RESEARCH ARTICLE OPEN ACCESS

Leveraging Machine Learning And Psychophysiology Data For Safer Skies

K. Gayathri[1], Dr. M. Dhanalakshmi[2]
[1]MCA Student, Department of Information Technology, Jawaharlal Nehru Technological University, India
[2]Professor of IT, Department of Information Technology, Jawaharlal Nehru Technological University, India

--************************----------------------------------

Abstract:
Air safety continues to be a critical concern, frequently affected by human mistakes like pilot workload, fatigue, stress, and emotional fluctuations. Addressing these challenges, recent advancements have emphasized the integration of machine learning with psychophysiological data to better understand and monitor pilot behavior. This project presents a systematic review of current research in this domain, following a rigorous methodology to analyze 80 peer-reviewed studies selected from a total of 3,352 articles across five prominent electronic databases. The review focuses on key dimensions such as behavioral indicators, data types, preprocessing methods, machine learning models, and evaluation metrics. Findings suggest a predominant focus on cognitive factors like workload and fatigue, while emotional responses and attentional dynamics remain underexplored. Conventional preprocessing techniques and classical machine learning algorithms—particularly decision trees and support vector machines—are widely adopted, whereas the application of deep learning approaches remains limited. Critical research gaps have been identified, including a lack of emphasis on the impact of preprocessing strategies, challenges related to data imbalance, insufficient diversity in data collection environments, and minimal attention to model interpretability. This study highlights the need for future research to explore advanced preprocessing techniques, incorporate explainable AI, and capture a broader spectrum of behavioral data. Such directions are essential for building more robust, accurate, and human-centric safety systems in aviation.

Keywords — **Air safety, behavioral indicators, machine learning, pilot workload, psychophysiology data.**

--************************----------------------------------

I. INTRODUCTION

The aviation industry is rapidly evolving, demanding that pilots act not only as system operators but also as real-time decision-makers in high-risk and dynamic environments. This shift underscores the importance of understanding human behavior under stress, cognitive load, and fatigue to ensure aviation safety. Recent research highlights the integration of machine learning (ML) with psychophysiological measures such as electroencephalogram (EEG), electrocardiogram (ECG), and galvanic skin response (GSR) as a promising approach to monitoring and evaluating pilot states. These indicators provide valuable insights into cognitive performance, attention, and emotional regulation, all of which directly affect flight safety. This paper presents a systematic literature review examining how ML techniques are applied in conjunction with psychophysiological data to analyze and predict pilot behavior. The review categorizes behavioral aspects studied, explores data collection and preprocessing strategies, evaluates applied ML models, and summarizes performance outcomes. The results reveal emerging trends alongside critical gaps, including limited focus on emotional and attentional factors, underutilization of deep learning methods, and insufficient emphasis on interpretability. Addressing these gaps is vital to advancing human-centered aviation safety systems capable of real-time behavioral monitoring and predictive intervention.

I. LITERATURE SURVEY

TABLE I

Author(s)	Focus Area	Methods/Data Used	Key Findings
C. V. Oster, J. S. Strong, C. K. Zorn	Human factors in aviation safety	Analysis of fatigue, workload, decision-making	Highlighted the role of psychophysiological monitoring in safety frameworks
Y. Liu, Y. Gao, L. Yue, H. Zhang, J. Sun, X. Wu	Real-time pilot workload detection	Non-intrusive sensors, HRV, EEG, biometric signals, ML classifiers	High accuracy in workload classification; potential for adaptive cockpits
A. Hernández-Sabaté, J. Yauri, P.	EEG-based cognitive load assessment	EEG preprocessing + ML classifiers	Consistent differentiation of cognitive load levels

Folch, M. À. Piera, D. Gil			
M. Cabrall, D. Almeida, J. B. L. Filho	Review of mental workload assessment	Subjective, behavioral, and physiological measures (EEG, ECG, eye-tracking)	Multimodal approaches recommended; ML crucial for interpretation
J. Ewing, R. Ahlstrom, S. O'Donnell	Physiological indicators for workload	HR, GSR, EEG in simulated flight tasks	Identified reliable physiological measures for workload classification

