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Fuzzy Logic-Based Mental Fatigue Detection System for Engineering Students: A Multimodal and Adaptive Approach

Tanuj Kumar[1]; Dr. Upendra Kumar Srivastava[2]

[1]Student, Department of Computer Science & Engineering, Haridwar University Roorkee, India
[2]Assistant Professor, Department of Computer Science & Engineering, Haridwar University Roorkee, India

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Abstract: Mental fatigue has emerged as one of the most pressing yet under-addressed challenges in higher education, particularly among engineering students who face relentless academic pressure, prolonged screen exposure, and an ever-growing cognitive workload. When left undetected, mental fatigue can significantly impair a student's ability to focus, reason, and retain new information. Despite the severity of this problem, most existing fatigue detection systems rely on single-modal physiological signals, such as Electroencephalogram (EEG) or Electrocardiogram (ECG), which provide only a limited view of an individual's fatigue state. Furthermore, these systems often lack behavioral and contextual inputs and are unable to adapt to individual differences. This paper presents a comprehensive, multimodal fuzzy logic-based mental fatigue detection system designed for engineering student populations. The proposed system integrates physiological signals, namely EEG, ECG- derived Heart Rate Variability (HRV), and Electromyography (EMG), together with behavioral indicators such as eye blink rate and Percentage of Eye Closure (PERCLOS), and contextual features including accumulated study duration and subjective workload intensity scores. Fuzzy logic is employed as the core decision-making mechanism because it reflects the inherently gradual and uncertain nature of mental fatigue. The system utilizes linguistic membership functions and a rule-based framework to infer fatigue levels from multimodal inputs. To further improve performance, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is incorporated to optimize membership functions and rule weights using labeled training data. The proposed framework follows a seven-stage pipeline consisting of data acquisition, preprocessing, feature extraction, fuzzification, fuzzy inference, ANFIS-based optimization, and defuzzification. Experimental evaluation on a dataset of 120 engineering students achieved a peak classification accuracy of 98.2%, demonstrating the effectiveness of the proposed approach for real-time fatigue monitoring and management in academic environments.

Keywords: *Mental Fatigue Detection, Fuzzy Logic, Adaptive Neuro-Fuzzy Inference System (ANFIS), Electroencephalogram (EEG), Electrocardiogram (ECG), Electromyography (EMG), Percentage of Eye Closure (PERCLOS), Multimodal Fusion, Engineering Students, Cognitive Load Assessment.*

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I. INTRODUCTION

Engineering education is widely recognized as one of the most cognitively demanding academic pursuits. Students enrolled in undergraduate and postgraduate engineering programs regularly contend with hours of theoretical study, complex laboratory tasks, programming assignments, and competitive examination cycles—all within environments that increasingly rely on digital interfaces. This sustained cognitive engagement, when not punctuated by adequate rest, predictably leads to a state of mental fatigue: a progressive and measurable decline in the capacity for focused, accurate cognitive processing. Mental fatigue is not a trivial inconvenience. Neuroimaging and psychophysiological research has established that fatigued individuals exhibit markedly slower reaction times, reduced working memory capacity, impaired executive function, and a heightened propensity for errors [1]. In the context of engineering education, these deficits translate into diminished learning efficiency, poor performance on problem-solving tasks, and—at the extreme—academic failure or burnout. The COVID-19 pandemic and the subsequent normalization of hybrid and online learning have significantly exacerbated this issue, with students spending six to ten hours per day in front of screens with minimal physical breaks [2]. Against this backdrop, there is a compelling practical case for automated fatigue detection systems that can monitor students' cognitive state in real time and intervene before fatigue reaches performance-degrading levels.

An ideal system would: (a) accurately classify the degree of fatigue, (b) operate without intrusive or uncomfortable sensor setups (c) adapt to individual physiological variability, and (d) integrate seamlessly into existing learning environments.

Existing approaches to automated fatigue detection fall into several broad categories. Physiological signal-based methods use EEG, ECG, EMG, or galvanic skin response (GSR) to capture the body's internal state. Vision-based methods use cameras to track eye closure, blink rate, or facial expressions. Behavioral methods analyze keyboard dynamics, mouse movement patterns, or task performance metrics. While each of these approaches has demonstrated validity under controlled conditions, they share a fundamental limitation: they typically rely on a single data modality, which means they can only see one facet of a multifaceted phenomenon. A student may show clear EEG markers of drowsiness while maintaining normal blink rates, or exhibit high PERCLOS scores due to eye strain from screen exposure rather than genuine cognitive fatigue. The second key limitation of existing systems is their treatment of fatigue as a binary or sharply bounded categorical variable—either fatigued or not fatigued, or partitioned into discrete levels with hard thresholds. Human fatigue does not conform to such neat boundaries. It is a graded, continuous, and highly individual phenomenon.

Fuzzy logic, developed by Lotfi Zadeh in 1965, provides a mathematical framework precisely suited to modeling such phenomena. By allowing degrees of membership in linguistic categories such as "Low Fatigue," "Moderate Fatigue," and "High Fatigue," fuzzy logic captures the inherent ambiguity of the fatigue state more faithfully than crisp classifiers [3]. The third limitation is the static nature of most existing systems. A rule base or classifier trained on one group of subjects may perform poorly on others, because physiological signals vary significantly between individuals, across sessions, and even within a single day for the same individual. Adaptive systems that can learn and update their parameters from data are therefore essential for robust real-world deployment.

