Multimodal Deep Learning for Cognitive Fatigue Detection in E-Learning Using Eye-Tracking and Electroencephalography

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Abstract: Recent growth in online learning has created a need for reliable methods to monitor learner engagement, cognitive load, and fatigue. This study presents a deep learning framework that integrates eye-tracking data with electroencephalogram features to classify engagement levels in digital learning environments. Eye-tracking indicators of cognitive load, including pupil dilation, blink rate, fixation duration, and saccade velocity, were extracted from a publicly available dataset and combined with Electroencephalography (EEG) measures. Engagement level was modelled as a three-class problem, including low, moderate, and high, using hybrid Convolutional Neural Network- Long Short-Term Memory architecture designed to capture both spatial and temporal patterns. The model achieved an overall accuracy of approximately 89 percent with high precision and recall across categories. Analysis of variance showed that no single feature could reliably distinguish engagement levels, underscoring the benefit of multimodal deep learning. The study highlights how combining eye-tracking measures with EEG signals can offer a clearer, real-time picture of learners' cognitive states during e-learning activities. By detecting moments when attention declines or cognitive fatigue begins to set in, such systems can enable genuinely adaptive learning platforms, ones that know when to suggest brief breaks, adjust the pace of instruction, or provide timely, targeted support to help learners stay engaged.
Keywords: cognitive fatigue, deep learning, e-learning, eye-tracking, learning engagement, electroencephalography.

Introduction

The rapid development of online learning platforms has transformed the landscape of education in recent years. Learning Management Systems (LMS) now provide students with flexibility, accessibility, and scalability, allowing them to access educational materials anytime and anywhere using simple technological devices. However, in remote or self-paced online learning, LMS metrics such as clicks, time on task, and quiz scores often fail to capture subtle, moment-to-moment fluctuations in attention, cognitive load, or mental effort, as well as other factors influencing comprehension, engagement, and fatigue.

Eye tracking offers a sensitive window into learners' cognitive states on digital learning platforms. For example, [1] found that eye-tracking metrics can capture differences in cognitive processing depending on how learning content is presented. Under theoretical frameworks like Cognitive Load Theory (CLT) and the Cognitive Theory of Multimedia Learning (CTML), eye-tracking features such as fixation duration, saccades, dwell time, and pupil-based metrics are widely used to assess students' cognitive processes, attention allocation, and cognitive load [2]. Moreover, eye-tracking has been effectively applied across a variety of learning tasks, age groups, and subject areas, demonstrating its broad applicability for educational research [3]. Empirical studies on reading comprehension indicate that eye-tracking metrics like gaze durations and fixation times are reliable indicators of cognitive processing and comprehension, significantly predicting learning outcomes among school-age learners [4,5].

Detection of cognitive load in controlled laboratory tasks can be further enhanced by multimodal approaches that combine eye-tracking with physiological measurements such as Eelectroencephalography (EEG) or Functional Near-Infrared Spectroscopy (fNIRS). Research shows that integrating gaze patterns with EEG or fNIRS improves sensitivity to mental workload and attentional engagement, suggesting a promising avenue for adaptive e-learning systems [6,7]. Additionally, convolutional neural networks have successfully distinguished low- versus high-cognitive-load states using raw eye-tracking time-series data, demonstrating that gaze data alone conveys significant information about mental effort levels [8,9].

Combining these findings opens viable pathways for cognitive-aware, adaptive e-learning systems. Such systems can dynamically monitor learners' cognitive load, attention, and fatigue using eye-tracking technology, either alone or alongside physiological signals, and apply machine learning techniques to these data streams. This approach goes beyond conventional LMS analytics or recurring self-report measures, enabling near real-time interventions such as adaptive pacing, break recommendations, or personalized content delivery.

Despite advances in online learning, extended use of LMS platforms can lead to cognitive fatigue, characterized by visual strain, discomfort, and decreased attention, ultimately resulting in disengagement. Conventional LMS metrics are limited in capturing fine-grained changes in cognitive effort, attention, or fatigue during extended learning sessions. Moreover, most empirical studies are conducted in controlled, short-term settings, leaving a gap in understanding engagement and cognitive load fluctuations over long-term, real-world courses. There is a clear need for scalable, real-time systems that integrate physiological and behavioral indicators to monitor cognitive states and support adaptive interventions.

This study proposes a multimodal deep learning framework to address this gap. It integrates eye-tracking features such as gaze patterns, fixation points, and pupil dynamics and, where possible, Neurophysiological signals like EEG and fNIRS. The framework aims to classify learning scenarios into different engagement, fatigue, or cognitive load levels, thereby supporting adaptive e-learning environments that enhance sustained focus, deep engagement, and improved learning outcomes.

