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

Classifying Physical Activity Levels in Early Childhood Using Actigraph and Machine Learning Method

Syifa Wandani[1A-E*], Adang Suherman[2AE], Jajat[3A-E], Kuston Sultoni[4D], Yati Ruhayati[5D], Imas Damayanti[6D], Nur Indri Rahayu[7D]

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

ABSTRACT

Actigraph is a widely used accelerometer for classifying physical activity levels in children, adolescents, adults, and older people. The classification of physical activity levels on Actigraph is determined through time calculations using cut-point formulas. The study aims to classify physical activity in young children according to the World Health Organization (WHO) guidelines using accelerometer data and machine learning methods. The study involved 52 young children (26 girls and 26 boys) aged 4 to 5 years in West Java, with an average age of 4.58 years. These early childhood physical activity and sedentary behaviours were simultaneously recorded using the Actigraph GT3X accelerometer for seven days. The data from the Actigraph were analyzed using two algorithm models: the decision tree and support vector machine, with the Rapidminer application. The results from the decision tree model show a classification accuracy of 96.00% in categorizing physical activities in young children. On the other hand, the support vector machine model achieved an accuracy of 84.67% in classifying physical activities in young children. The decision tree outperforms the support vector machine in accurately classifying physical activities in early childhood. This research highlights the potential benefits of machine learning in sports and physical activity sciences, indicating the need for further development.

Keywords: decision tree; physical activity; PA level; support vector machine

Corresponding author:
* Syifa Wandani, Fakultas Pendidikan Olahraga dan Kesehatan, Universitas Pendidikan Indonesia, Bandung, Indonesia
E-mail: wandanisyifa29@upi.edu

Article History:
Received: September15, 2023
Accepted after revision: October 10, 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:
Wandani, S., Suherman, A., Jajat, Sultoni, K., Ruhayati, Y., Damayanti, I., Rahayu, N. I. (2023). Classifying Physical Activity Levels in Early Childhood Using Actigraph and Machine Learning Method. *Indonesian Journal of Sport Management*, 3(2), 230-241. https://doi.org/10.31949/ijsm.v3i1.7173

INTRODUCTION

Early childhood refers to the age group from 0 to 9 years, and it's a critical period when children undergo significant physical, cognitive, and emotional development. This period is often called the "golden age," where 80% of their brain is actively developing. This phase is marked by rapid changes in physical, cognitive, emotional, moral, religious, and language development (Leonardo & Komaini, 2021). The pace of development varies among individuals and is influenced by genetics, physical health, nutrition, and the environment (Lin et al., 2021). Early childhood is a unique phase in life that should not be overlooked. It's a crucial time to stimulate individual development (Talango, 2020). This stimulation aims to make children active, healthy, and intelligent in their early years. Research indicates that children active in sports during early childhood tend to remain physically active in adulthood (Febrianta, 2016). The habits formed during early childhood often persist into later stages of life, which makes this period even more important.

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Over the last two decades, there has been progressing in global child birth rates and the survival of early childhood (Lawn et al., 2014). However, despite these advancements, many early childhooders still suffer from illnesses and, in some cases, even lose their lives. These tragic outcomes are often caused by factors such as premature birth complications, pneumonia, birth asphyxia, diarrhoea, and malaria (Vakili et al., 2015). Moreover, it's not uncommon for early childhood today to experience common health issues like congenital anomalies, injuries, and non-communicable diseases such as chronic respiratory conditions, heart disease, childhood cancer, diabetes, and obesity (Beattie & Lewis-Jones, 2006). Non-communicable diseases have become a top priority in child healthcare worldwide (Brumana et al., 2017). It should be noted that these diseases can be prevented in the future by paying attention to diet and physical activity, which play an important role (Saqib et al., 2020).

Physical activity is an indicator of early childhood development (motor, emotional, cognitive and psychosocial development). Physical activity is body movement produced by skeletal muscles that requires energy expenditure (Westerterp, 2013). Regular physical activity can improve a person's psychology by reducing stress, anxiety and depression (Welis & Sazeli, 2013; Leonardo & Komaini, 2021). Additionally, increasing physical activity can train the muscles, heart, and almost all other body parts to move actively and can prevent excessive fat accumulation in the body.

