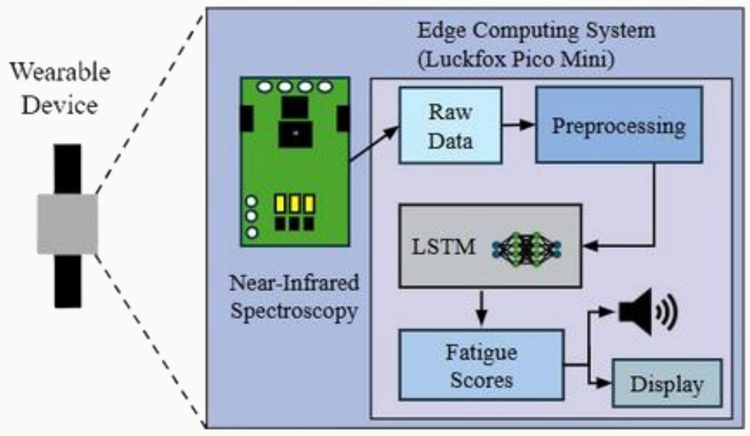
Real-Time Sensing System for Quantifying Muscle Fatigue by Artificial Intelligence and Near-Infrared Spectroscopy

Abstract

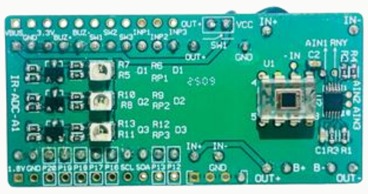
*This project presents an **intelligent wearable system** for real-time muscle fatigue monitoring. Using a near-infrared spectroscopy (NIRS) sensor, the device measures muscle oxygenation levels—specifically oxygenated (HbO_2) and deoxygenated hemoglobin (HHb). The data is processed by a pre-trained AI model on a Luckfox Pico Mini to classify fatigue levels. Visual or audible alerts notify the user when fatigue is detected, helping to prevent overexertion-related injuries.*

System Architecture



Hardware Architecture

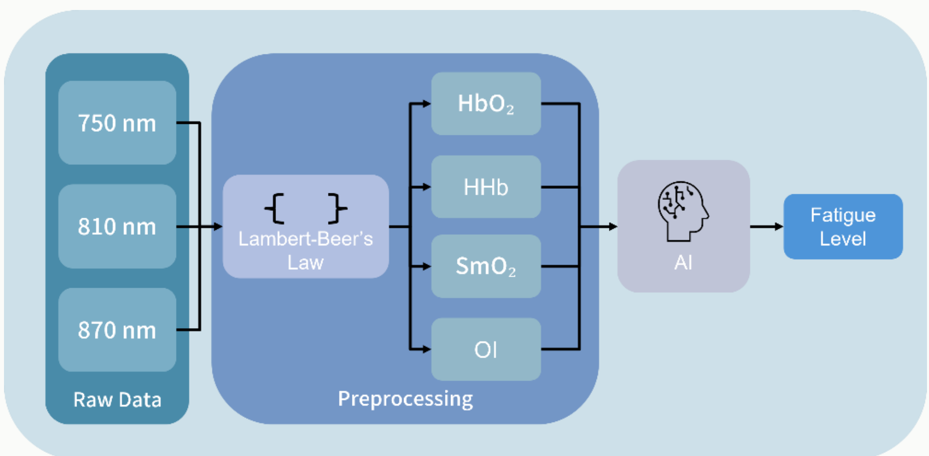
*The hardware device features a **self-designed** NIRS module. On the front of the PCB, three LED emitters are placed on the left, each controlled by an N-Channel MOSFET for sequential activation. On the right is the OPT101 sensor, which converts weak photocurrents into voltage signals, connected to a 16-bit ADS1114 ADC for digital conversion. The back of the PCB includes the Luckfox Pico Mini A board, a boost converter for stable 5V power, and a Type-C charging module for the lithium battery.*