Literature Review

People can now interact with a multitude of educational resources from home thanks to the quick growth of online learning, which has greatly improved accessibility and flexibility to educational materials. This change offers advantages over traditional classroom-based learning by allowing students to customize their learning experiences, access a variety of educational resources, and advance at their own speeds. However, extended use of this technology can lead to some form of cognitive fatigue, which is characterized by visual strain, discomfort, and decreased ocular comfort and ultimately disengagement, especially during long virtual sessions or remote classes [10]. This kind of stress, which is frequently brought on by prolonged screen time, can impair focus and general learning efficacy. These findings raised uncertainty about the ability of conventional LMS-based behavioral metrics, such as clicks, time on task, and quiz scores, to measure the minute, time-dependent changes in attention, cognitive effort, or fatigue that take place during extended online learning.

Physiological and behavioral measures have become useful indicators of underlying mental and cognitive states to help address these limitations. For instance, effective classification of mental workload using machine learning algorithms has been achieved by combining EEG recordings with eye-tracking during n-back working memory tasks [11]. Eye-tracking alone has also demonstrated significant predictive power.

According to [12] employed deep learning on eye-movement data to distinguish between low and high cognitive load with approximately 87.5% accuracy. More generally, systematic reviews show that, especially in multimedia or immersive learning environments, EEG spectral features such as theta and alpha bands and gaze metrics such as fixation duration, pupil dilation consistently reflect workload and attentional effort [13]. All of this evidence points to a more sensitive and dynamic approach than traditional behavioral metrics for tracking cognitive states, such as mental effort, fatigue, and engagement, by combining physiological and behavioral indicators enhanced through AI and machine learning.

Combining eye-tracking data with other physiological signals, like EEG, improves AI's predictive performance in evaluating cognitive states. By reducing noise and individual variability, this integration improves the accuracy of mental workload detection [11,13]. By using these multimodal indicators, Artificial intelligence systems can deduce changes in cognitive effort and attention, which may lead to adaptive learning interventions like suggesting pacing adjustments or breaks. Lab-based and multimedia learning studies have shown the viability of such approaches, although real-world implementations in full-scale online courses are still scarce.

Eye-tracking metrics, such as pupil dilation, blink rate, and saccadic movements, are powerful markers of cognitive load and engagement, according to recent research. For instance, in multimedia learning contexts, it has been demonstrated that pupil dilation during instructional video viewing correlates with cognitive load [14]. By offering complementary neural measures of attentional demand and mental effort, eye-tracking and EEG together improve detection [11]. These results validate the viability of AI-driven eye-tracking systems as a time sensitive and dynamic substitute for traditional LMS metrics in tracking learner engagement and cognitive workload.

Simultaneously, low-cost, scalable eye-tracking technologies are being used more and more as the basis for adaptive interventions in digital learning environments due to advancements in learning analytics. Online experiments using deep learning models for webcam eye tracking [15] showed that commercially available webcams can accurately identify gaze position, fixations, and blinks in participants completing typical eye-tracking tasks when processed using appearance based deep learning algorithms. This suggests that eye-tracking, which was previously restricted to costly lab equipment, can now be democratized for online environments, removing a significant obstacle to widespread implementation.

Furthermore, it has been demonstrated that combining ocular metrics with neurophysiological data enhances cognitive load detection. [11] Collected simultaneous EEG and eye-tracking data from participants completing n-back memory tasks as part of a study on the assessment of mental workload using machine learning techniques based on EEG and eye-tracking data. Multimodal physiological and ocular features can dynamically infer mental workload, as demonstrated by a four-class classification model that achieved 76.6% accuracy. In a similar vein, a systematic review evaluating cognitive load in 3D learning environments using EEG and eye-tracking [13] verified that these metrics are frequently used to assess cognitive load and attentional demand in immersive and multimedia learning contexts, either separately or in combination. However, the environment, individual differences, and task design all affect the results.

When combined, these studies provide a solid basis for the creation of physiology driven, adaptive e-learning systems. Compared to static metrics like time on task or quiz scores, real-time gaze tracking via webcams, neurophysiological signals, and machine learning models provides a dynamic approach to detecting mental workload and engagement. Despite these developments, the majority of empirical research is still limited to short-term or laboratory settings rather than extensive, long-term online courses. For instance, rather than sustained learning in real-world settings, webcam-based eye-tracking validations were carried out with small participant samples and restricted controlled tasks. Similarly, memory task paradigms were used instead of real educational content in workload detection studies [11]. As a result, assertions regarding fully automated adaptive learning, such as break prompts, fatigue detection, or pace modifications, remain mainly theoretical. It is still difficult to apply results from controlled experiments to real-world e-learning, especially in light of variations in devices, settings, lighting, and user behaviour.