Children, on average, are involved in activities like watching television, reading books, storytelling, playing with mobile phones, seeking help with tasks, and spending little time outdoors (Ludyanti, 2019). These activities result in a reduced expenditure of their body's energy, which increases the likelihood of adopting a sedentary lifestyle (Nurcahyo, 2015). This sedentary behavior can have negative effects on their motor skills, contribute to obesity, raise the risk of non-communicable diseases, and possibly hinder their developmental progress (Lontoh et al., 2021). Children who engage in significant sedentary behaviour, whether moderately or extensively, often face limitations in their creativity and are more likely to experience emotional issues, anxiety, and low self-esteem (Ludyanti, 2019).

This problem has received worldwide attention, including researchers in physical activity. One of the current trends is studying physical activity using Artificial Intelligence technology (Ahmed et al., 2022; Maher et al., 2020). In its implementation, physical activity researchers utilize artificial intelligence through machine learning modelling. Machine learning analyses predictions, classification, quantification, and others with different data sources and instruments. Machine Learning is useful for creating systems or algorithms in the form of predictions and results that can continue to develop specifically based on data and increase their accuracy over time (Telaumbanua et al., 2019). In machine learning applications, algorithms or sequences of statistical processes are trained to find certain patterns and features based on the amount of data obtained (Hasibuan & Rahayu, 2022). The better the algorithm, the better the accuracy of the system's decisions and predictions, and the more data, the more accurate the resulting output will be (Mahendra et al., 2022).

As mentioned earlier, machine learning has become crucial in our daily lives, particularly in physical activities. Researchers have extensively used machine learning to study physical activities, employing different data sources and instruments, which has resulted in varying findings and conclusions (Rossi & Calogiuri, 2018; Meng et al, 2019; Jones et al, 2021). This indicates that choosing data sources and instruments for predicting physical activities can lead to diverse outcomes (Sulistia et al., 2018).

In Indonesia, discussions regarding predictions in classifying physical activities using machine learning have also started to develop. However, the majority of datasets used come from questionnaire instruments, while datasets from accelerometers like ActivPal and Actigraph are relatively scarce. Meanwhile, ActivPal and Actigraph accelerometers have already seen widespread use in some countries due to their perceived accuracy in measuring physical activities (Santos-Lozano et al., 2013). The use of accelerometers has gained popularity in research due to their ability to provide highly accurate results, including detecting activity patterns, durations, and intensities and precise estimates of energy expenditure (Rowlands, 2007). Accelerometers are small devices worn on the waist, wrist, or ankle and don't interfere with the subject's daily activities (Long et al., 2009). They record data and then process it on a computer using the Actilife application (Berlin et al., 2006). This device has been widely applied in research because it can provide results with a relatively high accuracy. Therefore, this research aims to analyze physical activities using supervised machine learning with data sourced from the ActiGraph GT3X accelerometer, with the expectation of achieving high accuracy in predicting the classification of physical activities.

METHODS AND MATERIALS

Study Design

This study examines primary data derived from research conducted by the Physical Activity field within the Sports Science program at the Faculty of Sports and Health Education (FPOK) at the Universitas Pendidikan Indonesia (UPI). The data used for this study was collected between 2020 and 2021, employing Actigraph GT3X accelerometers on early childhood aged 4 to 5 years old in West Java. The Actigraph GT3X was worn by 120 early childhood samples in West Java for 5 days. Physical activity classification was carried out using a machine learning model through several processes: (1) Physical activity data set; (2) Time analysis; (3) calculation of Metabolic Equivalent of Task per second (METs) for data (cut point); (4) data preprocessing; (5) classification model; and (6) application of the model.

Physical Activity Data Set

The data for this study was gathered from 20 kindergartens in West Java between 2020 and 2021. A total of 120 early childhood, aged 4 to 5 years (with an average age of 4.58 + 4.58), participated in the study. After screening and verifying the collected data, 52 data points were found to be suitable for further analysis. These 52 data included 26 females and 26 males.

Steps Data

The Accelerometer Actigraph GT3X is employed to monitor the physical activities of early childhood. The Actigraph GT3X is affixed to the hip area of the subject for a duration of 7 days, and it is only removed during water-related activities such as bathing and swimming. Before usage, the Actigraph GT3X is initially configured using ActiLife Software to specify the start and end of the recording period. The recorded activities of the subject include sedentary behavior, sleep duration, and daily physical activity time. Subsequently, the recorded data is downloaded using ActiLife software for further processing and analysis.

