Metaheuristic Optimized Voting Ensemble for Recognizing Daily and Sports Activities

El-Sayed M. El-Kenawy[1], Abdelhameed Ibrahim[2], Abdelaziz A. Abdelhamid[3,4], Mohamed Saber[5], Marwa M. Eid[6]

[1] Department of Communications and Electronics, Delta Higher Institute of Engineering and Technology, Mansoura, 35111, Egypt
[2] Computer Engineering and Control Systems Department, Faculty of Engineering, Mansoura University, 35516, Mansoura Egypt
[3] Department of Computer Science, College of Computing and Information Technology, Shaqra University, Shaqra 11961, Saudi Arabia
[4] Department of Computer Science, Faculty of Computer and Information Sciences, Ain Shams University, Cairo 11566, Egypt
[5]Electronics and Communications Engineering Dep., Faculty of Engineering, Delta University for Science and Technology, Gamasa City, Mansoura, Egypt
[6] Faculty of Artificial Intelligence, Delta University for Science and Technology, Mansoura 35712, Egypt
Emails: skenawy@ieee.org;afai79@mans.edu.eg;abdelaziz@su.edu.sa;abdelaziz@cis.asu.edu.eg; mohamed.saber@deltauniv.edu.eg; marwa.3eeed@gmail.com;

Abstract

This research analyzes the effectiveness of several methods for categorizing human actions captured by inertial and magnetic sensor units worn on the chest, arms, and legs. Each device has tri-axial sensors, including a gyroscope, accelerometer, and magnetometer. Voting ensemble classification models, where votes are weighted and optimized with a new optimization technique, are offered as a means to actualize this classification problem. The optimization technique is a combination of the sine cosine and particle swarm optimization algorithms, and the ensemble model is made up of three classifiers: support vector machines, decision trees, and multilayer perceptron. The classifiers are checked for accuracy using three distinct cross-validation strategies. Classifiers' proper differentiation rates and computational costs are compared to help you choose the best one for your needs. When it comes to body location, sensor devices worn on the legs provide the most valuable data. From a comparison of the various sensor modalities, we can deduce that magnetometers, followed by accelerometers and gyroscopes, provide the best classification results when only a single sensor type is employed. Furthermore, the study contrasts three machine learning models—support vector machines, decision trees, and multilayer perceptron —with respect to their usability, controllability, and classifier performance. Results reveal that the suggested method performs well in categorizing both typical daily activities and athletic endeavors.

Keywords: human activity classification; accelerometer; gyroscope; inertial sensors; body sensor; wearable sensors; machine learning; metaheuristic optimization algorithms

1. Introduction

Over the past two decades, the size, weight, and cost of commercially available inertial sensors have drastically lowered due to the fast advancements in micro electro-mechanical systems (MEMS) technology [1]. Magnetometers are occasionally included to the miniature sensor units that sometimes include accelerometers and gyroscopes. When it comes to measuring rates of motion, accelerometers

Doi: https://doi.org/10.54216/JAIM.020201
Received: May 29, 2022 Accepted: November 16, 2022

may measure either linear or rotational velocity whereas gyroscopes only measure rates in relation to a certain axis. There are devices that are sensitive along a single axis, as well as devices that are sensitive along two and three axes. Tri-axial magnetometers can measure the vector magnitude and direction of Earth's magnetic field. Since inertial sensors are so expensive to produce, their usage was formerly restricted to the aerospace and marine industries until the 1990s. Low- to medium-priced inertial sensors with respectable performance levels have ushered in a plethora of fresh applications. Inertial sensors are advantageous because they offer information on dynamic motion through direct measurements in three dimensions; they are also self-contained, non-radiating, and hence not susceptible to being jammed. On the other hand, as they employ dead reckoning for their internal sensing, inaccuracies in the output quickly add up when integrated to obtain position information, and the position output has a tendency to wander over time. Every so often, when new data from external absolute sensing systems becomes available, the errors must be recalculated based on the models used to account for them.

