International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Validating Lightweight Webcam-Based Cognitive Load Estimation Against Neurovascular Gold Standards

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Abstract:

Real-time cognitive load estimation has wide applications in education, human-computer interaction, and healthcare, but remains limited by the high cost and intrusiveness of physiological sensors [1,2]. In this study, we present a feasibility analysis of a lightweight cognitive load classification system based on webcam-accessible behavioral proxies, and benchmark its performance against neurovascular gold standards—namely, electroencephalography (EEG) and functional Near-Infrared Spectroscopy (fNIRS). Using a publicly available multimodal dataset collected during a driving task overlaid with an n-back working memory paradigm (0-, 1-, 2-back) , we simulate webcam-based inputs using features such as blink rate, pupil dilation, fixation duration, and saccade metrics [3].

Supervised learning models were trained to classify cognitive load levels across both multiclass and binary setups. While all models, including those using EEG and fNIRS, performed near chance in the three-class task, a binary classification of high vs. low/moderate load achieved above-chance accuracy using only behavioral features. These results suggest that webcam-derived signals, although coarse, can support lightweight cognitive state monitoring under simplified load distinctions. This study provides a cross-modal validation of scalable, low-cost cognitive load assessment approaches and highlights important trade-offs between accessibility, resolution, and physiological fidelity.

Index Terms—Cognitive load, EEG, fNIRS, webcam estimation

1. Introduction

Understanding and measuring cognitive load—the mental effort exerted by an individual during task performance—is critical across domains such as education, healthcare, human-computer interaction, and neuroergonomics [4, 5, 6]. Elevated cognitive load can impair decision-making, reduce task efficiency, and even pose safety risks in high-stakes environments such as driving or surgery [7], [8]. As such, accurately detecting changes in cognitive load in real time has become a major interdisciplinary research objective [3].

Neurophysiological methods such as functional Near-Infrared Spectroscopy (fNIRS) and electroencephalography (EEG) are considered gold standards for monitoring cognitive load. These methods provide direct biological signals related to cerebral oxygenation (fNIRS) and neural oscillatory activity (EEG), enabling researchers to quantify cognitive states with high temporal precision [9]. However, their widespread use is constrained by cost, physical setup requirements, and limited portability—factors that make them impractical for use in everyday settings like classrooms, driver-assist systems, or remote work platforms.

Recent advances in computer vision and affective computing have opened new possibilities for lightweight, camera-based cognitive monitoring. Standard webcams can unobtrusively capture facial and ocular signals—such as blink rate, pupil dilation, and fixation duration—that reflect internal cognitive states [10]. These behavioral signals are inexpensive to capture and highly scalable, but they remain indirect proxies of mental workload and often lack rigorous physiological grounding.

In this study, we perform a systematic feasibility analysis of webcam-accessible cognitive load features by benchmarking them against gold-standard neurovascular measurements using a publicly available multimodal dataset collected during a simulated driving task that incorporates an n-back working memory paradigm [3]. While no actual webcam footage or real-time system was used, we isolate and evaluate a set of behavioral features that could be realistically extracted via standard webcams. Our goal is to assess whether these features, when processed using modern machine learning techniques, can approximate the discriminative power of high-fidelity physiological modalities.

Our contributions are threefold:

We isolate and analyze behavioral proxies for webcam-derived signals (e.g., blink rate, pupil dilation, fixation duration), and benchmark their ability to classify cognitive load in comparison with fNIRS and EEG features.

We implement a machine learning pipeline to evaluate performance across both multiclass (0-/1-/2-back) and binary (high vs. low load) classification tasks.

We conduct ablation and diagnostic analyses to examine the tradeoffs between accuracy, interpretability, and hardware accessibility across feature modalities.

By grounding webcam-accessible features in validated neurophysiological benchmarks, our study offers a preliminary yet important step toward scalable, low-cost cognitive monitoring systems. This work aims to bridge the gap between high-fidelity neuroscience and deployable human-centered technologies—with potential applications in adaptive learning, cognitive ergonomics, and mental health support.

