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Wearable sensor-based fuzzy decision-making model for improving the prediction of human activities in rehabilitation

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ABSTRACT

Sports actions are commonly recurrent due to the abnormal dynamic human activities. Detecting physical injuries based on the actions of the sportsperson helps to fasten rehabilitation treatments. Rehabilitation relies on the precise detection of activities and continuous monitoring of the actions of the sportsperson. In this paper, wearable sensor-based fuzzy decision-making (FDM) model is introduced for improving the prediction accuracy of different activities of the sportsperson. This model relies on altering sensor data aggregation and processing them using classification conditions for improving the prediction accuracy. The decision-making is performed by linearly classifying independent membership functions for different aggregation time and inputs. The combined processing of the inputs and time-based actions using independent decisions helps to improve the prediction accuracy of 93.3% with 26.081 ms decision time compared to conventional algorithms.

1. Introduction

A sport activity of an individual or group is monitored for their performance and abnormality using wearable sensor (WS) technology [1–5]. Players and sportspersons are equipped with body-mounted sensing devices that monitor physiological changes in the human body and transmit them to the rehabilitation centers for processing [6–8]. Rehabilitation for abnormal events such as gait, injury, and malfunctioning are diagnosed based on monitored changes. The physical changes are analyzed using decision-making and data analytics systems to precisely identify the cause and provide appropriate solutions/ diagnosis [9,10]. In a sports event, the activity of a person is subject to change with time and varying environmental conditions. Therefore, the volume of sensor data/ signals is accumulated for processing in the observation time [11–13]. Processing volumes of sensor data requires sophisticated methods and computing systems to generate less time-consuming diagnosis. WS technology interoperates with other communication and data processing paradigms, such as the internet of things (IoT), cloud infrastructures, and distributed computing systems to improve the aggregation and delivery of sequential sensing [6,14].

Predicting sports activities is a complex task due to the dynamic environment and time-dependent actions of the sportsperson. The body-mounted sensors such as three-axis gyroscopes, accelerometers, and magnetometers provide recurrent and time-dependent information to the rehabilitation centers [15]. The physical activities are predicted from the sensed information and correlated with the existing or previously observed instances. The prediction process is time-dependent rather than the actions; the time-synchronized sequence of actions form the activities to be detected [16]. The occurrence of abnormalities such as gait, fall, and injuries is common due to the change in the physical position of the sportsperson or the environment. Such instances are precisely identified for diagnosis, training, and performance improvement using the accumulated sensor data [17]. Abnormal events are identified from the accumulated sensor data by processing them in different levels and identifying optimal solutions for the cause/training. Therefore, both communication technology and computation systems are required for handling sensor data from a dynamic environment that enables real-time applications [18,19].

Fuzzy decision-making (FDM) systems enables multiple levels of analysis to improve its precision. Unlike conventional training and recurrence analysis systems, fuzzy systems rely on membership functions and timed responses for achieving reliable outcomes, as preferred by end users [20]. The application of the fuzzy model in sports and WS data processing is reliable and suitable to obtain more consistent outcomes [21]. Data mapping, modeling, and processing are the different stages in fuzzy models that

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rely on interference engines to handle volumes of sensor data. Fuzzy models provide both interdependent and cross-dependent validation of members and attributes using interference systems [22]. An adaptive fuzzy model in varying data environments, such as sports and activity monitoring, can differentiate the occurrence of instances based on time and actions. Therefore, the inclusion of FDM systems and models in sports and other real-time applications generates more optimal and precise solutions for abnormality detection by reducing errors [21,23].

The major contributions of the paper include the following:

- Development of fuzzy decision-making (FDM) model is introduced to improve the prediction accuracy of the activities of a sportsperson.
- The sensor data aggregation and processing has been carried out using classification conditions.
- The decision-making is designed and developed using linear classifying independent membership functions for various aggregation time and inputs.
- Simulation analysis has been carried out to improve the prediction accuracy with decision time ratio.

2. Related works

Cortell-Tormo et al. [24] proposed a WS to monitor lumbar spine motion. The lumbatex is an inertial sensor that is integrated as a wearable textile device, which is connected to Bluetooth. The system is processed in two types: the initial step is monitoring the accuracy, and the second type is used for better usability from the perspective of the user. Liu et al. [25] introduced a motion-capturing technology using a micro-inertial measurement unit (MIMU). The motion is detected using the velocity and gravity acceleration assessment through the modified Kalman data fusion method. This device-based technique reduces accumulative errors during monitoring real-time activities.

