Feasibility Analysis of Integrating Wearable Cortisol Sensor Data with Machine Learning for Physical Fatigue Identification in Construction Workers

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***Abstract*—Workplace fatigue caused by stress is a significant concern in physically demanding environments such as construction sites, where long hours and strenuous labor increase the risk of injuries and health issues. To address this challenge, we developed a wearable, user-friendly stress sensor capable of monitoring cortisol levels in human sweat—a key biomarker of physiological stress. The sensor incorporates a functionalized aptamer-based assay to enable real-time, on-site tracking of fatigue symptoms. Impedance-based measurements, specifically changes in charge transfer resistance, were recorded from 10 healthy individuals during a physical stress-inducing hammering task. The sensor showed an increase in charge transfer resistance following the onset of the hammering activity, indicating the physical stress experienced by the participants. Furthermore, cortisol sensor data, combined with other physiological metrics like heart rate variability, were incorporated into a machine learning framework to classify participants' fatigue levels. Of the various models evaluated, the support vector machine achieved the highest classification accuracy of 0.764, effectively distinguishing between low, medium, and high fatigue levels based on quantile-based distributions of signal changes. Hence, this work advances the development of a wearable platform for continuous stress and fatigue monitoring, supporting occupational health management in high-risk labor environments.**

Keywords*—*wearable sensor, cortisol, fatigue, machine learning, support vector machine, construction work.

I. INTRODUCTION

An ongoing challenge in physically intensive work environments, such as construction sites, is the lack of proactive tools to detect early signs of fatigue. Identifying fatigue caused by prolonged physical and psychological stress would enable management to take timely preventive measures to safeguard worker health and safety.

Cortisol, a glucocorticoid hormone commonly often called the "stress hormone," is central to the body's stress response via the hypothalamic-pituitary-adrenal (HPA) axis and serves as a key biomarker for stress and fatigue. Ma et al. reported that cortisol-mediated stress, combined with physical fatigue, significantly impacts the safety and health of construction workers [1]. Similarly, Adam et al. identified cortisol as a definitive stress marker for tracking fatigue [2]. Hence, real-time monitoring of cortisol levels can provide valuable insights into workplace-induced stress. Significant research has been devoted to detecting cortisol in human sweat [3], [4]. Hossain et al. designed a laser-induced graphene (LIG) electrode that detected cortisol in sweat at concentrations ranging from 0.1 pM to 1000 nM [5]. Chen et al. developed a molecularly imprinted polymer (MIP)-based wearable sweat sensor capable of detecting cortisol in the range of 0.1 pM to 5 μM, leveraging the diurnal rhythmic pattern of cortisol secretion [6]. Similarly, Wang et al. also proposed an MIP-based carbon nanotube (CNT) electrode that demonstrated cortisol detection within a range of 10^{-3} to 10^{4} nM, with a sensitivity of 189.2 nA/lg(nM) [7]. Despite these advancements, limited efforts have been made to apply sweat cortisol sensors specifically for monitoring physical fatigue in workers.

In this work, we present a wearable sweat cortisol sensor designed for real-world deployment among a sizable group of construction workers to monitor fatigue in high-stress, physically demanding environments. Our sensor leverages a functionalized aptamer-based assay for non-invasive, real-time tracking of cortisol levels in sweat, and demonstrates measurable changes in charge transfer resistance in response to stress-inducing activities. This study classifies construction workers' fatigue data with high accuracy using heart rate variability (HRV) features as the inputs and cortisol levels as the labels for machine learning models. The sensor's ease of use, long-term operability, and the potential to be applicable outside of controlled settings make it a promising tool for continuous occupational stress monitoring, contributing to improved worker health and safety in labor-intensive sectors.

II. CORTISOL SENSOR FABRICATION

A. Chemicals and Materials

Screen-printable carbon (C) and silver (Ag) inks were sourced from Kayaku Advanced Materials, Westborough, MA, USA. Silver-silver chloride (Ag/AgCl) ink and

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chloroauric acid ($HAuCl_4$) were purchased from Sigma Aldrich, St. Louis, MO, USA. Gold (Au) target was purchased from MicroNano Tools/Micromolding Solutions Inc., British Columbia, CA. Cortisol aptamer was procured from Integrated DNA Technologies, Inc., Coralville, IA, USA.

