INDONESIAN JOURNAL OF SPORT MANAGEMENT
Department of Physical Education, Universitas Majalengka, Indonesia
ISSN 2776-706X.

A Machine Learning Approach to Predicting Physical Activity Levels in Adolescents

Desvy Rahma Putri Mahendra[1A-E*], Jajat[2A-D], Imas Damayanti[3AD], Kuston Sultoni[4D], Yati Ruhayati[5D], Adang Suherman[6DE], Nur Indri Rahayu[7D]

[1-7]Fakultas Pendidikan Olahraga dan Kesehatan, Universitas Pendidikan Indonesia, Bandung, Indonesia

ABSTRACT

The ongoing evolution of technology has had both positive and negative effects on modern society. On the positive side, it has significantly improved the ease with which various activities can be performed. However, it has also had a negative impact by reducing physical activity. This reduction in physical activity, in turn, increases the risk of chronic diseases that contribute to global mortality rates. This research aims to assess the effectiveness of machine learning in predicting the physical activity levels of adolescents. The study utilizes data from accelerometers, specifically the ActiGraph GT3X. The research methodology employs a semi-supervised machine learning approach, using both the support vector machine and decision tree algorithms to make these predictions. The study sample consists of 61 adolescents (males = 17, female = 44), including high school students and university students aged 18-21, from the West Java region. The results from the machine learning model using the decision tree algorithm indicated a model accuracy of 97.50% in predicting physical activity levels. In contrast, the accuracy obtained from the performance analysis using the confusion matrix for the support vector machine model was 92.5%. Based on these accuracy levels, it can be concluded that the decision tree algorithm outperforms the support vector machine algorithm in terms of accuracy. Further analyses involving different models are necessary to determine which algorithm offers the highest level of accuracy.

Keywords: accelerometer; physical activity; descision tree; SVM

Corresponding author:
*Desvy Rahma Putri Mahendra, Universitas Pendidikan Indonesia, Jl. Dr. Setiabudhi No.229, Bandung, West Java, Indonesia, 40154. desvyrahma@upi.edu

Article History:
Received: September 25, 2023
Accepted after revision: October 23, 2023
First Published Online: October 30, 2023

Authors' contribution:
A) Conception and design of the study;
B) Acquisition of data;
C) Analysis and interpretation of data;
D) Manuscript preparation;
E) Obtaining funding.

Cite this article:
Mahendra, D. R. P., Jajat, Damayanti, I., Sultoni, K., Ruhayati, Y., Suherman, A., & Rahayu, N. I. (2023). A Machine Learning Approach to Predicting Physical Activity Levels in Adolescents. *Indonesian Journal of Sport Management*, 3(2), 261-272. https://doi.org/10.31949/ijsm.v3i1.7145

INTRODUCTION

In the modern era, technology continues to advance, yielding both positive and negative consequences. Technological progress has positively impacted society by enhancing the ease, convenience, and speed with which individuals can perform various tasks. However, it has also led to negative outcomes, including a decline in physical activity among individuals, as they are increasingly reliant on the conveniences provided by modern technology (Jeckzen et al., 2019). This trend is evident in rural areas, where farmers are more inclined to use tractors for ploughing fields instead of traditional buffalo ploughing methods. Similarly, in urban environments, contemporary children often prefer electronic gadgets over traditional outdoor games with their peers (Sulastri & Sonyo Rini, 2022).

The extensive use of technology in our modern society has made many work tasks more efficient (Pramono et al., 2014). However, this advancement in technology has also led to reduced levels of physical activity (Suherman et al., 2021). Physical activity plays a vital role in maintaining overall health and well-being, regardless of age, from early childhood to old age (Amtarina, 2017; Wicaksono, 2020). Conversely, inadequate physical activity is linked to risk factors such as elevated blood pressure (Hasanudin et al., 2018), a rise in degenerative diseases (Suryani et al., 2020) and a higher prevalence of overweight and obesity (Willumsen & Bull, 2020). Moreover, insufficient physical activity can contribute to the development of chronic diseases with implications for global mortality (Mamba & Surakarta, 2017). As a result, there is an urgent need for early preventive measures, particularly for children and adolescents, to counteract the decline in physical activity.

Researchers have employed various methods to assess physical activity in different age groups, using both subjective and objective approaches (Strath et al., 2013). These methods utilize a range of instruments, such as surveys, accelerometers, and pedometers (Sylvia et al., 2014; Westerterp, 2009; Tudor-locke et al., 2002). These instruments essentially quantify daily physical activity by estimating the duration and intensity of activities, often measured in Metabolic Equivalents (METs). Accelerometers are increasingly favoured due to their objectivity and precision, particularly for assessing physical activity in children and adolescents. They function as sensors to track steps and provide details about the frequency, intensity, and duration of activities (Ellis et al., 2014; Sliepen et al., 2019).

