Benchmarking Stress Detection: Fuzzy Logic vs. Deep Learning

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***Abstract*—Stress detection systems for airport environments must balance accuracy, interpretability, and practical deployability. A comparative benchmarking analysis of wearable physiological sensing-based stress detection techniques is presented in this paper, which contrasts cutting-edge deep learning and computer vision techniques with an interpretable fuzzy inference framework based on Design Science Research. The analysis takes into account typical wearable signals, such as electrocardiography (ECG), electrodermal activity (EDA), and heart rate variability (HRV), and assesses the consequences for real-time monitoring of both software and hardware deployment. Several benchmark datasets are used to test methods based on deployment-oriented characteristics, including robustness, interpretability, data requirements, computing cost, privacy, and sustainability. The results demonstrate that the fuzzy inference method offers transparent, stable, and privacy-preserving stress estimate with low computing overhead, while deep learning and vision-based models reach high accuracy in controlled circumstances. For ethical and sustainable airport applications, these results encourage the use of interpretable wearable-based stress monitoring.**

***Index Terms*—Stress detection, Benchmark testing, Fuzzy inference systems, Deep Learning models, Perceptual computing**

I. INTRODUCTION

Human well-being, cognitive function, and decision-making are significantly affected by stress, particularly in complex and time-constrained environments such as airports [1]. Passengers routinely encounter stressors including time pressure, security procedures, crowd density, and flight uncertainty. Reliable stress monitoring can therefore support enhanced passenger experience [2], operational efficiency, and safety in smart airport infrastructures. This study adopts the Design Science Research (DSR) methodology [3], which generates knowledge through the design and evaluation of artifacts addressing real-world problems. The process follows three phases: (i) problem identification and requirement definition based on airport constraints; (ii) artifact design, including model selection, sensing, and benchmarking dimensions; and (iii) evaluation through multi-dataset analysis and qualitative comparison across technical and ethical criteria.

Stress monitoring systems in public environments must be accurate, human-centered, privacy-preserving, and ethically sound. Humanistic engineering highlights that opaque and surveillance-oriented technologies can undermine trust and societal well-being, especially in safety-critical contexts [4]. This perspective motivates the exploration of interpretable, lightweight, wearable-based stress detection approaches that align technological capabilities with human values.

Recent research in stress detection for transportation environments [5] increasingly relies on advanced artificial intelligence techniques. Deep learning models applied to physiological signals such as ECG, EDA, and HRV achieve high classification accuracy using convolutional [6], recurrent, Transformer-based [7], and multimodal architectures [8]. Computer vision approaches infer stress from facial expressions [9], body movements [10], or speech [11], enabling contactless monitoring but raising concerns regarding privacy, robustness, and ethical use in public settings. Despite strong performance in controlled environments, these methods face deployment challenges due to data requirements, limited interpretability [12], and sensitivity to environmental conditions.

Advances in wearable sensing enable continuous, non-intrusive stress monitoring using low-power embedded systems. Platforms such as Arduino, Raspberry Pi, and ESP32 [13] support acquisition of physiological signals including ECG, EDA, temperature, and motion [14]. These systems offer low cost, flexibility, and energy efficiency, supporting real-time data collection and edge processing [15]. Within the DSR perspective, the main artifact of this study is a deployment-oriented benchmarking framework for stress detection in airport environments, complemented by an interpretable fuzzy inference system as a reference design. This framework enables systematic comparison across technical, ethical, and deployment dimensions.

Our previous work introduced an interpretable fuzzy inference framework for stress estimation using wearable signals and self-reported data [16]. Building on this, the present study benchmarks fuzzy inference against deep learning and computer vision approaches [17] from a deployment-oriented perspective. The contribution of this paper is a structured comparative analysis that evaluates predictive performance alongside interpretability, robustness, privacy, sensor requirements, and deployment feasibility. The goal is to inform the design of human-centered, ethical, and sustainable stress monitoring systems in real-world transportation contexts.

