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A wireless IOT system towards gait detection technique using FSR sensor and wearable IOT devices

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Abstract

Purpose – The recent advancement in gait analysis combines internet of things that provides better observations of person living behavior. The biomechanical model used for elderly and physically challenged persons is related to gait-related parameters, and the accuracy of the existing systems significantly varies according to different person abilities and their challenges. The paper aims to discuss these issues.
Design/methodology/approach – Deployment of wearable sensors in gait analysis provides a better solution while tracking the changes of the personal style, and this proposed model uses an electronics system using force sensing resistor and body sensors.
Findings – Experimental results provide an average gait recognition of 95 percent compared to the existing neural network-based gait analysis model based on the walking speeds and threshold values.
Originality/value – The sensors are used to monitor and update the predicted values of a person for analysis. Using IoT a communication process is performed in the research work by identifying a physically challenged person even in crowded areas.

Keywords Gait analysis, Body wearable sensors, Force sensing resistors

Paper type Research paper

Introduction

The interest in analyzing the physically challenged person in a particular area is to provide preference to that person and predict the nature of the walking style that will provide an immediate medical facility when they need. Many researchers' works in human identification systems, face recognition and gait recognition model for identifying a person but compared to human gait analysis had evident advantages over the others since it works without any interruption or interface of the subject cooperation. The basic model of gait analysis uses human walking styles so that it can be used in detection process more effectively from a long distance and can be used in surveillance application also in the public places. Figure 1 presents a basic walking style of a person from load response to pre-swing, while they walk the nodes used in walking styles are pointed in Figure 1(b), which is used for analysis.

The consequences in the analysis include the mobility, disability and, in particular, the disability in walking involves effects in a person walking style. The risk factor involving a person can be categorized into three categories such as fall detection, fall prediction, and fall prevention system. The fall detection system is used to notify the user in the case of fall occurrence, and it cannot provide any suggestion or notification to help users before they fall. The fall in this model is compulsory, and it just provides the information, so it is less effective than the other models. Many fall prediction models are available to estimate the nature of fall



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and the risk after fall based on the clinical assessment of the gait and other factors. Using some threshold value, the person is categorized into fallers and non-fallers. Real-time systems need a continuous monitoring system for the user so that a prevention system predicts the fall in real time and alerts a person, thereby reducing the health consequences after fall. The prediction and prevention system has common terms since it collects the data from the sensors and compute a feature set before the risk of fall occurs through classification algorithms. The use of sensors in investigating the parameters is common and it is considered as an easy process as it collects data without the need of any other factors, unlike the other systems such as camera and sound. Accelerometers and gyroscopes are considered as some common systems that provide data based on the nature of the person. Embedding smart phones to the feature extraction process has increases the ability of system in IoT, which has made it much convenient for the users.

The presented fall prediction system uses posture variables to analyze the movement of a person and a mathematical calculation to predict the fall. Since the fall time is very less and the system must compute the mathematical process and it must alert the user so that using complex algorithms in analyzing the performance reduces the system efficiency. Therefore, an effective algorithm is needed for analyzing the performance with a better accuracy and time reflex nature for consideration. A significant development of IoT in many application helps to improve the communication; the proposed model handles nonlinear motion of a person using gait analysis and combining IoT through the body wearable sensors and force sensors that is integrated into the mobile application. Handling the user acceleration, it predicts the behavior of gait through threshold values for a person with abnormal walking style. The research work is organized as follows: The second section describes about the related works in gait analysis and IoT models. The third section provides the proposed model mathematical formulation and the fourth section provides the summary about the experimental results along with discussion.

Related works

Many research works have been done and the process still continues; this section provides a summary about the existing research works in gait analysis and IoT applications. Research work (Qi *et al.*, 2018) describes about the sensor-based activity recognition system in health care applications related to IoT. The process involved in the research work combines the health care and IoT so that an effective data transfer is possible from one place to another place and the human cost is reduced. The usage of cloud networks in medical applications can provide suitable medical treatment from one place to another place without the need of physical presence. Research work (Qi *et al.*, 2017) describes about the various health care systems related to IoT as a survey. It provides a keen knowledge about integrating health