2. Related Work

2.1 Physiological Methods for Cognitive Load Estimation

Cognitive load has traditionally been measured using neurophysiological signals that reflect mental effort during task performance. Among these, functional Near-Infrared Spectroscopy (fNIRS) and electroencephalography (EEG) are among the most widely used non-invasive modalities [11]. fNIRS measures changes in oxygenated (HbO) and deoxygenated (HbR) hemoglobin concentrations in the prefrontal cortex, offering spatially localized indices of cortical activation. Numerous studies have demonstrated a consistent increase in HbO levels with higher working memory demand during paradigms such as the n-back task [12]. EEG, by contrast, offers high temporal resolution by capturing neural oscillations (e.g., theta and alpha band power), which have also been linked to cognitive workload intensity [13].

Together, fNIRS and EEG capture complementary aspects of neurovascular coupling—fNIRS through hemodynamic activity and EEG through electrical signals—making them effective for cognitive workload classification in laboratory contexts. However, both techniques typically require controlled environments, sensor calibration, and subject immobility, limiting their scalability in everyday settings.

2.2 Webcam-Based Cognitive Load Estimation

Recent advances in computer vision have enabled researchers to investigate lightweight, camera-based alternatives for inferring cognitive load. Standard webcams can capture facial and ocular cues—such as blink rate, pupil dilation, gaze entropy, and facial muscle tension—that serve as behavioral proxies of internal mental effort. For example, blink rate has been observed to decrease during high cognitive load due to increased attentional focus, while gaze entropy, a measure of spatial scanpath variability, tends to reduce as visual attention narrows [14].

Toolkits such as OpenFace and MediaPipe facilitate real-time extraction of these features, supporting deployment in domains ranging from e-learning to driver monitoring. However, unlike physiological signals, webcam-derived features are inherently indirect and may be affected by lighting conditions, emotional states, fatigue, and user variability. As a result, there is an ongoing need to validate these behavioral signals against neurophysiological baselines, to establish their reliability and robustness.

Although several studies have reported correlations between webcam-derived metrics and task difficulty or performance scores, few have directly benchmarked these features against concurrent fNIRS or EEG data [15]. This lack of cross-modal validation limits the interpretability and generalizability of purely behavioral systems for cognitive load assessment.

2.3 Multimodal and Cross-Validated Approaches

To improve the robustness of cognitive state recognition, researchers have increasingly adopted multimodal fusion strategies that combine behavioral and physiological inputs. For instance, hybrid EEG-fNIRS models have demonstrated improved classification accuracy over unimodal approaches, especially in dynamic or noisy task environments [16]. In parallel, affective computing frameworks have explored integrating facial expressions, speech features, and biosignals for comprehensive user state modeling.

Yet, in the specific domain of cognitive load monitoring, few studies employ synchronized datasets that contain both behavioral and neurophysiological signals collected during a controlled cognitive paradigm like the n-back task. Most existing datasets either focus exclusively on physiology or simulate behavioral data without corresponding neural benchmarks.

Our study contributes to this growing field by leveraging a publicly available multimodal dataset that includes eye-tracking-derived behavioral features (e.g., blink rate, fixation duration, pupil size) alongside fNIRS and EEG recordings, all captured during a cognitive task. By systematically comparing classification performance across these modalities, we offer one of the first cross-validated analyses of webcam-accessible features against dual neurophysiological standards. This approach lays the groundwork for future systems that aim to balance accessibility, accuracy, and real-world applicability.

3. **Methodology**

3.1 Dataset Description

This study utilizes the Multimodal Cognitive Load Classification Dataset, a large-scale open dataset comprising 86,435 samples, each corresponding to a 1-second time window of synchronized multimodal data collected during a simulated driving task [3]. Participants were exposed to varying levels of working memory demands using an n-back paradigm with three load conditions: 0-back (low load), 1-back (moderate load), and 2-back (high load). Each sample is labeled accordingly using the cognitive_load target variable.

The dataset integrates several data streams, including 384 electroencephalography (EEG) features derived from power spectral density (PSD) metrics across 24 channels, 20 functional near-infrared spectroscopy (fNIRS) features capturing oxygenated (HbO) and deoxygenated (HbR) hemoglobin concentration changes, and behavioral features such as pupil dilation, blink rate, fixation duration, and saccade duration, which serve as proxies for webcam-derived inputs [47]. Additionally, driving telemetry including vehicle speed, angular velocities along three axes, steering angle, and braking response is provided to contextualize cognitive load within the task environment.

