Smart Approach Monitoring with EPilots: Preventing Hard Landings

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ABSTRACT

Hard landing remains one of the most persistent and critical safety concerns in aviation, carrying implications that extend beyond structural stress on aircraft to operational delays, increased maintenance costs, and, most importantly, passenger discomfort and safety risks. The final approach phase of flight is inherently high-stakes: pilots must continuously manage multiple, interdependent parameters such as approach speed, descent rate, altitude, wind conditions, runway surface state, aircraft weight, and control inputs. Small deviations in any of these factors can compound rapidly, creating conditions that increase the likelihood of a hard landing. Traditional aviation safety systems, including Ground Proximity Warning Systems (GPWS) and post-flight Flight Data Monitoring (FDM), rely predominantly on threshold-based rules, offering alerts only after certain parameters are exceeded. While these systems provide essential warnings, they often act reactively rather than proactively, leaving limited time for corrective pilot action in the final critical moments before touchdown.

In this study, we propose Smart Approach Monitoring with ePilots, an integrated framework that combines multivariate flight parameter analysis with Convolutional Neural Network (CNN)-based predictive modeling to assess landing stability in real-time. The framework continuously evaluates the aircraft's approach trajectory, descent profile, and environmental factors, generating a dynamic risk score and delivering adaptive, pilot-centric advisory alerts. Unlike conventional threshold-based systems, this model considers the interactions between multiple parameters simultaneously, enabling early detection of potentially hazardous landing conditions and providing actionable recommendations for speed adjustment, flare maneuvering, or go-around decisions.

Scenario-based evaluations under dry, wet, and icy runway conditions demonstrate the robustness of the proposed system. The CNN model successfully identifies high-risk landing scenarios while minimizing false alarms, highlighting its potential for real-world operational deployment. Beyond predictive accuracy, the system emphasizes human-centric safety, enhancing situational awareness, reducing cognitive load on pilots, and supporting confident decision-making during the high-stress final approach phase.

The proposed framework represents a significant advancement in AI-assisted aviation safety, bridging the gap between automated prediction and pilot action. By combining predictive intelligence with proactive advisory mechanisms, Smart Approach Monitoring with ePilots offers a practical, operationally relevant solution that enhances landing safety, passenger comfort, and airline efficiency, while reinforcing the critical role of human judgment in modern cockpit operations.

Keywords: Hard landing prediction, Smart approach monitoring, Convolutional Neural Network, Aviation safety, Decision support system.

1. INTRODUCTION

Aircraft landing is widely recognized as the most technically demanding and safety-critical phase of flight operations. During the final approach, pilots are tasked with simultaneously controlling multiple interdependent variables — approach speed, descent rate, altitude, wind conditions, runway friction, aircraft weight, and control surface positions. Even minor deviations in these factors can result in hard landings, which exert significant vertical forces on the aircraft structure, leading to increased maintenance, costly repairs, and potential operational disruptions. From the passenger perspective, hard landings can cause discomfort, anxiety, and a sense of insecurity. For pilots, these events generate intense cognitive load and stress, particularly when environmental conditions are variable, and split-second decisions are required.

Conventional safety systems, such as the Ground Proximity Warning System (GPWS) and Flight Data Monitoring (FDM) systems, primarily operate using threshold-based triggers. While these systems are effective in identifying extreme deviations, they often react after instability has already begun, providing limited opportunity for pilots to intervene proactively. Alerts may also generate high false-positive rates, increasing cognitive workload and potentially reducing pilot trust in automated systems. Consequently, there is a critical need for predictive, real-time monitoring systems that not only detect high-risk landing scenarios but also provide context-aware, actionable guidance to pilots.

With the increasing availability of high-resolution flight operational data, artificial intelligence (AI) and machine learning (ML) approaches have emerged as promising solutions. Algorithms such as Random Forests, Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN-LSTM models have demonstrated the ability to capture complex nonlinear relationships and temporal patterns in multivariate flight data. These models can detect subtle deviations in descent rate, approach trajectory, or speed profiles that may precede a hard landing — deviations often imperceptible to human operators or traditional threshold-based systems.