Gym physical activity recognition performed by hybrid hierarchical framework using a WS is introduced by Yang et al. [26]. This two-layer recognition framework (TLRF) performs aerobic and weight-based activity monitoring. The first layer is using the SVM (OC-SVM) to classify activities. The second layer is used for recognition based on a hidden Markov model (HMM). The physical activity has been depending on certain measurement to improve the activity cycle. Tri-axial walking ground reaction forces (GRF) is measured using an optical network based on wearable units addressed by Shahabpoor et al. [27]. The author deals with correlation and accelerations of the body segments. The GRF is detected in the dimensions in sensor systems. The dimensions include vertical (V), medial-lateral (ML), and anterior-posterior (AnP) directions. Willy [28] presented running-related injuries monitored by rehabilitation using WSs. This paper aims to prevent injuries by continuous sensing of athletics training loads, bioappliance, and gait. The best therapist gives the guideline for athletics and improves the exercise.

Uddin [29] developed a WS based on prediction systems for the healthcare system. The activity prediction (AP) is based on the recurrent neural network (RNN). The input is obtained from multiple wearable healthcare sensors using Electrocardiography (ECG), the accelerometer of the wearable user. Applications were made for the classification of normal and abnormal beats in an ECG in the RNN. The technique used large quantities of standard data, (i.e., data in the ECG time series as long short-term memory network inputs). Training and testing subdata have been divided for data collection. A wearable accelerometer for knee loading at the time of running is detected by Havens, et al. [30]. The data are obtained from the runner's knee by determining activity speed. The motions are monitored by a marker-based system, using the accelerometer of the participants. The accelerometer gives the information of forwarding cruciate ligament renovation. Measuring the knee and tracing the angle by using stretchable conductive fabric sensors is presented by Watson, et al. [31]. The role of this fabric sensor is to calculate the resistance and length of the front knee, through which the angle of the knee is determined by using the device. The sensor collects the angles of the knee, and the average angle is estimated.

Rubio-Solis et al. [32] introduced a multilayer interval Type-2 fuzzy extreme machine learning (ML-IT2-FELM) to recognize walking activities and find the gait using a WS. Three types of activities were measured: level-ground walking (LGW), ramp ascent (RA), and ramp descent (RD). The fuzzy learning was used to find the appropriate result of the activities. Authors reported that the local access point serving as the local aggregator for gathering inputs from the WSs at different time instances has not been analyzed effectively using ML-IT2-FELM. Acute cruciate ligament (CL) rupture designed for rehabilitation using a WS is developed by Kordatos and Modestos [33]. The aim of this work was to reduce the risk of injury during practice. The feedback is given to the user for self-efficiency. The smart bracelets are connected to the smartphone to interact with the collected data.

Milosevic et al. [34] designed a kinetic and wearable sensor for rehabilitation. They conducted a survey, and the measurement of Kinect and rigid body were determined from the sensor data. It was also used to access the device for the sportsperson to practice at home. Lorussi et al. [35] proposed a wearable sensor that enables the digital application for the supervised muscular skeletal disorder. The designed application is quantitative and effective for the therapeutic to guide the participants. It also uses functional physical recovery through the rehabilitation program.

Therefore, fuzzy systems have achieved the precise detection of activities and continuous monitoring of sportsperson action using classification conditions. The decision-making is performed linearly by classifying independent membership functions for different aggregation time and inputs, which are discussed as follows.

3. Fuzzy decision-making for abnormality prediction

Wearable sensors are placed on the bodies of athletes to monitor their activities. They enable early detection of inappropriate postures that lead to injury and decrease the rehabilitation time. In case of any injuries, the assignment tools are used for treatment during rehabilitation. The main objective of this work was to continuously monitor the sportspeople and build an alert system before the injury takes place. Our scheme was based on the prediction using decision-making fuzzy logic. Fig. 1 presents the illustration of the proposed FDM used for activity monitoring.

The wearable sensors are responsible for sensing inputs from the sportsperson and transmit them to a local aggregator. A local access point serves as the local aggregator for gathering inputs from wearable sensors at different time instances. The aggregated information is transmitted to a rehabilitation center for further analysis and decision. This analysis is done based on FDM.