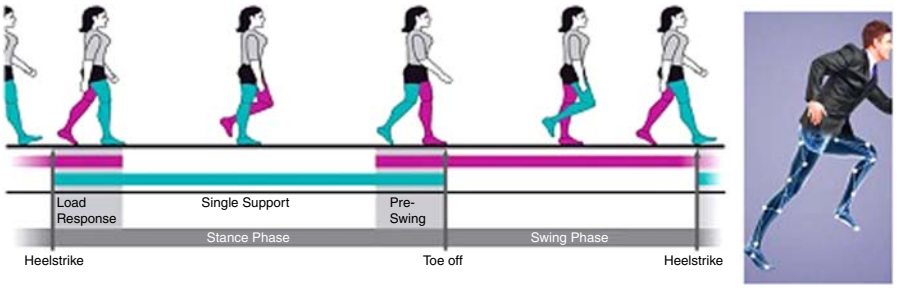


Figure 1.
(a) Walking style of person; (b) nodes points

care applications into IoT that is related to this proposed research model. Implementing gait analysis in IoT is based on this health care applications, and this literature provides the merits and demerits in the existing research works. The literature (Godfrey, 2017) reports about the issues present in the gait analysis prediction system and the advantage of using wearable models for an independent living of elderly persons. The monitoring system used in the model works based on the electro-mechanical movement based values, and there is a threshold level for each process. If the wearable sensor notices the level crossing the threshold value, then a warning or alert is provided to the person so that they can change the current process, which is much suitable for aged persons.

Research work (Gadaleta and Rossi, 2018) provides a smart phone-based recognition model that has recognition process obtained through neural network. The process involves smart phone application that monitors the data from the person and provides suitable communication or alert to the connected persons. The literature (Llamas *et al.*, 2017) provides a sensor-based platform in gait recognition using an open source hardware. The proposed work utilizes the sensors for accessing the information about the person walking behavior so that analysis identifies the person. As an alternative to normal authentication system the gait nature is used for the authentication process in some applications. Research works (Nweke *et al.*, 2018; Llamas *et al.*, 2016) describe about the wearable sensor application interconnected to mobile for human activity monitoring. The process has multiple sensors and each provides data from each location so that all of them are consolidated into application in the mobile providing an alert on unusual detection. Research work (Ing-Jr and Chang, 2017) provides details about the recognition system based on the gesture commands. The extraction process based on the features compares the present data and the existing data for better analysis and it also provides a better recognition system using data stream.

The literature (Zhang *et al.*, 2018) also describes about the gait analysis model based on sensors as a health care application. In order to provide a smart heal application, the proposed model uses sensor signals for processing and then a predictive analysis generates a report to the corresponding user. A research model (Gravina *et al.*, 2017) reports about the issues and solution in a cloud-based human activity process in mobile computing. The utilization of cloud in human detection system increases the accuracy and also reduces the errors. The literature (García *et al.*, 2019) describes about the health care application for detecting the stroke, and the results are transmitted through cloud network. The process provides a simple detection mechanism, and the issues present in this research work do not provide any prediction analysis. The literature (Gavrilova *et al.*, 2018) reports about the sensor-based activity recognition application for cognitive systems. The process differs from other activity monitoring systems. Due to its cognitive nature, the application is limited to a specific monitoring process. Research work (Stack *et al.*, 2018) describes about the wearable sensors and video-based identification system for the person having Parkinson's diseases. The findings from article (Kaur and Sood, 2017; Paraskevopoulos *et al.*, 2017) discuss about the resource constrained routing and scheduling in the service industry in allocation of scarce resources to various locations. The survey paper discusses various issues in the constrained routing of various authors and highlights the benefits of scheduling algorithms with respect to qualification, services and other modules of problems. Based on the above survey work, it is observed that earlier gait recognition model performs only either fall detection or fall prediction. They lag in efficiency if it locates the person in crowded places so that the accuracy level also decreases. The proposed model provides a better classification algorithm and an optimized routing model for fall prediction and detection analysis along with the communication model through Internet of things (IoT).

Proposed work

The proposed work includes an ANFIS model for classification and ant colony optimization for optimizing the efficient routing for the IoT network. This section provides the

mathematical of ANFIS and ACO and how it is related to the proposed work. Initially, the sensors and the data are used to identify the person with disabilities, and the information related to the user is passed into the cloud network for the transmission process. A simple illustration of an ANFIS model is depicted in Figure 2, and it includes five layers of architecture. The input layer and the second layer are used to validate the information received through the sensors and based on the threshold value that is set in the system model, and the classification is performed by processing the data set. This process is performed in the consecutive layers, and the final result is a summarization of all over data from the person wearable sensors and pressure sensors.

