Physical Activity Monitoring for Older Adults through IoT and Wearable Devices: Leveraging Data Fusion Techniques

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Abstract

The emergence of low-cost individual sensing devices has facilitated the application of data fusion methods to yield insights useful for score-level, rank-level, or hybrid-level fusion. Intelligent tools for fusion processing, such as fuzzy methods and optimization algorithms, may be used to the deluge of raw data generated by these devices. The use of numerous sensors allows for multi-level/hybrid-level fusion, and the combination of several models for intelligent systems allows for fusion system design optimized for score improvement. Multimedia data fusion applications and machine learning methods can be used to accomplish data fusion in cloud settings. For older people in independent living conditions, a physical activity assessment framework (PAAF) that uses deep learning models for fusion to identify activity and evaluate progress based on the spectral domain of each window is needed. This study highlights the significance of data fusion in outlining the needs for IoT devices in networked computers for distant patient monitoring. In order to provide for the health of the elderly without compromising their comfort or freedom of choice, we need a seniors network based on the Internet of Things and wearable health technology. The sensors' functionality was investigated by analyzing data gathered from the environment and the organisms within it. The proposed PAAF-IoT architecture has many layers, each one connected to a different device, with the most important part being the integration of data from all of them to classify types of physical activity. Cloud services geographically close to the customer are used to process the resulting mountain of data, reducing end-to-end delay and facilitating prompt responses from healthcare professionals. Data fusion in healthcare and remote patient monitoring are demonstrated through the deployment of an app that allows doctors to remotely administer prescriptions and maintain track of patients' medical histories.

Keywords: Elder Person; Free-Living; IoT; Physical Activity; Fusion data; Fusion-Based Techniques

1. Introduction

The Internet of Things (IoT) has several important uses, one of the most important being healthcare monitoring, which enables constant monitoring of patient states in an effort to keep them out of the hospital [1]. This is now feasible because to the incorporation of sensors and off-site servers into e-health systems. However, the direct interaction between the entry point client and the sensor network is not yet possible in traditional medical systems [2]. IoT has enabled the routing of many sensing devices across the internet, thanks to developments like IPv6. Recognizing human actions remains challenging despite technological advancements because humans conduct actions in different locations and for varying amounts of time. Extraction of spatio-temporal knowledge from massive datasets can help. In the same way that mobile phones have revolutionized people's lives, wearable devices have done the same for healthcare, activity monitoring, and entertainment, and they are expected to become much more common in the future years [3]. Technology has made it more safer for seniors to live alone, yet falls are still a huge issue for their health. To solve this problem, we can employ multi-sensor fusion system topologies and smart fusion processing approaches [4]. Fusion scores and intelligent system decision-making can both benefit from the use of several models combined with deep learning. Multimedia data

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fusion applications, such as those pertaining to E-Systems, might benefit from data fusion techniques in cloud settings and fuzzy approaches utilizing optimization algorithms. As a result, healthcare monitoring utilizing IoT and wearable devices might benefit greatly from employing data fusion techniques, particularly for the elderly [5].

When individual slips or stumbles while moving or standing, it is often referred to as a fall. Elderly individuals, according to studies, begin to experience one fall per year. The danger of falling grows as people become older, and most falls occur at home. If a person falls and stays on the ground for an extended period, health problems such as exhaustion, internal injuries, and freezing may occur, and half of them will die within six months [6]. A fall can result in various injuries, reduce a human's functional ability, and enhance their chance of dying young. According to statistics, one out of every five falls can result in serious injuries, concussions, or fractured ribs. Muscle pain is a significant risk factor for elderly persons, and individuals with low muscles have a higher chance of falling [7]. Existing care processes rely on human effort to handle all difficulties. The older society reaches a new high point in the coming years, and human work progressively diminishes in society [8]. The existing model is no longer viable and works on a transition that merges operating systems immediately to increase efficiency. Conventional fall detection systems necessitate specific wearable equipment [9]. Most fall monitoring systems are mounted to the hips or breast at the center of the specimen to obtain great precision. The primary goal of this study is to use high-tech items to improve people's standard of living. A fuzzy control threshold-based system for fall methods relies on the triaxial accelerometer in a wearable device [10]. Individuals' heights, mass, and running gestures are used to calculate the limit in this method. When a fall happens, a beacon uses a Received Signal Strength Indicator (RSSI) to conduct indoor localization, which can immediately pinpoint the position of a care recipient.

The following are the achievements of this study:

- The study shows the promise of data fusion techniques, including the application of intelligent techniques like fuzzy approaches and optimization algorithms, for processing the volume of raw data acquired from low-cost individual sensing gadgets.
- Using many sensors and a fusion system architecture targeted for score improvement, as well as cloud environments and machine learning approaches for data fusion, are all aspects of multi-level/hybrid-level fusion that are highlighted in this study.
- The study suggests a PAAF-IoT model that can classify physical exercise based on the results of all devices, and it discusses the potential advantages of data fusion in healthcare and remote patient monitoring, such as the ease with which doctors can prescribe medications and keep tabs on their patients' health over time.

The remainder of the article is as follows: section 2 illustrates the background to the physical activity analysis models. The proposed physical activity analysis framework is designed and illustrated in section 3. Section 4 discusses the software outcome evaluation and analysis of the suggeted system. The conclusion and future study of the model are discussed in section 5.

2. Related Works

To simplify the presentation of the following system, this section introduced the technological solutions used in this research, including an accelerometer, monitoring devices, and indoor location [11]. The study's key test aims were evaluated and described for several approaches. IoT technologies that didn't use event detection technologies can merely identify the patient's condition, and they were ineffective and therefore unable to forecast the patient's aberrant condition. Support vector machines (SVM) have been employed in several recent types of research to categorize abnormal behavior using collected data dependent on tactile sensors within a residence, although these were individually labeled. Padikkapparambil et al. suggested a method for recognizing aberrant conditions in homes aimed mainly at the aged and those who live alone [12]. This research was the most relevant to the job. The fundamental premise of this work was to show that by just examining the various positions of the occupants within a home, it was feasible to educate an automated process on the behaviors of these customers and so evaluate whether their actions are unusual [13]. On the other hand, the method was more precise since it considers data over time and location—the scholars' above-utilized sensors to gather patient activity data. However, the system employed two signals that anticipated the patient's next position and more reliably identified normal/abnormal status when combined with an ECG signal [14]. Vargemidis et al. suggested an abstraction architecture for an IoT medical system that transforms a patient's observational values into a welfare structure that groups people with chronic behaviors for symptoms assessment [15]. A forecasting mechanism for anomalies was included in their design, although a theoretical schema had not been deployed. The related studies either provided an abstract architecture or were insufficiently precise; they also required a large amount of previous data to determine a patient's aberrant condition [16]. Several studies have looked into the possibility of detecting aberrant behavior by looking for behavior patterns different from learned typical

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patterns [17]. Many research studies have shown that teaching a classifier to recognize a particular event, mainly falls, is possible. Clustering methods were also used to spot unusual patterns of behavior.