Automatic human activity detection and monitoring is a relatively new area of use for inertial sensing. The last ten years have seen an explosion of interest in this difficult but promising field of study. Numerous methods provide this activity monitoring function. Using vision systems with several video cameras is one example of a method that uses sensing systems that are permanently installed in the environment [2-5]. Applications in security and surveillance, entertainment, and personal archiving have all benefited greatly from the ability to automatically recognize, depict, and analyze human behaviors based on video pictures [6]. Recent investigations in this field are summarized in Reference [7], whereby many researchers pre-identify sites of interest on the human body by attaching visible markers like light-emitting diodes and then documenting their positions using optical or magnetic imaging techniques. For instance, using the Smart infrared motion capture technology, [8] examines six actions, including falls. The same method is used to identify walking abnormalities such limping, disorientation, and hemiplegia in [9]. In [10], many activity models are created for pose tracking, and particle filtering is used to investigate the pose space. When activities are contained inside a specific area of an interior space, it may be permissible to use permanently installed cameras (or other ambient intelligence technologies). If photographs are to be taken, the area must be brightly lit, almost like a studio. Nonetheless, fixed camera systems are impractical for activities like commuting, shopping, and jogging that take place both indoors and outdoors and require movement from one location to another, as it is challenging to acquire video data for long-term human motion analysis in such unrestricted environments. However, other drawbacks of camera systems, such as occlusion effects, the correspondence problem, the high cost of processing and storing images, the requirement of using multiple camera projections from 3D to 2D, the need for camera calibration, and cameras' intrusions on privacy, still exist despite recent proposals for wearable camera systems to overcome this issue [11].

Advantages exist in using wearable tiny inertial sensors rather than sensor systems permanently installed in the surroundings. Activity is best assessed at the site where it really takes place, as described in [12]. Contrary to optical motion capture systems, which need an unobstructed line of sight, small inertial sensors may be placed anywhere, including within or behind an item. Data in three dimensions may be derived directly from the one-dimensional signals obtained by multiple-axis inertial sensors. When compared to other computing and power-intensive devices, wearable systems benefit from being constantly present and using less resources. Activity detection through the use of wearable sensors has been studied extensively previously; for an overview, see [13-16]. There are more in-depth, sweeping literature reviews on rehabilitation and biomechanics in [17–19]. Many applications for camera systems and inertial sensors overlap. Although several research have employed video cameras to compare inertial sensor data [20–23], others have integrated or fused data from these two sensing modalities [24, 25]. The combination of optical and inertial sensors has been getting a lot of interest lately due to its high performance and broad potential applications [26, 27]. There are other reports in the literature [21, 28, 29] of the fusion of information from inertial sensors and magnetometers. However, due to the aforementioned benefits, we have opted to employ a wearable system for activity identification in this investigation. The activity spotting subclass of activity identification tasks is well-known [30] because it involves detecting the beginning and end times of predefined activities from a sequence of events. Classifiers for activity detection may be broken down into two groups: instance-based and model-based, with the latter being far more common. Instance-based classifiers have the benefit of being able to handle classes that are met for the first time during the testing phase, as well as having a simpler structure, reduced computing cost, and lower power consumption [31]. However, in tasks on a larger size, they are unable to adapt to new conditions, such as inter-subject variability, as efficiently.

Doi: https://doi.org/10.54216/JAIM.020201
Received: May 29, 2022 Accepted: November 16, 2022