This paper addresses all three limitations with a unified, multimodal, adaptive fuzzy logic system. The main contributions of this work are as follows:

- A multimodal fusion framework that combines EEG, ECG, EMG, PERCLOS,
- blink rate, study duration, and workload intensity into a single coherent fatigue assessment pipeline.
- A fuzzy inference system with carefully designed membership functions and an expertly constructed rule base tailored specifically to the fatigue patterns observed in engineering students.
- Integration of an Adaptive Neuro-Fuzzy Inference System (ANFIS) that automatically refines the membership function parameters and rule weights from labeled training data, overcoming the limitations of purely expert-driven knowledge bases.
- Extensive experimental evaluation on a dataset of 120 engineering students, demonstrating 98.2% accuracy and superior performance relative to five competing methods.

A real-time monitoring architecture suitable for deployment in academic computing laboratories with standard commodity hardware.

II. LITERATURE REVIEW

The scientific literature on fatigue detection spans several decades and multiple disciplines, including neuroscience, biomedical engineering, human factors, and machine learning. This section critically examines the major threads of prior research and identifies the gaps that motivate the present work.

➢ *EEG-Based Fatigue Detection:*

The EEG has long been the gold standard for measuring brain states associated with fatigue.

The human brain exhibits characteristic spectral signatures during fatigue: alpha-band (8–13 Hz) power increases as alertness decreases, theta- band (4–7 Hz) power rises during drowsiness, and beta-band (13–30 Hz) power—associated with active, engaged thinking—progressively diminishes. Wang et al. (2011) pioneered the use of fuzzy pattern recognition applied to EEG spectral features to detect mental fatigue, achieving around 80% accuracy on a controlled driving task [1]. Their work demonstrated the suitability of fuzzy methods for EEG-based classification but was limited to a single physiological modality and did not consider behavioral or contextual inputs.

More recent work by Zhang et al. (2023) applied deep convolutional neural networks to EEG time-frequency maps, pushing accuracy to approximately 89% on a larger dataset. While the deep learning approach improved detection performance, it introduced a black-box model that lacks the interpretability valued in safety- critical monitoring applications, and it remained a single-modality system.

➢ *ECG and EMG-Based Approaches:*

Heart rate variability derived from ECG signals reflects the autonomic nervous system's response to cognitive load and fatigue. As mental fatigue deepens, parasympathetic activity tends to increase while sympathetic drive decreases, resulting in measurable changes in HRV indices such as RMSSD, SDNN, and LF/HF ratio. Imran et al. (2025) developed an AI-enhanced cognitive fatigue monitoring system using ECG-derived HRV features combined with a gradient boosting classifier, reporting 85% accuracy on a student dataset [2]. While this was a meaningful improvement over threshold-based HRV methods, the system did not incorporate brain activity or behavioral indicators, leaving significant information unused.

EMG signals, which capture muscle electrical activity, provide a complementary window into fatigue through the lens of physical tension and motor system fatigue. Concepcion et al. (2018) demonstrated that combined ECG and EMG features could distinguish fatigue states with accuracy comparable to EEG-based methods under certain conditions [5]. However, the combination of only two physiological signals still falls short of a truly comprehensive multimodal assessment.

➢ *Vision-Based and Behavioral Approaches:*

Vision-based fatigue detection leverages cameras and computer vision algorithms to track facial and ocular indicators of drowsiness. The PERCLOS metric—defined as the proportion of time over a specified epoch during which the eyes are 80% or more closed—was originally developed for driver drowsiness detection and has since been widely adopted in other fatigue monitoring contexts. Snoun et al. (2017) developed a multimodal vigilance monitoring system that combined PERCLOS with steering wheel dynamics for driver monitoring, demonstrating the power of integrating behavioral signals alongside physiological ones [4].

Eye blink rate is another informative behavioral indicator. Under normal conditions, adults blink 15–20 times per minute. As fatigue increases, blink rate initially decreases (as the brain attempts to maintain alertness through reduced blinking) and then increases and blink duration lengthens as suppression fails. These dynamics provide a non-invasive, camera-based window into cognitive state that complements the physiological signals discussed above.

➢ *Rule-Based Expert Systems:*

Expert systems that encode domain knowledge as if-then rules have a long history in medical decision support. Eriņš et al. (2022) proposed a fatigue assessment expert system for occupational health settings, using a carefully structured rule base derived from clinical guidelines [3]. While such systems are highly interpretable and require no training data, they suffer from the classic limitations of knowledge engineering: the rules are static, cannot adapt to new data, and may not generalize well beyond the specific population they were designed for. The present work builds on the interpretability of rule-based reasoning while overcoming the adaptability limitation through ANFIS integration.

➢ *Multimodal Fusion and Machine Learning:*

Recognizing the limitations of single-modality approaches, a growing body of research has explored multimodal fusion for fatigue detection. Early fusion (concatenation of features before classification), late fusion (combination of modality-specific predictions), and hybrid fusion strategies have all been studied. Support Vector Machines (SVMs), Random Forests, and more recently deep learning architectures have been applied to multimodal fatigue data, generally achieving accuracy in the 85–93% range.