Hung et al. presented a dynamic online data habit modeling and detection (ODHMAD) model for lonely older individuals in their living environments to conduct daily activity identification, habit designing, and outlier detection [18]. The online activities recognition (OAR) framework and the dynamic day habit modeling (DDHM) element make up ODHMAD. Itanalyzed sensor information in real-time to detect old people activities and major incidents for the aged. This technology cannot forecast abnormal characteristics and necessitates additional sensors to observe the patient's behavior [19]. These forecasting approaches were critical since they can foresee a patient's aberrant condition and assist them to live.

Kang et al. described well-being to track the activities of elderly persons [20]. They used appliance-based behaviors to make real-time activity identification in older adults and assessed the health functionality for these individuals. In the user's environment, six variety of sensors are used. They identified inappropriate behavior based on informationgathered from the surroundings and the usage of the health feature, albeit their accuracy was limited [21]. It employed just two sensors in the research, ECG and stationary detectors, amid a preset cell, to forecast the ECG signal's future position. MobiCart, a medical system design presented by Al-Khafajiy et al., included a complete variety of health-related activities to provide treatment of portable patients [22]. (1) health-related solutions in healthcare gadgets for remote setup, self-activations, re-configuration, or perhaps even self-repairment with current health technologies and services; (2) secure and private, flexible simulation tool enhance or inform assistance, implemented to the codebase of a diagnostic components; and (3) distant enrollments and (re)configurations of sensing devices and distant electronic health record services, like client health document downloads and intermediate stage. This system was only focused on online services and lacked accurate predictions.

By implementing a Marko-vian logic circuit hierarchial, Mozaffari et al. discovered an aberrant condition for the client [23]. They believed that different detectors were located in various things throughout the house. The purpose of their technique was to determine the patient's state by taking into account: 1) the patient's belongings; 2) the arrival times in a location; 3) the time of service in a place; 4) the participant's activities, and 5) the potential of undertaking tasks simultaneously. They used two learning approaches: detecting various activities and deriving rules that reflect the link between components and abnormalities of the status. As a result, this approach had a significant overhead. They also didn't use ECG signals, commonly used in IoT medical systems.

Malwade et al. gathered data on bodily body movements, categorized them, and combined them with ECG signals to diagnose a patient's aberrant condition [24]. They believed that a participant's activity indicated their condition; nevertheless, their technique necessitated the patient wearing four additional sensors for action detection, which was inconvenient [25]. Based on the categorization methodologies utilized, specific research investigations have been recommended. An Artificial Neural Network was employed to design a fall detector, and the method was used to enhance reliability and decrease the number of false alarms. An Eigenspace mimic human drop detection method employed a multi-class SVM classifier to correctly categorize movements and predict fall events. The Gaussian mixture model (GMM) carried out specific fall or non-fall depending on form dynamic loading during the collapse. Motion assessment and interfering concerns were solved using a multiview fall algorithm to identify the layered hidden Markov model. A better activity analysis module was needed to monitor older adults.

3. Proposed physical activity analysis framework based on Fusion data

The physical activity analysis framework comprises the Local Environment Building Block (LEBB) and the Cloud Building Block (CBB).

The LEBB is in charge of acquiring raw input on actual sensors, regardless of their techniques or modulation schemes, and analyzing it to calculate consolidated data for the top layers. In further detail, it is in charge of extracting the diversity of physical systems to give the basic logic with a standard view of data. It is supplied with relevant software systems that can interface with sensing devices as per the necessary standards and frameworks, allowing for this strategy. This capability enables the development of new modules to extend the application's operation to emerging innovations. The information gathered by each module is subsequently communicated to the CBB via an application programming interface (API). The LEBB is implemented in various ways, including using the user's cellphone or a more capable device, including a windows machine, mounted in the user's house to gather original information from fundamental physical sensing or a fitness tracker. The platform's operational core can process incoming data and notify registered members in the event of potentially catastrophic conditions. The detailed information is also saved in a bespoke server and made available to doctors and approved users' relatives via an application programming interface. Even though the developed personal information collecting system can collect data for all of the groups indicated, only the companies listed below have been evaluated in this study.

Indoor positioning service: The LEBB's indoor navigation service operates on the smartwatch (or immediately on the smartphone application) and is based on a Bluetooth low energy (BLE) device network. It identifies the user's location and sends it to the server platform. The data about translation is saved and given access to other applications here.

Motility services: It can identify the user's bodily information and status. Notably, it can recognize the participant's movement with high precision and reliability by utilizing the accelerometer sensor incorporated in the smartwatch. The outcome of the processing cycle is then transferred to the CBB for additional examination using the LEBB's mobile communications channel. These program data aids in identifying senior people's behavior, their alterations, which serves as an early warning sign of more severe problems. Only low-cost and accessible hardware were used to construct the indoor tracking and motility subsystems, discussed in the following Sections. The preference was for the new SensorTag, which is multi-standard. The motion tracking gadget includes a 3-axis gyroscopes, 3-axis accelerometers, 3-axis magnetometers, and a Digital Signal Processors. Because of its small size, the Sensor Tag is ideal for wearing a bracelet since it does not obstruct the user's motions. Furthermore, the included BLE transponder makes connecting mobile telephone touchscreens much easier. Lastly, the redesigned Sensor Tag is driven by a Cortex M3 Microcontroller, which ultralow energy usage enables the Sensor Tag to run simultaneously rechargeable battery for an extended period.

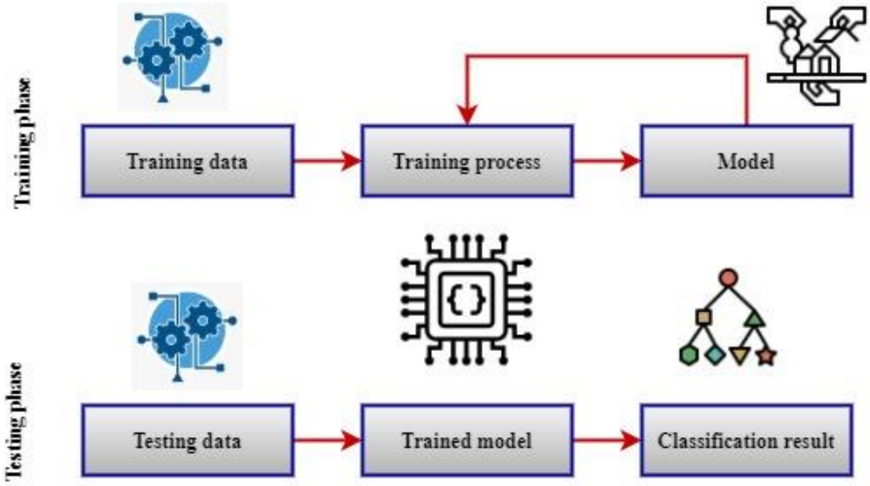

Figure 1: The training and testing of Fused model of the proposed PAAF-IoT model

The training and testing model of the proposed PAAF-IoT model is depicted in Figure 1. The proposed PAAF-IoT model is first trained, and the trained model is evaluated with the test model. This framework comprises both equipment and software. A diagram of the system illustrates the principle of the program.