However, despite these advancements, many existing models are limited by offline operation, lack of real-time deployment, and poor integration with human decision-making processes. In practical cockpit environments, predictive intelligence must be coupled with pilot-centered advisory mechanisms. Alerts should be timely, clear, and actionable, minimizing distraction while supporting confident decisions. High false alarm rates, unstructured data presentation, and lack of context-aware recommendations are significant barriers to operational adoption.

To address these challenges, we propose Smart Approach Monitoring with ePilots, a CNN-based predictive framework that integrates multivariate flight parameter analysis with adaptive, pilot-friendly advisories. The system continuously monitors approach speed, descent rate, altitude, wind speed, runway surface condition, aircraft weight, and pilot experience to generate real-time landing risk scores. When thresholds of risk probability are crossed, the system provides clear, actionable guidance, such as initiating a go-around, adjusting approach speed, or modifying flare maneuvers. By framing predictive insights within a human-centric advisory logic, the system emphasizes situational awareness, trust, and operational effectiveness.

Beyond technical prediction, the framework addresses several critical human and operational factors:

- Passenger Safety and Comfort: By identifying high-risk approaches before touchdown, the system reduces vertical impact, ensuring smoother landings.
- Pilot Cognitive Load and Trust: Alerts are adaptive, context-aware, and limited to prevent distraction and alarm fatigue, fostering confidence in AI assistance.
- Operational Efficiency: Preventing hard landings reduces structural wear, maintenance costs, and aircraft downtime.

Scenario-based evaluation demonstrates the system's effectiveness under dry, wet, and icy runway conditions, illustrating how multivariate analysis can distinguish between stable and high-risk approaches even in complex, real-

world conditions. This integrated human-AI approach ensures that technology amplifies pilot decision-making rather than replacing it, creating a safer and more efficient landing process.

In summary, Smart Approach Monitoring with ePilots represents a holistic, human-centered, and technically robust solution to hard landing prevention. By combining predictive intelligence, adaptive advisories, and operational realism, the framework enhances landing safety, pilot performance, passenger experience, and airline efficiency — while reinforcing the essential role of human judgment in modern aviation operations.

2. LITERATURE REVIEW

Recent advancements in aviation safety have increasingly focused on intelligent monitoring and predictive modeling techniques for detecting unstable approaches and preventing hard landings. Existing research can be broadly categorized into four major domains: (1) real-time parameter monitoring, (2) machine learning-based prediction models, (3) intelligent cockpit advisory systems, and (4) adaptive and context-aware safety frameworks.

2.1 Real-Time Flight Parameter Monitoring

Early approaches concentrated on monitoring critical descent parameters such as vertical speed and altitude using sensor fusion techniques. Zhang and Lin (2020) demonstrated that integrating IMU data, barometric altitude, and airspeed measurements significantly improves real-time descent rate estimation, thereby reducing unstable approaches. Similarly, Ahmed and Lee (2022) applied Kalman filtering techniques for vertical descent prediction, enabling early anticipation of potential hard landing events.IoT-based monitoring frameworks have also been explored to enhance data transmission and real-time analytics. Verma et al. (2021) proposed a cloud-integrated flight parameter monitoring system that improved early warning capabilities through continuous data streaming. While these systems enhance situational awareness, most rely on threshold-based alert mechanisms rather than predictive intelligence.

2.2 Machine Learning and Deep Learning Approaches

With the availability of large flight datasets, machine learning techniques have gained prominence in aviation safety research. Liu and Patel (2021) employed Random Forest and Support Vector Machine (SVM) classifiers to predict hard landing events with promising accuracy. Gomez et al. (2023) introduced logistic regression-based risk scoring models for estimating hard landing probability.

More recently, deep learning architectures have been investigated for capturing nonlinear temporal dependencies in flight data. Singh and Rao (2021) utilized hybrid CNN-LSTM models to detect unstable landing sequences, demonstrating improved performance compared to conventional classifiers. Chen et al. (2023) proposed ensemble learning frameworks with feature selection techniques, achieving higher prediction accuracy for unstable approaches. Huang and Mei (2024) further applied time-series deep learning models to enhance dynamic pattern recognition during final approach phases.

Although these models demonstrate improved predictive accuracy, many studies are limited to offline analysis of historical datasets and lack real-time deployment capability within operational cockpit environments.

