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Implementation of Artificial Intelligence (AI) Machine Learning for Analysis of Physical Activity Behavior, Sedentary Behavior, and Obesity Risk

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ABSTRACT

The prevalence of obesity has become a global issue affecting all countries. Physical activity and sedentary behavior are believed to be key factors contributing to obesity. This study aims to examine the relationship between physical activity and sedentary behavior with Body Mass Index (BMI) using machine learning algorithms. A total of 280 students from various programs at Universitas Pendidikan Indonesia participated in this study (101 males and 179 females), aged between 17 and 23 years. Physical activity was measured using the Actigraph GT3X accelerometer. Seven machine learning algorithms—including Naïve Bayes, Support Vector Machine (SVM), local k-nearest neighbors (KNN), Classification via Regression (CVR), decision tree, random forest, and artificial neural network (ANN)—were applied to predict obesity risk. The RapidMiner software was used for testing. Based on the variables of physical activity, sedentary behavior, and demographic factors, SVM demonstrated the highest accuracy (74.22%) among the algorithms. For sensitivity and specificity, ANN and decision tree performed best, with values of 72.27% and 77.5%, respectively. Physical activity, total Metabolic Equivalent of Task (MET), and sedentary duration are significant predictors of obesity risk. Promoting physical activity and implementing campus policies are essential to reduce obesity prevalence among students.

Keywords: algorithm; BMI; machine learning; obesity; physical activity

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INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) technologies have shown great potential across various sectors, including healthcare (Rubinger et al., 2023). In this field, AI and ML offer more effective and efficient solutions for analyzing complex and large datasets, enabling smarter, data-driven decision-making (Kibria et al., 2018). One promising application of AI and ML is in understanding patterns in physical activity behavior, sedentary behavior, and obesity risk (Farrahi & Rostami, 2024; Lavanya & Sivaraman, 2024), which is the main focus of this research.

Physical activity is a key component in maintaining physical and mental health (Ambrosio et al., 2024). Numerous studies have demonstrated that sufficient physical activity can reduce the risk of various chronic diseases, including obesity (Suminski et al., 2024; Chen et al., 2024; Brittain et al., 2024), type 2 diabetes (Amin et al., 2023; Gallardo-Gómez et al., 2024; Pai et al., 2024; Strain et al., 2023), heart disease (Cleven et al., 2020; Ko et al., 2018; Kyu et al., 2016), and other metabolic disorders. Conversely, sedentary behavior, or the habit of prolonged sitting without significant physical activity, has been identified as a major risk factor for obesity (Bell et al., 2014; Biddle, García, & Wiesner, 2017; Biddle et al., 2017; Silveira et al., 2022; van Poppel et al., 2019) and related diseases. The prevalence of sedentary behavior is currently increasing (Aldenaini et al., 2020; Basset et al., 2015; Du et al., 2019; Venetsanou et al., 2020; Yang et al., 2019) due to a modern lifestyle that is increasingly automated and sedentary.

Obesity has become a serious global health issue (Friedrich, 2017; Haththotuwa, 2020; Jaacks, 2019; Malik, 2022). According to World Health Organization (WHO) data, the number of people suffering from obesity has risen significantly over recent decades (WHO, 2018). Obesity not only increases the risk of chronic diseases but also has substantial economic and social impacts (Egger & Dixon, 2014; Chu et al., 2018), such as rising healthcare costs and decreased workforce productivity (Biener et al., 2018; Goettler et al., 2017; Okunogbe et al., 2021). Therefore, understanding the factors contributing to obesity, such as lack of physical activity and high sedentary behavior, is crucial for more effective prevention efforts.

However, a major challenge in studying physical activity and sedentary behavior is the complexity of the generated data (Jankowska, Schipperijn, & Kerr, 2015). With the increasing use of wearable devices, such as smartwatches and other sensors, data related to physical and sedentary activities can now be collected in real-time in massive amounts (Loveday et al., 2015; Staudenmayer et al., 2015). This data includes various variables, such as activity intensity, duration, time patterns, and context in which the activity occurs. Given the large volume and complexity of variables, traditional data analysis methods often fail to provide in-depth understanding (Sivarajah et al., 2017).

This is where AI and ML technologies are highly relevant. ML algorithms, which have the capability to learn from data and uncover hidden patterns, offer great potential in analyzing physical activity and sedentary behavior (Farrahi & Rostami, 2024; Kańtoch, 2018). By using AI, we can identify correlations and patterns that are difficult for humans to detect, such as how the interaction of various environmental, social, and individual factors affects obesity risk. Furthermore, AI can also provide predictions of potential future obesity risks based on individual behavioral data in real-time, allowing for early intervention (Ellahham, 2020; Stein & Brooks, 2017; Triantafyllidis et al., 2020).