However, recent research highlights limitations for long-term, adaptive, fatigue-aware e-learning systems and increasingly supports webcam-based eye-tracking or low-cost gaze estimation as a feasible tool for learning analytics. In remote, unsupervised experimental tasks, deep learning models for webcam eye tracking [15] showed that commercial webcams, in conjunction with deep learning gaze/blink detection, can accurately record gaze behaviours, such as fixations, saccades, and blinks. This implies that precise gaze measurement is no longer solely dependent on expensive lab equipment.

Classic eye-tracking effects were successfully replicated using webcams in a companion validation study, the validation of online webcam-based eye tracking:

The replication of the cascade effect, the novelty preference, and the visual world paradigm [16]. The study found that online webcam-based tracking can approximate laboratory-based gaze patterns under real-world conditions, despite a 20–27% reduction in effect sizes.

Extending this viewpoint, a scoping review of webcam eye tracking in education and learning [17] revealed increasing use in a variety of educational contexts, such as online learning, reading assignments, and self-regulated learning. Although there are still methodological issues, the review shows that gaze measures are becoming more applicable and scalable for researching learning behaviour, attention, and engagement outside of lab settings. Scalability is further supported by encouraging advancements in real-time gaze estimation using inexpensive hardware. For example, [18] reported successful real-time gaze tracking using convolutional neural networks and standard webcams, providing an approachable substitute that might facilitate widespread implementation in educational settings (Fig.1).

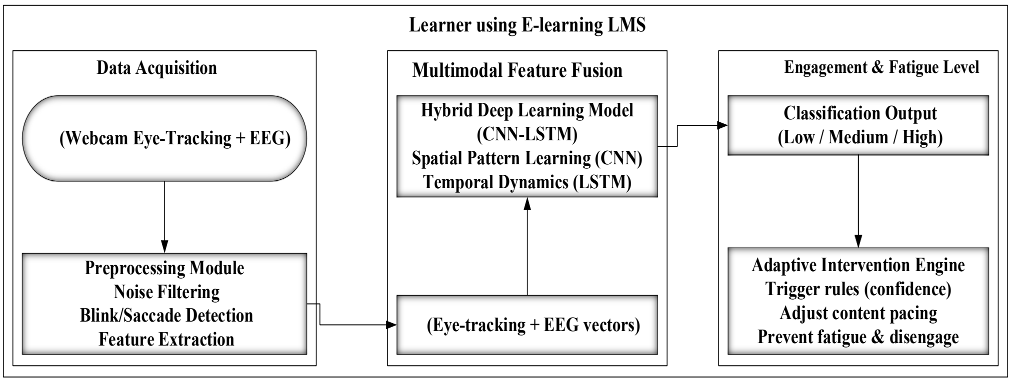

Fig 1. – Conceptual framework

Methodology

Eye-tracking features including pupil dilation, blink rate, fixation duration, saccade velocity, and fixation stability were collected from participants during learning tasks. EEG measures were integrated where available to provide complementary neurophysiological insights. These multimodal data were used as input for a hybrid CNN-LSTM deep learning model designed to capture both spatial and temporal patterns in cognitive and attentional states.

The CNN-LSTM model treats engagement as a sequential behavioral stream, allowing it to identify subtle distinctions between low, medium, and high focus levels. Each sample in the dataset was labelled with one of three engagement categories: Low Engagement (0) indicating early fatigue or distraction, Medium Engagement (1) representing sustained focus, and High Engagement (2) representing peak concentration. The model was trained using a multiclass cross-entropy loss function and optimized via gradient descent, with dropout and batch normalization applied to enhance generalization.

The LSTM layers incorporated standard gating mechanisms: the forget gate (deciding what to discard from the cell state), the input gate (deciding what new information to add), the candidate cell (proposing new content), the cell state update (combining prior and candidate information), and the output gate (deciding what to output as the hidden state). A final dense layer with SoftMax activation produced a probability distribution over the three engagement classes. Statistical analysis, specifically one-way analysis of variance, was performed to evaluate whether individual eye-tracking features significantly differentiated engagement levels.