3.1 System design

The hardware consists of three components: (1) a smartwatch made to wear by the consumer that quantifies average physical data and endorses wearable sensors and placement; (2) a Wi-Fi-based beacon machine for indoor localization and alerting transferring; and (3) an exterior air quality detector that quantifies the existing local air quality in this region and notifies if the pollution levels are ideal for the outdoor task. A caretaker and receiver cell phone app, the caretaker, can get a wealth of details about the care recipient from the platform. The app determines the position whenever the care recipient has an injury, and the treatment recipient can get medicine from the smartphone. A cloud RESTful web service that is centered on a website page is user-friendly. It has a Database management system to save valuable data. According to the data gathered, the wearable gadget is a popular high-tech product, similar to a smartphone or tablet. The free software Android operating system is increasingly prevalent; Smartwatch is an app created to meet the need for a smartwatch. The primary purpose of this device is to synchronize data with a cellular telephone. After connecting a cell device and a fitness tracker, the wearable technology receives all the data and responds. The Wearable application can also be immediately run on a smartwatch.

A fuzzy framework comprises a fuzzy component, a fuzzy reasoning engine, a fuzzy rule collection, and a defuzzy component, also known as a fuzzy system or fuzz logical controller. Crisp raw data is converted into correct fuzzy semantics via a fuzzy component. A fuzzification engine uses approximate thinking or fuzzy inferences to replicate expert thinking and decision methods. A fuzzy rule collection contains information and rules used to solve problems. A defuzzy module transforms fuzzy data into a crisp value from a fuzzy inference system.

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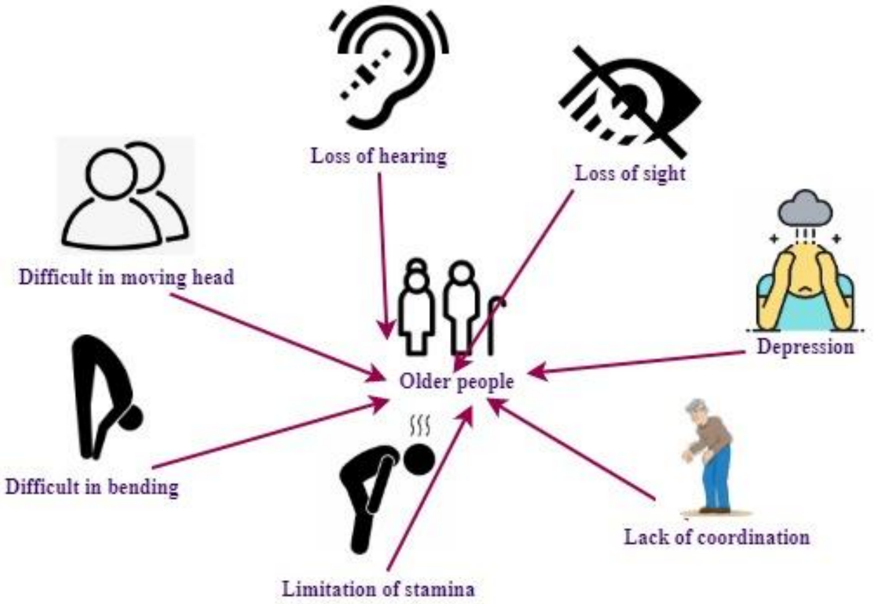

Figure 2: The activities of the elderly people

The activities of the older adults identified by the proposed PAAF-IoT model are shown in Figure 2. The identified activities are difficulty in bending, difficulty in moving head, limitation of stamina, lack of coordination, depression, loss of sight, and loss of hearing. The fuzzy inference base comprises a set of if-then fuzzifications that explain the platform's input-output connection. A multiple-input/multiple-output device can be broken down into several single-input/single-output systems. There are two types of fuzzy systems used in a multi-input/single-output scheme: (1) Sugeno Fuzzy Rule (2) Mamdani Fuzzy Guideline

The most successful and extensively used method is fuzzy management. In various fields, fuzzy control tackles hard to handle with classical control theories. A control technique is transformed to an appropriate control method, simply a set of IF-THEN rules relying on expert information and actions. THEN is the result of a fuzzy system; IF is a prerequisite of a fuzzy system, i.e., a collection of circumstances. This original study collapse detection method uses simple statistical modeling to address issues, and the design is essentially based on a fuzzy inference system (FIS). Data is categorized using fuzzy sets, fuzzy reasoning, and fuzzy IF-THEN principles to produce an IF-THEN fuzzification collection. As a result, the accident detection algorithm's limit selection becomes much more versatile and tailored to every individual.

The number and structure of fuzzy sets and the antecedents and subsequent sentence parameters in the fuzzy inference collection are defined first. An antecedents sentence in this approach comprises two factors: a and n; a describes the current speed, and n represents the upcoming velocity input. There is only one variable in the following statement: s is the current user status. Consider the following five fuzzy sets for every assertion parameter (a, n, s): negative significant (NB), negative small (NS), zero (Z), positive small (PS), and positive big (PB).

3.2 Fall detection algorithm

The following description of a fall is used considering a review of prior research: an unintended loss of balance that results in contact with the floor or a lower level. This research does not identify a fall using deep learning since it produces quick battery drain and danger of watch burning. A watch does not do intensive computation. The following describes the entire wearable device with the fall detection method. When the program detects a fall, the seriousness is assessed. Different procedures are used depending on the intensity: they extend from storing databases to informing and providing geolocation data to the correct caregiver.

A triaxial accelerometer calculates an SVM used to detect falls. At a particular instant, the arm swing magnitude is determined using this Equation to assess the likelihood of intense shaking. D_i, $D_j$and D_k reflect the accelerometer's velocity at instant x on the i-axis, j-axis, and k-axis, respectively. The accelerometer estimate of the Influence of gravity is not derived when a watch senses gravity velocity. The computation and identification are dependent on the watch's initial measurement. Since smoothing calculation simulation does not warrant substantial processing resources, the screen is deleted after studying the outcomes after filtering. As a result, the objective of this project is on the method configuration, which minimizes the watch computation difficulty and energy consumption rates. The SVM function is denoted in Equation (1)

$$SVM(x) = \sqrt{D_i^2(x) + D_j^2(x) + D_k^2(x)} \tag{1}$$

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The three-dimensional displacement of the older person is denoted $D_i(x), D_j(x) and\ D_k(x)$. When a typical individual walks, the wristband accelerometer SVM result swings between 6–14 m/s2 with a 25 percent variance, as seen in this graph. During jogging, the SVM value swings dramatically between 3–27 m/s2 with a 25% variation. After a drop, it takes around one second for a body to lose equilibrium, lean forwards, start falling, and contact the floor, as depicted in this diagram. An individual can walk or slowly stands depending on the hit severity. As a result, the wristwatch speed sampling frequency has been set to 250 milliseconds.