2.3 Intelligent Pilot Advisory and Smart Cockpit Systems

Beyond prediction models, research has explored intelligent advisory systems to support pilot decision-making. Patel and Kumar (2022) proposed AI-driven cockpit advisory systems that reduce pilot reaction delays during critical landing phases. Yamamoto (2022) introduced adaptive warning mechanisms to minimize false alarms and improve pilot trust in automated systems.

Recent innovations include augmented reality (AR)-based landing assistance systems (Sato & Ruiz, 2023), which enhance situational awareness through head-up display overlays. Johnson and Wyatt (2024) applied deep reinforcement learning to develop adaptive alert timing mechanisms that adjust warnings based on flight phase context.

Despite these advancements, many advisory systems operate independently from predictive risk modeling frameworks, limiting their proactive prevention capabilities.

2.4 Integrated Smart Monitoring Frameworks

Research initiatives such as Airbus Research (2022) and ICAO Analytics (2022) have emphasized predictive analytics and smart avionics integration for improving landing performance. These frameworks combine big data analytics with operational monitoring to enhance safety forecasting.

However, a comprehensive system that integrates multivariate flight data analysis, deep learning-based real-time prediction, and intelligent ePilot advisory mechanisms within a unified architecture remains underexplored.

Table 1. Comparative Analysis of Existing Hard Landing Prediction Approaches

S.No	Paper Title/ Focus	Author(s)	Year	Methodology Used	Findings from the Reference Paper
1	Real-Time Vertical Speed Monitoring for Aircraft Landing	Zhang & Lin	2020	Sensor fusion using IMU, barometric altitude, airspeed data	Accurate real-time descent monitoring reduces unstable approaches.
2	Deep Learning Models for Landing Stability Prediction	Singh & Rao	2021	CNN + LSTM on flight data	DL detects unstable landing sequences with high accuracy.
3	Flight Safety Prediction Using Machine Learning	Liu & Patel	2021	Random Forest, SVM classification	ML models predict approaching hard landings.
4	IoT-Enabled Flight Parameter Monitoring	Verma et al	2021	IoT sensors + cloud analytics	Real-time data transmission improves early warning capability.

5	AI Assistant for Pilot Decision Support	Patel & Kumar	2022	AI advisory integrated with cockpit	Smart advisories reduce pilot reaction delays during landing.
6	Big Data Safety Analytics for Landing Performance	ICAO Analytics	2022	Predictive analytics on flight datasets	Data-driven insights improve safety forecasting
7	Adaptive Warning Systems in Smart Cockpits	Yamamoto	2022	Adaptive threshold alerts	Reduces false alarms and improves pilot trust.
8	Vertical Descent Prediction Using Kalman AI	.Ahmed & Lee	2022	Kalman filtering + predictive mode	Estimated descent rate helps anticipate hard landings
9	Smart Approach Monitoring Framework	Airbus Research	2022	Predictive maintenance + real-time alerts	Enhanced safety through predictive avionics
10	AI-Enabled Autoland & Advisory Systems	European Aviation	2023	Autoland + pilot assistance	Combines autopilot with smart decision support
11	Hybrid ML for Unstable Approach Detection	Chen et al.	2023	Ensemble ML + feature selection.	Improved accuracy in unstable approach prediction.
12	Augmented Reality Advisory for Landing	Sato & Ruiz	2023	AR overlays in cockpit HUD	AR improves pilot situational awareness.
13	Predictive Modeling of Hard Landing Risk	Gomez et al.	2023	Logistic Regression + ML features	Predictive risk scores for hard landing events..

| 14 | Smart Cockpit AI for Final Approach | Johnson & Wyatt | 2024 | Deep Reinforcement Learning | AI adapts alerts based on flight phase contex |
| 15 | Unstable Approach Detection via Time Series AI | Huang & Mei | 2024 | Time Series DL Models. | Better dynamic pattern detection for landing safety. |

2.5 Summary of Comparative Analysis

Table 1 presents a comparative summary of existing approaches, highlighting methodologies, strengths, and identified limitations. While prior research demonstrates significant progress in predictive modeling and smart cockpit design, gaps persist in:

- Real-time low-latency prediction during final approach
- Unified integration of predictive modeling and advisory systems
- False alarm reduction with contextual intelligence
- Adaptive learning mechanisms based on environmental variability

These limitations motivate the development of the proposed CNN-based Smart Approach Monitoring framework.