B. Fabrication Process Flow

Initially, a 125-μm thick polyethylene terephthalate (PET) film measuring 1 cm × 2.5 cm was carefully cut to the required dimensions (Fig. 1). The film was then cleaned with a bath sonicator (Cole-Parmer, Vernon Hills, Illinois) at 40 kHz intensity for 10 minutes to ensure proper surface cleaning and removal of contaminants. Next, the working electrode (WE) and counter electrode (CE) were fabricated using carbon ink through a screen printing technique previously developed by our group [8], [9], [10]. After printing, the electrodes were cured in an oven at 120°C for 25 minutes to ensure proper fixation and durability. Following this, gold (Au) was electrochemically deposited onto both the WE and CE using a 5 mM of $HAuCl_4$ solution. This process was conducted using cyclic voltammetry, with 20 consecutive scans performed over a potential range of -1.4 V to -0.5 V. After deposition, the electrodes were rinsed with distilled water to remove any excess gold precursor. A mask was applied to protect the electrodes during subsequent steps. Next, a brush coating of silver-silver chloride (Ag/AgCl) was used to form the reference electrode (RE), ensuring its electrochemical stability. The RE was then cured in an oven at 120°C for 20 minutes. After curing, silver ink (Ag) was brush-coated at the bottom of the tracing to create a conductive path, allowing connection to a 3-pin smart connector for electrical measurements. In the final step, 10 μL of cortisol aptamer solution at a concentration of 10 μg/mL was drop-cast onto the working electrode. This aptamer was prepared from a 100 nmole stock of a DNA oligomer with the sequence: /5ThioMC6-D/GG AAT GGA TCC ACA TCC ATG GATGGGCAATGCGGGGTGGAGAATGGTTGCCGCAC TTCGGCTTCACTGCAGACTTGACGA AGCTT [11]. The aptamer contains a terminal thiol (-SH) group that facilitates strong attachment to the gold (Au) surface of the working electrode. The aptamer-conjugated sensor was then incubated overnight (12 h) at room temperature to allow for efficient binding of the aptamers to the electrode surface. Aptamer conformational switching improves the binding efficiency to its target antigen by offering greater spatial flexibility compared to conventional antibody–antigen interactions [12]. This structural adaptability enhances signal sensitivity and reduces measurement noise. The aptamer's ability to undergo structural rearrangement upon target binding allows for stable signal output following assay incubation, supporting its effectiveness in continuous, real-time monitoring of sweat cortisol directly on the human body.

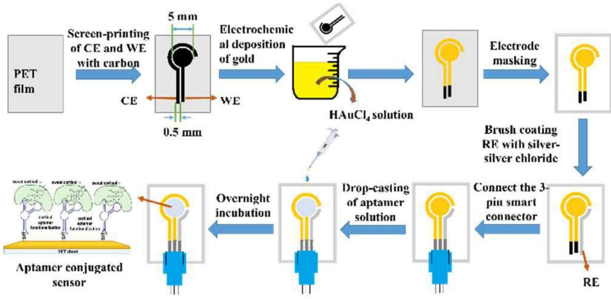

Fig. 1. Step by step fabrication process of the sweat cortisol sensor.

III. METHODOLOGY

A. Data Collection Protocol

Data collection was conducted outdoors at the University of Texas at Tyler during April and May 2025. 13 students participated in the data collection and valid cortisol signals were obtained from 10 individuals. The remaining three participants did not yield detectable sensor readings due to insufficient sweat production during the hammering task. The wearable sweat sensor was mounted on the forearm of these 10 participants and real-time sensor readings were collected using the commercial EmStat4S potentiostat, while each participant performed a controlled physical activity task consisting of hammering nails into a wooden block (Fig. 2). EmbracePlus was also worn by the participants to collect their blood volume pulse (BVP) signal. Each participant hammered 120 nails into the wooden block using two different types of hammers (60 nails per session, two sessions in total). In total, each participant completed around 45 minutes of hammering, divided into two 15-minute sessions, with a short break of 3–5 minutes in between. During the task, cortisol sensor readings, blood volume pulse, video recordings, and self-reported fatigue levels were collected.