Activity detection faces challenges such those presented by the need to optimize the number and configuration of sensors and synchronize their readings. Energy-aware systems that take into account the power-accuracy trade-off are proposed by Zappi et al. [32]. These systems employ sensor selection algorithms. Similarly, Ghasemzadeh [33] suggests distributed algorithms to cut down on power consumption, and he also presents the idea of "motion transcripts." Based on the data from a small number of inertial orientation sensors worn by the subject, a system for monitoring and recognizing human full-body poses and activities is created in [34]. Assembly and maintenance applications are the primary focus of the work cited in [35], which focuses on identifying actions denoted by a hand gesture and an associated sound. Refer to [36] for discussion on collaborative work. Inter-subject variation is the primary topic of [37], which examines a massive dataset. Opportunistic activity and situation recognition systems [38] are being created on the go as part of the European research project OPPORTUNITY. Another EU project (wearIT@work) seeks to create a wearable computing system that can recognize a worker's actions and provide timely information regarding maintenance or production tasks based on that data [39]. In [40], we get an overview of the state of research on wearable sensor systems for health monitoring and prognosis. The CONFIDENCE project, funded by the European Commission's seventh framework, aims to develop and integrate innovative technologies to create a care system for the early detection of short- and long-term abnormal events (like falls) or unexpected behaviors that may be related to a health problem in the elderly [41]. The goal of this system is to help the user feel safe and confident, increase the likelihood of prompt medical attention, and ultimately help the user maintain their independence for longer.

2. Proposed Methodology

There are Xsens Technologies MTx 3-degrees-of-freedom orientation trackers used in this study (Fig. 1). The sensor units of the MTx receive information on 3D acceleration, rate of turn, and the intensity of the Earth's magnetic field thanks to the unit's tri-axial accelerometer, gyroscope, and magnetometer. Through an interface application called MT Manager, each motion tracker may be instructed to sample at a rate of up to 512 hertz, capturing either raw or calibrated data.

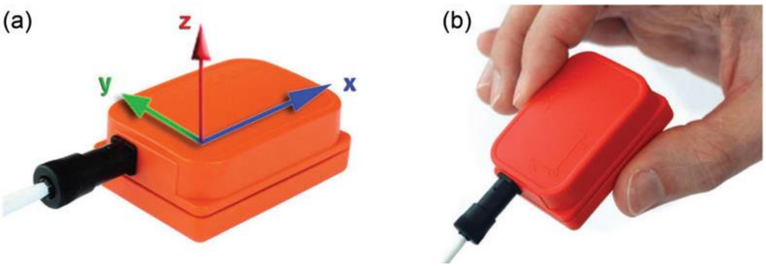

Figure 1: (a) MTx with overlaid sensor-fixed coordinate (b) Finger based MTx from [42].

Eight volunteers (four females and four males, aged 20-30) complete each of the aforementioned tasks for five minutes. In [60], we find in-depth descriptions of our test subjects. Participation in the trials was voluntary, and all participants provided written informed permission that was reviewed and approved by the Bilkent University Ethics Committee for Research Involving Human Subjects. Volunteers are given a lot of leeway in how they carry out the tasks we provide them. We intend to simulate real-world settings, where individuals walk, run, and exercise in their own way, which is why we purposefully chose not to give any directions regarding the exercises. Activities take place on a flat open area, the Bilkent University Sports Hall, and the Electrical and Electronics Engineering Building. Each sensor unit is optimized for a 25 Hz sampling rate. Features are derived from the 5-minute signals by breaking them down into 5-second chunks. For each action, this yields 480 (= 60 8) signal segments. Our data is hosted in the UCI Machine Learning Repository (http://archive.ics.uci.edu/ml/) for anybody to use.

Doi: https://doi.org/10.54216/JAIM.020201
Received: May 29, 2022 Accepted: November 16, 2022