3.1. Aggregation of sensor information

The rehabilitation center is the control unit where the received information is processed. The signal from the sensor is obtained from the athlete, and the information is given back as the feedback to the user. In rehabilitation, the information is based on the prediction process. The controller maintains up-to-date information

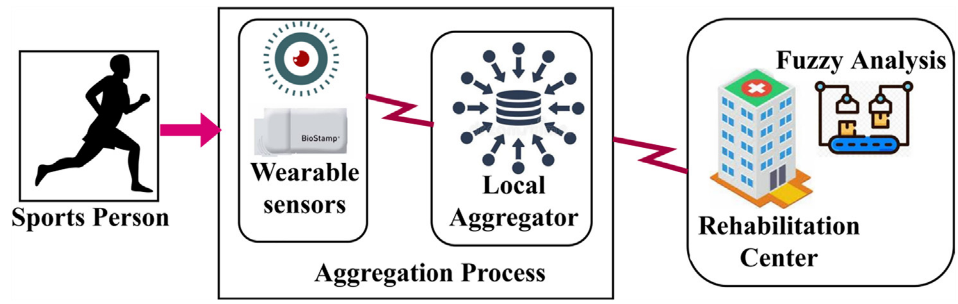

Fig. 1. FTDM in Sports Scenario.

for each sportsperson along with their medical history. It is used for easy prediction among the current and previous information. The workout for the sportsperson for a day is calculated using Eq. (1).

$$s = a * \left[\sum_{t=1}^{t=\alpha} \frac{w+r}{n} \right] \tag{1}$$

From Eq. (1), the sportsperson workout is calculated based on the start and fixed time, which is represented as$aand\alpha$. The time is denoted as$t$, the workout is represented as$w$. The time for relaxation is represented as$r$, and the total time required to complete the workout is denoted as$n$. In this equation, the start time is taken, and sportsperson observes the workout until the fixed time set by the therapist is monitored. In this section, the workout of the person is observed, and abnormal strain is detected. If there is a cause of any strain, then immediate feedback is given to the person to improve the workout. The sports rehabilitation obtains the input from the sensor as ECG, blood pressure, respiratory effort, joint angle, pain, and motion. The movement of the person is monitored using Eq. (2):

$$m_n = \frac{1}{m_t - m_{t-1}} * \prod_{e_d=1}^{n_m} \left[e_d - \frac{\alpha}{p_0} \right] \tag{2}$$

By using Eq. (1), workout time is measured for sportspersons, and movements are calculated based on Eq. (2). In Eq. (2), m represents the movement, e_d speed and p_0 denoted as several samples obtained during the workout. $m_t - m_{t-1}$are several movements obtained during the period. Based on Eq. (2), the sensor obtains the information of the movements and detects the chance of injury using Eq. (3); the movements are separated into risky and normal.

$$\partial = n * \begin{cases} (w+r), \delta + m_n < 1 \\ (w+r), \delta + m_n > 1 \end{cases} \tag{3}$$

By using Eq. (2), the movement of the person is calculated based on time. From that, the chance of injury or strain is calculated using Eq. (3). From the sensor data, the raw information of the person is obtained, ∂ is the sensor, and δ represents the input information of the person. In this equation, two conditions are used to satisfy the input data whether they are normal or abnormal. The first condition is$(w+r), \delta + m_n < 1$, the workout and relax time are considered for the sportsperson. The input data and movement are calculated based on time, which is lesser than 1, meaning that they have a lesser chance of injury.

In the second condition$(w+r), \delta + m_n > 1$, the input data is greater than 1, so it is denoted as a risk of strain and injury. The rehabilitation gives the following feedback to the person. By calculating Eqs. (2) and (3), the information from the sensor is aggregated. Eq. (4) is used to formulate time-based aggregation of sports person activity for further processing to improve the workout.

$$t_m = a + \alpha * \begin{cases} \prod_{e_d=1}^{n_m} \left[e_d - \frac{\alpha}{p_0} \right] + \delta + m_n = 0, First \\ \prod_{e_d=1}^{n_m} \left[e_d - \frac{\alpha}{p_0} \right] + \delta + m_n = 1, Second \end{cases} \tag{4}$$

By using Eq. (3), the chance of injury equated by their movements is detected from Eq. (4), which determines the time-based information observed from the sensor. In Eq. (4), it states two cases t_m is determined as a time-based movement. The first case is$\prod_{e_d=1}^{n_m} \left[e_d - \frac{\alpha}{p_0} \right] + \delta + m_n = 0$, speed, and sample information are obtained, and it is summed with the input information along with the time-based movement. The second condition is$\prod_{e_d=1}^{n_m} \left[e_d - \frac{\alpha}{p_0} \right] + \delta + m_n = 1$, which is the second processing of information. After the sensor information is aggregated, the analysis is carried out for the sportsperson regarding the rehabilitation.