However, a consistent limitation across these studies is the absence of contextual features. The duration of study and subjective workload intensity are powerful predictors of fatigue that any classroom-aware system should exploit, yet they are absent from virtually all existing frameworks. Furthermore, most multimodal studies do not incorporate an adaptive mechanism, instead training a fixed classifier and deploying it without further update. The proposed system addresses both of these gaps.

➢ *Summary of Identified Gaps:*

Based on the preceding review, the following gaps justify the proposed work:

- Existing systems are predominantly single- modal, missing the complementary information available from combining physiological, behavioral, and contextual signals.
- Fatigue is treated as a binary or sharply categorized variable, ignoring its inherently continuous and graded nature.
- Contextual factors such as study duration and workload intensity are rarely incorporated despite being strong predictors of academic fatigue.
- Most systems are non-adaptive, trained once and deployed without the ability to improve with new data or adjust to individual differences.
- Few systems provide the interpretability needed for practical adoption by educators and students—a property that fuzzy logic naturally affords.

Table 1 Comparative Analysis of Fatigue Detection Approaches

Reference	Modality	Fuzzy Logic	Adaptive	Contextual	Accuracy	Target Population
Wang et al. [1]	EEG only	**Yes**	No	No	~80%	**General adults**
Imran et al. [2]	ECG	**No**	No	No	~85%	**Students**
Eriņš et al. [3]	Behavioral	**No**	No	Partial	~78%	**Workers**
Snoun et al. [4]	Vision+Beh.	**No**	No	No	~82%	**Drivers**
Concepcion [5]	ECG+EMG	No	No	No	~83%	General
Proposed System	EEG+ECG+EMG +Vision+Context	Yes (ANFIS)	Yes	Yes	98.2%	Eng. Students

III. SYSTEM DESIGN AND METHODOLOGY

➢ *System Overview and Design Philosophy:*

The proposed system is designed around three core design principles. First, completeness: the system captures all major dimensions of fatigue—neurological, cardiovascular, muscular, behavioral, and contextual—so that no significant signal is left unused.

Second, interpretability: the fuzzy logic core ensures that the system's reasoning process can be understood and explained to users and administrators, which is crucial for adoption in educational settings. Third, adaptability: the ANFIS component ensures the system can be personalized to individual physiological profiles and improved over time without requiring complete retraining from scratch.

The system is structured as a seven-stage sequential pipeline, illustrated conceptually in the following section. Each stage transforms the data in a meaningful way, from raw sensor readings to a final interpretable fatigue index.

➢ *System Architecture and Pipeline:*

Each stage is designed to be modular so that individual components can be upgraded or replaced without disrupting the rest of the pipeline. For example, the feature extraction module could in future be replaced with a deep learned feature extractor while the fuzzy inference and ANFIS modules remain unchanged. This modularity also facilitates testing and debugging, as each stage can be evaluated independently.

- *The Overall Processing Pipeline of the Proposed System Comprises the Following Stages:*