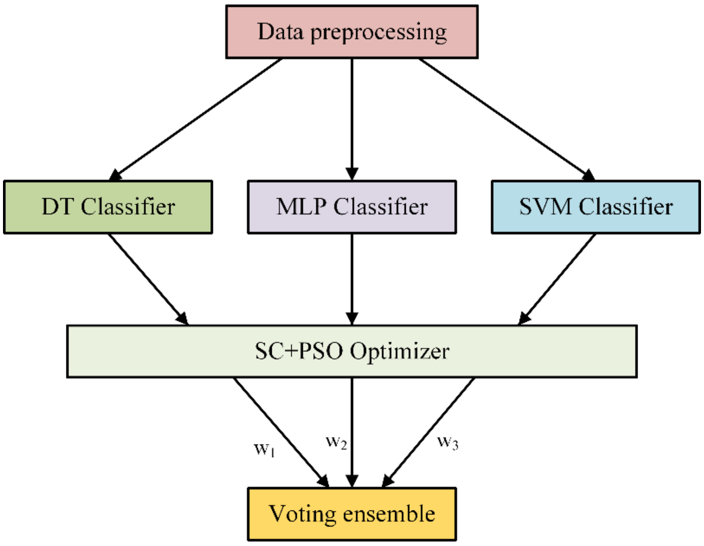

Figure 2: The proposed optimized voting ensemble approach

A. The Proposed Ensemble Model

We start by showing you the data we used to boat-train our classifiers after we let go, then we walk you through the processes we propose doing, and lastly we show you the results. Three distinct classification strategies were employed in the uploading of this image: Different kinds of classifiers include decision trees (DT), multilayer perceptron (MLP), and support vector machines (SVM). We employ the sine cosine algorithm (SCA) in conjunction with the particle swarm optimization technique to boost the weight of these classifiers' votes inside an ensemble model as shown in Figure 2.

B. Support Vector Machines (SVM)

Authors in [17-20] mark the debut of the SVM. One of the more recent developments in the realm of supervised machine learning is the support vector machine (SVM). It works well for a small dataset with few outliers. The concept is to identify a hyper segmentation lanes to divide information. The area is segmented along this hyperplane, with each sector holding a certain kind of information (Fig. 3). Multiple hyperplanes can be selected to differentiate between the two types of information. The aircraft with the largest margin is what we're looking for. To calculate the margin, find the two data points closest to the hyperplane that correspond to the two categories. In order to improve the method, support vector machines (SVMs) look for the super planar with the largest margin value, splitting the data into two equally-sized halves. The closest data points to the hyperplane are referred to as the "support vectors" (Fig. 3). Linear surface that cuts space in half, like a hyperplane does. If you want to divide up your space into two categories, then you need a hyperplane, which is a one-dimensional subspace.

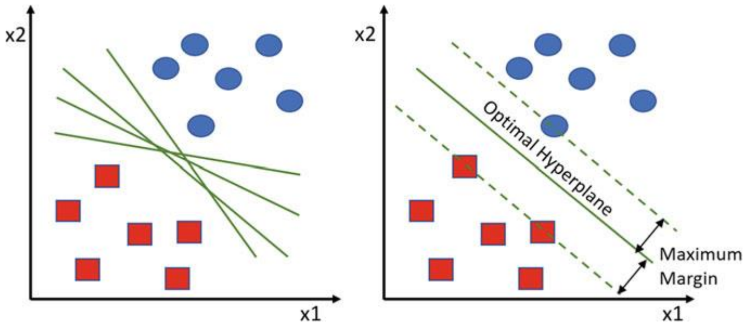

Figure 3: Structure of support vector machines.

C. Multilayer Perceptron (MLP)

It's been pointed out that you can use a multilayer perceptron neural network. For those situations when the variables cannot be separated in a straightforward manner. In order to address this issue, a multilayer perceptron is constructed by adding additional layers to a single-layer perceptron. As can be seen in Figure 4, the MLP network is a kind of feed-forward neural network that may have

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anywhere from one to many hidden layers. n neutrons are input to the network, which also includes n hidden neurons, and n neutrons are output.