However, accelerometers have limitations, including their inability to accurately capture some non-weight-bearing activities and their failure to detect increased energy expenditure during uphill walking (Pfeiffer et al., 2006). The choice of accelerometer placement, whether on the wrist, waist, or ankle, typically depends on the specific research objectives and the type of accelerometer used (Romanzini et al., 2014). On the other hand, questionnaires are less effective at measuring moderate and light physical activity (Jacobs et al., 1993). They also present the drawback of potentially containing ambiguous or challenging-to-interpret questions for respondents (Mardiana & Wiyat Purnanto, 2017). Nevertheless, questionnaires offer advantages in terms of cost-effectiveness, ease of administration, and accuracy in measuring high-intensity physical activity (Besson et al., 2010; Ishikawa-Takata et al., 2008), as well as the ability to rank individuals or groups based on their activity levels (Corder et al., 2009).

Currently, artificial intelligence, particularly machine learning, is extensively employed by researchers across various scientific domains, including the assessment of physical activity. Machine learning for predicting the type of physical activity from accelerometer data has gained attention due to its ability to process raw data from newer devices (Ellis et al., 2014) and solve complex problems (Roihan et al., 2019). Machine learning is also receiving considerable attention for its capacity to accurately predict various complex phenomena. Beyond prediction, it is increasingly recognized that machine learning can yield insights into the relationships inherent in the data, often referred to as interpretation (Murdoch et al., 2019).

Machine learning methods are used to analyze predictions, classifications, quantifications, and more (Adawiyah, 2023). The results of the analysis produced by each algorithm used vary in terms of accuracy. These differences are contingent on the data sources and instruments employed, resulting in a degree of variability. This underscores the significance of data sources and instrument types used in measuring physical activity, as they significantly influence the accuracy of physical activity predictions. In Indonesia, the majority of studies on physical activity and machine learning have relied on questionnaire-based data sources, while research utilizing machine learning methods with accelerometer data sources is relatively scarce or virtually non-existent. However, as previously explained, accelerometers offer higher objectivity and accuracy compared to questionnaires. Consequently, this study analyzes physical activity using machine learning methods with accelerometer data from the ActiGraph GT3X.

METHODS AND MATERIALS

Data Source

The data used in this study was collected from the Physical Activity Research Focus Group within the Sport Science program at the Faculty of Sports and Health Education, Universitas Pendidikan Indonesia. This initiative involved both faculty members and students specializing in physical activity. Data collection took place between 2021 and 2023 and targeted adolescents aged 18-21, with an average age of (M=19.79 + SD=1.13). We selected participants from various high schools and universities in West Java, resulting in a sample of 44 females and 17 males. Initially, we collected data from a total of 102 individuals, but due to missing data in some samples, the validated dataset included 61 individuals.

Physical Activity Dataset

The dataset used for this research was derived from three research projects that were conducted under the umbrella of the Physical Activity research focus group. Out of the 102 accelerometer datasets analyzed, 61 were obtained from Project A, 21 from Project B, and 20 from Project C.

Steps Data

For the collection of daily activity data in five-day intervals, we employed the ActiGraph accelerometer. This device was worn on the left hip for a total of seven days, with data collection occurring over five days, starting at midnight (00:00) and ending at the conclusion of the fifth day. We removed the accelerometer on the seventh day.

Figure 1. Placement Position of ActiGraph GT3X Accelerometer

Physical Activity Time and METs Data

The physical activity data obtained from the ActiGraph accelerometer includes sedentary activity time, low, moderate, high, and very high physical activity time, along with other relevant data. The recorded time intervals were subsequently analyzed using cut points in ActiLife V6.13.4 software to determine intensity classifications, which include light-intensity physical activity, moderate-intensity physical activity, vigorous physical activity, and moderate to vigorous physical activity (Ayabe et al., 2013). The cut points for determining moderate to vigorous physical activity were based on Freedson adult epoch values from 1998, available in the ActiLife V6.13.4 software. These values encompass Sedentary Bout Parameters, with a minimum length of 10 minutes, a minimum count value of 0 counts per minute, a maximum count value of 99 counts per minute, a drop time of 0 minutes, and a vector magnitude set to "false." The cut point values were defined as sedentary (0 to 99), light (100 to 1951), moderate (1952 to 5724), vigorous (5725 to 9498), very vigorous (above 9499), and moderate to vigorous physical activity with a minimum count of 1952.

Training and Test Data

The analytical methods in this study employed a semi-supervised model, wherein 70% of the valid dataset, out of the 61 recorded datasets, was used for supervised training, and the remaining 30% was designated for unsupervised testing.