Physical Activity Time and METs Data

The Accelerometer Actigraph GT3X records the duration of sample activities through body motion sensors. The recorded duration is then analyzed using cut point algorithms within the ActiLife software, customized for the characteristics of early childhood, who are the subjects. The subsequent calculations produce outputs, including the number of steps, energy expenditure, and METs, which are used to classify physical activity. METs is a measure of the amount of energy the body expends during different activities, such as resting (sedentary), walking (light-intensity physical activity), moderate physical activity (moderate-intensity), high-intensity physical activity (vigorous), and moderate to vigorous physical activity.

In the Sedentary Bout Parameters, data is stored with a minimum duration 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, with vector magnitude set to "false." The data for cut point values is as follows: sedentary (0 to 99 counts), light (100 to 1951 counts), moderate (1952 to 5724 counts), vigorous (5725 to 9498 counts), very vigorous (above 9499 counts), and moderate to vigorous physical activity with a minimum count of 1952 counts.

Train and Test Data

During the data collection phase, researchers first ensure that the parents of the study participants understand the process. They provide training and conduct trials to familiarize them with the use of the accelerometer, which will be worn for a period of 7 days to ensure accurate results. Out of the 52 valid data sets of physical activity recordings from early childhood, the researchers divided the data into two parts: 70% for training the algorithm model and 30% for testing.

Analytical Methods

The data recorded by the Actigraph GT3X accelerometer, which was downloaded using the ActiLife software, is subsequently analyzed using a machine learning model within the RapidMiner application (specifically, RapidMiner Studio Educational 10.1.002). The algorithms employed by the researchers for data analysis are the decision tree and the support vector machine. Both of these machine learning algorithms are widely used for classifying physical activities but differ in their algorithmic structures. The decision tree algorithm generates a decision tree, whereas the support vector machine algorithm produces a multi-model regression.

Pre-Processing

At this stage, the dataset is divided into two parts: training data and test data using cross-validation techniques, as illustrated in Figure 1. Subsequently, model selection takes place, and the generated models are tested. The model's performance is then evaluated using a performance vector, as shown in Figure 2. The results of the analysis are further described to draw conclusions about the generated algorithms.

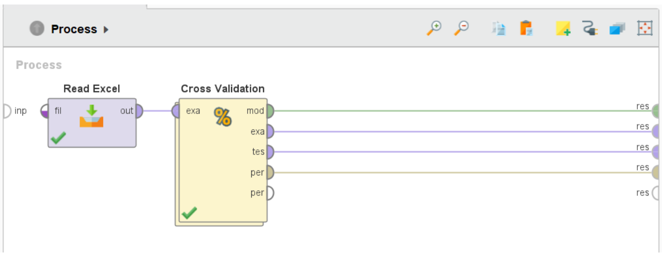

Figure 1. Classification Model Framework Using RapidMiner

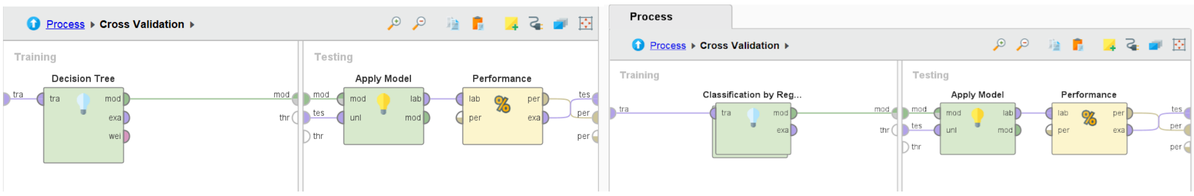

Figure 2. Framework for Data Cross-Validation Process Using RapidMiner

RESULTS AND DISCUSSION

The attribute variables used to classify physical activities in early childhood include gender, age, time spent in sedentary activities, time spent in low-intensity physical activities, time spent in moderate-intensity physical activities, time spent in vigorous-intensity physical activities, time spent in moderate to vigorous physical activities, and total time spent in physical activities. The analysis, as shown in Figure 3, reveals that the decision tree model indicates that the key variable for classifying physical activity is the "average time spent in moderate-intensity physical activities" and whether it aligns with the WHO's physical activity recommendations. In simpler terms, out of the seven variables used to classify physical activity in early childhood, the decision tree relies on just one variable. If the average time spent in moderate-intensity physical activities is more than 62.25 minutes per day, the model classifies the early childhood as meeting the WHO's physical activity recommendations. Conversely, if the average time spent in moderate-intensity physical activities is less than 62.25 minutes per day, the model classifies the early childhood as not meeting the WHO's physical activity recommendations.