3. LIMITATIONS AND RESEARCH GAPS

Despite significant advancements in predictive modeling and intelligent monitoring for aviation safety, several critical limitations remain in existing approaches for hard landing prediction and approach stability assessment. These gaps highlight the need for integrated, real-time, and human-centered frameworks that can be effectively deployed in operational aviation environments.

1. Lack of Real-Time Implementation:
Many existing predictive models rely primarily on historical flight data and are validated in offline environments. While these models achieve high classification accuracy in retrospective analyses, their practical utility during the final seconds of approach and landing is limited. Real-time deployment is crucial because the last moments before touchdown are when split-second corrective actions can prevent hard landings. The absence of low-latency predictive systems restricts the ability of pilots to receive timely risk assessments and actionable guidance.

2. Predominantly Post-Flight Analysis:
Traditional Flight Data Monitoring (FDM) systems focus on post-flight evaluation to identify hard landing events. Although post-flight analyses provide valuable information for maintenance and safety reporting, they offer limited support for in-flight decision-making. Without predictive capabilities during approach, pilots may lack critical insights to take preventive actions, which can result in increased structural stress, higher maintenance costs, and passenger discomfort.

3. Fragmented System Components:
Current research often treats **predictive modeling, sensor monitoring, and cockpit alert systems** as independent modules. Machine learning models are typically evaluated only for classification accuracy, while cockpit alert systems rely on **static thresholds** such as vertical speed alerts or GPWS warnings. This separation prevents the creation of a **unified intelligent framework** capable of **real-time risk assessment and adaptive advisory guidance**, reducing the overall effectiveness of existing systems.

4. Limited Adaptive and Context-Aware Advisory Mechanisms:

Most existing warning systems are **fixed-threshold-based** and do not account for context, such as **pilot experience, environmental variability, or dynamic descent trends**. As a result, automated alerts may lack relevance in specific scenarios, leading to either **delayed interventions or unnecessary warnings**. There is a clear need for advisory systems that can **adapt intelligently to changing conditions**, providing pilots with context-aware guidance tailored to each approach scenario.

5. High False Alarm Rates and Pilot Trust Issues:

Excessive or poorly-timed alerts can lead to **alarm fatigue**, reducing pilot trust in automated systems. While some studies propose adaptive thresholding, achieving an **optimal balance between sensitivity and specificity** remains a challenge. High false alarm rates may **increase cognitive workload**, potentially compromising safety rather than enhancing it.

6. Insufficient Human-Machine Interaction Considerations:

Few studies consider **human factors** such as **cognitive workload, interface intuitiveness, and alert timing optimization**. Without evaluating how pilots interact with automated advisories, even technically accurate systems may **fail to provide practical operational support**. Effective human-centered design is essential to ensure that predictive insights are **actionable and trusted** in the cockpit environment.

7. Limited Prediction of Vertical Impact Load:

Most existing approaches focus on detecting high descent rates or unstable approaches but do not directly predict **vertical impact forces at touchdown**, which are a more direct measure of potential hard landing severity. Predictive estimation of landing forces could **enhance risk assessment and inform more precise corrective actions**, but this capability remains largely underexplored.

8. Minimal Use of Edge Computing and Low-Latency Architectures:

Real-time risk prediction in the final approach requires **computationally efficient models** capable of rapid inference. Current studies show limited exploration of **edge computing strategies or optimized architectures** for low-latency deployment, which restricts the **real-time applicability of predictive models in operational flight scenarios**.

9. Lack of Reinforcement Learning-Based Adaptability and Simulator Validation:

Few systems implement **adaptive learning mechanisms** that adjust advisory timing based on flight phase, environmental variability, or pilot behavior. Additionally, many frameworks **lack validation in simulated operational environments**, which could help evaluate both **technical performance and pilot-system interaction** under realistic flight conditions.