The mathematical analysis is performed based on IF and THEN rules, and it is given as:

$$\left.\begin{array}{l}\text{Rule 1 : If}(x \text{ is } A_1) \text{ and } (y \text{ is } A_1) \text{ then } f_1(p_1x+q_1y+r_1)\\ \text{Rule 2 : If}(x \text{ is } A_2 \text{ and } (y \text{ is } B_2) \text{ then } f_2(p_2x+q_2y+r_2)\end{array}\right\}. \tag{1}$$

The independent information from the sources is considered as x for the body wearable sensors and y for the pressure sensor, and the fuzzy set is given as A_i and B_i and the parameters are defined based on the prediction procedure of fuzzy governance. In this a five-level neuron an identical layer which includes functional relations and an adaptive input layer considered as node terminals as the data collected from the sensors. The result after the fuzzy relationship is given as:

$$\rho_i^1 = \mu_{A_i}(x) i = 1, 2\,, \tag{2}$$

$$\rho_i^1 = \mu_{B_i - 2}(y) i = 3, 4\,. \tag{3}$$

The fuzzy membership function is formed in bell-shaped function, and the values are presumed as $\mu_{A_i}(x)$, $\mu_{B_i - 2}(y)$. The value of $\mu_{A_i}(x)$ is given as:

$$\mu_{A_i}(x) = \frac{1}{1+\left\{\left(\frac{x-c_i}{a_i}\right)^2\right\}^{b_i}}. \tag{4}$$

where a_i, b_i and c_i are the factors of the member ship function that is used in bell-shaped function, and the second layer, third layer and fifth layer in the ANFIS are given as:

$$L_i^2 = M_i = \mu_{A_i}(x)\mu_{B_i}(y)\,, \tag{5}$$

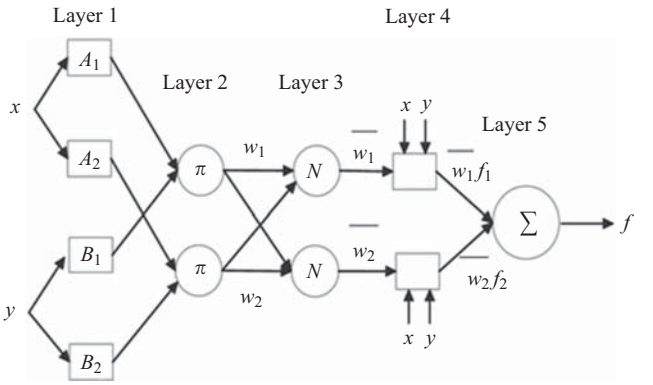


Figure 2.
Illustration of five layer ANFIS model

$$L_i^3 = w_i = \frac{w_i}{w_1 + w_2}, \tag{6}$$

$$L_i^4 = \tilde{w}_i f_i = \tilde{w}_i (p_i x + q_i y + r_i). \tag{7}$$

The final result of the model is a summary of the all the layer results and it is given as:

$$L_i^5 = \sum_{i=1}^{2} \tilde{w}_i f_i = \frac{\sum_{i=1}^{2} \omega_i f_i}{\omega_1 + \omega_2}. \tag{8}$$

The membership function defining the ANFIS model and the fuzzification is used to produce data from the inputs that is used to train the propagation network in the proposed classification model. The architecture includes the entire layer and its identical outputs in practical classification cases. The factors that can be modifiable a_i, b_i *and* c_i are linked with the input function and the polynomial function. The learning process in the ANFIS is used to build the results based on the data from the sensors such as body wearable sensors and foot pressure sensors. Once the classification process is completed the data from the prediction system shares the information into the cloud so that the person with disability can be identified easily and a preference will be provided along with the information sharing system to the related persons. For efficient communication in IoT, the system must provide end-to-end delivery system from one network to other network through cloud. Many routing models are available in present situation, and the proposed model uses ant colony optimization for efficient routing in IoT. The reason to choose ant colony optimization in efficient routing is due to the behavior of ant path selection for the food searching process. The mathematical model is obtained based on the nature of ants pheromones deposit methodology to obtain shortest path to reach the destination. The mathematical model of ACO is illuminated by considering the paths x and y obtained from the classification results. The number of paths of the ants is considered along with the time step function T and the probability of path choosing is considered as Px and Py. The step function-based probability of choosing the correct path is given as:

$$(T + 1) = \frac{[z + nx(T)]}{[[z + nx(T)] + [z + ny(T)]]}, \tag{9}$$

$$(T + 1) = 1 - Py(T + 1). \tag{10}$$

The degree of attraction is given as z and the bias toward pheromone deposits provides the decision process, and the updating process of new position from the existing position is given based on the random distribution process as:

$$\overrightarrow{l_{j,t}} = \overrightarrow{l}_{i,t} + \text{Real} \times \text{Rand int}\,[-1, 1], \tag{11}$$

$$\overrightarrow{l_{j,t}}(T+1) = \overrightarrow{l}_{i,t}(T) + \left(\overrightarrow{l_{j,t}}(T) - \overrightarrow{l}_{i,t}(T)\right) \times \text{Rand int}\,[0, 1]. \tag{12}$$

The process is repeated until it reaches the shortest path from the nest to food resource location, and for every displacement, the present position and the new position are updated.

The step movement is given as:

$$\overrightarrow{l_{j,t}}(T+1) = \overrightarrow{l}_{i,t}(T) + \left(\frac{\overrightarrow{l_{j,t}}(T) - \overrightarrow{l}_{i,t}(T)}{\varphi_{i,t}} \right) \times \text{Rand int}[0,1]. \quad (13)$$

$\overrightarrow{l_i}$ position of AF i follows the best $\overrightarrow{l_b}$. Figure 3 gives an illustration of ACO model path selection strategy that is related in the proposed model routing process.

The standard process in the IoT includes the size of information packet that is used in the routing process and the parameters used in finding the shortest path. The routing table is used in the optimization model in order to maintain the changes the routing process also to analyze the quality of services.

Figure 4 gives the proposed model process starting from the data from the sensors to the ANFIS classification model and the ACO optimization model. The proposed model provides efficient routing based on the factors such as route discovery and maintenance. A short summary of the proposed model routing efficiency is described as follows.