The speed of a fall varies from the maximum of regular action, given the strong impact. As a result, the activities are categorized using a binary tree depending on the cutoff setting. The active or static condition is identified first, and then an active ingredient condition or gesture is defined depending on the criterion. Falling, jogging, and walking are active states, whereas standing, resting, and lying are examples of stationary gestures. The body angle is computed by splitting the k-axis by the SVM. It is in a standing posture whenever the body inclination is between 0° and 60°, and it is in a reclining position when the head angle is between 60° and 120°. The angular displacement is denoted in Equation (2)

$$\emptyset = arc\tan(D_k) \qquad (2)$$

The height displacement is denoted D_k. For the distinctive peaks, a method is created. Five independent variables and a timeframe are established after the tri-axial information is retrieved. $L_{n-active}$, L_{low} and L_{high} are three accident detection criteria.

First, check to see if the SVM is in an exciting phase. The calculation comes to a halt if the SVM is inactive. Check if the SVM is in an exciting phase and if it surpasses L_{low}. Whenever the SVM is among $L_{n-active}$ and L_{low}, it may imply a shift in gesture or a little action. The clock is initiated if the SVM reaches L_{low}, and count activity is increased by one. Timer high grows by one whenever SVM activates a limit that surpasses L_{high}. The next step is to see if the time is within a specific range. The triaxial information is continually collected for identification if the period falls inside a timespan. If the time goes beyond the timeframe, it checks to see if the clock is inside the fall counter's scope, more than MIN and less than MAX. It can tell if the value is approaching a stable level if the clock is inside the range.

Multiple volunteers of different elevations and weights were selected to justify this approach for this report's testing. Patterns are discovered by analyzing the data. A 10% data variance is conceivable based on the obtained activity data. To improve reliability, this experimental procedure is then used to the L_{high} and L_{low} criteria. Then, detailed topic information and threshold choices are reviewed and assessed.

3.3 Automation system

Data gathering, preprocessing with training data, machine learning algorithms, and actual deployment are all part of the computerized method.

3.3.1. Data acquisition

The information is gathered via an automated system that employs a Zigbee protocol on the garment design and the base station. This module operates on the 2.4 GHz band, with a communication range of 10 to 25 meters indoors and up to 250 meters outdoors. During information gathering, ten distinct participants participated in 6 various functions. Volunteers range from 45 to 70 years old, with five males and five females. All of the tests were done with the people's permission. Data must be preprocessed once obtained to use deep learning techniques.

3.3.2. Data preparation

Pre-processing, information balance, and feature extraction are all used to prepare data. Pre-processing entails translating the information into an input-shaped format for every simulation with a 15% chance of getting a sample throughout the action. It also divides the Database into training and testing datasets. Three males and three ladies make up the train set, accounting for 75% of the total Database. The other 25% of the Database, which consists of two men and two girls and is wholly separate from the training data, was used as a test set to assess predictive accuracy.

The native source data exhibits an unequal training and testing data sources distribution. It had a good aim but low specificity due to imbalanced data gathered for different activities. Data balancing methods were applied to increase accuracy, and the concept of adequacy was selected according to an unexpected halt. Only one thing it thought about before stopping the balance was that any activity ratio would be less than 2. The data augmented method is denoted in Algorithm 1.

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Algorithm 1
Aug data $(D, x, y)$
$D_{x+1} = D_x$
$R = rand(1, x)$
$D_{x+1} = rand\ shift\ (k, D)$
$R = rand\ (1, y)$
$D_{x+1} = add\ (R - noise\ (R, D_{x+1}))$
```

The balancing database method is denoted in Algorithm 2.