To account for individual variability, the real-time cortisol sensor data were expressed as % changes in charge transfer resistance (ΔRct%) over the 45-minute hammering task. Labels were generated based on the ΔRct% from the baseline. Rct reflects the kinetics of the charge transfer process at the interface between the electrode surface and electrolyte (here sweat) in electrochemical impedance spectroscopy (EIS).

All data were collected following the protocol approved by the Institutional Review Board (IRB) at The University of Texas at Tyler, with IRB Protocol 2025-038.

B. Feature Selection and Machine Learning Framework

This study leverages the BVP signal collected by EmbracePlus to extract the HRV features. Previous studies show that HRV features decrease as workers' fatigue levels increase, making them useful indicators of fatigue [13]. Based on this, the BVP signal was segmented using a sliding window method [14]. Specifically, 30 seconds window size with 10 seconds as the moving size were selected for this study. The Neurokit python package was used to extract 68 HRV features, including time-domain features, HRV_Mean, HRV_SDNN, HRV_RMSSD, frequency domain features, HRV_HF, HRV_VHF, and non-linear features, HRV_SampEn, etc. The ΔRct% (Fig. 3) was used as the label for the participant's fatigue level. Fatigue was categorized into three levels - low, medium, and high - based on the quantiles of the signal change distribution. After removing the samples with missing feature values, a total of 886 valid samples were obtained: 421 labeled as low fatigue, 235 as medium fatigue, and 230 as high fatigue.

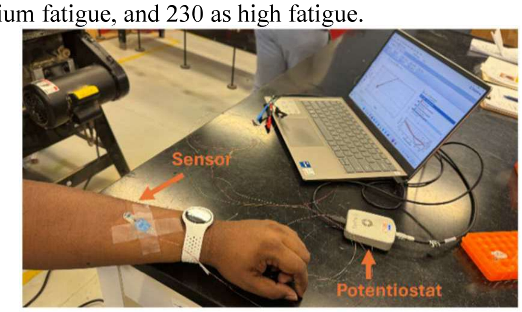

Fig. 2. Schematic representation of sensor mounted on the forearm and data acquisition with the EmStat4S potentisostat.