The rest of this paper is structured as follows. The benchmarking framework used in this study, which includes the evaluation dimensions and design-oriented comparison criteria based on design science research concepts, is introduced in Section II. The evaluation and discussion of representative stress detection methods are presented in Section III, which synthesizes findings from various datasets and modeling paradigms. The main conclusions of the benchmarking analysis are summarized in Section IV, with a focus on sensor and hardware-related issues, ethical and sustainable issues, and the methodological and practical ramifications for airport passenger stress monitoring. The work is finally concluded in Section V, which also suggests future research areas.

II. Benchmarking Framework

Design science research (DSR) principles and the humanistic engineering viewpoint, which prioritizes empowerment, sustainability, simplicity, and transparency over needless technological complexity, guide the selection of benchmarking criteria [4]. A comprehensive comparison between the suggested fuzzy inference system [18] and representative deep learning and computer vision-based stress detection methods documented in the literature [17] is made possible by the benchmarking framework used in this study.

An organized benchmarking method that blends design-oriented analysis and empirical validation was used to assess the artifact. Using agreement to self-reported stress as the main validation signal, the fuzzy inference system was first evaluated on several public and real-world datasets to investigate the stability of continuous stress estimations across different acquisition situations. Simultaneously, the presented datasets, sensor modalities, and performance characteristics of representative deep learning and computer vision-based techniques were examined. To facilitate cross-paradigm comparison, approaches were ranked qualitatively using deployment-oriented criteria, including interpretability, data needs, computational cost, robustness, privacy, and hardware feasibility. By evaluating both deployment suitability and functional validity in airport settings, this mixed assessment approach is consistent with design science research concepts.

In order to account for inter-individual variability, the system uses percentile-based membership functions that are directly derived from physiological signal distributions. It is based on a Mamdani-type fuzzy inference architecture [16]. Because fuzzy rules and linguistic variables may be directly examined, explained, and validated by domain experts, Mamdani inference is a highly interpretable method

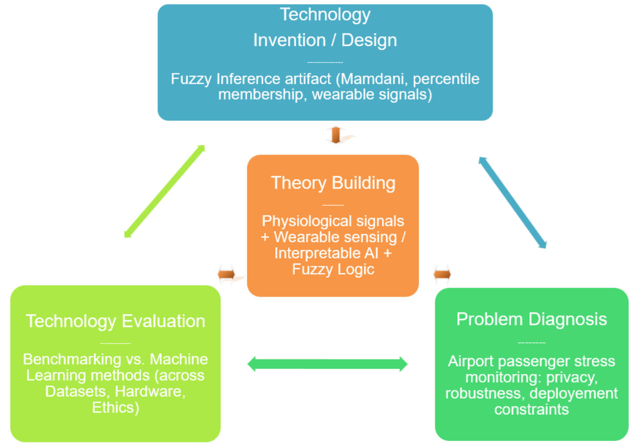

Fig. 1: Design Science Research framework instantiated for this study.

that naturally aligns with human logic. In public and safety-critical settings like airports, where open decision-making and stakeholder confidence are crucial, this characteristic is especially significant. Instead of using preset absolute thresholds, which are known to differ greatly between subjects, percentile-based membership functions are used to normalize physiological data in relation to each person's baseline.

Therefore, the goal of this work is to assess stress detection artifacts in terms of interpretability, resilience, ethical acceptability, and large-scale deployability in addition to optimizing predictive accuracy. The adopted DSR process, which includes problem identification, artifact design, benchmarking, and assessment, is shown in Figure 1.

While model training and inference are carried out on distant servers or cloud infrastructures, wearable sensors are mainly used as data collecting devices in the majority of deep learning-based stress detection systems [19]. This division raises issues with latency, energy usage, and privacy that are especially troublesome in public places like airports. Fuzzy inference systems, on the other hand, are ideal for embedded implementation on lightweight hardware platforms [20], allowing for real-time, on-device stress estimation with low data transmission and processing overhead. The usefulness of wearable sensor platforms as a link between physiological signal theory and deployable stress monitoring systems is reinforced by this hardware–software compatibility, which enhances privacy preservation and system sustainability [21].

The inclusion of deep learning and computer vision approaches in this study is not intended to propose additional data-driven models [22], but to benchmark the fuzzy inference artifact against prevailing AI paradigms. Figure 2 summarizes the stress detection paradigms analyzed in this work, distinguishing between data-driven deep learning models, computer vision-based approaches, and the proposed interpretable fuzzy inference framework.