III. METHODOLOGY

A. *Proposed Work:*

The proposed solution integrates machine learning algorithms with psychophysiological data monitoring to establish a proactive aviation safety framework. The system is designed to continuously monitor both environmental conditions and human performance metrics in real time, thereby facilitating the early detection of potential safety threats. Large volumes of physiological sensor data, including electroencephalogram (EEG), electrocardiogram (ECG), heart rate variability (HRV), and electrodermal activity (EDA), are processed to identify patterns associated with reduced alertness, elevated stress, or fatigue. The architecture incorporates a continuous feedback loop, wherein anomalies detected by the machine learning models automatically generate alerts or initiate adaptive system responses. These preventive measures assist pilots and air traffic controllers in mitigating risks before the occurrence of safety-critical incidents. Furthermore, the predictive accuracy of the system is progressively enhanced through incremental learning from both historical records and real-time operational data, ensuring robustness and adaptability under dynamic aviation environments.

B. *System Architecture*

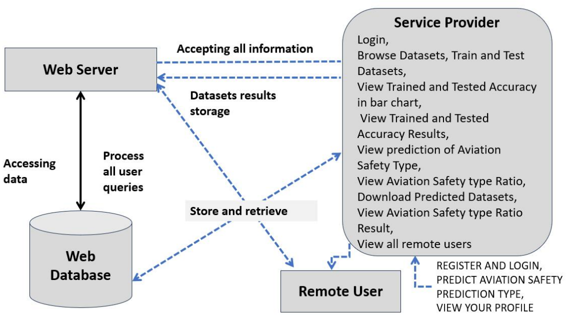

Fig. 1 Proposed Architecture

This architecture consists of two main components: the Admin interface and the User interface.

Admin Interface:

1) Dataset Selection/Creation: The aviation safety dataset is prepared by integrating physiological sensor data (EEG, ECG, HRV, EDA) with environmental parameters such as cabin pressure, temperature, and workload indicators. Features represent pilot psychophysiological states, while labels indicate safety status (e.g., normal, stressed, fatigued).

2) Data Preprocessing: Collected data undergoes filtering, normalization, and feature extraction to remove noise and standardize values. The preprocessed feature vectors are stored as X-train variables, and labels are stored as Y-train variables for further model development.

3) Model Training and Validation: The preprocessed dataset is divided into training and testing sets. Training data is used to train machine learning algorithms such as SVM, AdaBoost, MLP Classifier, and Random Forest, while testing data is used to evaluate accuracy, precision, recall, and F1-score.

User Interface:

1) Model Deployment: **Safety Prediction Model:** Machine learning models trained on physiological and environmental datasets are deployed to predict pilot states (alert, fatigued, stressed) and potential safety risks.

Anomaly Detection Model: Detects irregular patterns in real-time data and categorizes them into severity levels (low, medium, high risk).

Alert Generation System: Generates proactive warnings for both pilots and air traffic controllers when unsafe conditions are detected.

2) Web Application Development: **User Interface:** A web-based dashboard is developed using Flask/Django to allow remote users (pilots, air traffic controllers, administrators) to input or stream real-time physiological/environmental data and visualize prediction outcomes.

Backend Integration: The web application communicates with machine learning models and a MySQL database. Real-time input data is passed to the predictive models, and results are retrieved for analysis.

Results Display: Predictions (stress/fatigue levels, safety alerts, anomaly classifications) are displayed in a user-friendly dashboard, with color-coded alerts and historical trend analysis.

3) Frontend Development: The front-end of the application is built using HTML, CSS, and Flask with Python libraries to ensure a user-friendly interface. Users can register, log in, upload real-time physiological values, and view aviation safety predictions. All user data is stored securely in MySQL, and ML models are integrated for real-time predictions.

4) Testing and Validation: The performance of the models is evaluated using accuracy, precision, recall, and F1-score. The system is tested with both real-world aviation data and synthetic test cases to ensure smooth end-to-end functionality, robustness, and reliability in operational scenarios.

5) Algorithms Employed: **Support Vector Machine (SVM):** Constructs optimal hyperplanes to maximize separation between psychophysiological states, enabling robust classification.

AdaBoost: An ensemble learning method that combines multiple weak classifiers to enhance prediction accuracy and reduce bias.

Multilayer Perceptron (MLP) Classifier: A neural network-based classifier capable of modeling complex, non-linear relationships in psychophysiological data.

Random Forest: An ensemble of decision trees that enhances classification stability, minimizes overfitting, and provides reliable prediction results.

IV. EXPERIMENTAL RESULTS

Open Anaconda Prompt

Switch to TensorFlow environment to run the file change to the directory where the file is located then run the file and open the URL http://127.0.0.1:8000/ by clicking ctrl+click.