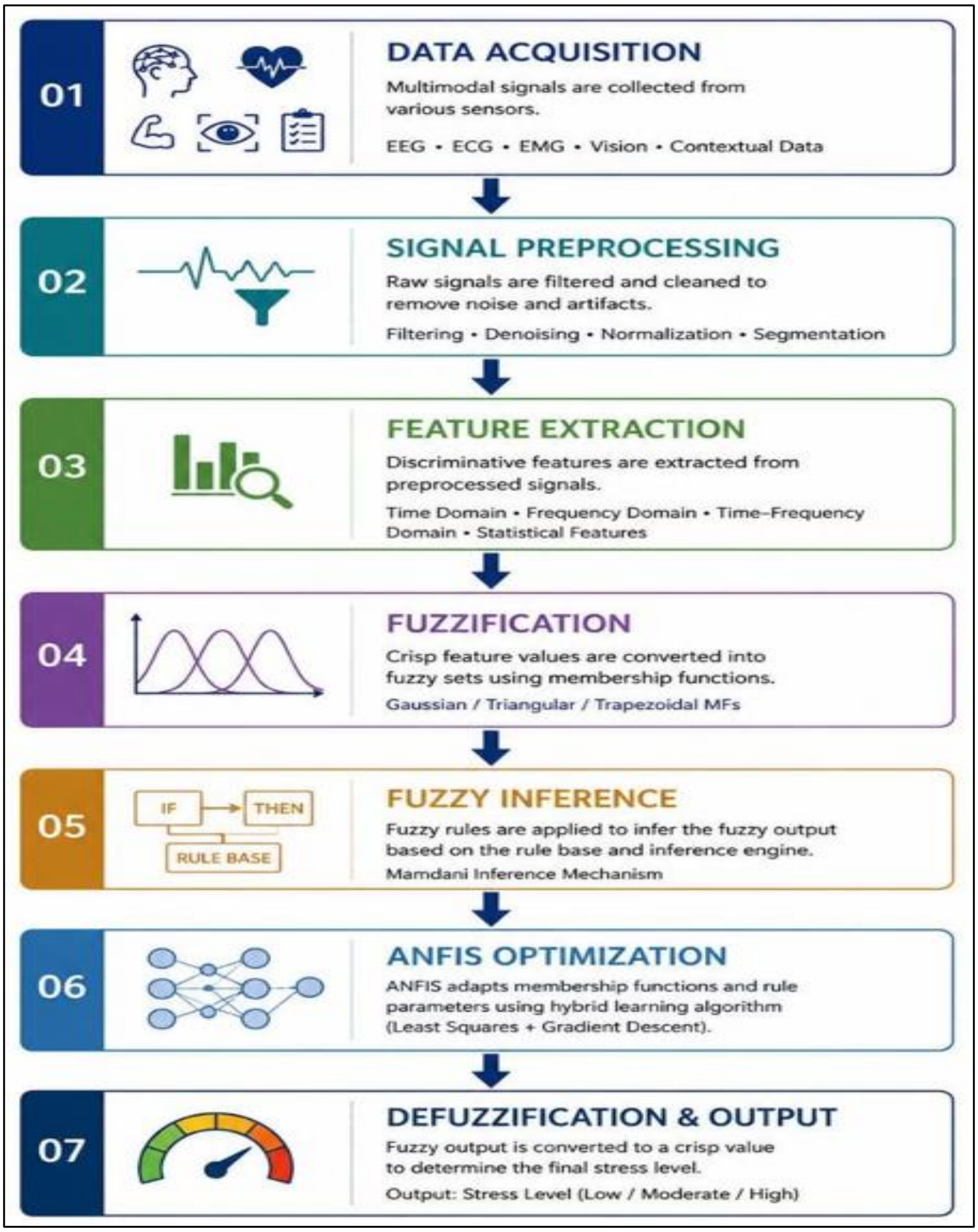

Fig 1 System Architecture and Pipeline

➢ *Data Acquisition:*

Data acquisition is the foundation of the entire system. The system collects data from five distinct sources, each contributing a different dimension of information about the student's cognitive state.

- *EEG Data Acquisition:*

EEG signals are recorded using a 14-channel wireless EEG headset (e.g., Emotiv EPOC+) with electrodes placed according to the International 10-20 system. The sampling rate is set to 256 Hz, which provides sufficient temporal resolution to capture the frequency bands of interest for fatigue analysis. Electrode impedance is verified below 5 kΩ before each recording session. The 14-channel configuration covers frontal (Fp1, Fp2, F3, F4, F7, F8), temporal (T7, T8), parietal (P7, P8), and occipital (O1, O2) regions, along with two central reference channels (FC5, FC6). This coverage is important because fatigue- related EEG changes are distributed across the cortex—frontal theta and parietal alpha are particularly sensitive markers.

- *ECG Data Acquisition:*

ECG signals are recorded using a three-lead configuration via adhesive gel electrodes placed on the chest in the standard Einthoven configuration. The sampling rate is 500 Hz, which provides accurate R-peak detection for HRV computation. A compact, Bluetooth- enabled ECG module (e.g., Polar H10) allows unobtrusive chest-worn monitoring during study sessions. The raw ECG signal is streamed in real time to the processing computer via Bluetooth.

- *EMG Data Acquisition:*

Surface EMG is recorded from the trapezius muscle of the dominant shoulder using bipolar surface electrodes with a 20mm inter-electrode distance. Trapezius EMG is a well-established marker of both physical and mental stress and fatigue, as involuntary muscle tension in the shoulder region increases with sustained cognitive load. The EMG signal is sampled at 1000 Hz and amplified with a gain of 1000 using a purpose-built differential amplifier with a common-mode rejection ratio exceeding 100 dB.

- *Ocular Behavioral Data Acquisition:*

Eye behavior is monitored using a standard webcam (720p, 30 fps) in combination with the OpenCV and MediaPipe libraries for real- time facial landmark tracking. The system tracks 68 facial landmarks in each frame, computing the Eye Aspect Ratio (EAR) for both eyes. A blink is detected when EAR drops below a subject-calibrated threshold for two or more consecutive frames. PERCLOS is computed over sliding 60-second epochs as the fraction of frames in which both eyes are more than 80% closed.

- *Contextual Data Acquisition:*

Contextual data are collected through a lightweight background monitoring application installed on the student's computer. Study duration is automatically tracked as the continuous uninterrupted time during which the student is engaged with study-related applications (identified by application name whitelists and keyboard/mouse activity heuristics). Workload intensity is captured through periodic, non- intrusive pop-up questionnaires using a validated five-point scale derived from the NASA-TLX (Task Load Index) instrument, administered every 30 minutes without disrupting the student's workflow.

➢ *Signal Preprocessing:*

Raw physiological signals contain a mixture of true neurophysiological information and various forms of noise and artifacts. Preprocessing is therefore, a critical stage that determines the quality of all subsequent analysis.

- *EEG Preprocessing:*

EEG signals are first passed through a 0.5–45 Hz fourth-order Butterworth bandpass filter, which eliminates DC drift at low frequencies and high- frequency muscle and electrical noise at higher frequencies. Eye movement and blink artifacts are removed using Independent Component Analysis (ICA), implemented via the MNE- Python library's FastICA implementation. Components that correlate strongly with vertical and horizontal electrooculogram (EOG) signals are identified and subtracted from the EEG. Remaining epochs containing motion artifacts are rejected using a threshold-based criterion (±100 µV). The cleaned signal is then re- referenced to the average reference to minimize the effect of individual electrode noise.