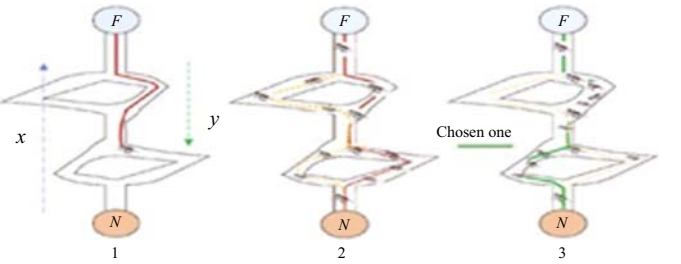


Figure 3.
Illustration of ant colony optimization

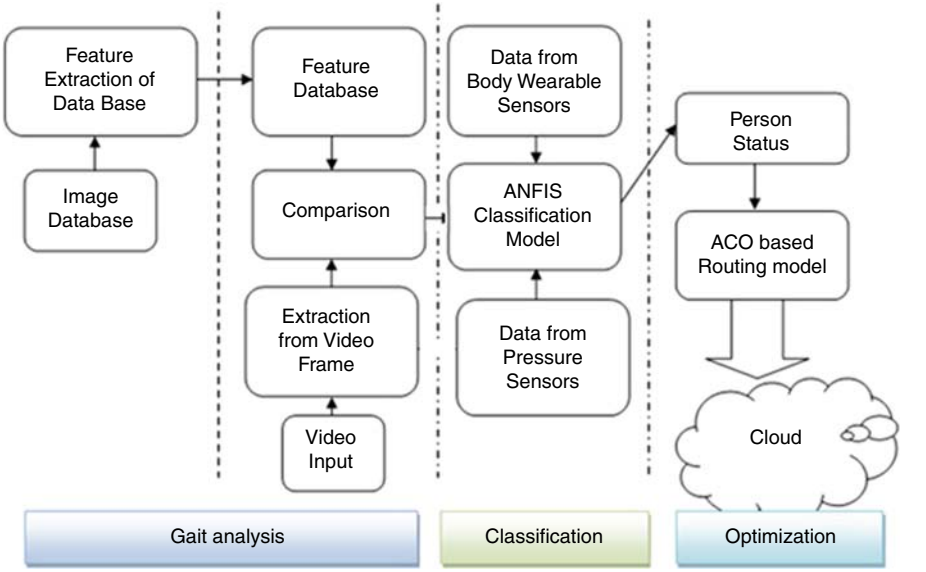


Figure 4.
Proposed ANFIS-ACO model

Algorithm for efficient routing in IoT Based on ant colony optimization

$Input$

$XX, YY, Xx, Yy, BS, Rs > r > 0$

$Output$

$Efficient\ Routing$

$choose\ the\ maximum\ paths\ in\ the\ network$

$number\ of\ maximum\ allowable\ paths = n$

$fixed\ initial\ conditions\ and\ the\ possible\ paths\ is\ p_i\ and\ the\ condition\ is\ pi \leq k.$

$select\ one\ pi\ in\ each\ a_r \in BS\ where$

$a_r.energy > threshold.energy.select\ Yy\ in\ each\ data\ node\ where\ y \in Yy\ and$

$b_r.energy > threshold_energy\ and\ value\ of\ 0 < b_r < pi - 1\ and$

$for\ a \in XX, r \in XX1, a \neq r\ and\ a.energy\ and\ r.energy > 0\ do$

$compute\ the\ distance\ between\ u\ and\ v$

$if\ dar \leq Rs\ then$

$add\ the\ network\ a\ and\ r\ to\ the\ set\ of\ Xx1\ in\ local\ area, set\ P(a, r) = 1$

$for\ each\ pi \leq k, repeat$

$transmit\ the\ data\ from\ v\ network\ (a \in XX1)\ to\ r\ network\ (a \in Xx1),$

$transmit\ data\ in\ order\ from\ j \rightarrow x \rightarrow y \rightarrow z\ network\ (a_r \in Xx, b_r \in Yy, z \in BS)$

$End\ for$

$for\ each\ pi \leq k, repeat$

$Compare: if\ a_r.energy\ and\ b_r.energy \leq threshold.energy\ Then$

$repeat\ process \quad else$

$Continue$

end

Result and discussion

The proposed model is experimented in MATLAB 2014 and the data set is used for gait recognition that is obtained from the person with disability, and the movement of twenty participants includes ten males and ten females and the experimentation is held at various locations. The participants are aged between 45 and 60 years and the experimentation is computed based on the observations and data collected. There are five sensors in the each leg nodes, and a pressure sensor is used in the foot base. The data which are collected from the sensors are processed through a processing unit and then transmitted to the classification section for analysis. After predicting the actual status of the person, an alert is provided to the user and also the other persons if there is chance to meet any critical situations. Table I provides the characteristic summary used in the proposed model classification process and optimization process.

S. No.	Type	Unhealthy gait
1	Gender	10 males 10 females
2	Age	45–60
3	Height	1.6–1.7
4	Weight	45–80

Table I. Subject characteristics summary

Placing sensors on the person plays a vital role while obtaining the desired classification output. The process of placing sensors on the foot and body is illustrated in Figure 5(a) and (b), respectively. The foot section is sub-divided into three sections as forefoot, mid-foot and hind-foot. Sensors are placed in all the three sections, and the in particular mid-foot contains the bones to support the walking style. The hind foot includes the heel bone and direct ankle joint. The body wearable sensors are placed on the legs and hip area and also in the hangs. Challenged persons use their sticks for balancing these sensors that are in contact with the physical movement sensors providing the information based on the movement and sending the collected information from five different places along with the information from the foot sensors. All the eight types of information are given to the ANFIS model for classification process.

The classification results from the ANFIS model are given in Figure 6 based on the sensor data from foot pressure. It is observed that the detection range varies for each time as the person movement changes and a sharp detection is obtained in the time period of 8 s.