Fig. 2 Anaconda Prompt

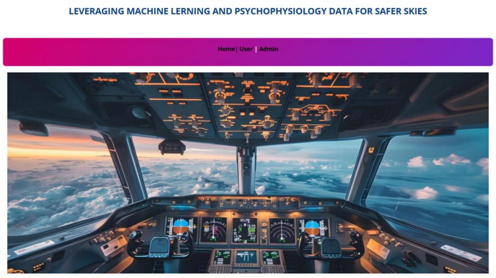

Fig. 3 Home Page

This is the Home Page, it has three options Home, User and Admin.

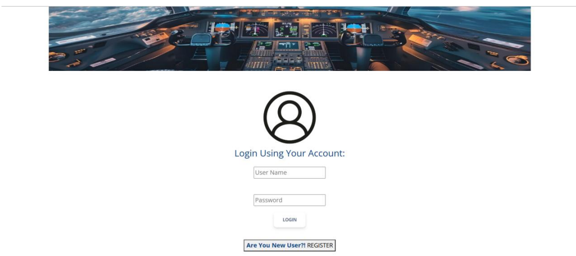

Fig. 4 User Login Page

This is User Login Page

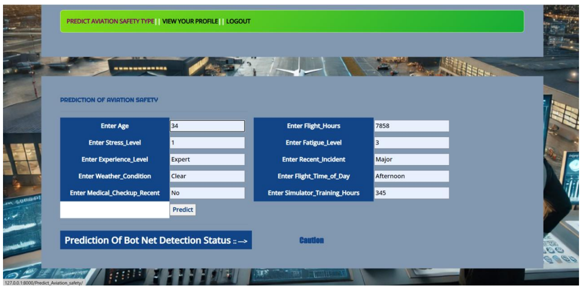

Fig. 5 Prediction Page

Once user logs in user can view their profile, predict and logout. User can predict the data, and find out the pilot's mental state using the psychophysiology data