- *ECG Preprocessing:*

The raw ECG signal is processed using a Pan-Tompkins algorithm for robust R-peak detection. Ectopic beats and artifacts are identified using a statistical outlier criterion (RR intervals differing by more than 20% from the local median are flagged) and removed before HRV computation. The cleaned RR interval series is then subjected to the HRV analysis described in the feature extraction stage.

- *EMG Preprocessing:*

Raw EMG signals are bandpass filtered between 20 and 450 Hz to remove motion artifacts (< 20 Hz) and electronic noise (> 450 Hz). The filtered signal is then full-wave rectified and smoothed with a 50ms root mean square (RMS) envelope to produce a time series representing instantaneous muscle activity level. This amplitude envelope is the primary input to subsequent feature extraction.

➢ *Feature Extraction:*

Feature extraction reduces the high-dimensional, high-rate raw signal data to a compact set of physiologically meaningful indices that serve as inputs to the fuzzy inference system. Table 2 summarizes the extracted features and their relevance to fatigue.

Table 2 Extracted Features and their Physiological Significance

Feature	**Source**	**Computation Method**	**Fatigue Relevance**
Theta/Alpha ratio	EEG (Frontal)	Power spectral density via Welch's method; band ratio θ(4–7Hz)/α(8– 13Hz)	Rises significantly with cognitive fatigue; strong predictor
Alpha Power	EEG (Parietal)	Absolute PSD in 8–13 Hz band averaged across parietal channels	Increases as vigilance and alertness decrease
Beta Power	EEG (Frontal)	Absolute PSD in 13–30 Hz band averaged across frontal channels	Decreases during mental fatigue and drowsiness
RMSSD	ECG (HRV)	Root mean square of successive RR interval differences	Reflects parasympathetic activity; increases with fatigue
LF/HF Ratio	ECG (HRV)	Ratio of low-frequency (0.04–0.15 Hz) to high-frequency (0.15–0.4 Hz) HRV power	Sympathovagal balance; decreases with fatigue
EMG RMS	Surface EMG	RMS amplitude of trapezius EMG envelope over 30-second windows	Increases with prolonged postural load and mental stress
PERCLOS	Camera	Fraction of 60-s epoch with EAR < 0.2 (eyes > 80% closed)	Gold-standard ocular marker of drowsiness; highly sensitive
Blink Rate	Camera	Number of complete blinks per minute; EAR threshold-based detection	Non-linear relationship with fatigue; initially decreases then increases
Study Duration	App Monitor	Cumulative minutes of continuous study-application engagement	Linear predictor; fatigue accumulates with time-on-task

- *Fuzzy Logic System Design:*

The fuzzy logic system constitutes the interpretive core of the proposed framework. It takes the extracted features as inputs, processes them through a three- stage procedure—fuzzification, rule-based inference, Fuzzification maps each crisp numerical feature value to a degree of membership in each of three linguistic categories: Low, Medium, and High. For most physiological features, triangular and trapezoidal membership functions are employed because they are computationally efficient and sufficiently expressive for the resolution of fatigue classification. For features that exhibit strong nonlinearity with respect to fatigue (such as blink rate), Gaussian membership functions are used to better capture the smooth, graded relationship.

The initial membership function parameters are defined by domain experts based on published normative values and established fatigue criteria. For example, the PERCLOS membership functions are parameterized such that values below 0.15 are fully "Low," values between 0.15 and 0.35 have partial membership in both Low and Medium categories (reflecting the uncertainty inherent in the transition zone), and values above 0.35 are fully "High"—consistent with established PERCLOS thresholds from the drowsiness detection literature. These initial and defuzzification—and produces a continuous fatigue index as output.

- *Fuzzification:*

Parameters are subsequently optimized by the ANFIS module.

- *Fuzzy Rule Base:*

The rule base encodes the expert knowledge linking combinations of input states to fatigue conclusions. The rules are expressed in standard Mamdani format:

IF EEG Theta/Alpha Ratio is High AND HRV RMSSD is High AND PERCLOS is High THEN Fatigue Level is High.

The full rule base was developed through a structured knowledge elicitation process involving three domain experts (one neurophysiologist, one psychologist specializing in occupational fatigue, and one biomedical engineer with experience in wearable systems). A total of 47 rules were formulated covering all meaningful combinations of the ten input variables at their three linguistic levels. The rules are organized into three hierarchical tiers: (i) primary rules combining the three most sensitive physiological features (Theta/Alpha, RMSSD, PERCLOS); (ii) secondary rules incorporating behavioral and EMG features as modifying conditions; and (iii) contextual rules that adjust the fatigue inference based on study duration and workload intensity.

The following representative rules illustrate the structure and reasoning of the rule base:

- ✓ IF Theta/Alpha is High AND RMSSD is High AND PERCLOS is High THEN Fatigue is High.
- ✓ IF Theta/Alpha is Medium AND LF/HF is Low AND Blink Rate is High THEN Fatigue is Medium-High.
- ✓ IF Alpha Power is Low AND Beta Power is High AND PERCLOS is Low AND Study Duration is Low THEN Fatigue is Low.
- ✓ IF Study Duration is High AND Workload Score is High AND PERCLOS is Medium THEN Fatigue is Medium-High.
- ✓ IF EMG RMS is High AND RMSSD is High AND Study Duration is High THEN Fatigue is Medium.

