Binary Classifier for Detecting Gas Exchange Shifts During Full Yoga Breathing Using Blood Microcirculation Data

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Abstract – **Full yoga breathing is a technique that involves deep, rhythmic, and conscious respiration aimed at improving physical and mental well-being. However, many practitioners perform it incorrectly, which reduces its effectiveness. Traditional assessment methods, such as visual observation or spirometry with gas analysis, have limitations in terms of accuracy and ease of use. This study presents the development of a binary classifier designed to automatically determine whether a respiratory exercise induces a gas exchange shift, based on blood microcirculation data acquired via a distributed system of Laser Doppler Flowmetry (LDF) analyzers. Data were collected from 28 experienced volunteers who performed full yoga breathing at frequencies of 3–3.5 and 1–1.5 times per minute. LDF sensors were positioned on the forehead and fingertips to capture microvascular responses before, during, and after the exercise. Spirometry with gas analysis was used as reference. The target variable was the achievement of moderate training hypocapnia, defined as end-tidal CO_2 ($PetCO_2$) $\geqslant$ 42 mmHg. Four machine learning models were evaluated: logistic regression, random forest, support vector machine and XGBoost. The XGBoost model achieved the best performance, with an AUC of 0.92 and balanced sensitivity and specificity. These results suggest the potential of LDF-based monitoring and machine learning for objective, non-invasive assessment of respiratory exercise effectiveness. Future work will aim to expand the dataset and validate the model across broader populations.**

Keywords – breathing exercises, blood microcirculation, laser Doppler flowmetry, machine learning, binary classifier, wearable analyzers

I. INTRODUCTION

Full Yoga Breathing (FYB), also known as «complete yogic breathing» is a foundational technique in respiratory rehabilitation and training programs. This practice characterized by the execution of respiratory cycles using the maximum attainable tidal volume – approaching the individual's vital lung capacity – while intentionally adjusting the respiratory rate. This modulation results in a voluntary increase or decrease in minute ventilation [1].

One of the key physiological outcomes of FYB is a shift in alveolar ventilation, which directly impacts blood gas composition. Depending on the breathing frequency and volume, different patterns may emerge, including hypocapnia (reduced arterial CO_2), hypercapnia, or normocapnia. Among these, moderate hypocapnia – defined as a measurable reduction in end-tidal CO_2 ($PetCO_2$) – has been associated with improved cerebral blood flow, and therapeutic effects in stress regulation, normalizing blood pressure and respiratory rehabilitation [2, 3]. Thus, the presence or absence of such gas exchange shifts may serve as a meaningful physiological marker of breathing exercise effectiveness [4].

Breath modulation induces adaptive responses in the microcirculatory system, particularly through activation of endothelial and neurogenic mechanisms. A previous study demonstrated that FYB practices influence skin blood perfusion and nutritive flow in both central (supraorbital) and peripheral (fingers, toes) regions, with especially strong effects observed under low-frequency breathing (1–1.5 breaths/min) [1]. These effects are measurable using Laser Doppler Flowmetry (LDF), a non-invasive optical method sensitive to changes in microvascular dynamics. In particular, changes in amplitude of oscillations associated with endothelial (Ae), neurogenic (An), and cardiac (Ac) regulation circuits have been shown to correlate with breathing depth and gas exchange parameters [1].

Despite its physiological significance, hypocapnia remains difficult to assess outside clinical settings, as it typically requires capnography or gas analysis. Visual assessment or wearable devices that monitor only breathing rate are insufficient for determining whether gas exchange has been meaningfully affected. To address this gap, modern approaches suggest utilizing indirect physiological markers, such as blood microcirculation, for assessing the efficacy of breathing practices. However, interpreting these data requires advanced analytical techniques capable of distinguishing meaningful patterns that reflect not just respiratory effort, but actual shifts in gas exchange.

Machine Learning (ML) offers a promising framework for such analysis. By training models on labeled datasets, it is possible to automatically detect complex patterns in physiological signals and classify breathing performance with high accuracy. Recent study has demonstrated successful application of ML in analyzing LDF signals [5].

The present study aims to develop a binary classifier capable of determining a respiratory exercise induces a gas exchange shift, using LDF-derived microcirculation features as input and spirometry with gas analysis-based level of end-tidal CO_2 as the ground truth label [2]. The classifier is trained and validated on data from yoga practitioners performing FYB at various frequencies. The ultimate goal is to provide a lightweight, non-invasive tool that enables real-time assessment of breathing quality.