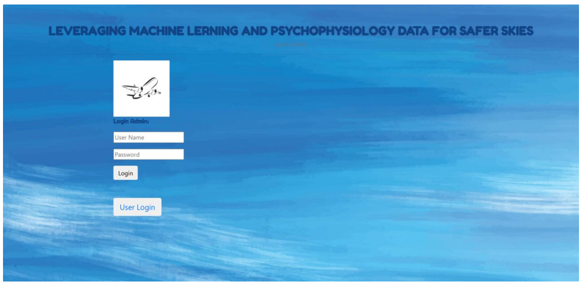

Fig. 6 Admin Login

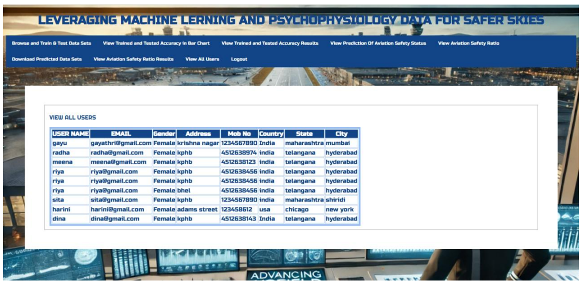

Fig. 7 View User Profile

Once admin logs in he can manage the users

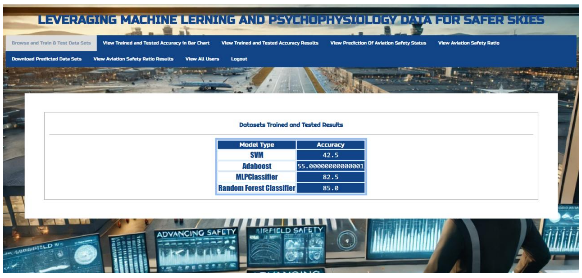

Fig. 8 Model Accuracy

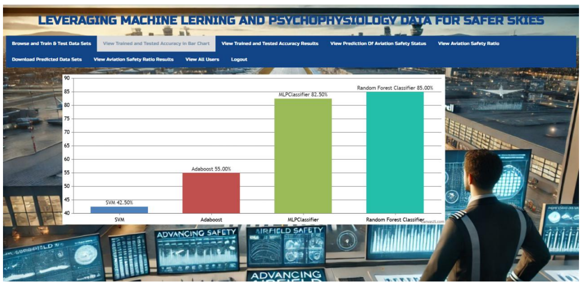

Fig. 9 Model Accuracy in Bar Graph

Amin can view model accuracy

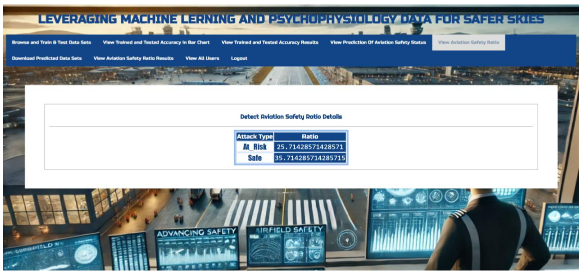

Fig. 10 Prediction Ratio

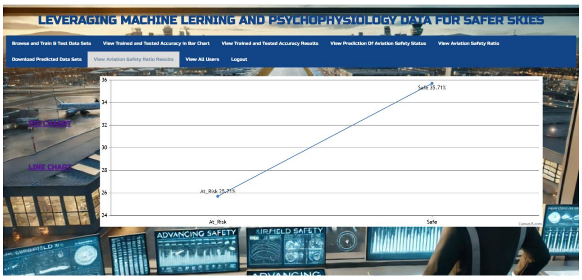

Fig. 11 Prediction Ratio in Line Chart

Admin can view prediction safety in both ratio form and chart form

V. CONCLUSIONS

This systematic literature review offers a detailed and comprehensive overview of current research applying Machine Learning (ML) models to the interpretation of psychophysiological data, with a specific focus on pilot behavior. The findings highlight significant variability in the types of psychophysiological data utilized across studies, with EEG emerging as the most commonly used modality. This preference for EEG reflects its established reliability in capturing cognitive states; however, it also underscores the limited use of other potentially valuable modalities such as ECG, GSR, and eye-tracking metrics. The review also reveals a notable research gap in the behavioral dimensions examined—particularly the underrepresentation of emotional responses and attention dynamics compared to the more frequently studied workload and fatigue. These overlooked aspects are critical not only for a more holistic understanding of pilot performance but also for enhancing aviation safety. Current methodological approaches often aggregate behavioral factors into broad categories, which may obscure the nuanced relationships between cognitive, emotional, and attentional states. From this analysis, it is evident that future research should adopt a more balanced and integrative approach—leveraging multi-modal data sources, applying advanced ML techniques, and focusing on underexplored behavioral variables. Such efforts could yield more accurate, interpretable, and operationally relevant models for pilot state assessment.

VI. FUTURE SCOPE

There remains considerable scope for expanding the current body of research in multiple directions. One promising avenue is multi-modal data integration, where combining EEG with eye tracking, galvanic skin response (GSR), and electrocardiography (ECG) could yield richer and more comprehensive representations of pilot states, thereby providing deeper behavioral insights. Similarly, the adoption of refined behavioral categorization—moving beyond broad classifications toward more granular definitions of emotional states, attentional shifts, and stress responses—can significantly enhance the precision of predictive models. Furthermore, the application of advanced machine learning and deep learning approaches, including hybrid techniques, ensemble learning, and explainable AI frameworks, offers the potential to improve both prediction accuracy and interpretability of results. In addition, the development of real-time monitoring systems powered by machine learning could enable continuous assessment of pilot states, offering immediate feedback within operational environments and thereby contributing directly to safety interventions. Finally, advancing this research will benefit greatly from cross-disciplinary collaboration, involving experts from neuroscience, psychology, aviation safety, and computer science, which can facilitate more holistic and robust solutions for aviation safety and human performance optimization.

VII. REFERENCES

[1] Wiegmann, D. A., & Shappell, S. A. (2002). *A human error analysis of commercial aviation accidents using the Human Factors Analysis and Classification System*. DOT/FAA/AM-02/2. Washington, DC: U.S. Department of Transportation.

[2] Kitchenham, B. (2007). *Guidelines for performing systematic literature reviews in software engineering*. EBSE Technical Report, Keele University and University of Durham, UK.

[3] Kitchenham, B., & Charters, S. (2009). *Guidelines for performing systematic literature reviews in software engineering*. EBSE Technical Report, Keele University and University of Durham, UK.