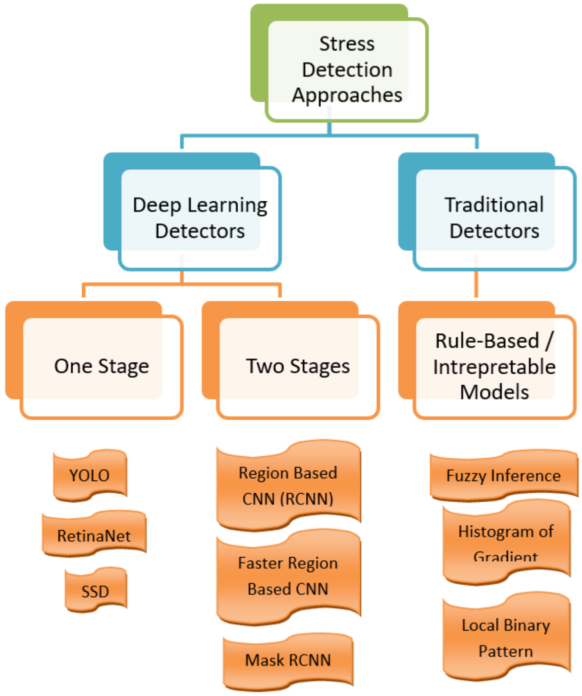

Fig. 2: Categorization of stress detection approaches considered in this study.

III. Evaluation and Discussion

This section presents a comparative analysis of stress detection approaches across benchmark datasets representing both controlled and real-world conditions. Deep learning and computer vision methods commonly rely on the SWELL Knowledge Work Stress (SWELL-KW) [23], Stress Recognition in Automobile Drivers (SRAD) [24], and Wearable Stress and Affect Detection (WESAD) [25] datasets. In parallel, results from our fuzzy inference framework are included, calibrated on the Wearable Exam Stress dataset [26], validated against self-reported stress in WorkStress3D [27], and externally tested on WESAD. This multi-dataset perspective enables contextual comparison across diverse stress settings and provides an interpretable, data-efficient reference for analyzing trade-offs between predictive performance, robustness, and deployment suitability in airport passenger stress monitoring.

The comparison criteria adopted in this study are grounded in design science research evaluation principles and prior work on human-centered and ethical information systems. In this perspective, artifacts are assessed not only by functional performance but also by interpretability, robustness, and real-world suitability. In public and safety-critical contexts such as airports, additional requirements related to privacy, transparency, scalability, and sustainability become central design constraints. Accordingly, the selected criteria combine (i) functional stress estimation quality (e.g., robustness and cross-dataset consistency), (ii) ethical and responsible AI considerations such as interpretability and data minimization [28], [29], and (iii) deployment constraints from wearable and ubiquitous computing literature, including computational cost and feasibility of embedded or edge-based implementation.

By basing stress inference on physiological reactions that are causally connected to situational stressors, the suggested framework [16] enhances alignment between sensor data and real-time stress-related facts. While continuous inference allows for smooth, temporally consistent stress trajectories appropriate for real-time monitoring, percentile-based fuzzy membership functions adjust stress interpretation to individual baselines. The semantic gap between operational stress situations in airport surroundings and raw sensor measurements is lessened by this design.

This evaluation does not aim to rank stress detection methods by accuracy alone, but to analyze their suitability for real-world airport deployment from a design science research perspective. To this end, three complementary comparison tables I, II and III are constructed, each addressing a distinct evaluation dimension: methodological capabilities, deployment constraints, and ethical feasibility. Together, these tables synthesize empirical results, reported performance in the literature, and design-oriented criteria to derive actionable insights for human-centered stress monitoring systems. Design decisions that put operational viability, ethical considerations, and interpretability first close the gap between the suggested framework and actual airport deployment. The framework enables real-time, on-device stress measurement without reliance on cloud infrastructure by utilizing wearable physiological sensors and an embedded fuzzy inference artifact. Context-aware sensor data interpretation is made possible by percentile-based membership functions, and human-readable monitoring that is in line with operational events is made possible by continuous stress outputs. These features guarantee that the framework stays firmly rooted in actual airport conditions rather than theoretical analytical presumptions.