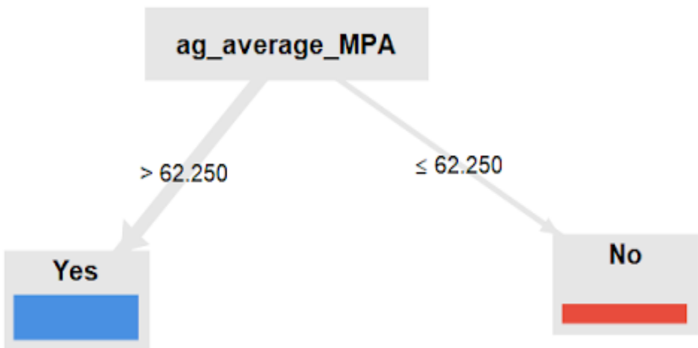

Figure 3. Decision Tree Physical Activity Classification Model

Figure 4 gives an overview of the results obtained during the training phase using the decision tree algorithm, showing how well the model performed on the data it was trained with. Figure 5 is a summary of how the decision tree model, which was created during training, performed when tested with new data. Out of the 52 Actigraph data records from early childhood, the decision tree model, based on the analysis, made incorrect classifications for 2 records, but correctly classified 50 records, just as it had been trained to do.

Child ID	Meet PA	Age	Sex	ag_average...	ag_average...	ag_average...	ag_average...	ag_average...	ag_average...
ID31002	Yes	4.650	2	555.583	167.667	100.833	16.250	117.083	284.750
ID31003	Yes	4.590	2	492	159.250	120.750	31	151.750	311
ID31004	Yes	4.340	1	564.417	133.333	82	12.417	94.417	227.750
ID31005	Yes	4.550	2	537.250	165.250	115.583	20.833	136.417	301.667
ID31006	Yes	4.950	1	448.667	165.750	175.500	70.167	245.667	411.417
ID31009	Yes	4.020	1	543.917	158.833	96.333	20.083	116.417	275.250
ID31010	Yes	4.380	1	575.750	117.250	92.583	29	121.583	238.833
ID31011	No	4.870	2	647.083	101.083	61.833	10.750	72.583	173.667
ID31012	Yes	3.980	1	539.125	91.500	73.875	16.125	90	181.500
ID31013	Yes	4.730	1	656.750	121.500	76.250	15.500	91.750	213.250
ID32015	No	4.280	2	624.167	96.417	49.917	13	62.917	159.333
ID33016	Yes	4.860	1	508.917	148.917	127.500	30.583	158.083	307.000

Figure 4. Summary of Data From the Decision Tree Algorithm Modeling

Child ID	Meet PA	prediction(...	con...	confi...	Age	Sex	ag_average...	ag_average...	ag_average...	ag_average...
ID31002	Yes	Yes	0	1	4.650	2	555.583	167.667	100.833	16.250
ID33017	Yes	No	1	0	4.820	1	604.667	102.250	62.667	19.583
ID33022	Yes	Yes	0	1	4.540	1	511.083	117.333	83.167	32.083
ID38038	No	No	1	0	4.210	2	555.917	86.917	50.500	19.083
ID06004	Yes	Yes	0	1	4.498	1	425.083	97.917	81.083	26.750
ID33018	Yes	Yes	0	1	4.560	1	602	123.750	78.833	16.417
ID36031	Yes	Yes	0	1	4.440	1	557.250	135.083	83.250	19.417
ID01006	No	No	1	0	4.463	2	510	93.750	54.625	17.375
ID02006	No	No	1	0	5.106	2	656	90	57.250	21.500
ID14004	Yes	Yes	0	1	4.578	1	570.917	119	81.167	27.500
ID34024	Yes	Yes	0	1	4.620	1	597.667	94	64	24.500
ID35025	No	No	1	0	4.590	2	701.750	87	43.750	5.750

Figure 5. Test Data Output Using Cross-Validation with the Decision Tree Algorithm

Next, an analysis is carried out to measure the performance of the machine learning decision tree algorithm obtained through testing using a performance vector. The analysis results are presented in Table 1.