```
Algorithm 2
Balance $(D, x, y)$
$R = rand(1, x)$
For activity belonging to the Database, do
If activity_length x2 > maximum activity then
Continue
If activity_length x2 < maximum activity then
$Sample = get\ data\ from\ activity$
For $l <= R$ do
$Sample\_new = Aug\ data\ (Sample, x, y)$
```

The balanced algorithm's fundamental software is also employed in feature extraction due to the absence of sample points for every operation. This program aims to increase comparable data to enrich the Database after taking important information for any activity. To accomplish so, it introduces changes to the original information and moves it left and right at randomized. The correlation analysis was considered for computing the distortion and shifting quantity. A correlations matrix has been built for each action to retain the closeness degree of every action kind in the gathered information.

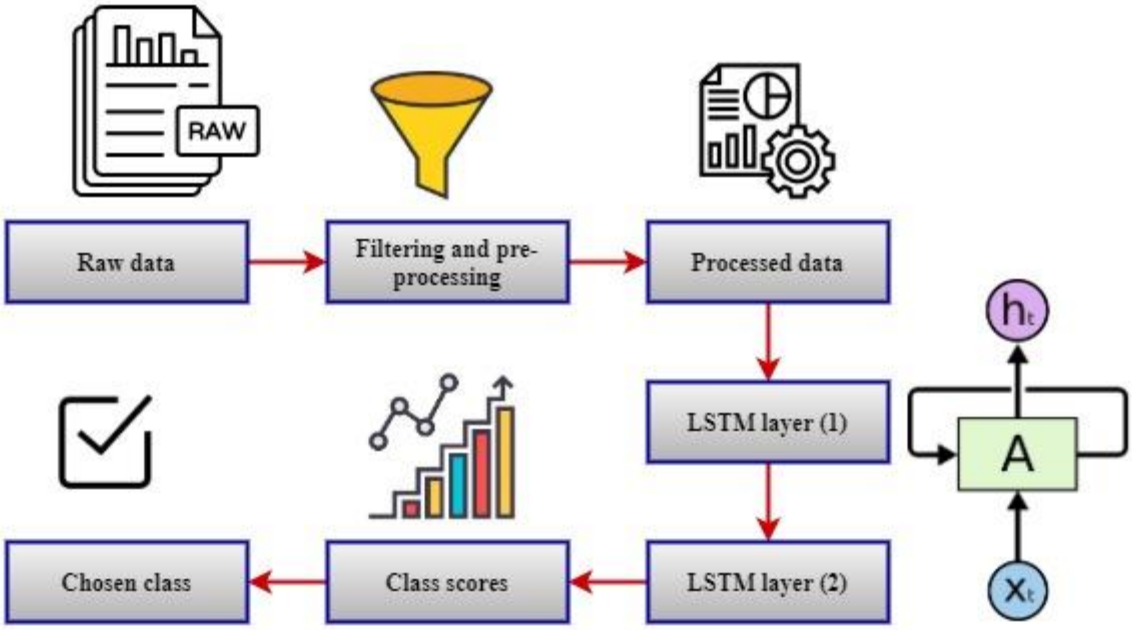

Figure 3: The workflow of the proposed PAAF-IoT model

The workflow of the proposed PAAF-IoT model is designed and shown in Figure 3. The raw data is collected and filtered, the preprocessed data is processed, and long short-term memory (LSTM) layers are used for the classification, and the best result is stored. Multiple values in correlation coefficients were reported after leveling and augmenting the Database, and that was the reference point for regulating and augmenting the randomness boundary.

3.3.4 LSTM models

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Several studies use wearables to make use of the capacity to evaluate sequence information for activity detection. The most often utilized architecture is proposed for constructing LSTM models. At moment p, an LSTM memory block consists of three gates: an input gate (ig), a forget gate (fg), and an output gate (og) that rewrite, retain, or extract the data from the memory module (mc).

Equations (3) and (4) are used to calculate the input gateway (ig_x) and forgetting gate (fg_x):

$$ig_x = sgn\left(B_{ig} \times i_x + G_{ig} \times g_{x-1} + F_{ig} \times f_{x-1} + W_{ig}\right) \tag{3}$$

$$fg_x = sgn\left(B_{fg} \times i_x + G_{fg} \times g_{x-1} + F_{fg} \times f_{x-1} + W_{fg}\right) \tag{4}$$

The bias weight of the input gate and forget gate are denoted $B_{ig}\ and\ B_{fg}$. The quality of the input gate and the forget gate are denoted $G_{ig}\ and\ G_{fg}$. The fuzzy function for input gate and forget gate are denoted $F_{ig}\ and\ F_{fg}$. The input and quality of the data are denoted $i_x\ and\ g_x$.

Following that, the present memory cell (f_x) is modified for remembering and the fresh memory ($\hat{f}$) is also changed by utilizing a quantity of the prior information (f_{x-1}). Equations (5) and (6) denote the predicted quality function.

$$\hat{f}_x = \tanh\left[B_{\hat{f}} \times i_x + G_{\hat{f}} \times g_{x-1} + W_{\hat{f}}\right] \tag{5}$$

$$g_x = c_x \odot f_{x-1} + i_x \odot \hat{f}_x \tag{6}$$

The predicted bias function predicted quality function, and the weighing function is denoted $B_{\hat{f}}, G_{\hat{f}}\ and\ W_{\hat{f}}$. The current input and previous data are denoted $i_x\ and\ g_{x-1}$. The predicted memory cell is denoted $\hat{f}_x$, and the previously stored data is denoted f_{x-1}. The computed function is denoted c_x.

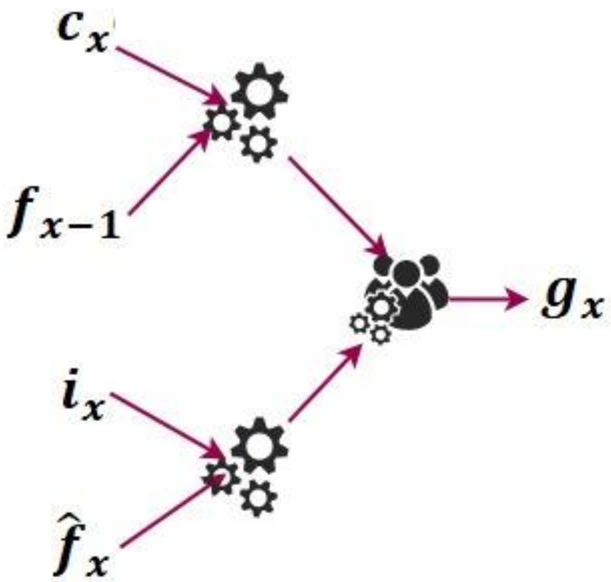

Figure 4: The mathematical model of the function g_x

The mathematical model of the function g_x is depicted in Figure 4. It uses present and previous memory functions and the input received from older adults. The predicted data is accurate with the help of the LSTM function. Lastly, the outputting gate (og_x) that controls the array of data produced is used to determine the ultimate activation at the present location (g_x). The output gate function is denoted in Equation (7), and the current location of the older adults is denoted in Equation (8).

$$og_x = sgn\left(B_{og} \times i_x + G_{og} \times g_{x-1} + F_{og} \times f_{x-1} + W_{og}\right) \tag{7}$$

$$g_x = og_x \odot \tanh(f_x) \tag{8}$$

While S is the source duration. The intake activity at the present moment (x−1) is i_x, while the output installations at the previous time (x) and g_{x-1}. B, G, and F values matrix are intake to gates, recurring links, and cells to entryways. They think things data can be provided from the present state of a typical LSTM network. Bidirectional LSTM networks need inputs to be of the exact dimensions. Furthermore, the present state can determine their upcoming data input. Bidirectional LSTM's fundamental principle links two concealed layers facing opposing orientations to the same exit. The output unit accesses results from past and upcoming states and understands them better because of this architecture.

3.4 Computing speed of motion and detection of fall

The relative change in velocity among two successive frames is determined using collected locations of critical points. Also calculated for every feature point are the angles concerning the x-axis (in a counter-clockwise direction), and the axis of rotation can be calculated using these calculations.

