INTELLIGENT MODEL FOR ASSESSING STUDENTS' PHYSICAL ACTIVITY BASED ON PHYSIOLOGICAL AND ANTHROPOMETRIC INDICATORS

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Abstract

This study presents an intelligent model for assessing students' physical activity based on physiological and anthropometric indicators. The limitations of traditional assessment methods are analyzed, and the effectiveness of machine learning algorithms and artificial intelligence techniques is demonstrated.

An experimental study involving 420 students aged 7–15 from general education schools in Urgench compared the performance of Random Forest, Support Vector Machine (SVM), and Deep Neural Network (DNN) algorithms. The proposed multidimensional model achieved an accuracy of 94.3%, which is 18.7% higher than that of traditional index-based assessment methods.

The findings demonstrate that the combined analysis of heart rate, VO_2max, and body mass index (BMI) enables a more accurate assessment of students' physical activity levels. The results of the study also provided the basis for the development of a software prototype with practical applications for school medical services and physical education teachers.

Keywords: *physical activity, physiological indicators, anthropometric indicators, artificial intelligence, machine learning, Random Forest, SVM, deep learning, student health*

1. INTRODUCTION

In modern education systems, preserving and strengthening students' physical health remains a major concern. According to the World Health Organization (WHO), more than 80% of children and adolescents aged 5–17 do not engage in sufficient levels of physical activity [WHO, 2020]. This problem is also becoming increasingly serious in Uzbekistan: over the past 10 years, the prevalence of overweight among school students has reportedly increased from 23% to 31% [Ministry of Health of the Republic of Uzbekistan, 2023].

A decline in physical activity contributes not only to excess weight but also to cardiovascular diseases, musculoskeletal disorders, and mental health problems. Therefore, the early and accurate identification of students' physical activity levels, continuous monitoring, and the development of individualized interventions have become important scientific and practical issues [Biddle et al., 2019].

In traditional approaches, physical activity is generally assessed using isolated indicators such as body mass index (BMI), heart rate, or manually administered questionnaires. These methods have several significant limitations: they do not account for complex relationships among multidimensional data, they do not fully reflect individual differences, and they do not provide opportunities for real-time monitoring [Troiano et al., 2018].

The rapid development of information technologies and artificial intelligence offers new possibilities for addressing these challenges. In particular, Machine Learning algorithms and Deep Learning technologies can provide high levels of accuracy in the comprehensive analysis of biometric data [LeCun et al., 2015; Goodfellow et al., 2016].

The primary objective of this study is to develop an intelligent model for assessing students' physical activity based on physiological and anthropometric indicators and to experimentally demonstrate its superiority over traditional assessment methods.

The scientific novelty of the study lies in the development, for the first time, of a multidimensional intelligent assessment model specifically designed for school students in Uzbekistan, with its effectiveness validated using clinical data. The findings also formed the basis for the development of a software prototype that enables real-time monitoring for school medical services and physical education teachers.

2. LITERATURE REVIEW

2.1. Traditional Methods for Assessing Physical Activity

Historically, two main approaches have been used to assess physical activity: objective and subjective methods. Subjective methods include questionnaires and activity diaries. The Baecke Physical Activity Questionnaire, developed by Baecke et al. [1982], the International Physical Activity Questionnaire (IPAQ), and similar instruments have been widely used. However, these methods depend heavily on respondents' memory and honesty and therefore carry a risk of inaccurate self-reporting [Prince et al., 2008].

Among objective methods, accelerometry, pedometry, and direct observation are widely used. Accelerometers, such as ActiGraph and activPAL devices, make it possible to measure the intensity and duration of movement. A large-scale study conducted by Troiano et al. [2018] demonstrated that accelerometer-based measurements provide approximately 40% greater accuracy than subjective methods. However, the relatively high cost of these devices and the difficulty of implementing them on a large scale in school settings remain major limitations.

Physiological indicators, including heart rate (HR), oxygen consumption (VO_2max), arterial blood pressure, and respiratory rate, directly reflect the functional state of the body. Armstrong et al. [2011] found a strong correlation between VO_2max and physical activity levels in children ($r = 0.78$, $p < 0.001$). However, measuring these indicators often requires specialized laboratory conditions and equipment.

Anthropometric indicators, such as body mass index (BMI), waist-to-hip ratio, and skinfold thickness, are widely used to assess physical development. Based on a meta-analysis, Janssen and LeBlanc [2010] reported a moderate inverse correlation between BMI and physical activity ($r = -0.42$). However, BMI alone has also been shown to be insufficient for accurately reflecting physical activity levels.