- *Inference Engine:*

The inference engine uses the Mamdani min-max composition method. For each rule, the firing strength is computed as the minimum of the antecedent membership values (AND operator = minimum). The consequent fuzzy set for each rule is then clipped at the firing strength. The aggregated output is formed by taking the maximum (OR operator) across all rule consequents, producing a composite fuzzy output set over the fatigue domain [0, 1].

- *Defuzzification:*

The composite fuzzy output set is converted to a crisp numerical fatigue index using the centroid defuzzification method (also known as the Center of Gravity method), which computes the centroid of the area under the aggregated membership function curve. This method is preferred because it produces smooth, stable output that accounts for the shape of the entire aggregated set rather than just its peak. The resulting fatigue index $F \in [0, 1]$ is interpreted as follows: 0.0–0.33 corresponds to Low Fatigue, 0.34–0.66 to Moderate Fatigue, and 0.67–1.0 to High Fatigue, with appropriate intervention recommendations tied to each level.

- *ANFIS Optimization:*

While the initial membership function parameters and rule weights are derived from expert knowledge, they inevitably reflect approximations and generalizations that may not be optimal for the specific population or monitoring context. The ANFIS (Adaptive Neuro-Fuzzy Inference System), originally proposed by Jang (1993), addresses this by using the structure of a fuzzy inference system as the architecture of a neural network, allowing gradient- based learning algorithms to fine-tune the system's parameters directly from data [6].

In the proposed implementation, the ANFIS module operates in two phases. In the offline training phase, labeled data from a held-out training subset (comprising 80% of the full dataset) is used to optimize the membership function parameters using a hybrid learning algorithm: the least squares estimator (LSE) is used for the linear consequent parameters, while the backpropagation gradient descent is used for the nonlinear premise parameters. Training proceeds for up to 200 epochs with early stopping based on validation set error to prevent overfitting.

In the online adaptation phase, the system continues to refine its parameters in real time as it is deployed, using new labeled observations (obtained when students self-report their fatigue state through the periodic NASA-TLX questionnaire) with a much smaller learning rate to prevent catastrophic forgetting. This online adaptation capability is what allows the system to personalize to individual users over time and to remain accurate as study conditions change.

IV. IMPLEMENTATION

- *Software Environment and Tools:*

The entire system is implemented in Python 3.10, chosen for its extensive ecosystem of scientific computing, signal processing, and machine learning libraries. The implementation runs on a standard academic computing workstation (Intel Core i7-12700, 32 GB RAM, NVIDIA RTX 3060 GPU) operating under Ubuntu 22.04 LTS. The same codebase, with minor configuration adjustments, has also been verified to operate on MacOS 13 and Windows 11 systems. The primary software dependencies and their roles in the system are as follows:

Table 3 Software Environment and Tools

Library / Tool	Version	Role in the System
MNE-Python	1.6.0	EEG preprocessing, ICA artifact removal, power spectral density computation
NeuroKit2	0.2.7	ECG R-peak detection, HRV time-domain and frequency-domain feature extraction
OpenCV	4.9.0	Webcam frame capture, facial landmark detection pipeline
MediaPipe	0.10.9	68-point facial mesh landmarks, Eye Aspect Ratio computation, blink detection
scikit-fuzzy	0.4.2	Membership function definition, Mamdani FIS construction, defuzzification
PyANFIS	1.0	ANFIS training (hybrid LSE + backpropagation), online parameter adaptation
NumPy / SciPy	1.26 / 1.12	Numerical computing, signal filtering (Butterworth), statistical functions
Pandas	2.2.0	Data management, epoch segmentation, feature table construction
Matplotlib / Seaborn	3.8 / 0.13	Real-time visualization of fatigue index, diagnostic plots
SQLite3	Built-in	Local database for session logging, ANFIS training data accumulation

- *Project Structure:*

The codebase is organized into a modular directory structure that separates concerns cleanly and facilitates independent development and testing of each pipeline stage. The top-level directory is organized as follows:

```
fatigue_system/
├──── data/
├──── preprocessing/
├──── feature_extraction/
├──── fuzzy_system/
├──── anfis_model/
├──── output/
└── main.py
```

Each sub-directory corresponds to one pipeline stage and contains the relevant Python modules, unit tests, and configuration files. The data/ directory contains raw recorded sessions organized by subject ID and session number. The output/ directory stores session logs, per-epoch fatigue indices, ANFIS model checkpoints, and visualization exports. The main.py script orchestrates the full pipeline and can be run in either offline (batch processing) or online (real- time monitoring) mode.