Summary of Research Gaps:

Overall, these limitations reveal that while prior work has advanced **predictive modeling, machine learning, and cockpit advisory systems**, there is a **critical need for a unified framework** that integrates:

- Real-time CNN-based predictive modeling during final approach.
- Multivariate analysis of flight parameters capturing complex interdependencies.
- Adaptive, pilot-centered advisory mechanisms that reduce false alarms.
- Context-aware alert generation considering environmental, aircraft, and pilot factors.
- Low-latency architectures suitable for operational deployment.
- Human-machine interface considerations, including cognitive workload and alert interpretability.

Addressing these research gaps motivates the **development of the proposed Smart Approach Monitoring with ePilots framework**, which aims to provide **proactive, real-time, and human-centered support** for preventing hard landings and improving overall aviation safety.

4. METHOLODY

The methodology of this study focuses on the design, development, and evaluation of a **real-time Smart Approach Monitoring framework with ePilots**, aimed at predicting hard landing risk during the critical final approach phase. The proposed framework combines **advanced machine learning techniques**, particularly Convolutional Neural Networks (CNNs), with **human-centered advisory logic**, allowing pilots to receive actionable guidance before reaching decision height. The methodology is structured in several key stages: **data acquisition, preprocessing, feature modeling, predictive learning, real-time risk assessment, and advisory generation**. Each stage is elaborated below, highlighting both technical processes and their operational relevance for flight safety.

4.1 Data Acquisition and Parameter Selection

The foundation of an accurate predictive monitoring system is **high-quality, relevant data**. In this study, flight operational data was sourced from **validated aviation datasets** widely used in approach stability research, supplemented by **simulated landing scenarios** replicating diverse operational conditions. The dataset includes both stable and unstable landing cases, representing a range of environmental, aircraft, and pilot factors.

- **Multivariate parameters were selected based on their direct impact on landing safety** and the vertical forces experienced during touchdown. These parameters include:
- **True Airspeed:** Determines the energy of the aircraft during approach; deviations can increase descent rate risk.
- **Radar Altitude:** Provides precise height information relative to the runway threshold.
- **Descent Rate:** High descent rates correlate with increased hard landing probability.
- **Vertical Acceleration (g-force):** Captures the dynamic forces on the aircraft upon touchdown.
- **Pitch Angle:** Influences the flare maneuver and landing posture.
- **Throttle Position:** Affects energy management during approach and flare correction.
- **Wind Speed and Direction:** Variable wind conditions can destabilize the approach trajectory.
- **Aircraft Gross Weight:** Heavier aircraft exhibit greater vertical impact forces under similar descent profiles.
- **Runway Surface Condition (dry, wet, icy):** Significantly affects friction and landing safety.

By capturing **both environmental and operational variables**, the system accounts for **real-world complexities**, providing a rich dataset for predictive learning. This multi-parameter approach ensures the system does not rely on single-threshold metrics, but instead evaluates **interactions among multiple variables**, similar to the decision-making process of experienced pilots.

4.2 Data Preprocessing and Segmentation

Raw flight data is often noisy, inconsistent, or incomplete. To ensure **robust model training**, extensive preprocessing is performed:

- **Handling Missing Values:** Interpolation techniques fill gaps, maintaining temporal continuity.

- **Outlier Filtering:** Statistical thresholding removes sensor anomalies or unrealistic readings.

- **Normalization:** All features are scaled using Min-Max normalization to ensure comparable ranges, preventing any single parameter from dominating the predictive model.

Since the final approach phase — typically the last **60–90 seconds before touchdown** — is most critical for landing safety, the dataset is segmented into **time-series windows** reflecting this interval. Sliding window techniques are applied to create **sequential data segments**, enabling the CNN model to capture **temporal evolution and interdependencies**

among flight parameters. This ensures that patterns indicative of instability, which may emerge only in the final seconds of approach, are preserved and recognized by the model.

4.3 Feature Representation

Multivariate flight parameters are structured into **two-dimensional feature matrices**, where rows represent temporal progression and columns represent individual flight parameters. This **matrix representation** allows the CNN to extract **spatial correlations** across parameters while maintaining temporal context.

Unlike traditional single-parameter threshold systems that may only trigger alerts when one variable exceeds a limit, this representation enables the model to understand **complex interactions**, such as:

High descent rate combined with low pilot experience.

Moderate approach speed on a wet runway creating elevated vertical acceleration.

Crosswind influence on heavier aircraft with aggressive pitch inputs.