Analytical Methods

The machine learning methods utilized in this study include decision trees and support vector machines. The decision tree algorithm is well-suited for this research, as it represents predictive models in the form of tree structures with nodes and branches. Support vector machines were also employed due to their high-performance track record in previous physical activity prediction research. Both algorithms were analyzed using RapidMiner (RapidMiner Studio Educational 10.1.002).

Pre-Processing

In the initial phase, data samples were recorded using the ActiGraph GT3X accelerometer to monitor daily physical activity over a span of five days. The recorded ActiGraph data was then scored using age-specific cut points within the ActiLife V6.13.4 software and subsequently downloaded. Following the download, the data was screened to ensure there were no extreme or missing data points. The screened data was then divided into two datasets for training and testing purposes. The training dataset was used to train both the decision tree and support vector machine models. Subsequently, the model's performance was assessed through data testing, incorporating the use of a confusion matrix.

RESULTS AND DISCUSSION

gender, average sedentary activity time, average light physical activity time, average moderate physical activity time, and average moderate to vigorous physical activity time (MVPA T). The analysis using the decision tree revealed that the prediction of physical activity relied solely on the average time spent in moderate to vigorous physical activity. This result is depicted in Figure 2, which illustrates the decision tree structure. This indicates that moderate to vigorous physical activity time is the sole indicator used by the decision tree algorithm to predict physical activity.

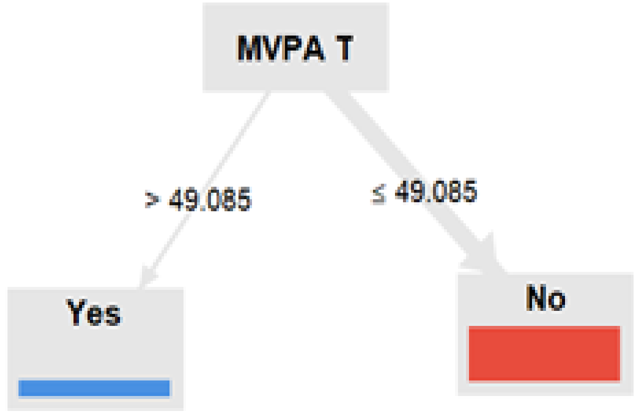


Figure 2. Decision Tree Predicting Physical Activity

Based on Figure 2, the decision tree predicts "Yes" for physical activity when the average time spent in moderate to vigorous physical activity among adolescents exceeds 49.085 minutes per day, and "No" if the average time spent in this activity is less than 49.085 minutes per day.

Subsequently, after obtaining the decision tree structure, the model was tested (model application), and the model's performance level was analyzed. In Figure 3, the output of the applied model generated by the RapidMiner application provides a summary of the label of physical activity versus the predictions from the model. It is evident in this figure that some data predictions do not match the labels.

Open in Turbo Prep Auto Model Filter (43 / 43 examples) all

Row No.	Pred	prediction(P...	confidence(...	confidence(...	Gender	ST	LT	MT
1	No	No	1	0	2	673.167	118.300	20.367
2	Yes	Yes	0	1	2	761.639	140.639	56.056
3	No	No	1	0	2	855.595	84.476	10.333
4	No	No	1	0	2	722.881	195.952	31.690
5	No	No	1	0	1	690.533	84.033	33.867
6	No	No	1	0	2	691.600	98.333	21.967
7	No	No	1	0	2	836.367	106.467	16.900
8	No	Yes	0	1	2	707.476	195.643	46.048
9	No	No	1	0	1	658.200	123.233	26.900
10	No	No	1	0	2	646.667	130.300	34.100
11	Yes	Yes	0	1	2	584.700	172.100	52.533
12	No	No	1	0	2	867.190	72.452	10.929

Figure 3. Summary of Physical Activity Prediction Data Results

Furthermore, Table 1 details the analysis of the decision tree model's performance, indicating that "Yes - True Yes" resulted in all nine data records being correctly predicted, achieving a 100% accuracy rate for predicting "Yes." For "No - True No," out of 34 data records, 33 were predicted as "No," and one was predicted as "Yes," with an accuracy rate of 97.06%. Based on cross-validation analysis, 33 out of 34 training datasets matched the example dataset, with only one mismatch (MVPA T > 49.085: Yes {Yes=9, No=0} MVPA T ≤ 49.085: No {Yes=0, No=34}). Therefore, the decision tree model's accuracy performance vector was determined to be 97.50%, indicating a high level of accuracy in predicting physical activity. For the 18 test datasets used to assess performance, all were correctly predicted, with an absolute number of 11 for "No" and a fraction value of 0.611, and an absolute number of 7 for "Yes" with a fraction value of 0.389 (Table 1).