The output of unhealthy gait and their feet distance between the legs is observed in Figure 7. The range varies from one point to another point with short duration of time

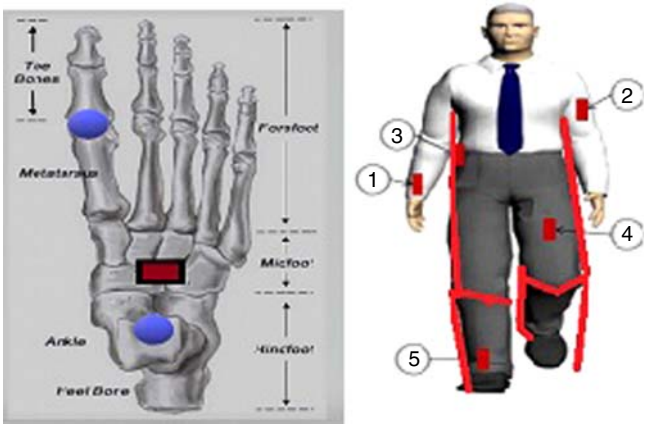


Figure 5.
(a) Placement of foot sensor; (b) wearable sensor

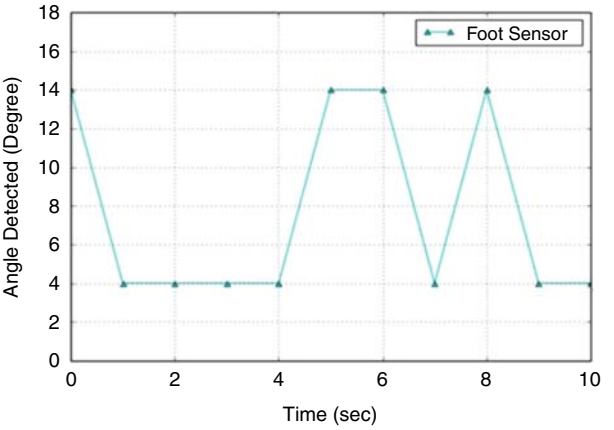


Figure 6.
Analysis of unhealthy gait using foot sensor data

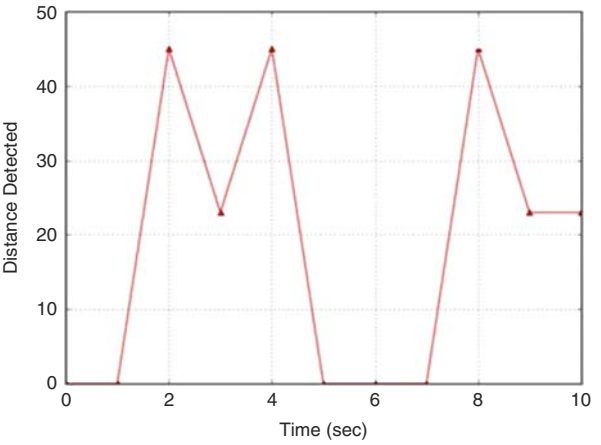


Figure 7.
Analysis of unhealthy gait Feet distance between legs

since the distance between the physically disabled person legs are close to each other and the reflex action takes place immediately from one position to another position.

Using the sensors in the proposed model, the recognition rate is measured in percentage and the sensors are placed in right arm, left arm, left leg, right leg, pelvis region. It is observed that the detection rate reaches maximum for the right leg and left leg compared to other portions (Figure 8).

Based on the walking speed, the detection rate changes and it is plotted in Figure 9 for the proposed model and the neural network model. It is observed that the proposed model has better recognition rate than the neural network model as the speed increases. The performance of neural network model lags as the speed crosses the 6–8 km/h.

The recognition rate based on the gait cycles is described in Figure 10 compared with the neural network model. The plot describes that the proposed model has better recognition rate than the existing model that is 20 percent higher recognition rate (Figure 11).