3.2 Webcam Feature Simulation and Mapping

While the dataset does not include raw video footage, several features were identified that serve as viable stand-ins for those obtainable via a standard webcam. Specifically, blink rate and pupil dilation were used as indicators of ocular fatigue and cognitive processing, both of which are accessible using real-time gaze estimation frameworks such as MediaPipe or OpenFace. Fixation and saccade durations were mapped to attention distribution patterns and visual scanning behavior.

This simulation allowed us to approximate a realistic lightweight cognitive load monitoring setup that does not rely on specialized sensors like EEG or fNIRS, making it feasible for real-time deployment in educational or HCI environments.

3.3 Preprocessing Workflow

Prior to modeling, a systematic preprocessing pipeline was applied to ensure feature consistency and reduce noise across modalities. First, missing values were handled using forward fill imputation, leveraging the temporal continuity of the data. All numeric features were then standardized to zero mean and unit variance using standardScaler, enabling robust convergence for models sensitive to feature scale, such as SVM and neural networks.

Given the high dimensionality of EEG data (384 features), we performed dimensionality reduction via Principal Component Analysis (PCA), retaining the top 40 components. This dimensionality was chosen to preserve over 95% of the original variance while mitigating the curse of dimensionality. No dimensionality reduction was applied to fNIRS or behavioral features due to their relatively low feature count and inherent interpretability.

For classification purposes, two labeling schemes were created:

1) The original three-class label indicating 0-back, 1-back, and 2-back conditions

2) A binary label where 2-back was treated as a high cognitive load condition and the other two classes were collapsed into a low/moderate load group.

This binary simplification enabled us to probe whether webcam-derived features are more effective at distinguishing coarse changes in load rather than fine-grained distinctions.

3.4 Feature Group Design and Rationale

To assess the effectiveness of webcam-simulated features in comparison to neurophysiological gold standards, we defined multiple feature groups, each corresponding to a practical deployment configuration.

The Webcam-only feature set included four behavioral signals: pupil dilation, blink rate, fixation duration, and saccade duration. The Behavior-only group included telemetry data: vehicle speed, angular velocities (X, Y, Z), and excluded steering angle and braking response due to their near-zero variance across samples. The fNIRS-only group included all 20 hemoglobin-based features, while the EEG-only group consisted of the 40 PCA-reduced components. The Gold Standard group was defined as the union of fNIRS and EEG features, representing sensor-based neurovascular signals. Lastly, the Hybrid group combined Webcam, EEG-PCA, and fNIRS features to assess whether fusion improves classification performance.

Initial feature diagnostics included both raw variance analysis and Pearson correlation with the cognitive load label. Features such as steering_angle and braking_response were removed due to negligible variance (< 0.05), and all behavioral features were found to have correlation coefficients $|r| < 0.01$, suggesting weak linear association with cognitive load. Nevertheless, they were retained for testing non-linear model capabilities.

3.5 Classifier Design and Training Procedure

We evaluated four machine learning classifiers: XGBoost, Random Forest, Support Vector Machine (SVM with RBF kernel), and a Multi-Layer Perceptron (MLP). XGBoost was used as the primary model due to its robustness to noisy features and superior performance on structured datasets. The Random Forest model served as a baseline for tree-based methods, while the SVM model was chosen for its ability to handle high-dimensional nonlinear boundaries. The MLP was included to assess the performance of a basic neural network architecture with one hidden layer and a maximum of 500 iterations.

Model training employed 5-fold stratified cross-validation to ensure proportional class representation in all training and test splits. No additional hyperparameter tuning was performed in this phase to preserve comparability across models and focus on the impact of feature modalities.

3.6 Evaluation Metrics

Classification performance was evaluated using accuracy, weighted F1-score, and macro F1-score. These metrics were chosen to balance overall predictive accuracy with class-level fairness, especially important for multiclass problems. Additionally, confusion matrices were generated for visualizing misclassification patterns, and Receiver Operating Characteristic (ROC) curves were plotted for the binary classification setup. Feature importance in the XGBoost models was interpreted using gain-based feature weights, with future work incorporating SHAP values for more interpretable models.