3.2. Rehabilitation analysis

The rehabilitation analysis can be performed in many ways, which are based on sportsperson injury and pain. The following measures are taken to address suffering using rehabilitation. The initial step is to reduce the pain and injuries of the person and then improve the healing. Fig. 2(a) and 2(b) presents the schematic representation of the overall process and data analysis using FDM.

The analysis (Fig. 2(b)) is done on the time-based movement of the person using Eq. (5):

$$l_m(t) = \partial \rightarrow \delta + \frac{\left[\prod_{m_l}^{n} p_0 * \left(\frac{\alpha}{p_0} \right) \right] + \left(\frac{1}{m_t - m_{t-1}} \right)}{m_n + e_d} \tag{5}$$

From Eq. (4), the aggregated data are first processed, and then, the analysis is done based on the time calculated by using Eq. (5). In Eq. (5), l represents the analysis: the movements of the person are aggregated and analyzed based on the time where the activities with time are not fixed. For every fixed time, the analysis is done which is derived in Eq. (2). After the continuous analysis is done on the data, the decision is made using the fuzzy model. The decision is done on the current and historical data of the sportsperson.

3.3. Fuzzy Decision-Making

FDM is used to predict the information of the person using the previous history of data. The data are already acquired from the sensor. The comparison of the data is done among the stored and current and validates the correct match. In this work, the fuzzy model is used for making decisions. The fuzzy membership function is denoted as$f \rightarrow \in either 0 or 1$, where $f$is the fuzzy: the result of this is either 0 or 1 for detecting the sportsperson data. The classification of$f$ for the member sets is presented in Fig. 3.

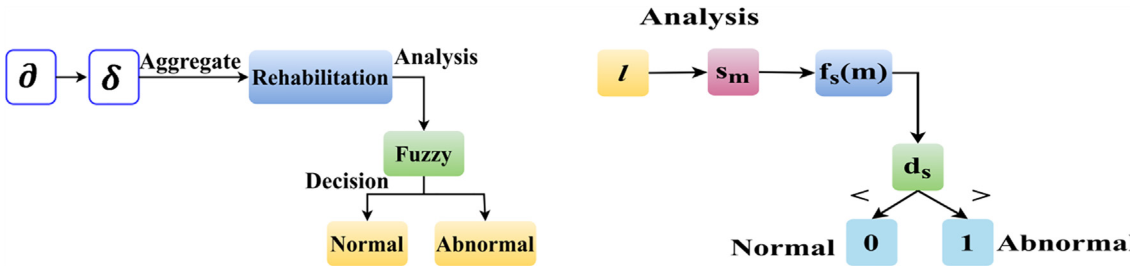

Fig. 2. (a) Rehabilitation Process 2(b) Data Analysis.

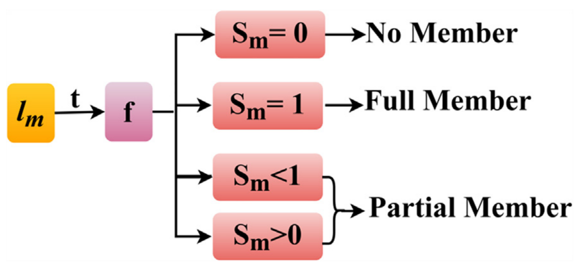

Fig. 3. ***f*** Classification.

The fuzzy set consists of two parameters: the membership function and grade of membership, and it is expressed as follows. $f \to b_0 \text{and} g_0$, where b_0 is the membership function and $g_0(x)$ is the grade of membership. So, the fuzzy set pair is denoted as$g_0 : b_0 \to either 0 or 1$. By deriving this, it has three sets of fuzzy classes given as below. By using these three sets of members, Eq. (6) is used to define the fuzzy set.

- No member in the set- $g_0(x) = 0$
- Full member in the set -$g_0(x) = 1$
- Partial member in the set -$g_0(x) < 1, g_0(x) > 0$.

$$f = \begin{cases} s_m = \partial, if g_0(x) = 0 \\ s_m = \partial + p_0, if g_0(x) = 1 \\ s_m = \partial + (1 - p_0), if g_0(x) < 1, g_0(x) > 0 \end{cases} \tag{6}$$

By using Eq. (5), the analysis is done for the sportsperson based on time; then, the fuzzy set is used to calculate the three classes, using Eq. (6), who are not active in the fuzzy set. The first case is no member set$s_m = \partial + p_0, if g_0(x) = 0$, which is obtained from the sensor along with the sample of data. This is a no member case where the grade member is equal to 0. The second condition is$s_m = \partial + p_0, if g_0(x) = 1$, here, it has a full set of the member in the fuzzy set.