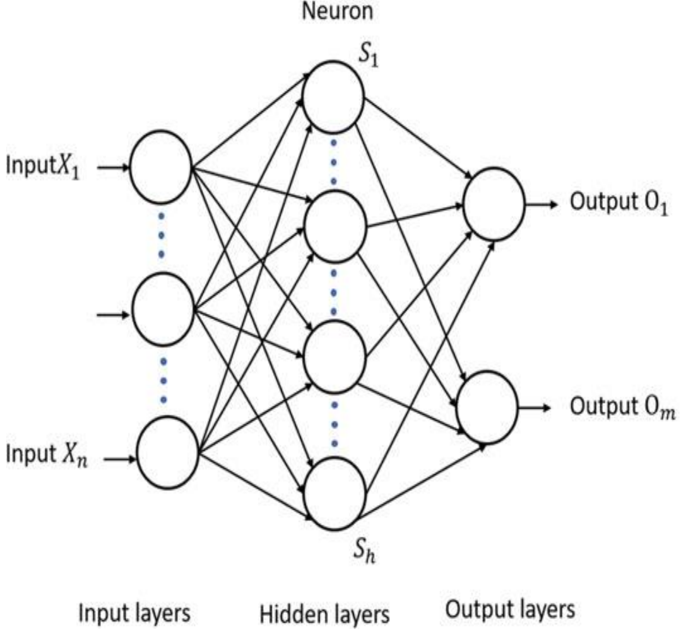

Figure 4: Structure of a multilayer neural network.

Because we'll be using a single hidden layer, our input matrix will have the form (batch size, number of attributes), and our weight matrices will contain one weight each for connections to and from the hidden layer and the output layer. So, the input layer is a matrix with the form of (number of features, number of hidden neurons), the hidden layer is a matrix with the form of (number of neurons, number of classes), and the output layer is a matrix with the form of (number of features, number of hidden neurons, number of classes) (batch size, number of classes).

D. Decision Trees (DT)

DT first appeared in [21, 22]. Each node in the tree represents a property, and each branch represents a possible value for that property. The decision tree's predictive value may be derived from it by tracing the tree's nodes in accordance with their associated property values. To begin, you need a tree algorithm to accurately anticipate the final result. Our data, its characteristics, and the categorical (dummy) values inside it require scrutiny. In addition, we can use the following formulae to deal with entropies and discriminative powers to determine the optimal characteristics for our tree. Presented below is a condensed version of the decision tree in Figure 5.

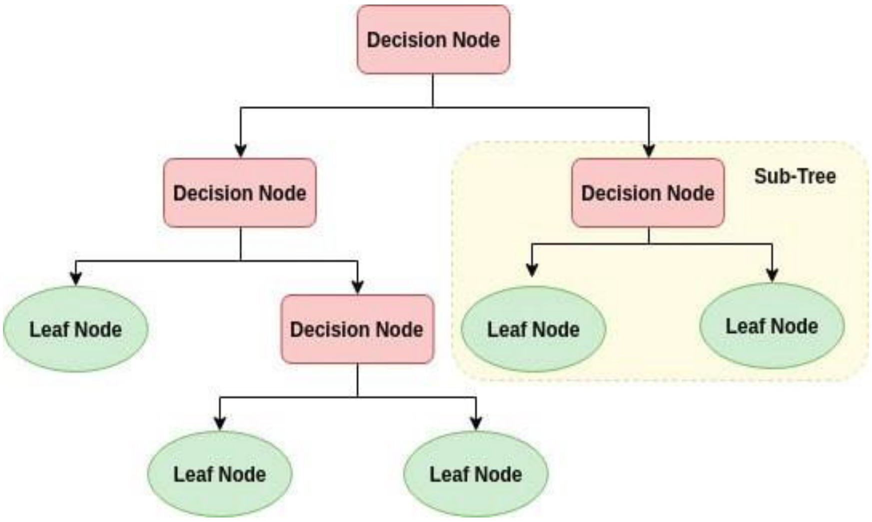

Figure 5: Structure of a decision tree.

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For example, we find that the median age is the perfect divider between two groups of people in our data. This method was also applied to additional characteristics. After that, we've reached a point where we've located the most promising opportunities to split, ultimately determining whether certain nodes in our tree would be on the left or the right. To divide our data in half, we use a certain column and value to identify the ideal splits while we are developing our tree with nodes (left child and right child of a node in a tree). In the recursive section, we apply the same strategies used in the previous sections to each successive level of the tree. There is no need to change the current node to a leaf node unless there is a question to be asked.

E. Metaheuristic Optimization

Metaheuristics are employed in the fields of computer science and mathematical optimization to find, construct, or choose a heuristic (partial search algorithm) that, despite a lack of full information or computational resources, may give a workable solution to an optimization problem. Without the aid of metaheuristics, it would be difficult to obtain a representative sample of the domain of possible solutions. Since metaheuristics may be applied in many contexts with little in the way of preparation or in-depth understanding of the optimization issue at hand, they are typically more versatile than other optimization approaches. Although metaheuristics are increasingly being used in favor of classical optimization techniques and iterative procedures, there is no assurance that the optimal solution to a problem class will be found through their application. Stochastic optimization is only one of numerous well-known metaheuristics whose ultimate solution may differ based on the values of the random variables.