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If the angle is between $\theta > 0^{\circ}$ and $\theta < 180^{\circ}$, the motion is upward; else, it is downwards. The sampling unit is an excellent example of this (a). The length between the original feature point and the exact location recorded in subsequent frames is calculated to discover the lateral amplitude of critical points. The criterion is compared to the most significant displacement. Using the assumption that a person's height limit is two-thirds the length of the framework, the most significant distance traveled by the feature point in the event of a fall is calculated and utilized as a comparative criterion.

An example video illustrates the most significant distance traveled by a critical point in the event of fall action. The length across the region of interest in the starting frame (with plank position) and the falling frame is displayed in this example. The upward and low movement points are also calculated throughout the subsequent frames. The system uses these numbers to identify the prevalent motion orientation.

The most recent locations of critical points are also examined to determine if they are close to the floor. Because the films are taken at residence, the camera is installed so that the ground of the space is covered for one-third of the house's length from the base. It is sometimes referred to as the zone near the floor in video frames. Suppose the comparative difference in movement performance in successive frames is substantial. The role of the restricting key points is close to the floor, the displacements of the feature point are higher than the critical, and the predominate orientation of movement is downward, the exercise is classified as a drop action; otherwise, it is classified as a non-fall action.

The proposed PAAF-IoT model is designed with a fuzzy system, support vector machine for feature extraction, and long short-term memory for the feature classification model. The internet of things model helps connect different physical activity monitoring model components.

4. Software outcome evaluation model

The findings were achieved with the identical hardware configuration, including an Intel i5 2.4 GHz CPU, 16 GB RAM, and 8 GPU. The Python language and the Tensorflow library created all the applications. All neural learning algorithms on databases were evaluated once the data was prepared, and several factors and comparison factors were explored to test it. The experiment utilized red, green, and blue (RGB) films from the fall database. The Database contains 70 films, 40 of which are non-fall and 30 collapse.

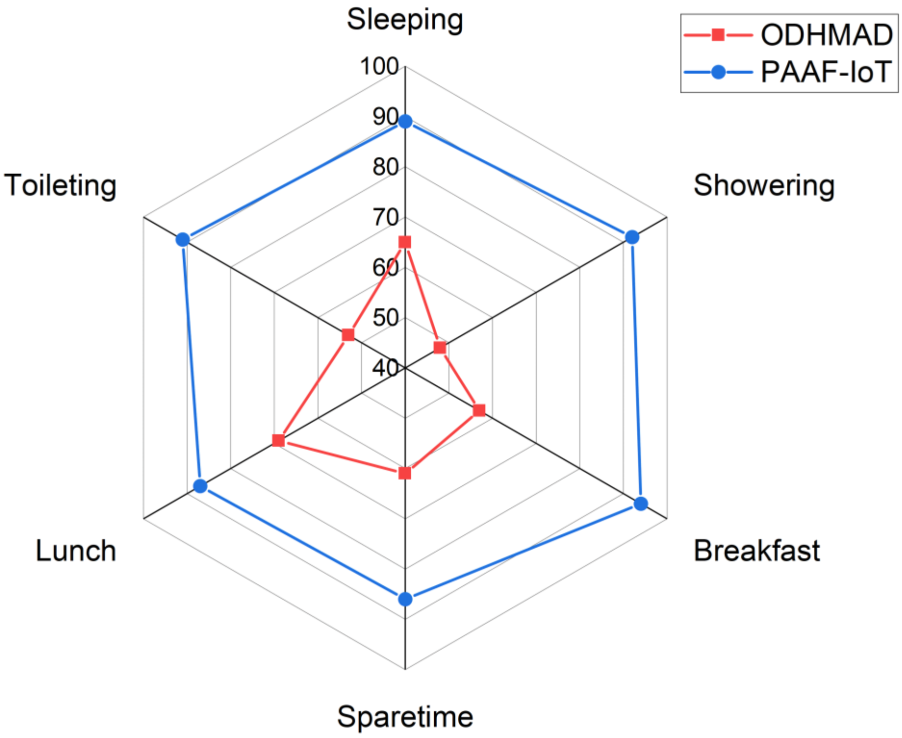

Figure 5: F score analysis of the proposed PAAF-IoT model

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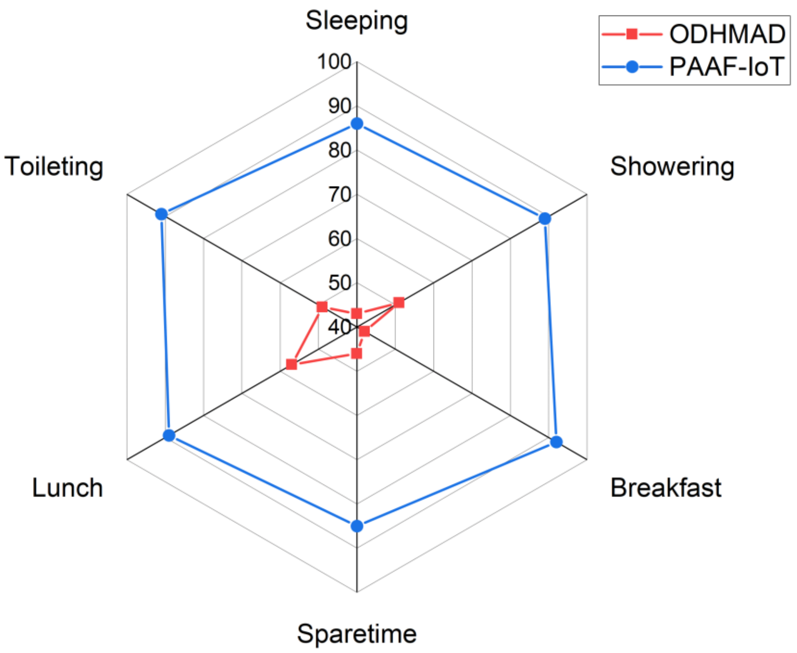

Figure 6 : Precision analysis of the proposed PAAF-IoT model

Figures 5(a) and 5(b) show the F score and precision analysis of the proposed PAAF-IoT model, respectively. The older adults monitored six physical activities: sleeping, showering, breakfast, spare time, lunch, and toileting. The performance of the proposed PAAF-IoT model is evaluated, and the outcomes are compared with the existing ODHMAD model. The proposed PAAF-IoT model is designed with IoT, fall detection, feature classification, and physical activity analysis. The proposed PAAF-IoT model outperforms the existing system in the entire simulation environment.

Table 1: Precision analysis of the proposed PAAF-IoT model

Activity	ODHMAD (%)	PAAF-IoT (%)
Sleeping	65	89
Showering	48	92
Breakfast	57	94
Spare time	61	86
Lunch	69	87
Toileting	53	91

Table 1 depicts the precision analysis of the proposed PAAF-IoT model. The older adults are continuously monitored, the physical activities are computed, and the result is tabulated. The monitored activities are compared with the existing model. The proposed PAAF-IoT model is initially trained with the training dataset, and the trained model is evaluated using the testing dataset. The proposed PAAF-IoT model with a fuzzy interference system simplifies the architecture and reduces the computation time. The fall detection model is used to analyze continuous physical activity.

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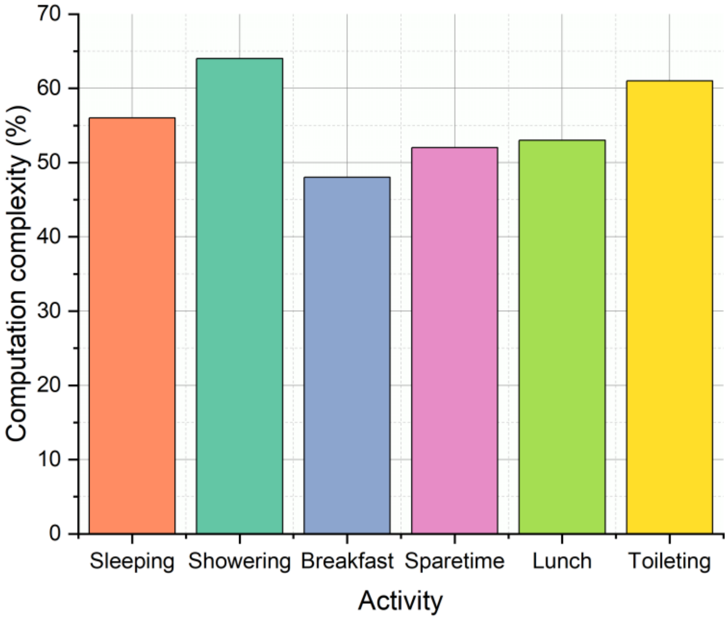

Figure 7: The computation complexity of the proposed PAAF-IoT model

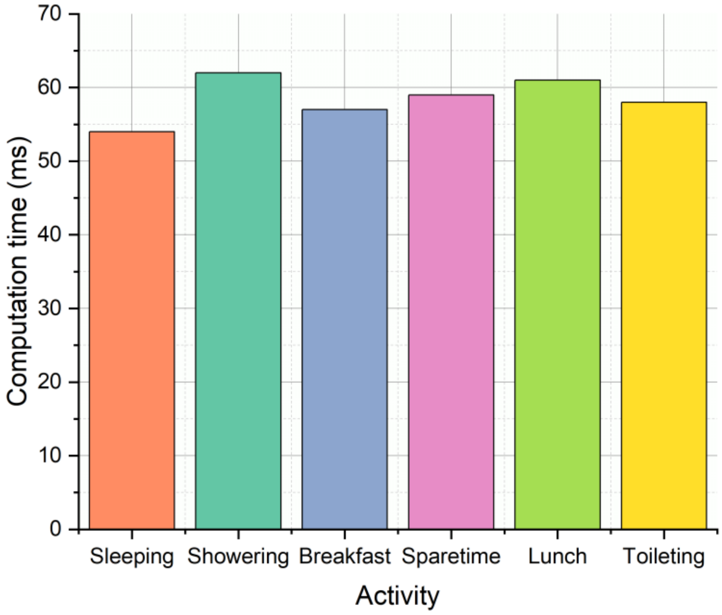

Figure 8: The computation time of the proposed PAAF-IoT model

Figures 6(a) and 6(b) show the computation complexity and computation time of the proposed PAAF-IoT model, respectively. The proposed PAAF-IoT model is designed with the help of internet of things modules and machine learning models such as support vector machine (SVM) and long short-term memory (LSTM). The machine learning models enhance the computation speed of the proposed PAAF-IoT model, and the fuzzy computation system reduces the complexity. The proposed PAAF-IoT model outperforms all the given simulation environments and test conditions.

Table 9: Physical activity evaluation of the proposed PAAF-IoT model

Number of persons	**Physical activity ratio (%)**	**Self-efficacy ratio (%)**
5	52	46
10	54	48

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15	56	52
20	58	56
25	60	49
30	61	57
35	63	45
40	64	58
45	65	51
50	67	59