The last condition is $\partial + p_0, if g_0(x) < 1, g_0(x) > 0$, the case of the partial member in the fuzzy set. After deriving Eq. (6), the no member in the fuzzy set is eliminated from the process. This process makes quick decisions among the full and partial member in the fuzzy. In this work, the decision is made on a full and partial member of the fuzzy set, the fuzzy model is obtained using Eq. (7):

$$f_s(m) = \sum_{n=1}^{n_0} w * \left(\left[\frac{\sum_{n=1}^{f} g_0[s_\alpha(a) + p_0(a) + s_r(a)] * \alpha}{\sum_{n=1}^{n_0} s_f * g_0} \right] \right) + \left[\frac{\sum_{f}^{n_0} w(l) + b_0}{s_m} \right] \tag{7}$$

By using Eq. (6), the fuzzy set of full and partial members are obtained from that the fuzzy model derived by Eq. (7). In Eq. (7), f_s is denoted as a fuzzy set, and n_0 is a specific time that is obtained from the sensor. Here the fuzzy set and membership function are calculated so that the sportsperson's time-bound movements can be observed. After the fuzzy model is derived, the grade member function is formulated for the input and output data using Eq. (8):

$$s_w(f) = f_s * \prod_{l=1}^{b_0=1} (f + \delta) * d \tag{8}$$

In Eq. (7), the fuzzy model is derived for the member set, and then, the grade member calculated to a large degree in the fuzzy set is observed by using Eq. (8). The variables$_w$ represents the sports member's workout. It is used to derive the decision of the member (either 0 or 1) by comparing Eqs. (4), (6) and (7), and Eq. (9) is derived as follows.

$$f_{s_m} = \prod_{l=1}^{b_0=1} (f + \delta) * d * \begin{cases} \left[\frac{\sum_{n=1}^{f} g_0[s_\alpha(a) + p_0(a) + s_r(a)]}{\sum_{n=1}^{n_0} s_f * g_0} \right] + \prod_{e_d=1}^{n_m} \left[e_d - \frac{a}{p_0} \right] < \alpha \\ \left[\frac{\sum_{n=1}^{f} g_0[s_\alpha(a) + p_0(a) + s_r(a)]}{\sum_{n=1}^{n_0} s_f * g_0} \right] + \prod_{e_d=1}^{n_m} \left[e_d - \frac{a}{p_0} \right] > \alpha \\ \left[\frac{\sum_{n=1}^{f} g_0[s_\alpha(a) + p_0(a) + s_r(a)]}{\sum_{n=1}^{n_0} s_f * g_0} \right] + \prod_{e_d=1}^{n_m} \left[e_d - \frac{a}{p_0} \right] = \alpha \end{cases} \tag{9}$$

By using Eq. (8), the grade member is used to obtain a large fuzzy set from which the decision is made. $f_{s_m}$is denoted as the sportsperson movement we observed along with their movements. Eq. (9) is the combination of Eqs. (4), (6) and (7). Eq. (9) has three conditions that are used to satisfy the fuzzy set. In Fig. 4(a)–(c) the fuzzy representation for$f$ and$g_0(x)$ is illustrated for these three conditions.

The first condition is denoted as $\left[\frac{\sum_{n=1}^{f} g_0[s_\alpha(a) + p_0(a) + s_r(a)]}{\sum_{n=1}^{n_0} s_f * g_0} \right] + \prod_{e_d=1}^{n_m} \left[e_d - \frac{a}{p_0} \right] < \alpha$, and states the grade and member function are observed based on the sample input data. By calculating this, the result is based on the required time and the fixed time, which is denoted as α. Here, the sportsperson speed and movement are lesser than α, so the data are processed first.

The second condition is $\left[\frac{\sum_{n=1}^{f} g_0[s_\alpha(a) + p_0(a) + s_r(a)]}{\sum_{n=1}^{n_0} s_f * g_0} \right] + \prod_{e_d=1}^{n_m} \left[e_d - \frac{a}{p_0} \right] > \alpha$, is having the analysis is greater than α, which means the process has been analyzed based on the sample input condition. The third condition is $\left[\frac{\sum_{n=1}^{f} g_0[s_\alpha(a) + p_0(a) + s_r(a)]}{\sum_{n=1}^{n_0} s_f * g_0} \right] + \prod_{e_d=1}^{n_m} \left[e_d - \frac{a}{p_0} \right] = \alpha$, satisfies they are equal to α is second processing member. The abnormal member records are sent to the rehabilitation center for further evaluation. The evaluation is based on recovery or gives a certain measurement for a member of the sports.