Table 1. Confusion Matrix for Decision Tree Model Accuracy Performance

	True *Yes*	True No	Class Precision
Pred *Yes*	**9**	1	90%
Pred No	0	**33**	100%
Recall %	100%	97,06%	

In addition to the decision tree, the analysis was also conducted using the support vector machine algorithm. Unlike the decision tree that yields a decision tree structure, the support vector machine generates a Kernel Model. Table 2 reveals that moderate to vigorous physical activity time (MVPA T) has the smallest weight (-0.794) compared to the other attributes. This indicates that MVPA T is the primary determinant indicator for the support vector machine in predicting the consistency of adolescent physical activity.

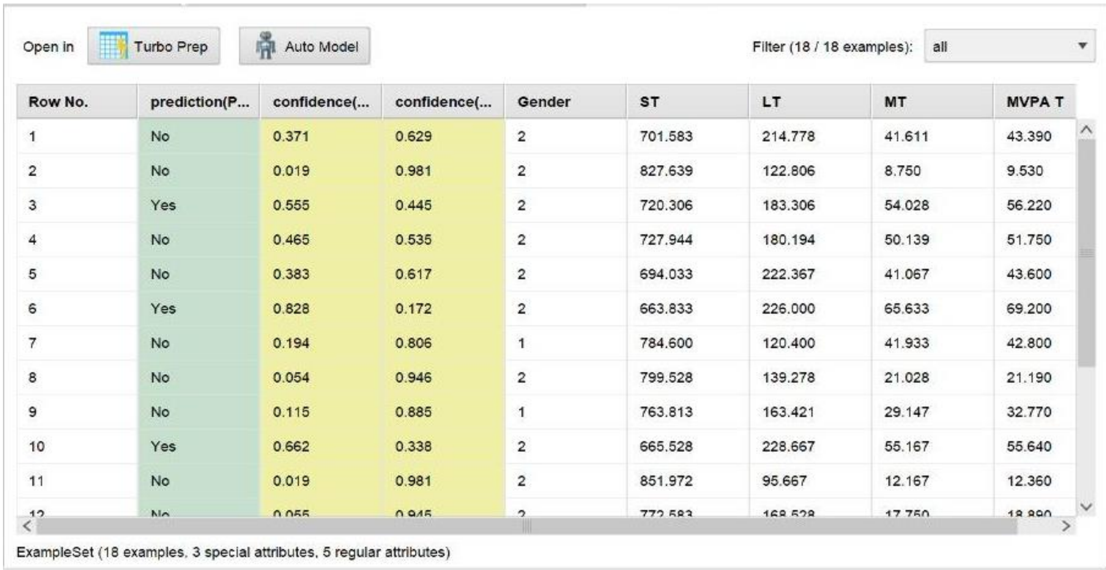
Table 2. Kernel Model of Support Vector Machine

Atribute	*Weight*
G	-0.074
ST	0.486
LT	-0.150
MT	-0.747
MVPA T	-0.794

G : Gender
ST : Sedentary time
LT : Light time physical activity
MT : Moderate time physical activity
MVPA : Moderate to vigorous physical activity

The next step involved testing the results of the generated model using the "apply model" function. Figure 4 provides a summary of the model's output results, differentiating it from the decision tree. The output of the support vector machine model includes predictions of physical activity along with the confidence levels of each data prediction.

Subsequently, the accuracy of the test results of the generated model was assessed, as presented in Table 3. Based on the performance data analysis of the support vector machine model, for "Pred Yes - True Yes," out of 9 datasets, 7 were correctly predicted, and 2 were predicted inaccurately, resulting in a recall accuracy rate of 77.78%. For "Pred No - True No," 33 data records were accurately predicted as "No," and one data record was incorrectly predicted, yielding a recall accuracy percentage of 77.78%. In conclusion, based on the confusion matrix analysis, the support vector machine model achieved an accuracy rate of 92.5% for data predicted correctly, and a micro-average of 93.02%. Comparing the accuracy rates of both models, the decision tree algorithm exhibited a higher level of accuracy than the support vector machine model.