Table 1. Confusion Matrix of Accuracy Analysis Using the Performance Vector with the Decision Tree Model

PerformanceVector (Performance)

Table View   Plot View

accuracy: 96.00% +/- 8.43% (micro average: 96.15%)

	true Yes	true No	class precision
pred. Yes	36	1	97.30%
pred. No	1	14	93.33%
class recall	97.30%	93.33%	

In Table 1, it is shown that for "pred Yes - true Yes," there are 36 data records predicted to fall into the "Yes" category (meeting WHO physical activity recommendations), and 1 data record is predicted to be in the "No" category (not meeting WHO physical activity recommendations). There is one misclassified data record, with an accuracy rate of 97.30%. Meanwhile, for "pred No - true Yes," out of the 15 data records, 14 are predicted correctly, and one is predicted wrongly, with an accuracy rate of 93.33%. Based on this data analysis, the accuracy of the decision tree's performance is found to be 96.00%. This means that the decision tree model exhibits high performance in classifying attribute variables related to physical activity in accordance with WHO recommendations.

In addition to using the decision tree algorithm, a second test was conducted with the support vector machine algorithm. The testing and data evaluation revealed that 8 data records were misclassified by the support vector machine algorithm. Unlike the decision tree algorithm, which produces a decision tree, the support vector machine model generates a multi-model regression. Here is the output of physical activity label predictions for young children through regression analysis produced by the support vector machine.

Multi Model By Regression (prediction model for label Meet PA)
Total number of Support Vectors: 52
Bias (offset): 0.462
w[Age] = 0.038
w[Sex] = -0.403
w[ag_average_SED] = -0.058
w[ag_average_LPA] = 0.141
w[ag_average_MPA] = 0.224
w[ag_average_VPA] = -0.053
w[ag_average_MVPA] = 0.153
w[ag_average_TPA] = 0.158

Based on the output, it is evident that the largest regression value is for the average time spent in moderate-intensity physical activities (MPA), which is 0.224 or 22.4%, while the lowest is for gender, which is -0.403 or -40.3%. This indicates that the variable or attribute of average time spent in moderate-intensity physical activities has the most significant influence on classifying physical activities in young children, while gender not only lacks a significant influence but tends to have a negative impact.

Subsequently, a testing was conducted on the support vector machine algorithm model that was generated from the training data. A summary of the test results for the generated model is presented in Image 6.

Row No.	Child ID	Meet PA	prediction(...	confidence(...	confidence(...	Age	Sex	ag_average...	ag_average...	ag_ave
3	ID33022	Yes	Yes	0	1	4.540	1	511.083	117.333	83.167
4	ID38038	No	No	1	0	4.210	2	555.917	86.917	50.500
5	ID06004	Yes	Yes	0	1	4.498	1	425.083	97.917	81.083
6	ID33018	Yes	Yes	0	1	4.560	1	602	123.750	78.833
7	ID36031	Yes	Yes	0	1	4.440	1	557.250	135.083	83.250
8	ID01006	No	No	1	0	4.463	2	510	93.750	54.625
9	ID02006	No	No	1	0	5.106	2	656	90	57.250
10	ID14004	Yes	Yes	0	1	4.578	1	570.917	119	81.167
11	ID34024	Yes	Yes	0	1	4.620	1	597.667	94	64
12	ID35025	No	No	1	0	4.590	2	701.750	87	43.750
13	ID37036	Yes	No	1	0	4.880	2	651.625	97.375	74.250

Figure 6. Summary of Test Data Results Using the Support Vector Machine Model

Table 3. Confusion Matrix of Performance Testing Results for the Support Vector Machine Model

accuracy: 84.67% +/- 24.50% (micro average: 84.62%)

	true Yes	true No	class precision
pred. Yes	30	1	96.77%
pred. No	7	14	66.67%
class recall	81.08%	93.33%	

To measure the performance of the Support Vector Machine model, a performance vector was used, as shown in Table 3. The confusion matrix indicates that for "true Yes," out of 37 data records, the Support Vector Machine model predicted 7 records incorrectly. Meanwhile, for "true No," out of 15 data records, 1 record was incorrectly predicted as "Yes." The overall accuracy of the Support Vector Machine's performance is 84.67%.

Based on the testing results of both models, the Decision Tree and the Support Vector Machine, it can be concluded that the Decision Tree algorithm outperforms the Support Vector Machine in classifying physical activities in young children.