3.7 Diagnostic Tests and Ablation Studies

To assess the informativeness of each modality, we conducted a series of ablation studies. Each model was trained independently on feature subsets (e.g., webcam-only, EEG-only) and combinations thereof. This allowed us to benchmark the marginal and joint contributions of lightweight and gold-standard signals.

Additionally, variance and correlation diagnostics were computed on raw features. Behavioral features were found to have low raw variance and extremely weak correlation to the target label. To further investigate their utility, we trained models in a binary setting, evaluating whether coarse load distinctions (e.g., 2-back vs 0/1-back) could be more easily predicted using webcam features.

3.8 Experimental Conditions

To comprehensively evaluate the performance of various modality combinations, we conducted experiments under two distinct classification schemes: a multiclass setting and a binary setting.

In the multiclass classification task, the objective was to discriminate between three levels of cognitive load corresponding to the 0-back (low), 1-back (moderate), and 2-back (high) task conditions. This formulation provides a fine-grained analysis of mental workload transitions and serves as the benchmark setup in cognitive neuroscience literature. However, the multiclass formulation also poses greater challenges due to class imbalances, overlapping feature distributions between adjacent load levels (e.g., 0-back vs 1-back), and inherent variability in physiological responses.

The binary classification task, in contrast, collapses the 0-back and 1-back labels into a single “low-to-moderate load” class, and treats 2-back as the “high load” condition. This dichotomous formulation reflects practical use cases, such as real-time alert systems that must detect cognitive overload with limited input features [71]. The simplified task reduces label ambiguity and is particularly relevant for evaluating the discriminative power of low-dimensional or proxy-based features such as those simulated from webcam data.

By examining both conditions in parallel, we are able to explore the trade-offs between classification granularity and practical deployability. This dual-task setup enables us to assess the extent to which webcam-accessible features can approximate the performance of neurophysiological modalities in both nuanced and threshold-based mental state classification scenarios.

4. Results

4.1 Multiclass Classification: 0-back vs 1-back vs 2-back

We first evaluated the performance of all defined feature sets in a multiclass classification task, targeting the three cognitive load levels (0-back, 1-back, 2-back). Models were trained using stratified 5-fold cross-validation, and average accuracy and weighted F1-scores were used as evaluation metrics.

Across all configurations, classification performance remained close to the theoretical baseline of 33.3%, with minimal differences between feature groups. The Webcam-only model, comprising blink rate, pupil dilation, fixation duration, and saccade duration, achieved an average accuracy of 33.27% and a weighted F1-score of 33.25%. These results indicate that while these features may reflect behavioral states, they do not exhibit sufficient separability to resolve fine-grained cognitive distinctions in this task.

Surprisingly, the Gold Standard model, which utilized both EEG (via PCA components) and fNIRS features, also failed to outperform chance, yielding an average accuracy of 33.38% and F1-score of 33.37%. The Hybrid model, which combined webcam, EEG, and fNIRS data, performed slightly worse at 33.23% accuracy. These results suggest a systemic limitation within the dataset: either the physiological responses to the different n-back levels are not robustly expressed, or high inter-subject variability masks discriminative patterns at the group level.

4.2 Binary Classification: High Load vs Low/Moderate Load

To address the limitations observed in the multiclass task, we reframed the problem as a binary classification challenge. Here, only 2-back trials were labeled as "high load," while 0-back and 1-back trials were collapsed into a "low-to-moderate load" category. This simplification reflects real-world monitoring scenarios where detecting overload is more important than resolving intermediate mental states.

Using only behavioral proxies including webcam-accessible features (e.g., blink rate, pupil dilation) and task-related telemetry (e.g., angular velocity, speed) (excluding EEG and fNIRS), the binary XGBoost model achieved a cross-validated average accuracy of 65.42% and a weighted F1-score of 54.58%. This performance is well above the statistical baseline of 50%, indicating that non-linear classifiers can extract cognitively relevant signals from even weakly correlated or noisy behavioral features.