The use of metaheuristics in combinatorial optimization to develop hypotheses about the optimal solution can be more effective than the use of optimization algorithms, iterative approaches, or even basic heuristics. That's why they could represent new approaches to optimization problems. In this regard, a plethora of articles already exist. Since most metaheuristics papers describe the author's personal experiences with putting the algorithm into practice, they inevitably have an experimental tone. Aside from empirical evidence, however, there are also formal theoretical conclusions that provide insight on questions of convergence and the feasibility of finding a global optimum. Several other metaheuristic approaches have been proposed in recent studies, and they may all have important consequences for the field as a whole. Previous research on this issue has been hampered by imprecise language, a failure to adequately cover essential themes, inadequate methodology, and a lack of suitable citations.

3. Results

In this research, we develop three distinct classifiers: DT, MLP, and SVM. The dataset is divided into two halves, with 70% used for training models and 30% used for testing the models in a mock data set. Additionally, we examine two separate sets of data (outlier data and elimination outlier data). Classifier approaches are compared in Table 1 according to their outlier-data-obtained accuracy, recall, precision, and F1 score. The results are most accurate when using the proposed ensemble model.

Table 1: Classification results using the proposed method compared to other methods

	Accuracy	Sensitivity	Specificity	Pvalue	Nvalue	F-score
NN	0.9497	0.9259	0.9859	0.9901	0.8974	0.9569
SVM	0.8723	0.8696	0.8791	0.9479	0.7273	0.9070
DT	0.9003	0.9091	0.8791	0.9479	0.8000	0.9281
SC+PSO	0.9884	0.9901	0.9859	0.9901	0.9859	0.9901

Table 2 displays the statistical evidence for the superiority of the voting ensemble classifier. The given optimal voting ensemble yields significantly enhanced performance.

Doi: https://doi.org/10.54216/JAIM.020201
Received: May 29, 2022 Accepted: November 16, 2022

Table 2: Statistical analysis of the results recorded by the proposed method

	NN	SVM	DT	SC+PSO
Number of values	10	10	10	10
Minimum	0.9397	0.8723	0.9003	0.9884
25% Percentile	0.9497	0.8723	0.9003	0.9884
Median	0.9497	0.8723	0.9003	0.9884
75% Percentile	0.9497	0.8748	0.9028	0.9884
Maximum	0.9597	0.8923	0.9203	0.9884
Range	0.02	0.02	0.02	0
10% Percentile	0.9407	0.8723	0.9003	0.9884
90% Percentile	0.9587	0.8913	0.9193	0.9884
95% CI of median				
Actual confidence level	97.85%	97.85%	97.85%	97.85%
Lower confidence limit	0.9497	0.8723	0.9003	0.9884
Upper confidence limit	0.9497	0.8823	0.9103	0.9884
Mean	0.9497	0.8753	0.9033	0.9884
Std. Deviation	0.004714	0.006749	0.006749	0
Std. Error of Mean	0.001491	0.002134	0.002134	0
Lower 95% CI of mean	0.9463	0.8704	0.8985	0.9884
Upper 95% CI of mean	0.9531	0.8801	0.9082	0.9884
Coefficient of variation	0.4964%	0.7711%	0.7472%	0.000%
Geometric mean	0.9497	0.8753	0.9033	0.9884
Geometric SD factor	1.005	1.008	1.007	1
Lower 95% CI of geo. mean	0.9463	0.8705	0.8985	0.9884
Upper 95% CI of geo. mean	0.9531	0.8801	0.9081	0.9884
Harmonic mean	0.9497	0.8752	0.9033	0.9884
Lower 95% CI of harm. mean	0.9463	0.8705	0.8985	0.9884
Upper 95% CI of harm. mean	0.9531	0.88	0.9081	0.9884
Quadratic mean	0.9497	0.8753	0.9033	0.9884
Lower 95% CI of quad. mean	0.9464	0.8704	0.8985	0.9884
Upper 95% CI of quad. mean	0.9531	0.8801	0.9082	0.9884
Skewness	0	2.277	2.277	
Kurtosis	4.5	4.765	4.765	
Sum	9.497	8.753	9.033	9.884