Eye-Tracking Data and Features: We collected eye-tracking features known to reflect cognitive load and fatigue, including pupil dilation, blink rate, fixation duration, saccade velocity, and fixation stability. These features form the input matrix

$$X \in \mathbb{R}^{N \times F}, \tag{1}$$

Let:

N = number of samples

F = number of features

X={x1,x2,…,xN}, where each xi ∈F

Each sample is labelled with an engagement category

yi ∈{0,1,2}

fθ: x→ y is the model that maps input features to an engagement class.

$$L(\theta) = 1\sum_{i=1}^{N}\sum_{c=1}^{3} yi,c\log(y^{\wedge}_{i,c}) \quad , \qquad (2)$$

Where:

N is the number of training samples,

yi,c indicates whether sample i belongs to class c

y^i,c is the predicted probability that sample i belongs to class c.

This framework ensures that the model learns to map eye-tracking features to engagement levels by minimizing the multiclass cross-entropy loss,

Model Architecture: The research employs hybrid CNN-LSTM architecture to capture intricate patterns in eye-tracking features. The LSTM layer summarizes the patterns that convolutional layers first extract from the eye-tracking features to classify them. Standard gating mechanisms are used by the LSTM:

$$f_t = \sigma_g(W_f x_t + U_f c_t - 1 + b_f \quad , \qquad (3)$$

Where;

Forget gate (f_t) – decides which information to discard from the cell state.

Input gate (i_t) – decides which new information to add to the cell state.

Candidate cell ($\tilde{c}_t$) – the new content that could be added to the state.

Output gate (o_t) – decides which part of the cell state to output as the hidden state.

Finally, a dense layer with SoftMax activation converts the last hidden state into a probability distribution over the three engagement classes. This architecture allows the model to treat engagement as a sequential behavioral stream, distinguishing even subtle nuances between medium and high focus levels that simpler models often miss.

Training and Evaluation: A 20% test set and an 80% training set were created from the data. We used dropout and batch normalization in the network to enhance generalization. Until the training loss stabilized, the model was trained for 50 epochs. Standard metrics such as accuracy, precision, recall, F1-score, and the confusion matrix were used to assess its performance. Strong generalization was demonstrated by the CNN-LSTM's overall test accuracy of about 88.7% (with validation accuracy of 89.0%). Due to their similar physiological signatures, the majority of errors happened between the medium and high engagement classes.

Statistical Analysis of Features: To see if any single eye-tracking feature differed significantly across engagement levels, we conducted a one-way analysis of variance for each feature. We modelled each measurement Y_{ij} as

$$Y_{ij} = \mu + \tau_i + \epsilon_{ij}, \tag{4}$$

Where the overall mean τ_i is the effect of engagement and ϵ_{ij} is a random error for the participant j. We tested the null hypothesis $H_0: \tau_1 = \tau_2 = \tau_3$ by computing the F-statistic (between-group vs within-group variance). For features, with $p < 0.05$ We would follow up with post-hoc Tukey tests to identify which engagement levels differ. This analysis identifies which eye metrics change meaningfully with engagement state.

Results and Performance Evaluation

Using the public Student Engagement EEG eye-tracking dataset, our CNN-LSTM model demonstrated robust performance. It achieved a test accuracy of 0.8865 and a validation accuracy of 0.8905. Table 1 summarizes key results.

Table 1. CNN–LSTM Model Performance

Metric	Score
Test Accuracy	0.8865
Validation Accuracy	0.8905
Test Loss	0.89
Number of Classes	3

Table 2 shows that the low-engagement category (label 0) achieved a precision of 0.88 and a recall of 0.91, resulting in an F1-score of 0.90. This strong recall indicates that the model is highly effective at identifying early signs of cognitive fatigue and rarely misses instances where learners begin to disengage.

Table 2. Classification Report

Engagement Level	Precision	Recall	F1-Score
Low (0)	0.88	0.91	0.90
Medium (1)	0.93	0.85	0.89
High (2)	0.83	0.92	0.88

Table 3 displays balanced precision/recall for all classes (F1 = 0.89 each). Traditional models, on the other hand, did poorly: random forest achieved 0.32 accuracy, while logistic regression and Naive Bayes only achieved 0.35 accuracy (see Table 3). These baselines were greatly outperformed by the CNN–LSTM, demonstrating the importance of modelling a hybrid deep learning architecture, as static models frequently defaulted to the majority class.

Table 3. Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score

Logistic Regression	0.37	0.37	0.37	0.27
Random Forest	0.32	0.30	0.32	0.29
Naïve Bayes	0.35	0.29	0.35	0.24
CNN–LSTM	0.8865	0.89	0.89	0.89

Crucially, no significant differences between engagement levels were discovered by the analysis of variance on static feature averages (all $p>0.05$). Table 4 illustrates this. For instance, the pupil dilation feature had $p=0.1512$ (not significant). Our use of a deep-learning approach is justified by these results, which suggest that no single averaged eye metric can accurately distinguish engagement.