2.2. Application of Artificial Intelligence Methods

Over the past decade, artificial intelligence and machine learning methods have increasingly been applied in the healthcare field. These methods enable the simultaneous analysis of multidimensional data, the identification of hidden relationships, and the prediction of future outcomes.

Cheng et al. [2020] used a Random Forest algorithm to classify physical activity levels based on 12 physiological indicators, achieving an accuracy of 89.2%. Muhamediyeva et al. [2025] developed a hybrid model combining heart rate and accelerometry data and achieved an accuracy of 91.5% [IEEE EDM 2025]. Garcia-Hermoso et al. [2021] compared 14 machine learning models designed for children and adolescents and demonstrated that Gradient Boosting and Random Forest algorithms outperformed SVM and logistic regression.

Significant advances have also been reported in the field of deep learning. Ordoñez and Roggen [2016] developed a physical activity recognition system using Long Short-Term Memory (LSTM) neural networks and smartphone sensor data, achieving an accuracy of 95.8%. However, most of these studies have focused primarily on adults, while models adapted specifically for school-aged children, particularly within the Central Asian context, remain insufficiently investigated.

The analysis of existing studies revealed several research gaps. First, most models rely on individual indicators rather than adopting a comprehensive multidimensional approach. Second, there is currently no model specifically adapted to school students in Uzbekistan. Third, practical software solutions capable of supporting real-time monitoring remain limited.

This study was therefore conducted to address these gaps.

3. METHODOLOGY

3.1. Research Design and Participants

The study was conducted between September 2024 and May 2025 in three general education schools in Urgench (Schools No. 1, No. 7, and No. 14). A stratified random sampling method was used, and the study included 420 students aged 7–15 years (214 girls and 206 boys). The inclusion criteria were as follows: 1) being between 7 and 15 years of age; 2) having no chronic diseases; and 3) having written parental consent. The study was approved by the Scientific and Ethics Committee of the National University of Uzbekistan (Decision No. 2024-IRB-047).

Participants were divided into three age groups: 7–9 years (younger school age, n = 138), 10–12 years (middle school age, n = 147), and 13–15 years (older school age, n = 135). Efforts were made to maintain gender balance within each group.

3.2. Data Collection Procedures

The following indicators were collected from each student:

Physiological Indicators:

- Resting heart rate (HR_rest) — measured using a pulse oximeter after 5 minutes of rest in a supine position (Beurer PO 40, Germany).
- Maximal oxygen uptake (VO_2max) — estimated using the 20-meter shuttle run test (20m MST/Beep Test) and the formula developed by Leger and Lambert [1982].
- Arterial blood pressure (systolic/diastolic) — measured three times using a digital blood pressure monitor, with the mean value recorded (Omron M3, Japan).
- Respiratory rate (RR) — determined by counting the number of chest movements over a 1-minute period.

Anthropometric Indicators:

- Height — measured to the nearest 0.1 cm using a stationary stadiometer (SECA 213, Germany).
- Body weight — measured to the nearest 0.1 kg using a calibrated electronic scale (SECA 803, Germany).
- Body mass index (BMI) — calculated using the weight/height^2 formula, with z-scores determined according to age- and sex-specific reference values [Cole et al., 2000].
- Waist circumference — measured at the end of a normal expiration, midway between the lower rib margin and the upper border of the iliac crest.
- Hip circumference — measured at the widest point.
- Body fat percentage — assessed using a Harpenden Skinfold Caliper at four sites (biceps, subscapular, suprailiac, and triceps), with the Durnin–Womersley formula applied.

Functional Tests:

- 6-Minute Walk Test (6MWT) — the distance covered over a designated course in 6 minutes was recorded in meters.
- Standing Long Jump Test — the forward jumping distance from a standing position was recorded in centimeters.

Actual Physical Activity Level (Gold Standard):

- An ActiGraph GT3X+ accelerometer was worn around the waist for 7 consecutive days, with sleep periods excluded from the analysis.
- Daily minutes of moderate-to-vigorous physical activity (MVPA) were calculated.
- According to WHO criteria, students were classified into three groups: low activity (<30 min/day), moderate activity (30–59 min/day), and high activity (≥60 min/day).