This study aims to explore in more depth how AI and ML can be implemented in the analysis of physical activity behavior, sedentary behavior, and obesity risk. This research will use machine learning methods, such as supervised learning for predicting obesity risk based on past behaviors and unsupervised learning to identify behavior groups with higher obesity risk. This way, an accurate and reliable model is expected to be developed to understand and predict obesity risk, which can ultimately be used to design more effective prevention and intervention strategies.

METHODS

A cross-sectional study method is used in this research to investigate the variables of physical activity behavior, sedentary behavior, and their relationship to obesity risk. The research was conducted from February to August 2024 at the Indonesia University of Education in Bandung. The target population and subjects of this study are adolescents, specifically 384 university students from various departments at the Indonesia University of Education who were willing to volunteer for the research. The primary outcomes of this study are Body Mass Index (BMI) and overweight or obesity status. BMI is calculated using the formula: weight (kg) divided by height squared (m^2). We adopted the Asia-Pacific BMI classification table, where normal weight is defined as $18.5 \leq BMI < 22.9$ kg/m², overweight as $23 \leq BMI < 24.9$ kg/m², and obesity as $BMI \geq 25$ kg/m² (Lim et al., 2017).

Physical activity levels are categorized into five groups: sedentary (intensity < 100 counts/min), light (100 ≤ intensity < 760 counts/min), lifestyle (760 ≤ intensity < 2200 counts/min), moderate (2200 ≤ intensity < 6000 counts/min), and high (intensity ≥ 6000 counts/min) (Wanner et al., 2017). Initially, researchers recruited participants willing to volunteer for the study. Participants were then asked to provide their biodata/demographic information, including BMI data and a consent form. Those who agreed to participate were requested to wear an accelerometer for seven days to collect daily physical activity data. The Actigraph GT3X accelerometer was used to collect data on the daily physical activity of research participants. This device records activity duration through body motion sensors. The recorded duration was then analyzed using the cut-point algorithm in the ActiLife software, adjusted to the characteristics of the participants. The results include step count, energy expenditure, and MET, which were used to classify physical activity levels. This study uses seven traditional classification algorithms and logistic regression to examine the relationship between physical activity and weight status. The seven classification algorithms include Naïve Bayes, Support Vector Machine (SVM), local k-nearest neighbors (KNN), Classification via Regression (CVR), decision tree, random forest, and multilayer classification (Cook et al., 2001; Lewis, 2000). Data analysis was conducted using RapidMiner Studio Version 10.1.

RESULTS AND DISCUSSION

Findings

Table 1 presents the characteristics of the research sample, including gender, residence status, participation in extracurricular activities or student organizations, and BMI status. The study involved 384 students from various programs, with 63.54% of them being female. The participants' ages ranged from 17 to 23 years. Nearly 30% of both male and female students fell into the overweight and obesity categories, with a higher proportion among females than males. Regarding residence status, students were divided into two groups: those living with parents and those staying in dorms or rented rooms. More than 15% of students living with their parents were categorized as obese, while the percentage was lower for students living in dorms or rented rooms. In terms of extracurricular involvement, more than 26% of students not participating in extracurricular activities were classified as overweight or obese. Similarly, over 26% of those involved in extracurricular activities, whether sports-related or non-sports, were also categorized as overweight or obese.

Table 1. Participants Characteristics

Variables	Normal 18.5 ≤ BMI < 22,9 kg/m2		Overweight 23 ≤ BMI < 24,9 kg/m2		Obesity BMI ≥ 25 kg/m2	
	N	**Average (%)**	**N**	**Average (%)**	**N**	**Average (%)**

Gender						
Male	101	72,14	21	15	18	12,86
Female	179	73,36	29	11,89	36	14,75
Residence						
With Parents	202	71,38	36	12,72	45	15,9
Boarding house/dormitory	78	77,23	14	13,86	9	8,91
Extracurricular						
Non-	175	73,53	26	10,92	37	15,55
Extracurricular	74	71,15	18	17,31	12	11,54
Non-Sport	31	73,81	6	14,29	5	11,90
Sports						

The next analysis aims to predict BMI, particularly overweight and obesity, based on gender, physical activity level, and sedentary behavior. Participants were divided into two groups: obese and non-obese (including overweight and obese). Table 2 presents the classification performance results of machine learning algorithms analyzed with Rapidminer. SVM had the highest accuracy compared to six other algorithms in classification, with 74.22%, while CVR had the lowest accuracy at 46.09%. ANN showed the highest sensitivity, at 72.27%, while Naïve Bayes and SVM had a sensitivity of 0.00%. For specificity, the decision tree algorithm had the highest percentage at 77.5%, while the lowest was ANN at 0.00%.