Notably, features such as blink rate and pupil dilation exhibited high raw variance, but very low linear correlation with the cognitive load labels ($|r| < 0.01$). This suggests that their predictive value emerges only when modeled via non-linear interactions or higher-order combinations. The learned decision boundary successfully identified patterns associated with elevated mental workload, even though the original features appeared statistically weak in isolation.

A one-sample t-test comparing fold-wise accuracy scores to a chance-level baseline of 50% yielded $p < 0.01$, confirming that the observed above-chance performance was statistically significant

4.3 Confusion Matrix Analysis and Class-Level Observations

To further examine model behavior, confusion matrices were plotted for both the multiclass and binary classification settings. In the multiclass case, the matrices were nearly uniform along the diagonal, with misclassifications evenly distributed and a tendency to predict the dominant class. This indicates that the model failed to detect any structured difference between load levels, consistent with the near-random performance.

In contrast, the binary classifier produced more asymmetrical matrices. The model correctly classified approximately two-thirds of the high-load (2-back) samples, revealing a moderate capacity to detect elevated cognitive effort. However, recall for the high-load class was notably higher than precision, indicating a tendency to over-predict 2-back conditions, likely as a compensatory bias under class imbalance or noise.

These results highlight that while webcam-based behavioral features may lack the resolution for fine-grained classification, they hold promise for coarse, threshold-based cognitive state detection — a critical feature for low-intrusion, real-time monitoring systems in applied settings such as education or adaptive interfaces.

4.4 Summary of Observations

The combined results of both experimental settings highlight two critical findings:

1. **Webcam-accessible features**, though individually weak and linearly uninformative, can collectively support above-chance classification when used for coarse binary distinctions. This makes them promising candidates for threshold-based cognitive state monitoring systems.

2. **EEG and fNIRS features**, while traditionally considered gold standards for cognitive workload assessment, did not yield meaningful classification performance in the current dataset when applied globally across participants. This may reflect individual differences in neurovascular responses or the need for personalized modeling.

These observations reinforce the importance of modality selection based on task granularity: webcam-based systems may be viable for basic high-vs-low load differentiation, while fine-grained classification likely requires more sophisticated sensing or individualized baselines.

5. Discussion

This study set out to explore whether lightweight, webcam-accessible features could serve as viable indicators of cognitive load in a non-invasive setup suitable for eventual real-time deployment. Using a rich multimodal dataset comprising EEG, fNIRS, simulated webcam proxies, and driving behavior, we benchmarked the performance of various feature subsets in classifying cognitive load across multiple levels. Our findings offer several key insights regarding the capabilities and constraints of webcam-based cognitive load estimation.

First, our results reveal a consistent inability of all feature sets—including EEG and fNIRS—to reliably differentiate between the three cognitive load conditions (0-back, 1-back, and 2-back). Despite the physiological richness of EEG spectral features and the neurovascular specificity of fNIRS measurements, all models performed at or near random chance in the multiclass setting. This suggests that the cognitive load signal in this dataset, while theoretically present, may be either too subtle, too individualized, or too temporally diffuse to be captured by 1-second feature snapshots. Alternatively, the cognitive state induced by the 1-back condition may not be sufficiently distinct from 0-back or 2-back to support categorical separation—a hypothesis supported by prior research showing overlapping neural signatures in adjacent working memory loads.

The binary classification task, by contrast, produced more promising results. When reframed to distinguish 2-back trials from 0/1-back conditions, the XGBoost model trained exclusively on webcam-accessible behavioral and telemetry features achieved a mean accuracy of 65.4% and a weighted F1-score of 54.6%. A one-sample t-test across 5-fold accuracies confirmed that this result was statistically significant relative to the 50% chance baseline ($p < 0.01$). Although modest, this performance suggests that even weakly informative features—when processed through non-linear models—can capture the overall shift in attentional demand and mental workload associated with more cognitively demanding tasks.

It is noteworthy that this performance emerged despite the near-zero Pearson correlation between any individual feature and the target label. This underscores the importance of considering complex, multivariate relationships in cognitive modeling and validates the use of non-linear classifiers such as XGBoost in scenarios where linear separability is not achievable. These findings also support the view that webcam-derived indicators, while limited in granularity, can still serve as useful surrogates for detecting coarse cognitive state transitions.

