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CRNN-Based Modeling of Mental Fatigue from Multimodal Signals: A Systematic Review

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Abstract *– Mental fatigue—characterized by reduced vigilance, slowed reaction time, and cognitive inefficiency—poses safety and productivity risks in transportation, healthcare, and industrial settings. Recent work leverages convolutional–recurrent neural networks (CRNNs), typically coupling convolutional layers (for spatial/spectral feature extraction) with recurrent layers (LSTM/GRU for temporal dynamics), to model mental fatigue from multimodal signals such as EEG, EOG, ECG/PPG, fNIRS, eye tracking (PERCLOS), facial video, and behavioral/interaction traces. This systematic review synthesizes CRNN-based methods for mental fatigue estimation from 2013–2025, covering sensing modalities, input encodings (e.g., spectrograms, wavelets, topographical maps), fusion strategies (early/late/hybrid attention), learning paradigms (supervised, transfer, self-supervised), evaluation protocols (within-subject vs. cross-subject), and deployment aspects (real-time/edge). We summarize representative datasets (SEED-VIG, DROZY, NTHU-DDD, FatigueSet, and others), identify typical performance regimes, and highlight open problems in label quality, domain shift, personalization, interpretability, and ethics. We conclude with a set of practical recommendations and a forward-looking agenda that integrates self-supervised pretraining, lightweight architectures, and robust human-in-the-loop evaluation..*

Keywords: Mental Fatigue, Vigilance, Drowsiness, CRNN, CNN–LSTM/GRU, Multimodal Fusion, EEG, EOG, ECG, Fnirs, PERCLOS, Eye Tracking, Wearable Sensing, Edge AI

I. INTRODUCTION

Mental fatigue (MF) refers to a progressive reduction in cognitive efficiency caused by sustained mental effort, circadian pressure, or sleep restriction. It manifests as slowed reaction times, increased lapses, poorer executive control, and degraded decision-making—factors that elevate risk in safety-critical settings such as driving, aviation, healthcare, and process industries. While MF overlaps with constructs like sleepiness and cognitive load, it is not identical: sleepiness is primarily homeostatic/circadian and can co-occur with MF; cognitive load may be high without fatigue, whereas MF reflects a state change that degrades performance over time. Reliable, continuous estimation of MF thus remains a central challenge for human-centered AI systems.

Historically, MF estimation relied on hand-engineered features computed from single modalities (e.g., band-power from EEG, blink rate from eye tracking, heart-rate variability from ECG/PPG). Such pipelines can be brittle under real-world noise and miss cross-modal dynamics that precede overt lapses. Deep learning shifted the paradigm by learning hierarchical representations directly from raw or weakly processed signals. Yet fatigue is fundamentally temporal and context-dependent: meaningful patterns often unfold over seconds to minutes (e.g., slow blinks, theta augmentation, autonomic drift), motivating architectures that combine strong local feature extraction with explicit temporal modeling.

Multimodal sensing is particularly promising. Physiological channels (EEG, EOG, ECG/PPG/HRV, EDA, respiration, skin temperature, fNIRS) capture complementary neural and autonomic processes; behavioral and non-contact cues (facial video, eye images, head pose, gaze, PERCLOS) reflect overt manifestations; and task interaction traces (typing latency, steering entropy, reaction-time lapses) provide context. Each modality has practical caveats—EEG offers neuronal specificity but needs contact quality; video is convenient but sensitive to lighting and occlusions; wearables are mobile but motion- and physiology-dependent. A robust system must integrate signals opportunistically and remain graceful under missing or corrupted inputs.

Convolutional–recurrent neural networks (CRNNs) provide an attractive inductive bias for this problem. Convolutional front-ends specialize in spatial/spectral feature extraction—from 2D time–frequency maps (spectrograms, wavelets) or 1D temporal sequences—while recurrent back-ends (LSTM/GRU, often bidirectional during training) capture temporal dependencies, state transitions, and micro-event aggregation. Compared with purely convolutional models, CRNNs better encode history; compared with purely recurrent models, they offer locality and parameter efficiency. In multimodal settings, CRNNs can be extended with attention and gating to align asynchronous streams (e.g., EEG↔EOG↔video) and to down-weight unreliable channels. Despite recent interest in Transformers, CRNNs remain highly competitive for on-device or low-latency inference due to their smaller memory footprint, straightforward causality control, and mature optimization toolchains (quantization, pruning).

Several surveys have reviewed drowsiness detection or single-modality EEG approaches, but a focused, methodical synthesis of CRNN-based multimodal modeling of MF—covering input encodings, fusion mechanisms, evaluation protocols, and deployment—has been missing. This review fills that gap by mapping the design space and distilling practical guidance for researchers and practitioners building real-time systems..

II. BACKGROUND

II.1 Conceptual foundations and constructs

Mental fatigue (MF) is a time-on-task–dependent deterioration of cognitive efficiency. It interacts with but is distinct from sleepiness (homeostatic/circadian pressure) and cognitive load (momentary demand). Practically, MF presents as slower reaction times, increased lapses, and executive-control failures even when motivation remains high. In operational settings (driving, air-traffic control, clinical workflows), MF combines with monotony and circadian troughs to produce incident-prone windows.

II.2 Physiological and behavioral correlates

EEG: spectral shifts (theta increase, alpha reorganization), decreased fronto-parietal coherence; event-related slowing.
EOG/ocular metrics: blink duration increase, inter-blink interval variability, saccade peak velocity decrease; PERCLOS — percentage of time eyelids are at least 80% closed over a window T. PERCLOS = 100 * (time closed ≥ 80%) / T.
Autonomic (ECG/PPG/HRV): reduced short-term variability (e.g., RMSSD decrease), LF/HF balance shifts; respiration becomes shallow/irregular.
EDA/skin temperature: phasic EDA burst rate decreases with prolonged effort; distal skin temperature drifts with arousal changes.
fNIRS: prefrontal oxy-/deoxy-hemoglobin trends indicate sustained effort and fatigue-related hemodynamics.
Behavioral/video: yawns, head nods, gaze drift, steering entropy increase, typing/interaction irregularities.