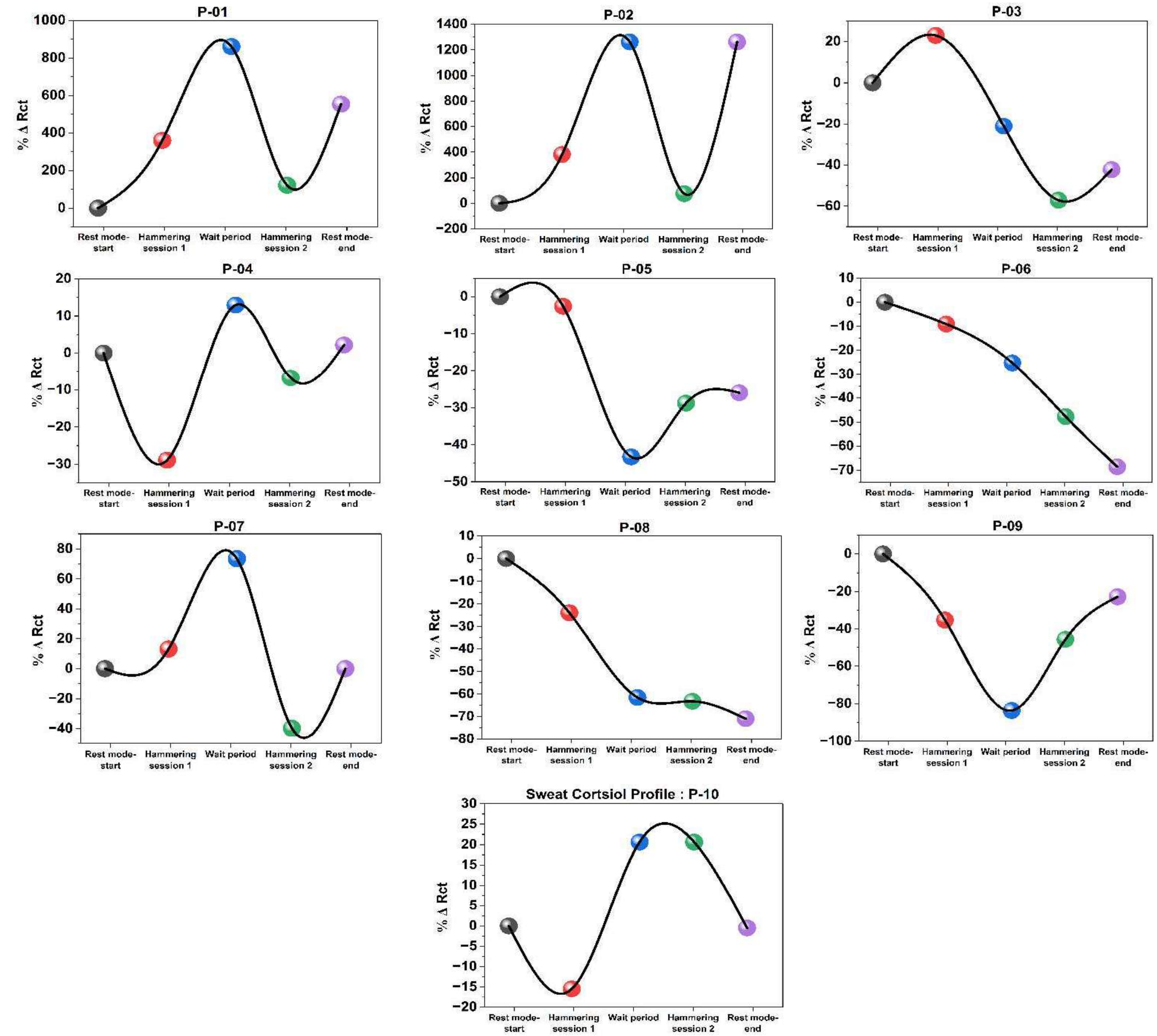

Fig. 3. Real-time sensor responses from 10 participants measured as % change in Rct at different time points.

Feature selection is a critical step in machine learning model development for improving accuracy. Principal Component Analysis (PCA) has proven to be an effective technique for reducing the dimensionality and redundancy of the original features [15]. In this study, PCA was performed on the original set of 68 features, and the converted PCA features which explained 90% of the total variance were selected for model training. In total, 15 PCA features were selected for the machine learning model training. Then, the training and test dataset was split into the ratio of 80% and 20%. Random forest, K Nearest Neighbors (KNN), and Support Vector Machine (SVM) were selected for the machine learning training due to their performance in previous classification tasks.

IV. Results and Discussion

Fig. 3 shows the ΔRct% responses measured in 10 participants across four key time intervals: the first 15-min hammering session, a 5-min waiting period, a second 15-min hammering session, and a final 5-min rest period. All measurements were referenced to the initial resting state. In most participants, Rct values increased during the active hammering sessions or during the wait period between the two hammering sessions, consistent with cortisol release in sweat due to physiological stress. The variations in ΔRct% are attributed to differences in individual sweat cortisol release rates, which can vary widely depending on a person's lifestyle, physical fitness, immunity, and physiological metabolism. These dynamic patterns in sensor readings (i.e., Rct) demonstrate the sensor's capability to capture variations in sweat cortisol levels in real-time. However, some deviations were noted. For example, participant P-06 showed an atypical downward trend in ΔRct%. Participant P-08 also exhibited a gradual decline in sensor signal that stabilized. These observed delays in Rct increase could be attributed to the known physiological time lag associated with cortisol release. Following a stressful event, cortisol is released through activation of the hypothalamic-pituitary-adrenal (HPA) axis and generally appears in blood and saliva within 15 to 30 minutes, and then gradually returns to baseline levels over the next 60 to 90 minutes [16]. Since sweat reflects systemic cortisol with an additional delay due to sweat gland activation and diffusion dynamics, the Rct increase observed during or shortly after the stress activity aligns with this expected physiological lag. These deviations highlight the need for extended on-body monitoring in future phases to better capture individual variability in physiological responses such as sweating rate and stress intensity.