The Wilcoxon signed-rank test is used to evaluate the proposed method against the alternatives. The data collected throughout the course of this investigation is shown in Table 3. The p-values presented in the table serve as evidence.

Table 3: Wilcoxon signed rank test of the recorded results of the proposed method

	NN	SVM	DT	SC+PSO
Theoretical median	0	0	0	0
Actual median	0.9497	0.8723	0.9003	0.9884
Number of values	10	10	10	10
Wilcoxon Signed Rank Test				
Sum of signed ranks (W)	55	55	55	55
Sum of positive ranks	55	55	55	55
Sum of negative ranks	0	0	0	0
P value (two tailed)	0.002	0.002	0.002	0.002
Exact or estimate?	Exact	Exact	Exact	Exact
P value summary	**	**	**	**
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes
How big is the discrepancy?				
Discrepancy	0.9497	0.8723	0.9003	0.9884

Comparison of the optimum voting ensemble classifier's results to those of the baseline models is depicted graphically in Figure 7. For an example of the enhanced efficacy of the proposed method is shown superior when compared to the other methods.

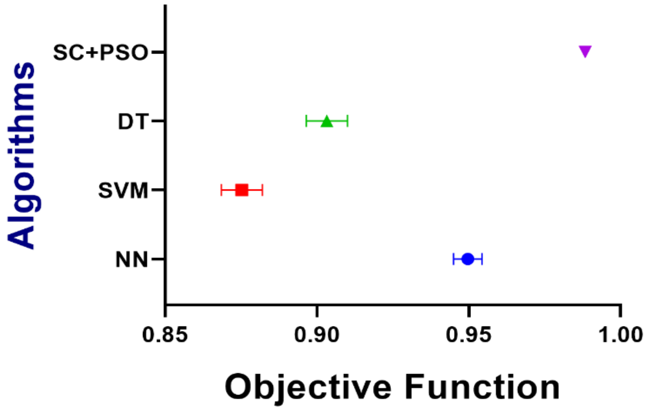

Figure 7: The accuracy of the proposed method compared to other methods.

4. Conclusion

The data from small inertial sensors and magnetometers were analysed, and the characteristics retrieved were utilized to categorize human actions, and the findings are presented here. The main contributions of this research are the identification of the most informative sensor modality and/or combination, as well as the identification of the most suitable wearable sensor configuration, and the comparison and identification of the classifier(s) that satisfy the performance requirements and design criteria for an activity recognition system on a common basis. We evaluate many classifiers on the same dataset and contrast their accuracy, processing requirements, and confusion matrices. We think it's crucial to compare classifiers on a level playing field, therefore we collected data from a large number of people engaging in a wide variety of tasks and used that data in our analysis. By contrasting the performance of several sensor types, we find that magnetometers, followed by accelerometers and gyroscopes, provide the best classification results when only a single type of sensor is employed. Adding a magnetometer to a group of sensors can boost their overall performance. Remember, nevertheless, that metal surfaces and ferromagnetic objects close to the sensor can readily distort magnetometer signals, leading to erroneous conclusions. The most useful data from activity sensors is gathered from those worn on the legs. Researchers in the field of wearable, mobile, and ubiquitous computing may find this paper's detailed evaluation of the many combinations of sensor modalities and their location on the body to be helpful.

Doi: https://doi.org/10.54216/JAIM.020201
Received: May 29, 2022 Accepted: November 16, 2022

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

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Received: May 29, 2022 Accepted: November 16, 2022

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Doi: https://doi.org/10.54216/JAIM.020201
Received: May 29, 2022 Accepted: November 16, 2022