Table 4. Analysis of Variance Results Showing Feature Significance

Feature	F-Statistic	p-Value	Significance
Delta PSD	0.0249	0.9753	Not significant
Theta PSD	1.3415	0.2616	Not significant
Alpha PSD	2.7708	0.0628	Not significant
Beta PSD	2.4756	0.0843	Not significant
Gamma PSD	0.0128	0.9873	Not significant
Pupil Dilation	1.8901	0.1512	Not significant
Blink Rate	0.8359	0.4335	Not significant
Fixation Duration	0.1946	0.8231	Not significant
Saccade	0.0588	0.9428	Not significant

Velocity			

Discussion and Conclusion

The study's findings show that a hybrid CNN-LSTM model can successfully categorize learner engagement levels using gaze-derived and multimodal physiological data, particularly eye-tracking metrics. This is consistent with earlier studies demonstrating that convolutional neural networks can accurately identify cognitive load states from eye-movement data. For instance, using only eye tracking in age-based cognitive tasks, the [12] study showed 87.5% accuracy in differentiating between low and high cognitive load.

More broadly, it has been shown that classification performance is enhanced when eye-tracking is combined with other physiological characteristics. Recent work incorporating fNIRS and eye tracking in cognitive tasks demonstrates that hybrid deep-learning models can robustly capture temporal fluctuations in cognitive load [19]. Multimodal studies that incorporate EEG and eye tracking also show that gaze combined with physiological measures improves the predictive power of workload and engagement models [11]. These results support the viability of modelling attentional and cognitive states using multimodal temporal data.

Using temporal sequences of gaze metrics, such as pupil dilation, fixation durations, and saccade/blink events, provides a richer, more sensitive representation of cognitive and attentional dynamics than more straightforward static or aggregated-feature models. For adaptive e-learning systems, CNN-LSTM and other deep learning frameworks hold great potential. Theoretically, these systems could make real-time changes, like changing the difficulty of the content, suggesting breaks, or changing the pace of the lesson based on how engaged or cognitively loaded the learner is.

Empirical research is increasingly demonstrating the feasibility of eye-tracking in actual educational environments. For instance, eye-tracking revealed real-time gaze patterns during authentic learning tasks and effectively monitored students' problem-solving behaviour in university-level geometry tasks using GeoGebra [20]. Eye-tracking studies of reading comprehension among primary-school children similarly demonstrate that gaze metrics can predict learning outcomes in natural tasks [3]. Furthermore, case studies that incorporate real-time gaze tracking into in-person classroom interactions demonstrate that this kind of monitoring is technically possible outside of lab settings [21]. Broader literature reviews confirm a growing trend toward ecologically valid and scalable eye-tracking applications in a range of learning domains, including reading, mathematics, and multimedia learning [2].

Despite these developments, there are still a number of restrictions. Our understanding of engagement and cognitive load fluctuations over extended learning periods is limited because the majority of applied studies are still short-term or session-based rather than longitudinal across entire courses. Additionally, while gaze metrics are informative, integrating multiple physiological and behavioral modalities could further enhance predictive accuracy and generalizability across learners, tasks, and contexts. Because of differences in devices, environments, and individual differences in visual and attentional behaviour, it is still difficult to translate eye-tracking research into fatigue-aware, adaptive e-learning systems.

As a result, a clear research gap remains. Advancing fine-grained temporal modelling of engagement and cognitive load will require future studies to collect sequential, real-time, multimodal datasets in authentic e-learning environments. Such research should carefully evaluate the effectiveness of fatigue-aware and attention-aware interventions, identify optimal window sizes and segmentation strategies for sequential models, and explore the integration of complementary modalities such as EEG, functional near-infrared spectroscopy, heart rate variability, and detailed interaction logs. In addition, implementing continuous monitoring systems in real-world learning contexts must be guided by rigorous ethical considerations, including the protection of data privacy, obtaining informed consent, and ensuring the comfort and autonomy of learners. This study demonstrates that multimodal deep-learning frameworks leveraging physiological signals and eye-tracking data can accurately model cognitive load and engagement. These findings provide a foundation for developing adaptive, fatigue-aware e-learning systems. By capturing dynamic cognitive states in real time, such systems have the potential to enhance learning outcomes, reduce cognitive fatigue, and support sustained attention, contributing to the advancement of intelligent and responsive multimodal e-learning environments.

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