Table 2 describes the physical activity evaluation of the proposed PAAF-IoT model. The number of elderly persons in the simulation is varied from a minimum of 5 persons to a maximum of 50 persons with a step size of 5 persons. As the number of persons in the simulation increases, the respective physical activity ratio and self-efficacy ratio of the proposed PAAF-IoT model also increase. The higher physical activity ratio leads to better physical and mental health for older adults. The higher self-efficacy ratio of the person leads to higher feature extraction and classification model.

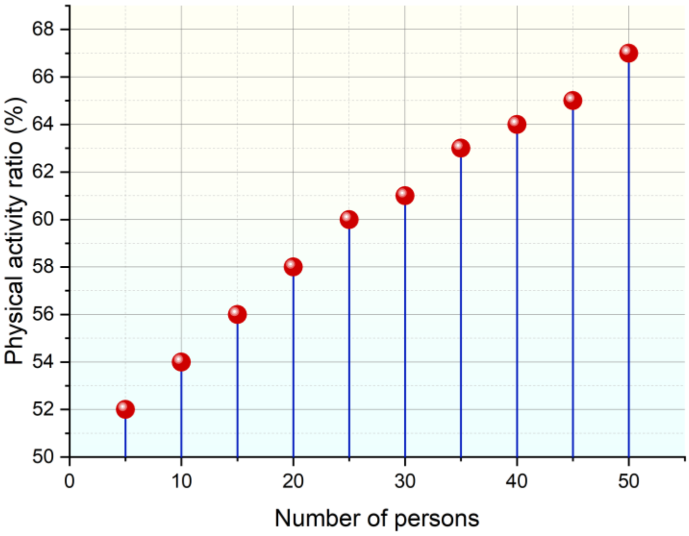

Figure 9: Physical activity ratio analysis of the proposed PAAF-IoT model

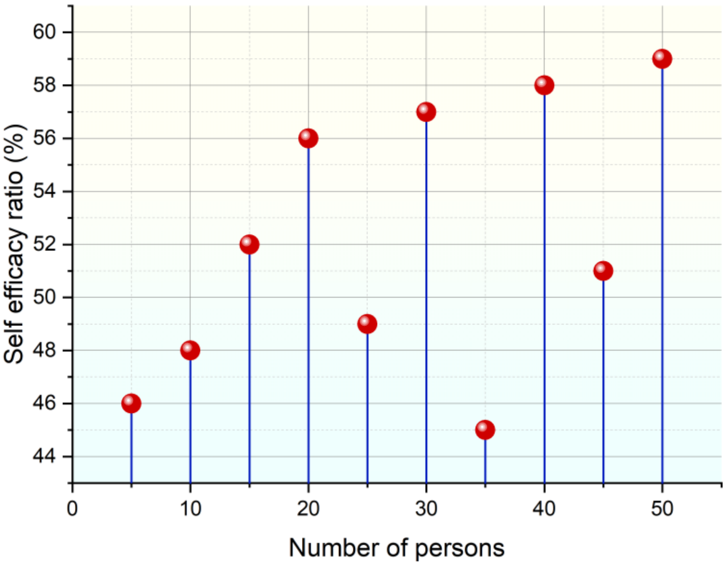

Figure 10: Self-efficacy ratio analysis of the proposed PAAF-IoT model

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Figures 7(a) and 7(b) show the physical activity ratio and self-efficacy ratio analysis of the proposed PAAF-IoT model, respectively. The numbers of elderly persons for the simulation analysis are varied from a minimum of 5 persons to a maximum of 50 persons with a step size of 5 persons. The proposed PAAF-IoT model produces better simulation outcomes with the highest accuracy. The IoT module helps to better connectivity of the devices, and the fuzzy system reduces the system complexity of the proposed PAAF-IoT model. The machine learning model such as support vector machine (SVM) and long short term memory (LSTM) reduces the error at the output and produces better results at higher accuracy.

The proposed PAAF-IoT model is developed, analyzed, and evaluated in this section. The simulation findings show that the proposed PAAF-IoT model outperforms the existing model. The proposed PAAF-IoT model with IoT, fuzzy system, SVM based feature extraction model, and LSTM based feature classification model.

5. Conclusion

This research paper introduces a novel approach to personal health forecasting, which relies on the proposed PAAF-IoT model with two signals, and uses a tree-structured system to estimate the health condition of nursing older people. The method intuitively detects actions in every cell without utilizing specific sensors to capture the patient's overall status, items, or ambient factors. The article also highlights that the ECG data collected is not precise and a client's health condition cannot be predicted reliably based solely on the information from this device. The research is another addition to the dispersed online forecasting of node mobility data in IoT-based healthcare systems, which prior research has not studied. The proposed approach employs intelligent techniques for fusion processing and fusion system design, which include multi-level/hybrid-level fusion, multi-classifier/decision-level fusion, and fusion with deep learning models. The fusion optimization is done by combining multiple models for intelligent systems, which can improve the fusion score and rank-level fusion. The research also discusses various fusion system architectures, such as multi-sensor fusion system architectures and multimedia data fusion applications.

Furthermore, the article highlights the use of fusion in robotics and decision-making, and how data fusion can be implemented in cloud environments. The research also discusses the use of machine learning for data fusion and fuzzy approaches for data fusion applications. Optimization algorithms for data fusion are also explored in this research. Overall, this paper presents an innovative approach to personal health forecasting that utilizes various intelligent techniques for fusion processing and design, highlighting the importance of data fusion in the field of IoT-based healthcare systems. Existing systems that use action recognition algorithms to identify a patient's medical condition are not cost-effective because they require a variety of sensors that are both expensive and cumbersome for individuals to wear. The efficiency of using the date of delivery within a cell, ECG output, length, and position to improve the accuracy of the suggested technique is demonstrated by simulated results. It is intended to forecast patient mobility at varying day moments and use smartphone sensors attached to their bodies to anticipate uncommon health conditions. It uses a complex tree-structured system to make it easier to forecast node mobility information, the patient's condition state, and the addressing/routing/forwarding of wireless sensor information from and/or to the gateway. In a senior treatment center, forecasting is supplied by a customized proposed PAAF-IoT model of two outcomes applying these principles to a participant's telemetry data and mobile ad hoc network information. The length of every state is taken into account by the proposed PAAF-IoT model, which improves the accuracy of the forecast. The findings demonstrate that the suggested technique is better in the process of the online health state of individuals without the need for any additional sensors. The simulations show that the suggested method is employed for wearable sensors. The model's performance is increased by specifying more parameters and employing various learning strategies in the future.

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References

[1] Qi, J., Yang, P., Waraich, A., Deng, Z., Zhao, Y., & Yang, Y. (2018). Examining sensor-based physical activity recognition and monitoring for healthcare using Internet of Things: A systematic review. *Journal of biomedical informatics*, *87*, 138-153.