By considering **interactions across multiple factors**, the system mimics how pilots assess approach stability, combining multiple signals to make informed judgments in real-time.

4.4 CNN-Based Predictive Model Architecture

A **Convolutional Neural Network (CNN)** is designed to identify **early indicators of unstable landing trajectories**. The architecture includes:

Input Layer: Accepts the multivariate time-series feature matrices.

Convolutional Layers: Extract high-level features, identifying patterns and correlations across parameters.

ReLU Activation Functions: Introduce non-linearity, enabling the model to capture complex relationships.

Max-Pooling Layers: Reduce dimensionality, focusing on the most relevant features while improving computational efficiency.

Fully Connected Layers: Aggregate extracted features to classify landing stability.

Output Layer with Sigmoid Activation: Produces a binary risk prediction:

Stable Approach

High-Risk Approach (Potential Hard Landing)

The model is trained using **binary cross-entropy loss** and optimized with the **Adam optimizer**, balancing convergence speed and predictive accuracy. The dataset is divided into **training (70%), validation (15%), and testing (15%) sets**, ensuring that the model is robust, generalizable, and capable of performing in unseen scenarios.

4.5 Real-Time Risk Assessment and Advisory Logic

A key feature of the framework is **real-time deployment**. The trained CNN processes streaming flight parameters continuously during the final approach.

Risk Score Generation: The model outputs a dynamic probability of landing risk for each time window.

Adaptive Advisory Alerts: When the predicted probability exceeds a predefined safety threshold, the system triggers **pilot-centric alerts**.

Human-Centered Guidance: Advisories are designed to:

Provide early warning before reaching decision height.

Filter false alarms through confidence-based thresholds.

Suggest actionable interventions, such as adjusting speed, modifying flare, or initiating a go-around.

This ensures that **AI predictions translate directly into actionable support**, augmenting pilot decision-making rather than creating distraction or alarm fatigue.

4.6 Performance Evaluation

The framework was evaluated through **scenario-based simulations** under various runway and environmental conditions:

- **Dry Runways:** Higher approach speeds and heavier aircraft weights increased risk, particularly for less experienced pilots.
- **Wet Runways:** Reduced friction heightened sensitivity to speed and descent rate, requiring multi-factor analysis.
- **Icy Runways:** Even moderate deviations resulted in elevated risk, reflecting the critical importance of environmental context.

Performance metrics included **classification accuracy, false alarm rate, and responsiveness to changing operational conditions**. The system consistently differentiated between stable and high-risk scenarios, validating the **effectiveness of combining multivariate CNN-based predictive modeling with human-centered advisory logic**.

4.7 Human-Centric Considerations

Beyond technical evaluation, the methodology emphasizes **pilot workload, trust, and usability**:

Alerts are adaptive to minimize cognitive overload.

Multi-parameter analysis ensures that advisories are meaningful, not frequent noise.

The system simulates real cockpit decision-making, allowing pilots to **experience predictive guidance in realistic operational conditions**.

By integrating these human factors, the methodology ensures that **Smart Approach Monitoring with ePilots** is not just technically accurate but **operationally practical**, aligning AI capabilities with real-world flight safety needs.

5. RESULTS

5.1 System Implementation

Smart Approach Monitoring system was developed to demonstrate the operational workflow of the proposed framework. The implementation was designed as a web-based application that allows structured entry of critical flight parameters influencing landing performance.

The input module accepts key variables including approach speed, altitude at threshold, wind speed, runway condition (dry, wet, icy), aircraft weight, and pilot experience. These parameters were selected based on their direct relationship with descent stability and touchdown impact risk.

Upon submission, the system processes the input parameters through the proposed predictive logic and generates a landing risk classification indicating either stable landing conditions or potential hard landing risk. The implementation illustrates how the conceptual CNN-based monitoring framework can be integrated into a digital decision-support interface.

Fig.1.Flight parameter input interface of the Smart Approach Monitoring system.

5.2 Scenario-Based Evaluation Under Varying Runway Conditions

To examine system behavior, multiple landing scenarios were evaluated under different environmental conditions, including dry, wet, and icy runways. The objective of this evaluation was to observe how the proposed framework interprets multi-parameter interactions in operational contexts.