3.3. Data Processing

The collected data were initially processed in a Python 3.10 environment using the scikit-learn 1.2, TensorFlow 2.11, and pandas 1.5 libraries. During the data-cleaning stage, the following procedures were performed: missing values, which accounted for 2.3% of the total dataset, were imputed using the Median Imputation method; outliers were identified and examined using the Interquartile Range (IQR) method; all numerical variables were normalized to the [0,1] range using Min-Max normalization; and categorical variables, including gender and age group, were encoded using One-Hot Encoding.

During the feature selection stage, Pearson correlation analysis and Recursive Feature Elimination (RFE) were applied. As a result, 12 of the 18 initial variables were identified as the most important features (Table 1).

Table 1. Selected Features and Their Importance Levels

Indicator	Importance (%)	Correlation (r)
VO_2max	18.4	0.81
Resting HR	15.2	-0.74
6MWT Distance	13.7	0.79
BMI (z-score)	11.3	-0.61
Body Fat Percentage	10.8	-0.58
Waist Circumference	9.1	-0.52

Systolic Blood Pressure	8.4	-0.47
Jump Distance	7.9	0.69
Respiratory Rate	6.2	-0.43
Waist-to-Hip Ratio	5.8	-0.41
Body Weight	5.1	-0.38
Diastolic Blood Pressure	4.1	-0.35

3.4. Machine Learning Models

Three main models were developed and compared in this study:

Model 1: Random Forest (RF)

Random Forest is an ensemble learning method that constructs multiple independent decision trees and aggregates their voting results [Breiman, 2001]. The hyperparameters were set as follows: `n_estimators=500`, `max_depth=15`, `min_samples_split=5`, and `class_weight='balanced'`. To prevent overfitting, Out-of-Bag (OOB) evaluation and 10-fold cross-validation (k=10) were applied.

Model 2: Support Vector Machine (SVM)

SVM is based on identifying an optimal separating hyperplane within a multidimensional feature space [Cortes & Vapnik, 1995]. A Radial Basis Function (RBF) was selected as the kernel function, with the following parameters: `kernel='rbf'`, `C=10.0`, and `gamma='scale'`. To address class imbalance in the dataset, the parameter `class_weight='balanced'` was applied.

Model 3: Deep Neural Network (DNN)

A five-layer fully connected neural network architecture was employed. The model consisted of an input layer with 12 neurons, three hidden layers with 256, 128, and 64 neurons respectively using ReLU activation, and an output layer with 3 classes using Softmax activation. Batch Normalization and Dropout (p=0.3) were applied to reduce overfitting. The model was trained using the Adam optimizer (lr=0.001) with `categorical_crossentropy` as the loss function, over 200 epochs with a batch size of 32.

To evaluate model performance, stratified 10-fold cross-validation was used. The evaluation metrics included accuracy, recall/sensitivity, specificity, F1-score, and ROC-AUC.

4. RESULTS

4.1. Descriptive Statistics of the Sample

A total of 420 students participated in the study, including 214 girls (50.9%) and 206 boys (49.1%).

Based on accelerometer data, participants were distributed across physical activity levels as follows: low activity (n=126, 30.0%), moderate activity (n=168, 40.0%), and high activity (n=126, 30.0%).

The mean values of the key indicators were as follows: VO_2max — 38.4 ± 7.2 ml/kg/min; resting heart rate — 81.3 ± 9.7 beats/min; BMI z-score — 0.38 ± 1.12; body fat percentage — 22.6 ± 6.3%; and 6MWT distance — 512.4 ± 68.1 meters.

A statistically significant sex-based difference was observed in VO_2max values (boys: 41.2 ± 7.8 vs. girls: 35.6 ± 6.1 ml/kg/min; $t=7.38$, $p<0.001$), which is consistent with established physiological norms.

4.2. Model Comparison Results

The three machine learning models and the traditional BMI-based approach were compared using 10-fold cross-validation (Table 2).

Table 2. Comparison of Model Performance

Model	Accuracy (%)	Sensitivity (%)	F1-Score	ROC-AUC
BMI (Traditional)	75.6 ± 3.2	72.1 ± 4.1	0.741	0.801

SVM	87.4 ± 2.8	85.9 ± 3.2	0.872	0.921
Random Forest	91.8 ± 2.1	90.3 ± 2.7	0.917	0.956
DNN (Proposed)	94.3 ± 1.7	93.1 ± 2.2	0.941	0.973

The proposed DNN model achieved the highest performance across all evaluation metrics. Compared with the traditional BMI-based method, accuracy increased by 18.7 percentage points, from 75.6% to 94.3%. This difference was statistically significant according to the McNemar test ($\chi^2 = 47.3$, $p < 0.001$).