DISCUSSION

This research focuses on classifying physical activities in early childhood based on accelerometer data and analyzes it using machine learning models. The primary goal of this study is to classify whether physical activities in early childhood align with WHO's physical activity recommendations based on the measured activity duration using the ActiGraph accelerometer. Based on the analysis, both the decision tree and support vector machine machine learning algorithms can be used to classify physical activities in early childhood.

The findings of this research align with previous studies that state that machine learning methods have high accuracy in classifying physical activities (Mannini & Sabatini, 2010; Alsareii et al., 2022; Seng et al., 2020; Mesanza et al., 2020). Moreover, other studies examining the differences in accuracy of physical activity intensity prediction using machine learning classification versus cut point methods in preschool children indicate that machine learning classification models exhibit higher accuracy than the cut point method (M. N. Ahmadi & Trost, 2022). Furthermore, research exploring machine learning models for measuring physical activity and energy expenditure shows consistent results, where machine learning models accurately label the type of physical activity, intensity, and energy expenditure in various age groups (Mardini et al., 2021). Machine learning methods can also be used to predict physical activity in individuals with special needs. A study found that three machine learning models, namely decision tree, support vector machine, and random forest, trained on accelerometer data from different body parts, effectively classified physical activities in children with cerebral palsy (Goodlich et al., 2020).

Regarding the decision tree model, as shown in Figure 3, the average time spent in moderate physical activities has the highest accuracy in classifying physical activities in early childhood. This means that the average time spent in moderate physical activities is the attribute variable that can classify the suitability of physical activities in early childhood according to WHO recommendations. This finding is consistent with previous research on artificial neural network models, which found that Moderate Physical Activity (MPA) reaches its maximum value during activities such as walking and playing (Fergus et al., 2017).

Furthermore, there is a difference in accuracy between the decision tree model and the support vector machine model, where the decision tree model exhibits higher accuracy than the support vector machine in classifying physical activities in early childhood based on Actigraph GT3X accelerometer data. This differs from the results of a previous study that tested three machine learning models: random forest, support vector machine, and binary decision tree to classify physical activities, which found that random forest and support vector machine models had better classification accuracy than the binary decision tree (M. Ahmadi et al., 2018). Support vector machine exhibited an accuracy range of 82.0-89.0%, and random forest ranged from 82.6-88.8%, while the binary decision tree had an accuracy range of 76.1-86.2%.

The differences in these findings could be attributed to various factors, including sample characteristics, attribute variables, dataset size, and more. Evaluating overall model performance is a complex task influenced by numerous attributes such as sample size, participants' demographic characteristics, the variety of physical activities tested, the type of accelerometer, body position, and the algorithm used (Mardini et al., 2021). Further studies are needed to establish precise formulas.

The advantage of this research is that the dataset is derived from the Actigraph accelerometer, which, as per previous studies, offers higher objectivity compared to questionnaires. However, limitations of this study include a relatively small dataset and a limited set of attribute variables used for classifying physical activities, which are restricted to age, gender, and average time spent in physical activities. Other attributes, such as the environment, parental care, motivation, and more, which are predicted to influence physical activity behavior in young children, need to be included in future research. Additionally, this study employed only decision tree and support vector machine algorithms, while other algorithms like deep neural networks with accuracy up to 96.81% (Bozkurt, 2022), random forests with 99% accuracy (Lee & Kwan, 2018), and other models were not assessed. Other research classifying physical activities in the 4-9-year-old age group using a random forest model based on accelerometer data also showed high accuracy in classifying children's movement behavior in real-life conditions (Ahmadi et al., 2020). Furthermore, feature selection plays a significant role in enhancing machine learning model performance for physical activity classification (Chong et al., 2021). Thus, further research is required to address these limitations and achieve improved research results.

CONCLUSION

This research demonstrates that machine learning algorithms can classify physical activities in early childhood based on accelerometer data. The performance of the decision tree and support vector machine models shows higher accuracy compared to the decision tree in classifying physical activities in early childhood. Surprisingly, it's possible to achieve this level of accuracy in classifying physical activities in early childhood by solely considering the attribute of the average time spent in moderate physical activities, without the need to account for age and gender attributes.

ACNKOWLEDGEMENT

Thank you to the Indonesian Physical Activity Research Group at Universitas Pendidikan Indonesia for their support in this research.