Open in | Turbo Prep | Auto Model | Filter (18 / 18 examples): all

Row No.	prediction(P...	confidence(...	confidence(...	Gender	ST	LT	MT	MVPA T
1	No	0.371	0.629	2	701.583	214.778	41.611	43.390
2	No	0.019	0.981	2	827.639	122.806	8.750	9.530
3	Yes	0.555	0.445	2	720.306	183.306	54.028	56.220
4	No	0.465	0.535	2	727.944	180.194	50.139	51.750
5	No	0.383	0.617	2	694.033	222.367	41.067	43.600
6	Yes	0.828	0.172	2	663.833	226.000	65.633	69.200
7	No	0.194	0.806	1	784.600	120.400	41.933	42.800
8	No	0.054	0.946	2	799.528	139.278	21.028	21.190
9	No	0.115	0.885	1	763.813	163.421	29.147	32.770
10	Yes	0.662	0.338	2	665.528	228.667	55.167	55.640
11	No	0.019	0.981	2	851.972	95.667	12.167	12.360
12	No	0.055	0.945	2	772.583	168.528	17.750	18.890

ExampleSet (18 examples, 3 special attributes, 5 regular attributes)

Figure 4. Confusion Matrix of Support Vector Machine Model Accuracy Performance

Table 3. Confusion Matrix for Support Vector Machine Model Accuracy Performance

	True *Yes*	True No	Class Precision
Pred *Yes*	**7**	1	87,50%
Pred No	2	**33**	94,29%
Recall %	77,78%	97,06%	

DISCUSSION

The objective of this study was to analyze the effectiveness of machine learning in predicting physical activity behavior among adolescents using data from the ActiGraph GT3X accelerometer. The results of this research indicate that machine learning algorithms, including both the decision tree and support vector machine, can effectively predict physical activity behavior among adolescents. This finding aligns with previous research, which has shown that machine learning methods perform exceptionally well in studying physical activity (Aziz et al., 2021). Several earlier studies that predicted physical activity using machine learning, specifically the support vector machine model (Cheng et al., 2021; Chong et al., 2021; Vanstrum et al., 2023; Wang, 2022; Zhou et al., 2019), also reported that the support vector machine model demonstrates high accuracy in predicting physical activity.

Future applications of machine learning for predicting physical activity aim to develop two versions of the Discontinuation Prediction Score. The results indicate that the Discontinuation Prediction Score achieves testing accuracy of approximately 80% and accurately predicts the potential to resume exercise with a sensitivity of 85% and specificity of 67% (Zhou et al., 2019). Machine learning can be applied to predict physical activity in individuals with special needs. For instance, a study exploring physical activity in children with cerebral palsy, utilizing machine learning and mobility-assistive devices, found that three machine learning models—decision tree, support vector machine, and random forest—trained with accelerometer data from various body parts effectively classified types of physical activities in children with cerebral palsy (Ahmadi et al., 2018).

Another study focused on predicting physical activity using information collected through hardware in applications installed on smartwatches and smartphones, referred to as Human Activity Recognition (HAR). HAR leverages gyroscope and accelerometer sensors and applies classification algorithms within machine learning models. It helps identify various everyday physical activities such as walking, sitting, and running using data collected from accelerometer and gyroscope sensors. The results of this study demonstrated that the Deep Neural Network (DNN) model achieved an accuracy rate of 96.81% (Bozkurt, 2022). This highlights that machine learning methods could predict physical activity with a relatively high level of accuracy. Furthermore, in a comparison between machine learning and deep learning, one study concluded that machine learning models outperformed deep learning models (Bharti et al., 2021).

Machine learning is not limited to prediction; it can also classify physical activities (Alsareii et al., 2022). For example, research on classifying physical activities using the Gravity Estimator of Normal Everyday Activity (GENEA) accelerometer and the Waikato Environment for Knowledge Analysis (WEKA) software achieved an accuracy rate of 95.8% (Zhang et al., 2012).

Subsequent analysis shows that the decision tree machine learning algorithm achieves a model accuracy rate of 97.50%, while the accuracy from the confusion matrix analysis for the support vector machine model is 92.5%. This implies that the decision tree surpasses the support vector machine in predicting adolescent physical activity based on ActiGraph accelerometer data. This result aligns with previous research comparing support vector machine and decision tree algorithms to predict death in patients with sepsis in the ICU, which concluded that the decision tree algorithm outperforms the support vector machine (Li et al., 2021)

However, in contrast to this research, one study analyzed five machine learning models for human activity prediction. The models is logistic regression, linear Support Vector Cluster (SVC), support vector machine classifier, decision tree, and random forest. Among these models, the SVC machine learning model achieved the highest accuracy of 96.54%, while the decision tree machine learning model yielded the lowest accuracy of 86.29% among all the models (Pratama, 2020). These differences may be attributed to factors such as dataset size and the number of attributes used, which can impact the precision and accuracy of model performance (Osisanwo et al., 2017).