Table I shows the performance of three machine learning models, with SVM achieving the highest accuracy of 0.764, outperforming both the Random Forest and KNN models. Each model's performance was measured by accuracy, precision, recall, and F1-score. The SVM model outperformed the other two approaches across all four metrics. This finding aligns with previous research, which also identified SVM as more effective for fatigue classification using HRV features compared to KNN and tree-based models [17].

The confusion matrix for the SVM model is shown in Fig. 4. The results show that SVM model has the highest accuracy (90.59%) for the medium fatigue level, while accuracy values of 65.96% and 60.87% were obtained for low and high fatigue classes, respectively. However, severe misclassifications are relatively uncommon. For instance, low fatigue being misclassified as high occurred in only 2.13% of cases, while high fatigue being misclassified as low occurred in 15.22% of cases. The latter highlights a critical area for improvement that future study aims to address. The future study will be designed to improve the model's classification accuracy by using deep learning models with a larger dataset, or data fusion of multimodal data, such as HRV and accelerometry features.

V. Conclusion and Future Studies

In summary, we conducted a successful pilot study involving 10 healthy individuals to monitor cortisol levels in sweat generated under stress-inducing conditions. The initial findings demonstrate both the feasibility of the wearable sensor for detecting fatigue and its potential for broader application through integration with machine learning algorithms. These results pave the way for expanded studies aimed at real-time, scalable monitoring of sweat cortisol as an indicator of physical fatigue in operational environments, such as construction sites. In the next phase, a continuous dose-response (CDR) study will be conducted to correlate the Rct with sweat cortisol levels. This calibration plot will be used to derive cortisol concentrations from the measured ΔRct values recorded from the human sweat during physical activity (Fig. 3). Due to the limited number of participants in this study, future study will be designed with larger participants pool to investigate the correlation between HRV features and workers' physical fatigue levels in hammering task. The authors also acknowledge that the hammering tasks were performed over a short duration and not under real construction site conditions. Future work should emphasize large-scale data collection in actual construction settings with diverse participant groups.

TABLE I. Comparison of the Machine Learning Classifiers

	Accuracy	*Precision*	*Recall*	*F1-score*
SVM	0.764	0.79	0.72	0.74
Random Forest	0.747	0.76	0.70	0.72
KNN	0.685	0.69	0.67	0.67

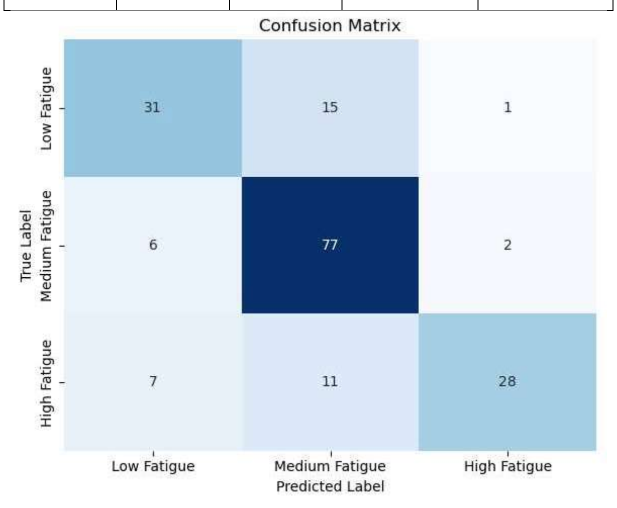

Fig. 4. Confusion matrix for the SVM classifier.

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