CONFLICT OF INTEREST

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

FUNDING

All funding for this research came from personal funds and the Indonesian Physical Activity Research Group at Universitas Pendidikan Indonesia

REFERENCES

Ahmadi, M. N., & Trost, S. G. (2022). Device-based measurement of physical activity in pre-schoolers: Comparison of machine learning and cut point methods. *PLoS ONE*, *17*(4 April), 1–17. https://doi.org/10.1371/journal.pone.0266970

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.

Ahmed, A., Aziz, S., Qidwai, U., Farooq, F., Shan, J., Subramanian, M., ... & Sheikh, J. (2022). Wearable Artificial Intelligence for Assessing Physical Activity in High School Children. Sustainability, 15(1), 638.

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), 1103.

Berlin, J. E., Storti, K. L., & Brach, J. S. (2006). Using activity monitors to measure physical activity in free-living conditions. *Physical Therapy*, *86*(8), 1137–1145.

Beattie*, P. E., & Lewis-Jones, M. S. (2006). A comparative study of impairment of quality of life in children with skin disease and children with other chronic childhood diseases. *British Journal of Dermatology*, *155*(1), 145-151.

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

Brumana, L., Arroyo, A., Schwalbe, N. R., Lehtimaki, S., & Hipgrave, D. B. (2017). Maternal and child health services and an integrated, life-cycle approach to the prevention of non-communicable diseases. *BMJ Global Health*, *2*(3), e000295.

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*(January), 45–53. https://doi.org/10.1016/j.gaitpost.2021.06.017

Faisal Candrasyah Hasibuan, & Andri Ulus Rahayu. (2022). Identifikasi Persediaan Makanan di dalam Lemari Pendingin Berbasis Raspberry Pi dan Deep Learning. *Electrician*, *16*(1), 94–101. https://doi.org/10.23960/elc.v16n1.2231

Febrianta, Y. (2016). Alternatif Mengembangkan Kemampuan Motorik Kasar Anak Usia Dini Dengan Aktivitas Akuatik (Berenang). *Al Athfal: Jurnal Pendidikan Anak*, *2*(2), 85–95. http://ejournal.uin-suka.ac.id/tarbiyah/index.php/alathfal/article/view/1269

Fergus, P., Hussain, A. J., Hearty, J., Fairclough, S., Boddy, L., Mackintosh, K., Stratton, G., Ridgers, N., Al-Jumeily, D., Aljaaf, A. J., & Lunn, J. (2017). A machine learning approach to measure and monitor physical activity in children. *Neurocomputing*, *228*, 220–230. https://doi.org/10.1016/j.neucom.2016.10.040

Goodlich, B. I., Armstrong, E. L., Horan, S. A., Baque, E., Carty, C. P., Ahmadi, M. N., & Trost, S. G. (2020). Machine learning to quantify habitual physical activity in children with cerebral palsy. *Developmental Medicine and Child Neurology*, *62*(9), 1054–1060.

Brumana, L., Arroyo, A., Schwalbe, N. R., Lehtimaki, S., & Hipgrave, D. B. (2017). Maternal and child health services and an integrated, life-cycle approach to the prevention of non-communicable diseases. *BMJ Global Health*, *2*(3), e000295.

Lawn, J. E., Blencowe, H., Oza, S., You, D., Lee, A. C. C., Waiswa, P., Lalli, M., Bhutta, Z., Barros, A. J. D., & Christian, P. (2014). Every Newborn: progress, priorities, and potential beyond survival. *The Lancet*, *384*(9938), 189–205.

Lee, K., & Kwan, M. P. (2018). Physical activity classification in free-living conditions using smartphone accelerometer data and exploration of predicted results. Computers, Environment and Urban Systems, 67, 124-131.

Leonardo, A., & Komaini, A. (2021). Hubungan Aktivitas Fisik Terhadap Keterampilan Motorik. *Jurnal Stamina*, *4*(3), 135–144. http://stamina.ppj.unp.ac.id/index.php/JST/article/view/764

Lin, Y., Yuan, J., Long, Q., Hu, J., Deng, H., Zhao, Z., Chen, J., Lu, M., & Huang, A. (2021). Patients with SARS-CoV-2 and HBV co-infection are at risk of greater liver injury. *Genes and Diseases*, *8*(4), 484–492. https://doi.org/10.1016/j.gendis.2020.11.005

Long, X., Yin, B., & Aarts, R. M. (2009). Single-accelerometer-based daily physical activity classification. *Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009*, 6107–6110. https://doi.org/10.1109/IEMBS.2009.5334925