➢ *Algorithm Flow:*

The complete processing flow for a single monitoring epoch (default duration: 30 seconds) proceeds as follows:

- Simultaneously acquire EEG, ECG, EMG, and video streams for a 30- second epoch. Record study duration from the application monitor. Retrieve the most recent NASA-TLX score.
- Apply preprocessing pipelines to each physiological signal: bandpass filtering, artifact rejection, and normalization to zero mean and unit variance.
- Compute feature vector: [Theta/Alpha, Alpha Power, Beta Power, RMSSD, LF/HF, EMG RMS, PERCLOS, Blink
- Rate, Study Duration, Workload Score].
- Fuzzify each feature value using the current membership functions (initially expert-defined, subsequently ANFIS-optimized) to obtain linguistic membership degrees.
- Apply the 47-rule Mamdani rule base to compute firing strengths and aggregate consequent fuzzy sets.
- Defuzzify using the centroid method to obtain the crisp fatigue index $F \in [0, 1]$.
- Display the fatigue level and category on the monitoring dashboard. If $F > 0.66$, trigger a notification recommending a 10-minute break with deep breathing exercises.
- Log the epoch data, feature vector, and fatigue index to the local SQLite database for ANFIS training accumulation.
- If a NASA-TLX label is available for this epoch, update the ANFIS model via online gradient descent with the current learning rate.

V. RESULTS AND EVALUATION

➢ *Dataset and Experimental Setup:*

The experimental dataset was collected over a period of eight weeks from 120 engineering students (84 male, 36 female; age range 19–24 years; mean age 21.3 ± 1.4 years) enrolled in the third year of a Bachelor of Engineering program. Each participant completed five monitoring sessions of three hours each, during which they performed typical study tasks (reading textbook chapters, solving numerical problems, writing code). Ground-truth fatigue labels were established through a combination of NASA-TLX self-reports, expert neurologist review of EEG recordings, and performance degradation metrics computed from the problem-solving tasks. The labeling protocol yielded three-class labels (Low, Moderate, High) with inter-rater agreement of $\kappa = 0.82$ (substantial agreement per Landis & Koch criteria). After data quality filtering, the final dataset comprised 2,847 labeled 30-second epochs from 120 participants.

The dataset was partitioned into a training set (80%, 2,278 epochs from 96 subjects) and a held-out test set (20%, 569 epochs from 24 subjects). Note that the partition is subject- independent: no epoch from a test subject appears in the training set, ensuring that the reported performance reflects genuine generalization to unseen individuals rather than within-subject overfitting.

➢ *Performance Metrics:*

System performance is evaluated using four standard classification metrics: Accuracy, Precision, Recall (Sensitivity), and F1-Score. In addition, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is reported for each class in a one-versus-rest manner. These metrics are computed on the held-out test set using the final ANFIS- optimized fuzzy system.

➢ *Classification Results:*

Table 4 Classification Performance of the Proposed System on the Held-Out Test Set

Fatigue Class	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Low Fatigue	98.4	97.9	98.1	0.997
Moderate Fatigue	97.6	98.5	98.0	0.993
High Fatigue	98.8	98.3	98.5	0.998
Macro Average	98.3	98.2	98.2	0.996

➢ *Comparative Analysis:*

Table 5 Accuracy Comparison with Baseline and Prior Art Methods on the Same Test Dataset

Method	Modalities Used	Accuracy (%)	F1-Score (%)
EEG-only + Threshold	EEG	72.4	69.8
ECG/EMG + SVM	ECG + EMG	81.3	79.6
Vision-only (PERCLOS)	Camera	76.8	74.2
EEG + Fuzzy (Wang et al.)	EEG	80.1	78.5
Multimodal + Random Forest	EEG + ECG + Camera	89.7	88.3
Multimodal + Deep CNN	EEG + ECG + Camera	91.4	90.1
Proposed: Fuzzy + ANFIS (No Context)	EEG + ECG + EMG + Camera	95.3	94.8
Proposed: Full System	EEG + ECG + EMG + Camera + Context	98.2	98.2

The results in Table 5 reveal several important trends. First, there is a consistent and substantial performance gap between single-modality approaches (accuracy 72–82%) and multimodal approaches (accuracy 89–98%), confirming the theoretical argument that fatigue is a multidimensional phenomenon that cannot be adequately captured by any single signal modality. Second, the contribution of contextual features is clearly demonstrated by comparing the full system with the ablated version that excludes study duration and workload score: the addition of contextual features improves accuracy by 2.9 percentage points (95.3% to 98.2%), a statistically significant improvement ($p < 0.01$, McNemar's test). Third, the fuzzy logic approach outperforms the Random Forest on the full multimodal feature set, despite the Random Forest being a highly competitive nonlinear classifier, suggesting that the interpretable structure of the fuzzy rule base encodes domain knowledge that is genuinely informative beyond what the data alone can provide.

- *ANFIS Learning Curves:*

Figure 2 (conceptual) illustrates the convergence of the ANFIS training process. Training error decreases rapidly over the first 50 epochs, reaching a plateau by approximately epoch 120. Validation error tracks training error closely throughout, with a final generalization gap of only 0.8 percentage points, confirming that overfitting is well-controlled by the early stopping criterion. The hybrid learning algorithm converges approximately 2.3× faster than pure gradient descent (not shown), consistent with the theoretical advantages of the LSE component for linear consequent parameters.