The algorithms employed in this research were limited to the decision tree and support vector machine. Therefore, further analysis using other algorithms is needed to determine which model yields better accuracy in predicting adolescent physical activity based on ActiGraph accelerometer data. Previous research that employed the random forest model to predict physical activity from accelerometer data reported relatively high accuracy (Ellis et al., 2014). Additionally, another study found that random forest was the best-performing machine learning model with an accuracy rate of 0.93, while the decision tree model had an accuracy of 0.75 (Dijkhuis et al., 2018). Other machine learning models, such as linear regression, achieved accuracy rates of 97-99% in predicting physical activity (Biró et al., 2023). A study that systematically reviewed literature on machine learning model selection concluded that the most suitable model is Principal Component Analysis (PCA) (Jones et al., 2021). This highlights that model selection and problem context can yield varying performance, emphasizing the need to test different models to identify the most suitable one.

In addition to the limitations regarding the algorithms used in this study, the sample size and attributes used, there is also a limitation related to the ActiGraph GT3X accelerometer, which is not waterproof. Participants were required to remove the ActiGraph when engaging in water-related activities such as swimming and bathing, leading to a lack of data for those activities. Therefore, recording or confirming with the participants when and for how long they removed the ActiGraph is essential.

CONCLUSION

The results of this study demonstrate that machine learning algorithms can predict physical activity behavior among adolescents based on ActiGraph accelerometer data, whether utilizing the support vector machine or decision tree models. The decision tree model outperforms the support vector machine model in terms of performance accuracy in predicting adolescent physical activity. The attribute of activity time is a key variable that significantly influences the prediction of future physical activity behavior among adolescents.

ACKNOWLEDGMENTS

Acknowledgments to Indonesia Physical Activity Research Group, Universitas Pendidikan Indonesia.

CONFLICT OF INTEREST

We certify that there is no actual or potential conflict of interest in relation to this article.

FUNDING

All forms of financing in this research are sourced from personal fund and Indonesia Physical Activity Research Group, Universitas Pendidikan Indonesia.

REFERENCES

Adawiyah, R. (2023). Eksplorasi kapasitas pengkodean amplitudo untuk model quantum machine learning. Jurnal teknik informatika dan multimedia, 3(1), 38-58.

Ahmadi, M., O'Neil, M., Fragala-Pinkham, M., Lennon, N., & Trost, S. (2018). Machine learning algorithms for activity recognition in ambulant children and adolescents with cerebral palsy. Journal of neuroengineering and rehabilitation, 15(1), 1-9.

Alsareii, S. A., Awais, M., Alamri, A. M., AlAsmari, M. Y., Irfan, M., Aslam, N., & Raza, M. (2022). Physical Activity Monitoring and Classification Using Machine Learning Techniques. Life, 12(8). https://doi.org/10.3390/life12081103

Amtarina, R. (2017). Manfaat aktivitas fisik teratur terhadap perbaikan fungsi kognitif pasien dengan mild cognitive impairment. Jurnal Ilmu Kedokteran (Journal of Medical Science), 10(2), 140-147.

Ayabe, M., Kumahara, H., Morimura, K., & Tanaka, H. (2013). Epoch length and the physical activity bout analysis: an accelerometry research issue. BMC research notes, 6(1), 1-7.

Aziz, F. (2021). Klasifikasi Physical Activity Berbasis Sensor Accelorometer, Gyroscope dan Gravity Menggunakan Algoritma Multi-Class Ensemble Gradientboost. Deepublish.

Besson, H., Brage, S., Jakes, R. W., Ekelund, U., & Wareham, N. J. (2010). Estimating physical activity energy expenditure, sedentary time, and physical activity intensity by self-report in adults. The American journal of clinical nutrition, 91(1), 106-114.

Bharti, R., Khamparia, A., Shabaz, M., Dhiman, G., Pande, S., & Singh, P. (2021). Prediction of heart disease using a combination of machine learning and deep learning. Computational intelligence and neuroscience, 2021.

Biró, A., Szilágyi, S. M., Szilágyi, L., Martín-Martín, J., & Cuesta-Vargas, A. I. (2023). Machine learning on Prediction of Relative Physical Activity Intensity Using Medical Radar Sensor and 3D Accelerometer. Sensors, 23(7). https://doi.org/10.3390/s23073595

Bozkurt, F. (2022). A Comparative Study on Classifying Human Activities Using Classical Machine and Deep Learning Methods. Arabian Journal for Science and Engineering, 47(2), 1507–1521. https://doi.org/10.1007/s13369-021-06008-5

Cheng, X., Lin, S. Y., Liu, J., Liu, S., Zhang, J., Nie, P., Fuemmeler, B. F., Wang, Y., & Xue, H. (2021). Does physical activity predict obesity—a machine learning and statistical method-based analysis. International Journal of Environmental Research and Public Health, 18(8). https://doi.org/10.3390/ijerph18083966

Chong, J., Tjurin, P., Niemelä, M., Jämsä, T., & Farrahi, V. (2021). Machine-learning models for activity class prediction: A comparative study of feature selection and classification algorithms. Gait and Posture, 89, 45–53. https://doi.org/10.1016/j.gaitpost.2021.06.017

Corder, K., van Sluijs, E. M., Wright, A., Whincup, P., Wareham, N. J., & Ekelund, U. (2009). Is it possible to assess free-living physical activity and energy expenditure in young people by self-report?. The American journal of clinical nutrition, 89(3), 862-870.