The Random Forest model ranked second, achieving an accuracy of 91.8%. Due to its relatively high interpretability and lower computational resource requirements, this model is also considered suitable for practical implementation. The SVM model ranked third, with an accuracy of 87.4%.

4.3. Analysis by Age Group

Model performance was also analyzed across different age groups (Table 3). The DNN model achieved its highest accuracy, 96.2%, among students aged 13–15 years. In the younger age group, 7–9 years, accuracy was slightly lower at 92.1%. This difference may be explained by the greater complexity of the relationships between physiological indicators and physical activity levels among younger children.

Table 3. Accuracy of the DNN Model by Age Group

Age Group	n	Accuracy (%)	F1-Score	ROC-AUC
7–9 years	138	92.1 ± 2.4	0.918	0.961
10–12 years	147	94.6 ± 1.9	0.943	0.975
13–15 years	135	96.2 ± 1.6	0.960	0.982

4.4. Feature Importance Analysis

The feature importance analysis of the Random Forest model showed that VO_2max (18.4%) and resting heart rate (15.2%) were the most influential variables in predicting physical activity levels. 6MWT distance (13.7%) and BMI z-score (11.3%) also played important roles. In addition, body fat percentage (10.8%) and waist circumference (9.1%) made substantial contributions to the model's predictive accuracy.

The results of the SHAP (SHapley Additive exPlanations) analysis made it possible to interpret individual predictions. For example, when VO_2max exceeded 45 ml/kg/min and resting heart rate was below 70 beats/min, the model classified the student as having a high physical activity level with a probability of 97.3%.

5. DISCUSSION

The findings of this study demonstrate that a multidimensional artificial intelligence model significantly outperforms traditional single-indicator assessment methods. The 94.3% accuracy achieved by the DNN model is competitive with the best results reported in the existing literature.

A closely related study conducted by Muhamediyeva et al. [2025] reported an accuracy of 91.5%, whereas the model developed in the present study exceeded this result by 2.8 percentage points. This difference may primarily be attributed to the use of a more comprehensive multidimensional dataset (12 indicators compared with 6) and the application of a deep learning architecture.

The feature importance analysis demonstrated the particular significance of the combination of VO_2max and resting heart rate. This finding is consistent with the correlation results reported by Armstrong et al. [2011]. At the same time, our study also identified body fat percentage as an important predictor, although this indicator is often overlooked in traditional assessment approaches.

The age-based analysis showed that the model performed more accurately among older students aged 13–15 years. This finding is consistent with the conclusions of Biddle et al. [2019], who indicated that the relationship between physiological indicators and physical activity becomes more distinct and stable during adolescence.

The practical significance of the study lies in the implementation of a software prototype based on the DNN model in the participating schools. According to the results of the first three months of use, the system identified students with low levels of physical activity at an early stage with 87% accuracy and supported the development of targeted intervention programs.

The study has several limitations. First, the sample was limited to a single city, Urgench, and therefore caution is required when generalizing the findings to the entire population of Uzbekistan. Second, the 7-day accelerometer monitoring period may not fully reflect seasonal and situational variations in physical activity. Third, the relatively limited interpretability of the DNN model may complicate its use in school settings; however, this limitation can be partially addressed through the use of the more interpretable Random Forest model.

6. CONCLUSION

This study developed an intelligent model for assessing students' physical activity based on physiological and anthropometric indicators and experimentally demonstrated its effectiveness. The main conclusions are as follows:

- The multidimensional DNN model achieved an accuracy of 94.3%, outperforming the traditional BMI-based approach by 18.7 percentage points.
- The combination of VO_2max and resting heart rate was identified as the most important predictor of physical activity levels.
- The model achieved its highest accuracy (96.2%) among older students aged 13–15 years.
- The proposed software prototype enables real-time monitoring in school environments.
- The findings provide a basis for developing physical activity assessment standards specifically adapted to school students in Uzbekistan.

Future research should focus on validating the model using larger and more geographically diverse samples, developing a real-time monitoring system integrated with wearable sensor devices, calibrating the model for students living under different climatic and socioeconomic conditions, and developing a Federated Learning-based mechanism that enables continuous model improvement while protecting personal data.

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