Several limitations must be acknowledged. First, the webcam-accessible features used in this study were not collected from actual webcam input but instead derived from specialized eye-tracking hardware. While pupil dilation, fixation, and blink rate are commonly available via modern computer vision frameworks such as MediaPipe and OpenFace, their fidelity and noise characteristics may differ substantially in webcam-based systems. Therefore, our results represent an upper bound on what might be achievable in real-world webcam-based settings.

Second, the lack of participant-level personalization may have further constrained performance. Cognitive load responses are known to vary across individuals, and person-specific baselines can dramatically improve the signal-to-noise ratio in physiological monitoring. Our models operated in a participantagnostic setting, which, while generalizable, may have obscured subtler load-related effects. Future work should explore per-subject fine-tuning or hybrid systems that combine global and individualized models.

Finally, the models trained on EEG and fNIRS did not outperform webcam-only models, contrary to expectations based on their status as gold standards. This could be attributed to high intra-individual noise, inadequate signal preprocessing (e.g., lack of artifact rejection or ICA denoising for EEG), or insufficient temporal context in the feature design. Real-time cognitive load unfolds over seconds, not milliseconds, and future work should consider sequence modeling techniques (e.g., LSTM, GRU, or Transformer architectures) to capture these dynamics more effectively. Incorporating temporal context could also help disambiguate transitions between ambiguous cognitive states such as 1-back and 2-back.

6. Conclusion and Future Work

This study investigated the feasibility of using lightweight, webcam-accessible features to estimate cognitive load in real-time, and benchmarked their performance against neurophysiological gold standards such as EEG and fNIRS. Using a publicly available multimodal dataset collected during a simulated driving task, we evaluated both multiclass and binary classification paradigms to assess the discriminative power of behavioral, ocular, and physiological features.

Our findings demonstrate a clear distinction in the utility of different feature groups depending on task complexity. In the multiclass setting (0-back vs 1-back vs 2-back), all models—including those leveraging EEG and fNIRS—failed to surpass random-chance performance. This suggests that fine-grained distinctions in cognitive load may not be detectable using 1-second feature snapshots or may require participant-specific baselines and temporal modeling approaches. In contrast, when the task was reframed as a binary classification problem, behavioral and webcam-proxy features were able to distinguish high-load (2-back) trials from lower-load (0/1-back) trials with above-chance accuracy. These results indicate that webcam-derived signals, while limited in granularity, can serve as useful indicators for threshold-based cognitive state monitoring.

This has practical implications for the design of non-invasive, real-time cognitive monitoring systems in educational, automotive, and HCI settings[17]. A webcam-based system capable of flagging moments of elevated cognitive demand—without requiring EEG caps or fNIRS headgear—could support adaptive learning interfaces, mental fatigue detection, and operator workload monitoring in a scalable manner.

Future work should focus on four major directions. First, transitioning from simulated webcam features to real webcam data is essential. This involves using computer vision libraries such as MediaPipe or OpenFace to extract blink rate, gaze direction, head pose, and facial microexpressions directly from video streams, enabling end-to-end real-time deployment. Second, to improve classification fidelity, especially in the multiclass setting, future systems should incorporate temporal modeling using recurrent or attention-based architectures (e.g., LSTM, GRU, Transformer) that account for cognitive dynamics over time rather than single-frame summaries.

Third, building personalized models using a small calibration phase per user could dramatically enhance model sensitivity by capturing baseline variations in blink rate, gaze behavior, and neurophysiological response. Finally, validating the webcam-based system in a real-world task environment, such as live classroom settings or multitasking simulations, will provide more ecologically valid benchmarks and highlight system robustness under noisy, uncontrolled conditions.

Overall, this study contributes a critical step toward democratizing cognitive load measurement by demonstrating that even coarse behavioral signals—when modeled appropriately—can offer meaningful insight into internal mental states. The proposed system bridges a critical gap between accessibility and fidelity, laying the groundwork for scalable, real-time cognitive sensing with minimal hardware requirements.

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