II. Materials and Methods

A. Participants

The dataset from the 28 experienced participants (22 men and 6 women; mean age: 41 ± 9 years) was used for model development and internal evaluation via cross-validation. An independent validation group consisting of 9 participants (5 men and 4 women; mean age: 35 ± 11 years) was used to evaluate the model's generalization to unseen individuals. This group was not involved in model training and served as a real-world proxy for out-of-sample inference. All participants were self-reported as healthy, non-medicated, and free from chronic cardiovascular or respiratory diseases. The study protocol was approved by the local ethics committee, and written informed consent was obtained.

B. Breathing Protocol

Participants included in the model cohort performed FYB at two controlled frequencies:

- 1-1.5 breaths per min (0.0167-0.025 Hz) with an inhalation-to-exhalation ratio ranging from 30:30 to 20:20 s.
- 3-3.5 breaths per min (corresponding to 0.05-0.06 Hz) with an inhalation-to-exhalation ratio of approximately 10:10 s.

Each breathing session lasted 5 min and was preceded and followed by a 6 min resting phase with spontaneous breathing (Fig. 1).

As demonstrated in prior research, 3 breaths per min led to alveolar hypocapnia, while 1–1.5 breaths per min produced mild hypercapnia, a hallmark of hypoxic-hypercapnic training with neuroprotective potential [4].

Participants in the validation group followed a similar breathing protocol. Three experienced practitioners performed FYB at the frequencies of 1–1.5 breaths per min. The remaining six participants, who had no prior experience, performed FYB at a frequency of 6 breaths per min (0.1 Hz) with a 5:5 second inhalation-to-exhalation ratio. This higher-frequency pattern is associated with mild hyperventilation and typically results in a decrease in end-tidal CO_2 ($PetCO_2$) [6].

C. Data Acquisition

1) Laser Doppler Flowmetry (LDF)

Microcirculation data were recorded using a distributed system of wearable LDF analyzers LAZMA PF (LAZMA Ltd., Russia), which measure perfusion and the amplitudes of oscillations associated with various regulatory mechanisms [7].

The analyzers were attached bilaterally to the forehead (over the supraorbital arteries) and to the middle fingertips of both hands, as shown in Fig. 2.

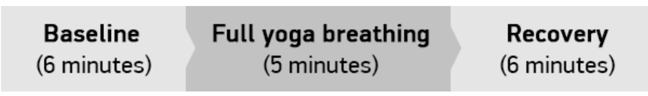

Fig. 1. Breathing protocol phases

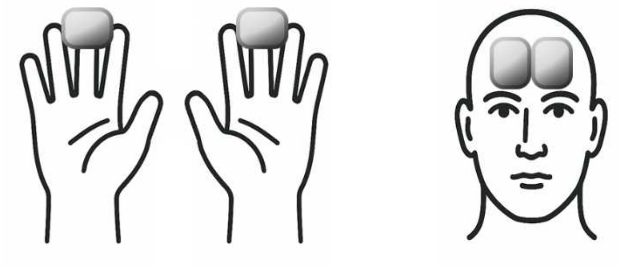

Fig. 2. LDF analyzers arrangement in the experiments

LDF signals were recorded during three phases of breathing protocol. The following features were extracted from LDF signals – index of microcirculation (IM), nutritive blood flow (Imn), coefficient of variation (Kv), standard deviation (σ), amplitudes of endothelial (Ae), neurogenic (An), myogenic (Am), respiratory (Ar) and cardiac (Ac) oscillations.

2) Spirometry and Gas Analysis

A calibrated MAC-2C spirometer with gas analysis and pulse oximetry capability (Belintelmed, Belarus) was used to assess respiratory parameters: Respiratory Rate (RR), Tidal Volume (TV), Minute Ventilation (MV), end-tidal carbon dioxide ($PetCO_2$), end-tidal oxygen (FeO_2), O_2 saturation (SpO_2). Participants performed breathing through a mouthpiece with nasal airflow blocked to ensure accurate volume measurements.

D. Target Variable and Labeling

The target variable was defined as the presence or absence of a physiologically meaningful shift in gas exchange, specifically the achievement of moderate hypercapnia during the breathing exercise. End-tidal carbon dioxide ($PetCO_2$) was used as the reference parameter, measured via spirometry with gas analysis. A threshold of $PetCO_2 \geqslant 42$ mmHg was selected based on prior findings indicating this level as a marker of effective alveolar hypoventilation and engagement of hypoxic-hypercapnic training mechanisms [4].