[4] Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group. (2009). *Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement*. *PLoS Medicine, 6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

[5] Oster, C. V., Strong, J. S., & Zorn, C. K. (2013). *Analyzing aviation safety: Problems, challenges, opportunities*. *Research in Transportation Economics, 43*(1), 148–164. https://doi.org/10.1016/j.retrec.2012.12.008

[6] Wickens, C. D., & Hollands, J. G. (2000). *Engineering psychology and human performance* (3rd ed.). Upper Saddle River, NJ: Prentice Hall.

[7] Parasuraman, R., & Hancock, P. A. (2001). Adaptive control of mental workload. In P. A. Hancock & P. A. Desmond (Eds.), *Stress, workload, and fatigue* (pp. 305–320). Mahwah, NJ: Lawrence Erlbaum Associates.

[8] Wilson, G. F. (2002). An analysis of mental workload in pilots using multiple psychophysiological measures. *The International Journal of Aviation Psychology, 12*(1), 3–18. https://doi.org/10.1207/S15327108IJAP1201_2

[9] Byrne, E. A., & Parasuraman, R. (1996). Psychophysiology and adaptive automation. *Biological Psychology, 42*(3), 249–268. https://doi.org/10.1016/0301-0511(95)05161-9

[10] Brookings, J. B., Wilson, G. F., & Swain, C. R. (1996). Psychophysiological responses to changes in workload during simulated air traffic control. *Biological Psychology, 42*(3), 361–377. https://doi.org/10.1016/0301-0511(95)05167-8

[11] Lee, D.-H., Kim, S.-J., Kim, S.-H., & Lee, S.-W. (2023). Decoding EEG-based workload levels using spatio-temporal features under flight environments. *arXiv*. https://arxiv.org/abs/2312.09423

[12] Li, X., Zhou, D., Jia, Z., Xiao, J., Liu, C., & Zhai, L. (2023). An EEG channel selection framework for driver drowsiness detection via interpretability guidance. *arXiv*. https://arxiv.org/abs/2304.14920

[13] Sharma, P., Justus, J. C., Thapa, M., & Poudel, G. R. (2023). Sensors and systems for monitoring mental fatigue: A systematic review. *arXiv*. https://arxiv.org/abs/2307.01666

[14] Zhang, Q., Wang, Z., & Wang, Y. (2024). Decoding fatigue levels of pilots using EEG signals with hybrid deep neural networks. *arXiv*. https://arxiv.org/abs/2411.09707

[15] Wright, M. J., Veitch, J. A., & Eardley, A. (2024). Visual attention distribution of pilot flying vs. pilot monitoring during different flight phases. *International Journal of Human–Computer Interaction*. Advance online publication. https://doi.org/10.1080/10447318.2024.2380949

[16] Hämäläinen, R., De Wever, B., Sipiläinen, K., Heilala, V., Helovuo, A., Lehesvuori, S., … Kärkkäinen, T. (2023). Using eye tracking to support professional learning in vision-intensive professions: A case of aviation pilots. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-12814-9

[17] Fernández-Castro, Á., Díaz, S., & Martínez, P. (2023). Eye-tracking technologies for facilitating multimodal interaction in aviation. *Sensors and Systems, 90*(1), 110. https://doi.org/10.3390/2673-4591/90/1/110

[18] Ji, L., Yi, L., Li, H., Han, W., & Zhang, N. (2024). Detection of pilots' psychological workload during turning phases using EEG characteristics. *Sensors, 24*(16), 5176. https://doi.org/10.3390/s24165176

[19] Taheri Gorji, H., Wilson, N., VanBree, J., Hoffmann, B., Petros, T., & Tavakolian, K. (2023). Using machine learning methods and EEG to discriminate aircraft pilot cognitive workload during flight. *Scientific Reports, 13*, 2507. https://doi.org/10.1038/s41598-023-29514-2

[20] Dehais, F., Causse, M., Vachon, F., Régis, N., Menant, E., & Tremblay, S. (2014). Missing critical auditory alarms in aeronautics: Evidence for inattentional deafness? *Human Factors, 56*(6), 631–641. https://doi.org/10.1177/0018720814534510

[21] de Reus, A. J. C., Zon, R., & Ouwerkerk, R. (2012). Exploring the use of an eye tracker in a helmet mounted display. *National Aerospace Laboratory Technical Report*, NLR-TP-2012-001.

[22] Lu, N., et al. (2025, May 29). 'E-tattoo' could track mental workload for people in high-stake jobs. *The Guardian*.