Table 2. Performance of Accuracy, Sensitivity, Specificity

Method	**Naïve Bayes**	**SVM**	**Local KNN**	**ANN**	**Decision Tree**	**Random Forest**	**CVR**
Accuracy	71,09%	74,22%	59,38%	72,26%	67,97%	71,09%	46,09%
Sensitivity	0,00%	0,00%	14,81%	72,27%	36,67%	37,50%	29,92%
Specificity	73,39%	74,22%	71,29%	0,00%	77,5%	75,89%	76,00%

Two algorithm models, decision tree and CVR, had accuracy below the average of the other models. Meanwhile, three out of seven algorithm models—Naïve Bayes, SVM, and KNN—had percentages below the average of the other four models. Although SVM had the highest accuracy among the six other algorithms, its sensitivity was the lowest among them. Meanwhile, although ANN had the highest sensitivity among the six other algorithms, its specificity was the only one below average, even the lowest.

Discussion

This study examines the risk of overweight and obesity in college-aged adolescents using objectively measured physical activity data and machine learning techniques. The results indicate that moderate to high physical activity and sedentary behavior are key factors in predicting the risk of overweight and obesity in this population. Additionally, the amount of metabolic equivalent of task (MET) and the duration of sedentary behavior contributed the most compared to other variables. These findings suggest that energy expenditure and physical activity duration are more important than activity intensity. Physical activity increases energy expenditure, helping individuals maintain energy balance or even lose weight, provided energy intake does not offset energy expenditure (Strasser, 2013). Residential environments indirectly impact the likelihood of overweight and obesity risks (Sallis et al., 2020), although some studies have shown inconsistent relationships between the environment and physical activity behavior (Van Cauwenberg et al., 2011). Physical activity intensity and sedentary behavior contribute more than residential status and extracurricular involvement in predicting obesity risk.

This study also compares the performance of various machine learning algorithms in predicting BMI status, where SVM achieved the highest accuracy among the six other models. However, ANN's accuracy was slightly below SVM and slightly above Naïve Bayes and random forest. Although SVM had the highest accuracy among the six algorithms, its sensitivity and specificity were not as strong. SVM's sensitivity was significantly lower than five other models and on par with Naïve Bayes in predicting obesity. ANN's sensitivity was far above the six other models, even 36.77% higher than random forest, which ranked second. Meanwhile, the decision tree had the highest specificity among the six models, though only slightly above CVR by 1.5%.

Previous research found that the random subspace algorithm had the highest accuracy compared to 10 other models in predicting weight status (Cheng et al., 2021). Another study found that the Naïve Bayes machine learning model achieved the highest accuracy, 52.38%, among three other models in predicting BMI based on physical activity levels (Saputra et al., 2024). Another study that predicted early childhood obesity found that the ID3 algorithm model had an accuracy of 85% with a sensitivity of 89%, the highest among six machine learning models used (Dugan et al., 2015). Although empirical findings vary, machine learning techniques generally offer far better predictive accuracy than simpler methods such as regression analysis or other statistical techniques (Safaei et al., 2021). The variation in dataset size and predictor variables likely explains the differences in research results.

Some limitations of this study include the limited number of Actigraph GT3X devices used, resulting in incomplete physical activity recording. Additionally, as the Actigraph GT3X is not waterproof and needs to be removed, activities related to water, such as bathing and swimming, were not recorded; although participants were asked to log these activities, these records are not entirely reliable. Second, sedentary activity in this study relied solely on Actigraph GT3X recordings without confirmation from participants, particularly regarding screen time. These two limitations will be addressed in future research. Despite these limitations, the study has strengths. Its strength lies in applying machine learning, including supervised and unsupervised learning, to predict obesity risk and identify high-risk behavior groups. With this approach, the study not only produces an accurate predictive model but also provides valuable insights into factors such as physical activity and sedentary duration that significantly predict obesity. This model can support physical activity promotion and guide campus policies to reduce obesity prevalence among students.

CONCLUSION

This study demonstrates that physical activity, total Metabolic Equivalent of Task (MET), and the duration of sedentary behavior are key factors contributing to predicting obesity risk among college students. Using various machine learning algorithms, Support Vector Machine (SVM) delivered the best accuracy performance (74.22%) in predicting obesity risk. Meanwhile, the artificial neural network (ANN) and decision tree algorithms showed the highest sensitivity and specificity, at 72.27% and 77.5%, respectively.

These results underscore the importance of physical activity in reducing obesity risk among college students. Therefore, promoting physical activity and implementing campus policies that support an active lifestyle are essential in reducing obesity prevalence. The implementation of these policies is expected to help lower obesity rates and improve student health in the campus environment.

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CONFLICT OF INTEREST

The authors declare no conflict of interest regarding the publication of this article. The research was conducted independently, and the authors affirm that there are no financial or personal relationships with other people or organizations that could inappropriately influence or bias the content of this article. Any funding received to support this study did not influence the study design, data collection, analysis, interpretation of results, or the decision to publish. The authors are solely responsible for the content and writing of the article.

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