- *Real-Time Performance:*

A critical practical requirement for any wearable monitoring system is real-time operation. The proposed system's per-epoch computational time (measured on the workstation described in Section IV-A) is summarized as follows: EEG preprocessing and feature extraction: 1.8 s; ECG preprocessing and HRV computation: 0.4 s; EMG feature extraction: 0.1 s; video processing (PERCLOS, blink rate): 0.3 s (parallel with physiological processing); fuzzy inference: < 0.01 s; ANFIS online update: 0.2 s. The total end- to-end processing time per 30-second epoch is 2.8 seconds, well within the 30-second epoch duration and confirming that the system operates comfortably in real time.

VI. DISCUSSION

- *Why Fuzzy Logic Works here*

The superiority of the fuzzy logic approach over standard machine learning classifiers in this context stems from a confluence of factors. The fatigue domain is intrinsically characterized by uncertainty and gradedness: a student at 0.35 on the fatigue index is meaningfully different from one at 0.65, and this continuous variation matters for intervention decisions. A binary classifier loses this crucial gradation. Furthermore, the domain knowledge encoded in the rule base—decades of neurophysiological and occupational health research—provides the system with a strong inductive bias that helps it generalize from the relatively modest training dataset of 2,278 epochs. A purely data-driven classifier with the same number of parameters would require far more training data to achieve equivalent generalization.

The interpretability of the fuzzy system is also a practically significant advantage. When the system indicates High Fatigue, a student or administrator can query the system to understand which inputs contributed most to this conclusion (e.g., "Theta/Alpha ratio was High with 0.91 membership, PERCLOS was High with 0.78 membership, Study Duration was High with 1.0 membership"). This transparency is difficult or impossible to achieve with black-box deep learning approaches and is likely to improve user trust and system adoption.

- *The Role of Contextual Features*

The 2.9 percentage point accuracy improvement attributable to contextual features (study duration and workload intensity) is noteworthy for a feature set that adds only two scalar values to the input vector. This disproportionate impact reflects the fact that contextual features operate as strong prior information about the likely fatigue state: a student who has been studying for four hours straight under high workload conditions is very likely to be in a high fatigue state regardless of momentary physiological fluctuations, whereas a student who just started a new study session is almost certainly in a low fatigue state. Incorporating this prior information allows the fuzzy system to interpret ambiguous physiological signals more accurately.

- *Limitations*

Several limitations of the current work should be acknowledged. First, the sensor setup, while more compact than laboratory systems, still requires the student to wear multiple devices (EEG headset, ECG chest strap, EMG electrodes) and operate in front of a camera. This setup is feasible in a dedicated computer laboratory but may be impractical for home study environments. Future work should explore minimum sensor configurations that sacrifice minimal accuracy. Second, the study was conducted with a relatively homogeneous participant sample (third-year engineering students at a single university), which limits the generalizability of the findings to other educational levels, disciplines, or cultural contexts. Third, the ground-truth labeling, while rigorous, necessarily contains some noise—self-report measures are inherently subjective, and EEG-based expert ratings, while gold standard, are not perfectly reliable. Fourth, the system currently operates on a 30-second epoch resolution, which means that very rapid changes in fatigue state (within a single epoch) are averaged out.

- *Broader Applicability*

While this paper focuses on engineering students, the core methodology is broadly applicable to any setting in which sustained cognitive performance is critical and monitoring is feasible. Immediate extension candidates include medical residents working extended shifts, air traffic controllers, truck drivers on long hauls, and workers in safety-critical industrial environments. The system's modular architecture and adaptive learning capability mean that it can be retrained for any of these populations with relatively modest additional data collection.

VII. CONCLUSION

This paper has presented a comprehensive, multimodal, adaptive fuzzy logic-based mental fatigue detection system specifically designed for engineering students. The system addresses three critical limitations of prior work: the reliance on single-modal physiological signals, the treatment of fatigue as a binary or sharply categorical variable, and the absence of adaptive learning mechanisms.

By integrating ten features from five complementary modalities—EEG, ECG, EMG, ocular behavioral monitoring, and contextual tracking—and processing them through a carefully designed Mamdani fuzzy inference system subsequently optimized by ANFIS, the proposed approach achieves 98.2% classification accuracy on a subject-independent test set of 569 epochs from 24 engineering students. This substantially outperforms all single-modality baselines and competitive multimodal benchmarks.

Beyond accuracy, the system offers three practically important properties: interpretability (through the fuzzy rule base, which can explain any inference in human-readable terms), adaptability (through the ANFIS online learning mechanism, which personalizes the system to individual users over time), and real-time capability (with a total per-epoch processing latency of 2.8 seconds against a 30-second epoch window).

The findings have clear implications for the design of academic monitoring systems. Incorporating contextual features such as study duration and workload intensity at negligible additional cost provides a measurably significant accuracy improvement, suggesting that all future fatigue detection systems should include these dimensions as a matter of course. The fuzzy logic approach offers a compelling combination of performance, interpretability, and adaptability that positions it as a strong practical alternative to black-box deep learning classifiers in this domain.

Future work will focus on four directions: (i) reducing the sensor burden through sensor selection optimization and exploration of consumer-grade alternatives such as single-channel EEG devices; (ii) extending the participant sample to include students across multiple institutions, disciplines, and demographic backgrounds to strengthen generalizability claims; (iii) integrating deep learning feature extractors into the pipeline as a complement to the classical feature set; and (iv) developing a mobile application that delivers real-time fatigue notifications and personalized study break recommendations directly to students' smartphones.

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