E. Machine Learning Approach

Five supervised learning algorithms were trained to classify gas exchange shifts: Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVC) and Extreme Gradient Boosting – XGBoost (XGB).

The input feature set consisted of microcirculatory parameters derived from LDF sensors, including both absolute values and delta features – temporal differences between baseline and recovery after FYB, which enabled the model to capture dynamic vascular responses to respiratory effort. Additionally, the respiratory rate (frequency of FYB) was included as a global feature. The target label was defined using $PetCO_2$, but this parameter was not used as an input. Thus, the model relied entirely on microcirculation and respiratory rhythm data to infer physiologically meaningful gas exchange shifts induced by the breathing protocol.

A 5-fold cross-validation procedure was applied to assess model performance and ensure robustness across different data splits. Performance metrics included sensitivity (Sn), specificity (Sp), f1-score (f1) and area under the receiver operating characteristic curve (AUC).

III. Results

A. Model Performance

Table I presents the classification metrics across all models on the validation set.

The Extreme Gradient Boosting (XGB) model demonstrated the best overall performance during training (Fig. 3), with an AUC=0.92, f1=0.80, Sn=0.85 and Sp=0.76. It also maintained good generalization on the validation set, achieving an AUC=0.71, f1=0.67, Sn=0.50 and Sp=1.00, indicating its suitability for identifying gas exchange shifts during respiratory exercises.

B. Feature Importance

To identify which physiological features most strongly influenced the classifier's decision, a permutation importance analysis was conducted using the XGB model. The most informative predictors were: the change in the coefficient of variation of perfusion in the forehead area, respiratory rate and the change in endothelial oscillation amplitude on the forehead. Signals from the forehead contributed more substantially than those from the fingertips.

IV. Discussion

This study demonstrated that features of blood microcirculation, measured non-invasively using LDF, can be used to detect physiologically meaningful shifts in gas exchange during full yoga breathing practices. Specifically, the developed XGB model was able to predict the presence of moderate training-induced hypercapnia showing balanced performance on both internal and external validation.

Feature importance analysis revealed that the model relied on changes in the overall variability of perfusion, respiratory rate and endothelial-related oscillatory signals from the forehead region. This finding supports that cerebral microvascular beds are highly sensitive to CO_2 fluctuations induced by respiration, highlighting the diagnostic potential of forehead microcirculation for gas exchange assessment. At the same time, the model indicated that the physiological response to gas exchange shifts may be localized within specific analyzers, reinforcing the importance of targeted analyzers placement in future research.

However, several limitations must be acknowledged. The sample size was small, especially in the external validation group. While cross-validation helps mitigate overfitting risk, larger and more diverse datasets are necessary to ensure broader generalizability. Future work should explore alternative analyzers configurations and adaptive modeling approaches optimized for deployment in wearable systems.

TABLE I. Classifier Performance

Model	Performance Metrics			
	Sensitivity	*Specificity*	*f1-score*	*AUC*
XGB	0.85	0.76	0.80	0.92
RF	0.77	0.42	0.31	0.98
LR	0.68	0.45	0.42	0.77
SVC	0.61	0.26	0.21	0.82

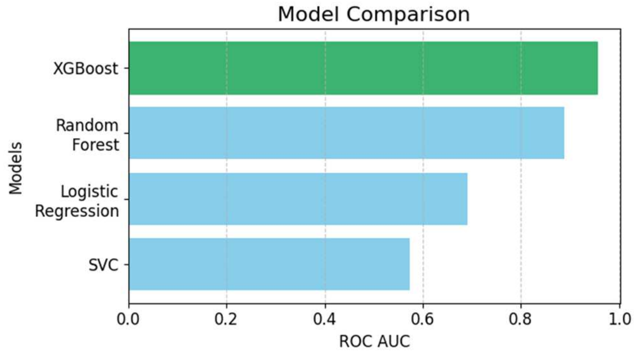

Fig. 3. Model comparison by ROC AUC

V. Conclusion

Developed and evaluated a machine learning classifier capable of detecting whether a full yoga breathing session induces a physiologically significant shift in gas exchange – specifically, moderate hypercapnia – based on microcirculatory data obtained via wearable LDF analyzers. This approach offers a novel, non-invasive method for assessing the physiological effectiveness of respiratory training. It can potentially be integrated into wearable biofeedback systems for self-guided breathing therapy, stress regulation, or respiratory rehabilitation. Future work will focus on expanding the dataset, refining analyzers placement, and testing the model across broader populations.

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