Lontoh, P. F., Suryawan, A., & Utami, S. (2021). Hubungan Lama Paparan Televisi Terhadap Perkembangan Motorik Halus Balita. *Indonesian Midwifery and Health Sciences Journal*, *3*(1), 77–84. https://doi.org/10.20473/imhsj.v3i1.2019.77-84

Ludyanti, L. N. (2019). Perilaku Kurang Gerak (Sedentary Behaviour) Dengan Perkembangan Psikososial Anak Pra Sekolah. *Care : Jurnal Ilmiah Ilmu Kesehatan*, *7*(2), 22. https://doi.org/10.33366/jc.v7i2.1290

Mahendra, M., Chandra Telaumbanua, R., Wanto, A., & Perdana Windarto, A. (2022). Akurasi Prediksi Ekspor Tanaman Obat, Aromatik dan Rempah-Rempah Menggunakan Machine Learning. *KLIK: Kajian Ilmiah Informatika Dan Komputer*, *2*(6), 207–215. https://doi.org/10.30865/klik.v2i6.402

Maher, C. A., Davis, C. R., Curtis, R. G., Short, C. E., & Murphy, K. J. (2020). A physical activity and diet program delivered by artificially intelligent virtual health coach: proof-of-concept study. JMIR mHealth and uHealth, 8(7), e17558

Mannini, A., & Sabatini, A. M. (2010). Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors*, *10*(2), 1154–1175. https://doi.org/10.3390/s100201154

Mardini, M. T., Bai, C., Wanigatunga, A. A., Saldana, S., Casanova, R., & Manini, T. M. (2021). Age differences in estimating physical activity by wrist accelerometry using machine learning. *Sensors*, *21*(10), 1–15. https://doi.org/10.3390/s21103352

Mesanza, A. B., Lucas, S., Zubizarreta, A., Cabanes, I., Portillo, E., & Rodriguez-Larrad, A. (2020). A machine learning approach to perform physical activity classification using a sensorized crutch tip. IEEE Access, 8, 210023-210034.

Nurcahyo, F. (2015). Kaitan Antara Obesitas Dan Aktivitas Fisik. *Medikora*, *1*, 87–96. https://doi.org/10.21831/medikora.v0i1.4663

Rowlands, A. V. (2007). Accelerometer assessment of physical activity in children: An update. *Pediatric Exercise Science*, *19*(3), 252–266. https://doi.org/10.1123/pes.19.3.252

Saqib, Z. A., Dai, J., Menhas, R., Mahmood, S., Karim, M., Sang, X., & Weng, Y. (2020). Physical activity is a medicine for non-communicable diseases: A survey study regarding the perception of physical activity impact on health wellbeing. *Risk Management and Healthcare Policy*, *13*, 2949–2962.

Santos-Lozano, A., Santin-Medeiros, F., Cardon, G., Torres-Luque, G., Bailon, R., Bergmeir, C., ... & Garatachea, N. (2013). Actigraph GT3X: validation and determination of physical activity intensity cut points. *International journal of sports medicine*, 975-982.

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.

Sulistia, T., Djamahar, R., & Rahayu, S. (2018). Hubungan kualitas tidur dan aktivitas fisik dengan hasil belajar kognitif sistem koordinasi manusia. *Jurnal Penelitian Pendidikan Biologi*, *2*(2), 113–120. http://jurnal.um-palembang.ac.id/index.php/dikbio

Talango, S. R. (2020). Konsep Perkembangan Anak Usia Dini. *Early Childhood Islamic Education Journal*, *1*(1), 92–105. https://doi.org/10.54045/ecie.v1i1.35

Telaumbanua, F. D., Hulu, P., Nadeak, T. Z., Lumbantong, R. R., & Dharma, A. (2019). Penggunaan Machine Learning. *Jurnal Teknologi Dan Ilmu Komputer*, *3*(1), 57–64.

Vakili, R., Khademi, G., Vakili, S., & SAEIDI, M. (2015). Child mortality at different world regions: a comparison review.

Westerterp, K. R. (2013). Physical activity and physical activity induced energy expenditure in humans: Measurement, determinants, and effects. *Frontiers in Physiology*, *4 APR*(April), 1–12. https://doi.org/10.3389/fphys.2013.00090

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), 1–11. https://doi.org/10.1186/s12911-019-0890-0