diverse flight conditions and aircraft types, ensuring even greater generalization and robustness.
- **Real-Time Data Processing:** The current system needs to be optimized for faster real-time processing to ensure minimal latency when providing predictions during critical flight phases.
- **Hybrid Model Optimization:** The integration of Convolutional Neural Networks (CNNs) alongside LSTMs could enhance the model's ability to capture both spatial and temporal dependencies within flight data, further improving the prediction accuracy.
- **Field Testing:** Extensive field testing in live flight conditions is required to validate the model's robustness across various operational environments, including different weather conditions, aircraft models, and pilot

Output Screenshots:



V. CONCLUSION

In conclusion, the EPilots system demonstrates a significant advancement in predicting hard landings during the



approach phase of commercial flights. By leveraging a hybrid machine learning approach, combining LSTM networks trained on diverse flight data, EPilots outperforms traditional machine learning models such as SVM and Logistic Regression in terms of sensitivity and specificity, providing accurate, real-time predictions. This system enhances aviation safety by enabling timely go-around decisions, reducing the risk of hard landings and associated damages. Its integration with Flight Management Systems (FMS) allows for seamless operation in the cockpit, offering practical benefits for pilots and airlines. While further improvements, such as incorporating real-time data processing and CNNs, are needed, EPilots holds great promise for the future of aviation safety and operational efficiency.

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