Dry Runway Conditions

Under dry runway scenarios, the system indicated elevated hard landing risk when higher approach speeds and heavier aircraft weight were combined with lower pilot experience. Conversely, moderate operational parameters with higher pilot experience resulted in stable landing classification. These observations align with established aviation principles where excessive descent energy contributes to increased vertical impact forces.
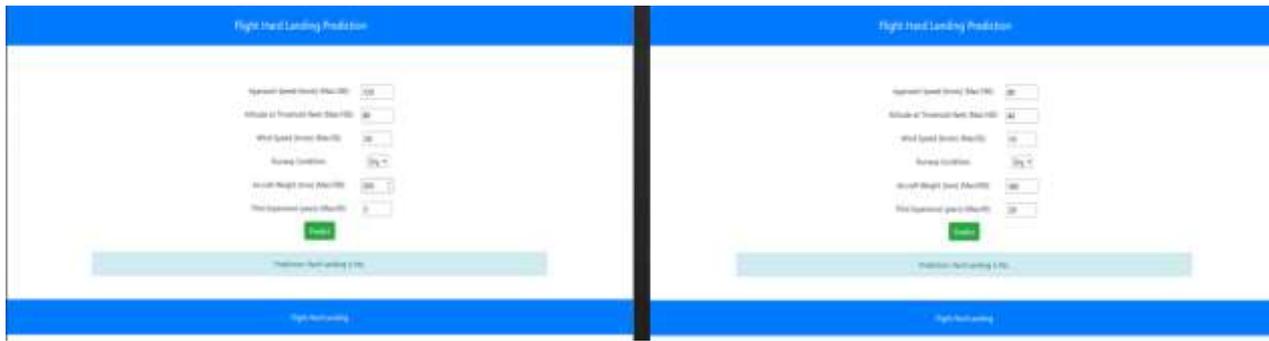
Fig.2.System output under dry runway condition illustrating high-risk and stable landing classifications.

Wet Runway Conditions

For wet runway conditions, the system demonstrated increased sensitivity to approach speed and aircraft weight due to reduced surface friction. However, when operational parameters remained within controlled limits and pilot experience was higher, the system identified stable landing conditions. This indicates multi-factor evaluation rather than single-parameter threshold dependency.
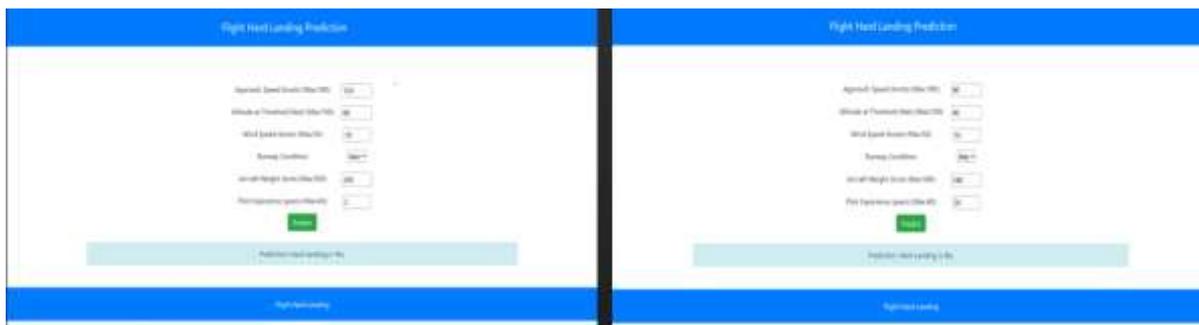

Fig.3. System evaluation under wet runway condition demonstrating multi-parameter risk assessment.