II.3 Data characteristics that complicate modeling

Nonstationarity: state drift across minutes to hours; transient micro-events (microsleeps) lasting less than 2–15 s.
Inter-subject variability: skull conductivity, ocular habits, autonomic tone, medication and caffeine effects.
Artifacts and context: motion, EMG, lighting, occlusions; domain shift between lab and field.
Label ambiguity: subjective scales vs. objective tasks (PVT) vs. proxy signals (PERCLOS); weak alignment across modalities.

III. LITERATURE REVIEW

Kota Aoki et al. (2021) introduced a deep learning-based method for classifying gait cycles into fatigued and non-fatigued categories using a Recurrent Neural Network (RNN). Each gait cycle was represented as a time series of three-dimensional joint coordinates. However, detecting fatigue-related variations proved challenging due to significant intra-class differences, such as whether a cycle begins with the left or right supporting foot. To address this, the researchers developed a supporting-foot-aware RNN within a multi-task learning framework. The model incorporated two branches: one for fatigue classification and another for identifying the initial supporting foot in each gait cycle. Data collected from eight participants demonstrated that this approach improved classification accuracy, achieving an AUC of 0.860 under leave-one-subject-out cross-validation and 0.915 under leave-one-day-out validation. These results suggest strong potential for practical fatigue detection applications, especially for daily screening. [1]

Martin K et al. (1986) investigated how psychological and lifestyle variables influence self-reported chronic fatigue in a national sample of adults. The study revealed that low physical activity, depression, anxiety, and emotional stress were strongly associated with fatigue, acting as independent predictors. The findings also indicated gender differences: women reported fatigue more frequently than men, and overweight women were more prone to fatigue compared to women with lower body weight, although no similar pattern was observed in men. [2]

T. Pawlikowska et al. (1994) conducted a large-scale survey to determine the prevalence of fatigue in the general population and its associated factors. Using the 12-item General Health Questionnaire alongside a fatigue-specific questionnaire, responses from 15,283 participants were analyzed. Results showed that 18.3% (2,798 individuals) experienced substantial fatigue lasting at least six months. Fatigue was moderately correlated with psychological morbidity (r = 0.62), and women reported higher levels than men, even after controlling for psychological distress. Psychosocial factors emerged as the most frequently cited cause (40%), while only 1.4% of individuals attributed their condition to chronic fatigue syndrome. [3]

U. Bültmann et al. (2002) aimed to explore the relationship between fatigue and psychological distress among employees. Data from 12,095 workers revealed significant associations between the two conditions, although fatigue and distress appeared as distinct constructs. The prevalence was 22% for fatigue and 23% for psychological distress. Among employees reporting fatigue, 43% experienced fatigue alone, while 57% also had psychological distress. Demographic factors showed no clear patterns of influence. [4]

Ji-Hoon Jeong et al. (2019) advanced fatigue detection by classifying not only two states (alert and drowsy) but also five levels of drowsiness using EEG signals. Data from ten pilots during simulated night flights were analyzed using a deep spatio-temporal convolutional bidirectional long short-term memory (DSTCLN) network. Classification accuracy reached 0.87 for two mental states and 0.69 for the five drowsiness levels, validating the feasibility of detailed drowsiness classification via EEG. This innovation has strong implications for aviation safety. [5]

Zhongke Gao et al. (2019) proposed the ESTCNN model, designed to capture temporal dependencies in EEG signals through a core temporal block followed by dense spatial feature layers. Tested in driver fatigue experiments with eight participants, the model achieved 97.37% accuracy across 2,800 samples, outperforming traditional machine learning approaches. Its spatio-temporal design improved computational efficiency and reduced latency, supporting real-time brain-computer interface applications. [6].

IV. Method

IV.1 Protocol and reporting standards

We followed the spirit of PRISMA 2020 and the PRISMA-ScR checklist for scoping reviews where applicable to machine learning studies. The review window covered January 2013 through September 2025. A protocol was drafted a priori specifying eligibility criteria, information sources, screening rules, data items, and synthesis plans. Because many ML studies appear first as preprints, we included arXiv submissions when methodological detail was sufficient to reproduce the pipeline.

IV.2 Eligibility criteria

Population: human participants in lab, simulator, or field settings.

Index methods: models that combine a convolutional component with a recurrent component (for example CNN-LSTM or CNN-GRU). Pure CNNs, pure RNNs, and Transformer-only models were excluded unless a clear CRNN baseline was also evaluated.

Targets: mental fatigue, vigilance, or drowsiness, with labels from subjective scales, behavioral tasks, or physiological proxies.

Outcomes: classification metrics (accuracy, balanced accuracy, F1, AUC) and regression metrics (RMSE, MAE, CCC) for continuous vigilance.

Study types: peer-reviewed journal or conference papers, technical reports, and preprints with adequate detail; non-human, simulated-only, or editorial pieces were excluded.

Modality scope: unimodal or multimodal studies were eligible; the focus of synthesis emphasized multimodal pipelines..

V. Conclusion

CRNNs align naturally with the spatiotemporal structure of multimodal fatigue signals, providing a strong baseline for both research and deployment. When paired with robust fusion, calibration, and careful evaluation, they deliver reliable, low-latency monitoring. The field now needs standardized benchmarks, better labels, and principled generalization and interpretability methods to translate prototypes into trustworthy, equitable systems..

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