Dijkhuis, T. B., Blaauw, F. J., van Ittersum, M. W., Velthuijsen, H., & Aiello, M. (2018). Personalized physical activity coaching: A machine learning approach. Sensors (Switzerland), 18(2). https://doi.org/10.3390/s18020623

Ellis, K., Kerr, J., Godbole, S., Lanckriet, G., Wing, D., & Marshall, S. (2014). A random forest classifier for the prediction of energy expenditure and type of physical activity from wrist and hip accelerometers. Physiological measurement, 35(11), 2191.

Hasanudin, H., Ardiyani, V. M., & Perwiraningtyas, P. (2018). Hubungan aktivitas fisik dengan tekanan darah pada masyarakat penderita hipertensi di wilayah Tlogosuryo Kelurahan Tlogomas Kecamatan Lowokwaru Kota Malang. Nursing News: Jurnal Ilmiah Keperawatan, 3(1).

Ishikawa-Takata, K., Tabata, I., Sasaki, S., Rafamantanantsoa, H. H., Okazaki, H., Okubo, H., Tanaka, S., Yamamoto, S., Shirota, T., Uchida, K., & Murata, M. (2008). Physical activity level in healthy free-living Japanese estimated by doubly labelled water method and International Physical Activity Questionnaire. European Journal of Clinical Nutrition, 62(7), 885–891. https://doi.org/10.1038/sj.ejcn.1602805

Jacobs Jr, D. R., Ainsworth, B. E., Hartman, T. J., & Leon, A. S. (1993). A simultaneous evaluation of 10 commonly used physical activity questionnaires. Medicine and science in sports and exercise, 25(1), 81-91.

Li, K., Shi, Q., Liu, S., Xie, Y., & Liu, J. (2021). Predicting in-hospital mortality in ICU patients with sepsis using gradient boosting decision tree. Medicine, 100(19).

Turege, J. N., Kinasih, A., & Kurniasari, M. D. (2019). Hubungan Antara Aktivitas Fisik Dengan Obesitas Di Puskesmas Tegalrejo, Kota Salatiga. Jurnal Ilmu Keperawatan Dan Kebidanan, 10(1), 256-263.

Jones, P. J., Catt, M., Davies, M. J., Edwardson, C. L., Mirkes, E. M., Khunti, K., Yates, T., & Rowlands, A. V. (2021). Feature selection for unsupervised machine learning of accelerometer data physical activity clusters – A systematic review. In Gait and Posture (Vol. 90, pp. 120–128). Elsevier B.V. https://doi.org/10.1016/j.gaitpost.2021.08.007

Mardiana, T., & Purnanto, A. W. (2017). Google form sebagai alternatif pembuatan latihan soal evaluasi. URECOL, 183-188.

Murdoch, W. J., Singh, C., Kumbier, K., Abbasi-Asl, R., & Yu, B. (2019). Definitions, methods, and applications in interpretable machine learning. Proceedings of the National Academy of Sciences, 116(44), 22071-22080.

Osisanwo, F. Y., Akinsola, J. E. T., Awodele, O., Hinmikaiye, J. O., Olakanmi, O., & Akinjobi, J. (2017). Supervised machine learning algorithms: classification and comparison. International Journal of Computer Trends and Technology (IJCTT), 48(3), 128-138.

Pfeiffer, K. A., Mciver, K. L., Dowda, M., Almeida, M. J., & Pate, R. R. (2006). Validation and calibration of the Actical accelerometer in preschool children. Medicine & Science in Sports & Exercise, 38(1), 152-157.

Pramono, A., & Sulchan, M. (2014). Kontribusi makanan jajan dan aktivitas fisik terhadap kejadian obesitas pada remaja di kota Semarang. Gizi Indonesia, 37(2), 129-136.

Pratama, R. R. (2020). Analisis Model Machine learning Terhadap Pengenalan Aktifitas Manusia. MATRIK : Jurnal Manajemen, Teknik Informatika Dan Rekayasa Komputer, 19(2), 302–311. https://doi.org/10.30812/matrik.v19i2.688

Roihan, A., Abas Sunarya, P., & Rafika, A. S. (2019). IJCIT (Indonesian Journal on Computer and Information Technology) Pemanfaatan Machine learning dalam Berbagai Bidang: Review paper. In IJCIT (Indonesian Journal on Computer and Information Technology) (Vol. 5, Issue 1).