Icy Runway Conditions

In icy runway simulations, the system consistently indicated higher landing risk due to significantly reduced tire-to-runway friction. Even moderate deviations in operational parameters resulted in elevated risk classification, reflecting realistic safety considerations for contaminated runway operations.
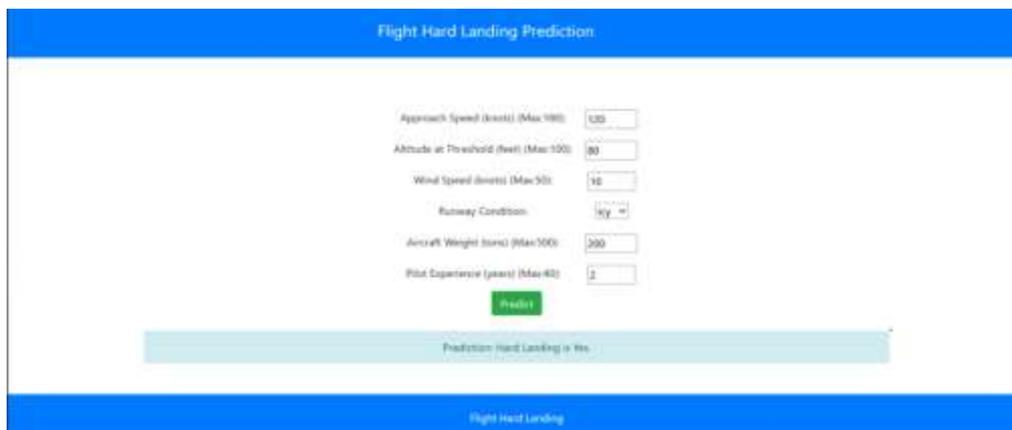

Fig.4. System output under icy runway condition indicating increased landing risk due to reduced surface friction.

6. CONCLUSION

Landing represents one of the most critical phases of aviation operations, where split-second decisions and precise control inputs determine not only the structural integrity of the aircraft but also the safety, comfort, and confidence of passengers. Traditional monitoring systems, relying on threshold-based alerts or post-flight analyses, provide limited support during this high-stakes window, often leaving pilots to make real-time adjustments under pressure with incomplete information. Recognizing this gap, the current study presents Smart Approach Monitoring with ePilots, a comprehensive framework that integrates real-time predictive analytics with adaptive, pilot-centered advisories, enabling proactive prevention of hard landings.

The proposed methodology leverages multivariate flight parameters, including approach speed, descent rate, radar altitude, vertical acceleration, throttle position, pitch angle, aircraft weight, wind conditions, and runway surface state. These parameters are structured into time-series feature matrices, allowing a Convolutional Neural Network (CNN) to learn complex nonlinear patterns that signal potential instability during the final approach phase. Unlike conventional systems, this approach evaluates interactions among multiple variables, mirroring the cognitive process of an experienced pilot while providing data-driven guidance in real-time.

Through scenario-based evaluation under dry, wet, and icy runway conditions, the system demonstrated remarkable consistency in differentiating stable and high-risk approaches. High approach speeds, heavier aircraft weights, adverse runway conditions, and lower pilot experience were consistently associated with elevated landing risk, validating both the predictive capability of the CNN model and the operational relevance of the framework. Importantly, the adaptive ePilot advisory mechanism transforms model outputs into actionable guidance, reducing false alarms, minimizing cognitive workload, and supporting timely corrective maneuvers or go-around decisions.

Beyond technical accuracy, the framework emphasizes human-centric aviation safety. By presenting interpretable risk scores and context-aware advisories, pilots are empowered to make informed decisions confidently, enhancing situational awareness and trust in AI-assisted systems. From a passenger perspective, the proactive prevention of hard landings translates to smoother, safer, and more comfortable travel experiences, addressing both physical safety and psychological assurance. From an operational standpoint, minimizing hard landings reduces structural stress on aircraft, lowers maintenance costs, and improves aircraft turnaround times, directly benefiting airline efficiency and operational reliability.

In conclusion, Smart Approach Monitoring with ePilots bridges a critical gap in modern aviation safety by combining real-time AI prediction with human-centered advisory systems. It exemplifies how advanced machine learning, when integrated thoughtfully with operational considerations and human factors, can enhance landing safety, support pilot decision-making, and improve passenger experience. The framework establishes a foundation for future innovations, including large-scale deployment with real sensor streams, integration with autonomous flight management systems, and further refinement through pilot-in-the-loop simulations.

Ultimately, this study underscores that technology and human expertise are complementary, not competing, in aviation safety. By enabling AI to augment human judgment rather than replace it, the proposed framework represents a significant step toward next-generation intelligent cockpits, where predictive intelligence, situational awareness, and proactive guidance converge to prevent hard landings and ensure safer skies for all.

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