Front of the PCB

Back of the PCB

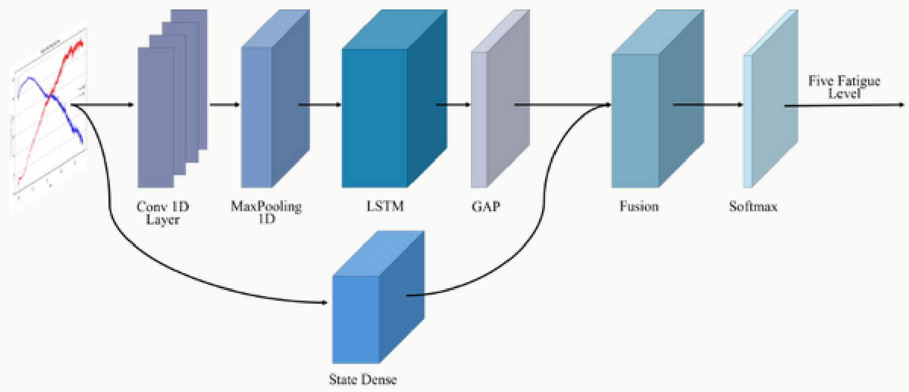
AI Training



This diagram illustrates the training workflow of our model. Signals from three NIRS wavelengths are first processed using the modified Lambert-Beer law to calculate physiological features. These features are then used to train an AI model capable of classifying muscle fatigue into five distinct levels.

AI Model Architecture

This is our designed hybrid deep learning model, which combines a CNN-LSTM architecture for processing time series data with an MLP for statistical features. First, we segment the NIRS data into fixed-length time windows. The time series segments are fed into the CNN-LSTM branch, where the convolutional layers extract local patterns, and the LSTM layers capture temporal dependencies, allowing the model to understand how changes over time affect fatigue states. Simultaneously, we extract statistical features from each time segment, such as the mean and standard deviation, and input these into the MLP branch to capture the overall trends and stability of the data. Finally, the outputs from the time series and statistical feature branches are fused and passed through fully connected layers to classify the data into five fatigue levels.



Results

*This figure compares the performance of our model with other methods. Our hybrid deep learning model achieved the highest accuracy **88.28%**, outperforming LSTM, Transformer, and all traditional models. Classic methods like Random Forest and SVM showed poor generalization on physiological signals, with accuracy around 30%. The results confirm our model's effectiveness in muscle fatigue classification.*

Model Comparison

Model	Accuracy	F1 Score
Our Model	0.8828	0.8835
LSTM	0.8506	0.8519
CNN	0.7707	0.7727
Transformer	0.8050	0.8073
Random Forest	0.3141	0.3062
Bagged Trees	0.3057	0.2981
Boosted Trees	0.3585	0.3406
RBF-SVM	0.3491	0.3144
Cubic SVM (deg = 3)	0.3553	0.3174
Quad SVM (deg = 2)	0.3565	0.3159

Conclusion

Comparison of Muscle Fatigue Assessment Methods

Study	Signal Types	Portable	Real-Time	Quantified Fatigue	Accuracy
Ours	NIRS	Yes	**Yes**	**Yes (5-level)**	88.35%
Zhang et al. (2025)	sEMG	No	No	Yes (3-level)	84.11%
Chua et al. (2025)	Strain sensor	No	Yes	Yes (2-level)	N/A
Li et al. (2025)	sEMG	No	No	No	N/A
Fernandez Schroeder et al. (2024)	sEMG, EIM	No	Yes	No	N/A
Kimono et al. (2023)	EMG, MMG, NIRS	No	No	No	N/A
Gut et al. (2022)	sEMG, MMG, NIRS	No	No	No	N/A
Muramatsu et al. (2013)	NIRS	No	No	No	N/A

*We developed the **first** portable, real-time muscle fatigue monitoring system using only NIRS signals. Unlike prior methods requiring sEMG or MMG, our standalone device features embedded AI to classify fatigue into five levels. It enables personalized feedback during training and supports rehabilitation. A patent has been filed, showing its potential in sports tech and smart healthcare.*