IV. Key Findings

A. Sensor and Hardware-Related Findings

The findings of the benchmarking show that the viability of stress detection techniques in airport settings is significantly influenced by the selection of wearable technology and sensing hardware. High-quality wearable sensors coupled with centralized processing architectures where raw biosignals are sent to servers or cloud platforms for feature extraction and inference are the foundation of the majority of deep learning-based physiological stress detection techniques. This reliance raises latency, energy consumption, and system complexity, especially when scaling to high passenger numbers.

By requiring fixed camera infrastructures, high-resolution video capture, and GPU-enabled processing units, computer vision-based techniques significantly increase hardware requirements, limiting flexibility and increasing maintenance and operating expenses. On the other hand, the

TABLE I: Comparison of state-of-the-art stress detection methods based on results reported in the literature

Model Type	Signals	Dataset	Reported Performance
DNN, KNN [30]	ECG	SRAD	AUC. ≈ 93.8%
CNN + Transformer [7]	ECG	WESAD, SWELL	Acc. ≈ 91.1%
CNN, VGG16 [31]	ECG	SWELL	Acc. ≈ 98.99%
Contrastive SSL [32]	ECG	WESAD	Acc. ≈ 94.09%
Autoencoder (SSL) [33]	ECG	SWELL	Acc. ≈ 98%
CNN, SHALLOW [34]	PPG	WESAD	Acc. ≈ 99.18%
Multimodal CNN [5]	HR, GSR	SRAD	Acc. ≈ 95.67%
LSTM [35]	ECG, GSR	WESAD	Acc. ≈ 88%
CNN [36]	Multi-physiological	WESAD	Acc. ≈ 96.62%
MLP [37]	Multi-physiological	SRAD	Acc. ≈ 98.86%
Ours Fuzzy Inference System	**Multi-physiological**	**Wearable / WESAD / WorkStress3D**	**Interpretable & stable trajectories**

TABLE II: Deployment-Oriented Comparison of Stress Detection Paradigms for Airport Environments

Dimension	DL (Physiological)	DL / CV-Based	Fuzzy Inference (Ours)
Software Paradigm	CNN, LSTM, Transformer	CNN, Attention, Multimodal Fusion	Rule-based fuzzy inference
Primary Sensors	ECG, EDA, PPG	Cameras, Microphones, Video	ECG, EDA, Temp., HRV
Hardware Architecture	Wearables + Server/Cloud	Fixed cameras + GPU servers	Wearables + Embedded MCU
Embedded Deployment	Limited	Not suitable	Arduino, ESP32, Raspberry Pi
On-device Inference	Low	Very Low	High
Data Requirements	High (labeled datasets)	Very High (video/audio labels)	Low (no training required)
Interpretability	Low	Very Low	High (linguistic rules)
Output Type	Discrete classes	Discrete classes	Continuous stress score (0–10)
Robustness to Noise	Medium	Low (lighting, occlusion)	High
Computational Cost	High	Very High	Low
Energy Consumption	High	Very High	Low
Privacy and Ethics	Medium	Low	High
Cross-Dataset Generalization	Limited	Limited	High
Sustainability	Limited	Low	High
Suitability for Airport Deployment	Medium	Low	High

TABLE III: Computer Vision-Based Stress Detection Approaches and Deployment Constraints

Approach	Typical Algorithms	Advantages	Limitations for Airport Deployment
Facial Expression Analysis [11]	CNN, CNN + Attention, Region-based CNN (e.g., Faster R-CNN)	Contactless sensing; rich affective cues; mature DL pipelines	High privacy risk; sensitive to lighting, occlusion, camera placement; requires GPU-based processing
Speech-Based Stress Detection [9]	CNN, RNN, CNN–LSTM, Transformer-based audio models	Captures cognitive and emotional stress; complementary to vision	Background noise; multilingual variability; consent and recording legality; high preprocessing complexity
Body Movement and Posture Analysis [10]	CNN, Spatiotemporal CNN, CNN–RNN	Behavioral stress cues; non-contact monitoring	Occlusion in crowds; viewpoint dependency; large camera infrastructure; limited robustness

suggested fuzzy inference framework works with embedded systems [38] like Arduino, ESP32, or Raspberry Pi-based devices as well as lightweight wearable sensor platforms. On-device stress assessment is made possible by its low computing complexity, which supports real-time operation and lessens need on external processing resources. These results demonstrate that, in contrast to data-intensive deep learning and vision-based architectures [39], wearable sensor-centric [40] and edge-compatible models, including fuzzy inference systems, provide a more workable and scalable hardware solution for continuous stress monitoring in airport environments [41].