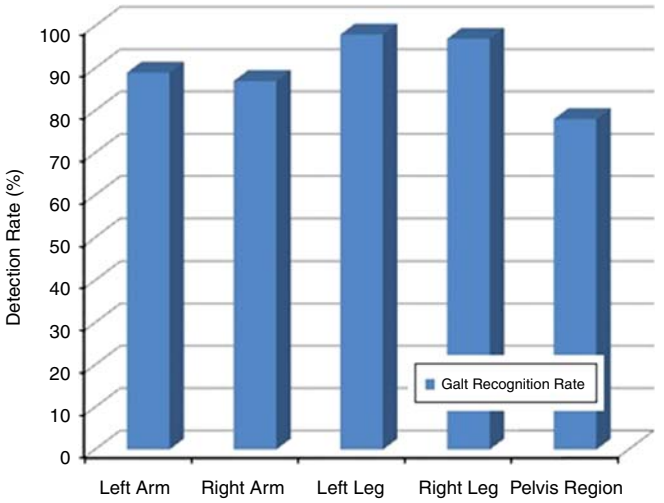


Figure 8.
Gait recognition rate for different placements of the sensor nodes

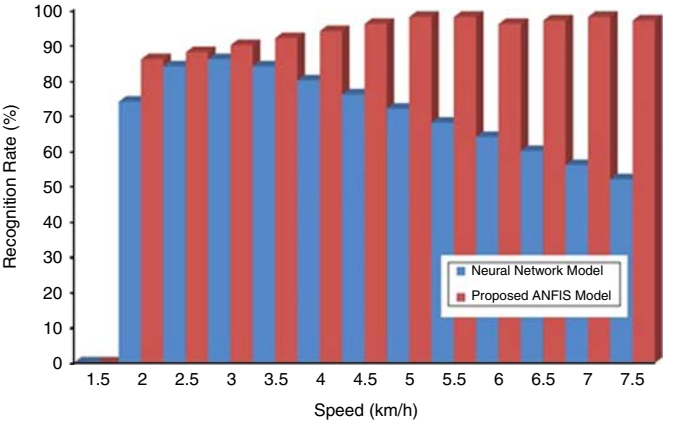


Figure 9.
Recognition rate vs walking speed

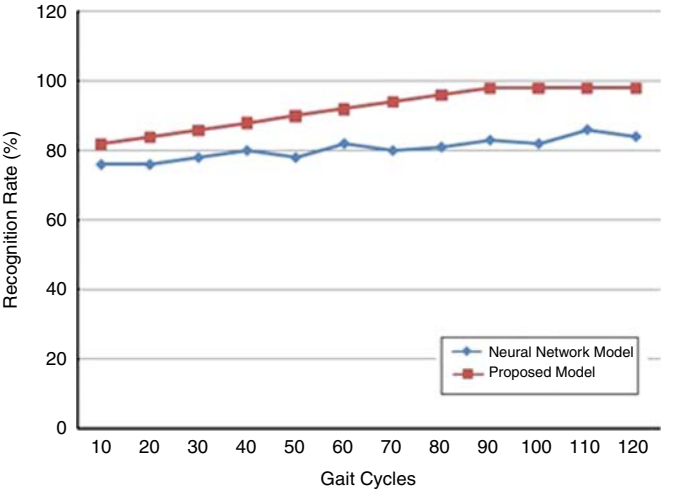


Figure 10.
User recognition rate vs the number of gait cycles

Conclusion

The proposed model is a combination of adaptive neuro fuzzy inference system and ant colony optimization for a better recognition of physically disabled person identification system in a crowded region for analyzing the behavior of a particular person. Different sensors are used to collect the information from the person and based on that information the ANFIS model provides classification results as prediction mechanism if there is a change in the walking style. The corresponding classification results are forwarded to a team of doctors or the other persons through the cloud IoT network that is suitable for elderly persons and physically disable persons in order to avoid fall. If changes are found in the walking style, then the information is passed to the corresponding caretakers so that medication facilities can be provided easily at correct time without any delay.

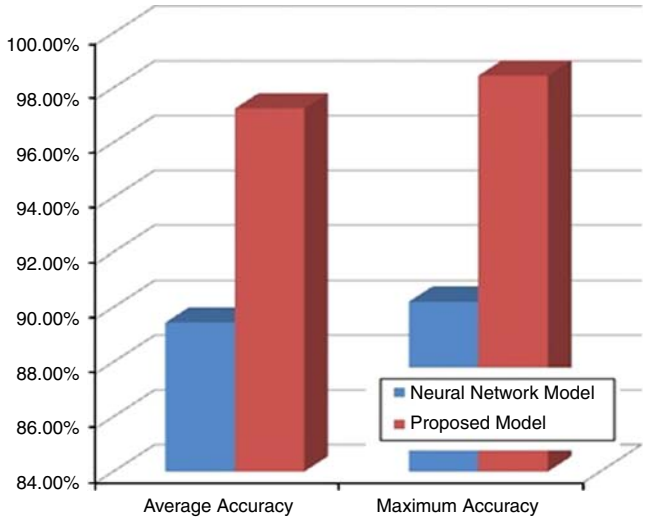


Figure 11.
Performance comparison

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