Romanzini, M., Petroski, E. L., Ohara, D., Dourado, A. C., & Reichert, F. F. (2014). Calibration of ActiGraph GT3X, Actical and RT3 accelerometers in adolescents. European Journal of Sport Science, 14(1), 91–99. https://doi.org/10.1080/17461391.2012.732614

Sheng, B., Moosman, O. M., Del Pozo-Cruz, B., Del Pozo-Cruz, J., Alfonso-Rosa, R. M., & Zhang, Y. (2020). A comparison of different machine learning algorithms, types and placements of activity monitors for physical activity classification. Measurement, 154, 107480.

Sliepen, M., Lipperts, M., Tjur, M., & Mechlenburg, I. (2019). Use of accelerometer-based activity monitoring in orthopaedics: Benefits, impact and practical considerations. EFORT Open Reviews, 4(12), 678–685. https://doi.org/10.1302/2058-5241.4.180041

Strath, S. J., Kaminsky, L. A., Ainsworth, B. E., Ekelund, U., Freedson, P. S., Gary, R. A., ... & Swartz, A. M. (2013). Guide to the assessment of physical activity: clinical and research applications: a scientific statement from the American Heart Association. Circulation, 128(20), 2259-2279.

Sylvia, L. G., Bernstein, E. E., Hubbard, J. L., Keating, L., & Anderson, E. J. (2014). Practical guide to measuring physical activity. Journal of the Academy of Nutrition and Dietetics, 114(2), 199–208. https://doi.org/10.1016/j.jand.2013.09.018

Suherman, A., Sultoni, K., & Zaky, M. (2021). Physical Activity and Sedentary Behavior in University Student During Online Learning: The Effect of Covid-19 Pandemic. In Malaysian Journal of Medicine and Health Sciences (Vol. 17, Issue SUPP14).

Sulastri, S., & Rini, S. H. S. (2022). Hubungan Jenis Aplikasi Gadget Terhadap Perkembangan Anak Usia Pra Sekolah Di Kecamatan Weleri. Jurnal Surya Muda, 4(2), 118-132.

Suryani, N., Noviana, & Libri, O. (2020). Hubungan Status Gizi, Aktivitas Fisik, Konsumsi Buah dan Sayur dengan Kejadian Hipertensi di Poliklinik Penyakit Dalam RSD Idaman Kota Banjarbaru. The Indonesian Journal of Health.

Tudor-locke, C., Ainsworth, B. E., Thompson, R. W., Matthews, C. E., Ainsworth, B. E., Thompson, W. W., & Matthews, C. E. (2002). Comparison of pedometer and acceler-ometer measures of free-living physical activity. Med. Sci. Sports Exerc, 34(12), 2045–2051. https://doi.org/10.1249/01.MSS.0000039300.76400.16

Vanstrum, E. B., Choi, J. S., Bensoussan, Y., Bassett, A. M., Crowson, M. G., & Chiarelli, P. A. (2023). Machine learning Analysis of Physical Activity Data to Classify Postural Dysfunction. Laryngoscope. https://doi.org/10.1002/lary.30698

Wang, M. (2022). Prediction Analysis of College Students' Physical Activity Behavior by Improving Gray Wolf Algorithm and Support Vector Machine. Advances in Multimedia, 2022. https://doi.org/10.1155/2022/4943510

Westerterp, K. R. (2009). Assessment of physical activity: a critical appraisal. European journal of applied physiology, 105, 823-828.

Wicaksono, A. (2020). Aktivitas Fisik Yang Aman Pada Masa Pandemi Covid-19. Jurnal Ilmu Keolahragaan Undiksha, 8(1), 10-15.

Willumsen, J., & Bull, F. (2020). Development of WHO guidelines on physical activity, sedentary behavior, and sleep for children less than 5 years of age. Journal of Physical Activity and Health, 17(1), 96–100. https://doi.org/10.1123/jpah.2019-0457

Zhang, S., Rowlands, A. V., Murray, P., & Hurst, T. L. (2012). Physical activity classification using the GENEA wrist-worn accelerometer. Medicine and Science in Sports and Exercise, 44(4), 742–748. https://doi.org/10.1249/MSS.0b013e31823bf95c

Zhou, M., Fukuoka, Y., Goldberg, K., Vittinghoff, E., & Aswani, A. (2019). Applying machine learning to predict future adherence to physical activity programs. BMC Medical Informatics and Decision Making, 19(1). https://doi.org/10.1186/s12911-019-0890-0