B. Ethical and Sustainability Findings

This study emphasizes the significant ethical and sustainable ramifications of various stress detection techniques. In public spaces like airports, computer vision and audio-based techniques constantly record identifiable visual or speech data, creating significant privacy, consent, and legal issues. These surveillance-driven devices are a prime example of criticisms made in humanistic engineering, which contend that improving technology does not always improve human welfare [4]. In contrast, wearable-based fuzzy inference provides privacy-preserving stress monitoring while retaining individual autonomy and is based on physiological signals. While some surveillance threats are mitigated by deep learning models applied to wearable data, these algorithms still rely on large-scale data gathering, centralized processing, and energy-intensive computation, raising concerns about data security and sustainability. Low computational overhead and increased energy efficiency are the outcomes of the suggested fuzzy inference framework's emphasis on immediate, edge-based processing without model training or long-term data storage. Interpretable, wearable-based fuzzy systems are better suited for large-scale, ethical, and sustainable deployment in airport stress monitoring scenarios because of these features.

C. Methodological and Practical Implications

The results of this study have significant methodological and practical ramifications for research on stress detection and its application in intricate public settings like airports. From a methodological standpoint, many deep learning-based stress detection models perform well when trained and assessed on the same dataset; nonetheless, their efficacy is frequently strongly correlated with sensor configurations, labeling tactics, and acquisition protocols unique to each dataset. When applied to diverse, real-world environments, where training and deployment circumstances seldom coincide, this dependence restricts their resilience and generalizability.

From the standpoint of design science research, the findings highlight that deployment-oriented requirements, not just forecast accuracy, should inform modeling decisions. Although deep learning and computer vision techniques show remarkable classification abilities, their suitability for operational stress monitoring in airports is limited by their dependence on large labeled datasets, opaque internal representations, centralized computation, and privacy-sensitive sensing modalities.

The observed agreement between the fuzzy inference approach's continuous stress scores and self-reported stress levels, which shows coherent alignment with subjective stress perception, further supports the methodological robustness of the approach. Practically speaking, its low computational complexity permits real-time deployment on embedded or edge computing systems, and its reliance on wearable physiological inputs permits non-intrusive and privacy-preserving monitoring. The ongoing stress output additionally facilitates the early identification of increasing stress levels and adaptive measures like individualized support, crowd control, or environmental modifications.

V. Conclusion and Future Research

With an emphasis on airport passenger monitoring, this study provided a comparative benchmarking analysis of deep learning and fuzzy inference techniques for stress identification utilizing wearable physiological information. Although deep learning models show excellent predicted accuracy in controlled conditions, their computational complexity, restricted interpretability, and reliance on large labeled datasets make them impractical for use in public situations. On the other hand, the fuzzy inference approach demonstrated transparent decision-making based on physiological knowledge, consistent alignment with self-reported stress levels, and robust and stable stress estimation across varied datasets. These results demonstrate the importance of interpretable, rule-based models for ethical, reliable, and deployable stress monitoring in intricate settings like airports, where privacy, generality, and human-centered design are crucial.

Future work will extend this research along three main directions. (1) A systematic ethical evaluation framework should be developed to assess deep learning, computer vision, and fuzzy inference-based stress detection systems under common criteria such as consent, transparency, data minimization, and fairness, enabling principled comparison beyond predictive performance.

(2) Large-scale and longitudinal data collection in operational airport environments is needed to capture diverse passenger profiles, cultural factors, and temporal stress dynamics, and to further refine fuzzy membership functions and rule bases.

(3) Hybrid modeling approaches that combine fuzzy inference with data-driven adaptation mechanisms represent a promising avenue for enhancing flexibility while preserving interpretability, alongside the integration of privacy-preserving contextual information such as crowd density or flight disruptions.

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