[2] Shams N. Abdul-wahab, Mostafa Abdulghafoor Mohammed, & Omar A. Hammood. (2021). Theoretical Background of steganography. Mesopotamian Journal of CyberSecurity, 2021, 22–32. https://doi.org/10.58496/MJCS/2021/005

[3] Tun, S. Y. Y., Madanian, S., & Mirza, F. (2021). Internet of things (IoT) applications for elderly care: a reflective review. *Aging clinical and experimental research*, *33*(4), 855-867.

[4] Jaber, M.M., Yussof, S., Ali, M.H., Abd, S.K., Jassim, M.M., Alkhayyat, A. and Mubarak, H., 2022. PIRAP: PPDA-FAF: Maintaining Data Security and Privacy in Green IoT-Based Agriculture. *International Journal of Cooperative Information Systems*.

Doi: https://doi.org/10.54216/FPA.110204
Received: November 13, 2022 Accepted: March 23, 2023

[5] Naeemullah Khan, Ismael Khaleel, & Elika Daghighi. (2021). Improved feature selection method for features reduction in intrusion detection systems . Mesopotamian Journal of CyberSecurity, 2021, 9–15. https://doi.org/10.58496/MJCS/2021/003

[6] Qian, K., Zhang, Z., Yamamoto, Y., & Schuller, B. W. (2021). Artificial intelligence internet of things for the elderly: from assisted living to healthcare monitoring. *IEEE Signal Processing Magazine*, *38*(4), 78-88.

[7] Zhong, C. L. (2020). Internet of things sensors assisted physical activity recognition and health monitoring of college students—m*easurement*, *159*, 107774.

[8] Hosseinzadeh, M., Koohpayehzadeh, J., Ghafour, M. Y., Ahmed, A. M., Asghari, P., Souri, A., ... & Rezapour, A. (2020). An elderly health monitoring system based on biological and behavioral indicators in the internet of things. *Journal of Ambient Intelligence and Humanized Computing*, 1-11.

[9] Yacchirema, D. C., Sarabia-Jácome, D., Palau, C. E., & Esteve, M. (2018). A smart system for sleep monitoring by integrating IoT with big data analytics. *IEEE Access*, *6*, 35988-36001.

[10] Huang, H., Li, X., Liu, S., Hu, S., & Sun, Y. (2018). TriboMotion: A self-powered triboelectric motion sensor in wearable Internet of Things for human activity recognition and energy harvesting. *IEEE Internet of Things Journal*, *5*(6), 4441-4453.

[11] Rahman, M. A., & Hossain, M. S. (2019). A cloud-based virtual caregiver for elderly people in a cyber-physical IoT system. *Cluster Computing*, *22*(1), 2317-2330.

[12] Alsudani, M.Q., Jaber, M.M., Ali, M.H., Abd, S.K., Alkhayyat, A., Kareem, Z.H. and Mohhan, A.R., 2023. Smart logistics with IoT-based enterprise management system using global manufacturing. *Journal of Combinatorial Optimization*, *45*(2), p.57.

[13] Boukhennoufa, I., Amira, A., Bensaali, F., & Esfahani, S. S. (2020). A novel gateway-based solution for remote elderly monitoring. *Journal of Biomedical Informatics*, *109*, 103521.

[14] Ali, M.H., Al-Azzawi, W.K., Jaber, M., Abd, S.K., Alkhayyat, A. and Rasool, Z.I., 2022. Improving coal mine safety with internet of things (IoT) based Dynamic Sensor Information Control System. *Physics and Chemistry of the Earth, Parts A/B/C*, *128*, p.103225.

[15] Vargemidis, D., Gerling, K., Spiel, K., Abeele, V. V., & Geurts, L. (2020). Wearable physical activity tracking systems for older adults—a systematic review. *ACM Transactions on Computing for Healthcare*, *1*(4), 1-37.

[16] Kang, S. (2020). A study on smart homecare for daily living ability and safety management of the elderly. In *Information Science and Applications* (pp. 707-710). Springer, Singapore.

[17] Wan, J., Al-awlaqi, M. A., Li, M., O'Grady, M., Gu, X., Wang, J., & Cao, N. (2018). Wearable IoT enabled a real-time health monitoring system. *EURASIP Journal on Wireless Communications and Networking*, *2018*(1), 1-10.

[18] Hung, L. P., Chao, Y. H., & Chen, C. L. (2019). A Hybrid Key Item Locating Method to Assist Elderly Daily Life Using Internet of Things. *Mobile Networks and Applications*, *24*(3), 786-795.

[19] Forkan, A. R. M., Branch, P., Jayaraman, P. P., & Ferretto, A. (2019). An Internet-of-Things solution to assist independent living and social connectedness in the elderly. *ACM Transactions on Social Computing*, *2*(4), 1-24.

[20] Kang, S. (2018). A Study on Programs Applying the Internet of Things (IoT) for Prevention of Falls in the Elderly. In *IT Convergence and Security 2017* (pp. 49-53). Springer, Singapore.

[21] Mardini, M. T., Iraqi, Y., & Agoulmine, N. (2019). A survey of healthcare monitoring systems for chronically ill patients and elderly. *Journal of medical systems*, *43*(3), 50.

[22] Al-Khafajiy, M., Baker, T., Chalmers, C., Asim, M., Kolivand, H., Fahim, M., & Waraich, A. (2019). Remote health monitoring of the elderly through wearable sensors. *Multimedia Tools and Applications*, *78*(17), 24681-24706.

[23] Mozaffari, N., Rezazadeh, J., Farahbakhsh, R., Yazdani, S., & Sandrasegaran, K. (2019). Practical fall detection based on IoT technologies: A survey. *Internet of things*, *8*, 100124.

[24] Malwade, S., Abdul, S. S., Uddin, M., Nursetyo, A. A., Fernandez-Luque, L., Zhu, X. K., ... & Li, Y. C. J. (2018). Mobile and wearable technologies in healthcare for the ageing population. *Computer methods and programs in biomedicine*, *161*, 233-237.

[25] Praveen, S.P., Ali, M.H., Jaber, M.M., Buddhi, D., Prakash, C., Rani, D.R. and Thirugnanam, T., 2022. IOT-Enabled Healthcare Data Analysis in Virtual Hospital Systems Using Industry 4.0 Smart Manufacturing. *International Journal of Pattern Recognition and Artificial Intelligence*.

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