After identifying the fuzzy set, the movement of the member is examined in the rehabilitation and feedback is given to improve the physical activity.

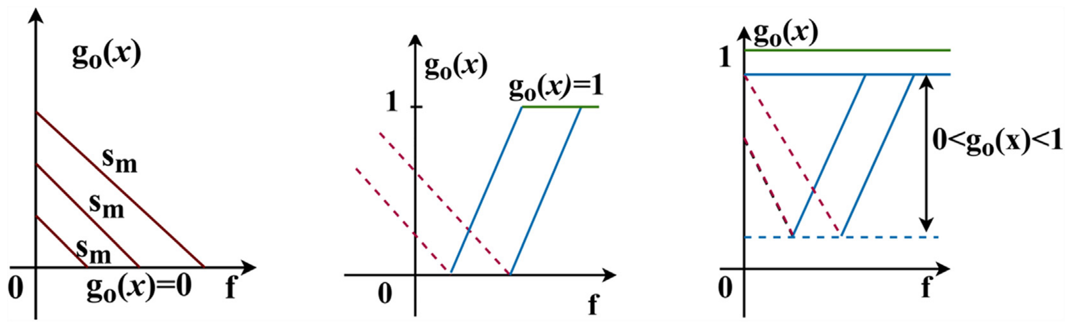

Fig. 4. (a) $\mathbf{g}_0(\boldsymbol{x}) = 0$ 4(b) $\mathbf{g}_0(\boldsymbol{x}) = 1$ 4(c)$0 < \mathbf{g}_0(\boldsymbol{x}) < 1$

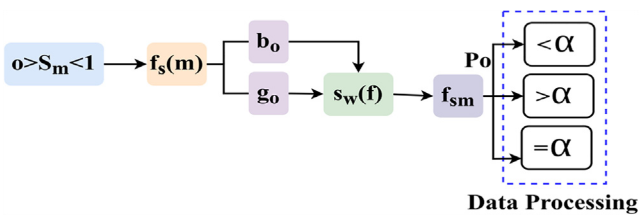

Fig. 5. FTDM Data Processing.

The decision is made on analyzed data from aggregated rehabilitation. The following Eq. (10) is used to predict the data from history. The prediction is done by matching the correct data and provides the results.

$$d_s = \delta + \sum_{a=1}^{\alpha} p_0 \begin{cases} c(\delta) = f_{s_m} + \left[\frac{\sum_f^{n_0} w(l) + b_0}{s_m}\right] < h, = 0 \\ c(\delta) = f_{s_m} - \left[\frac{\sum_f^{n_0} w(l) + b_0}{s_m}\right] > h, = 1 \end{cases} \tag{10}$$

From Eq. (9), the sports member status is obtained based on time. From that in, put data are obtained and evaluated by using Eq. (10). In Eq. (10), d_s is denoted as the decision made for sports members. Here, the input data are obtained time-based, and the fuzzy model is used to find whether the activity is normal or abnormal. In Fig. 5, the data processing using FDM is presented.

The first condition is having$c(\delta) = f_{s_m} + \left[\frac{\sum_f^{n_0} w(l) + b_0}{s_m}\right] < h$, having the fuzzy member function and grade member function using this, the input data are lesser than the history h, and it is denoted as a normal member. The second condition is $(\delta) = f_{s_m} + \left[\frac{\sum_f^{n_0} w(l) + b_0}{s_m}\right] > h$, here, the data are greater than the historical data, meaning that they are stated as an abnormal member, and the feedback is given to them. In Fig. 6(a)–(c), the solutions of FTDM for f and$g_0(x)$ for the data analysis is presented.

By using Eq. (10), it detects the normal and abnormal activity and provides instruction. In Table 1(a) and 1(b), the outputs of the decision-making before and after the conditional analysis is presented.

The proposed work first aggregates the data from the sensor based on time (Table 1(a)). Then, the data are analyzed by using a fuzzy approach. The fuzzy model is used to decide for a member of the sports by using Eq. (7). The time-based data are obtained using Eq. (9). Finally, the decision is made by using Eq. (10) (Table 1 (b)). The accuracy in detecting the exact action in rehabilitation is high in the proposed method. In Figs. 7(a) and 7(b), the membership function outputs before and afterd_s are presented.

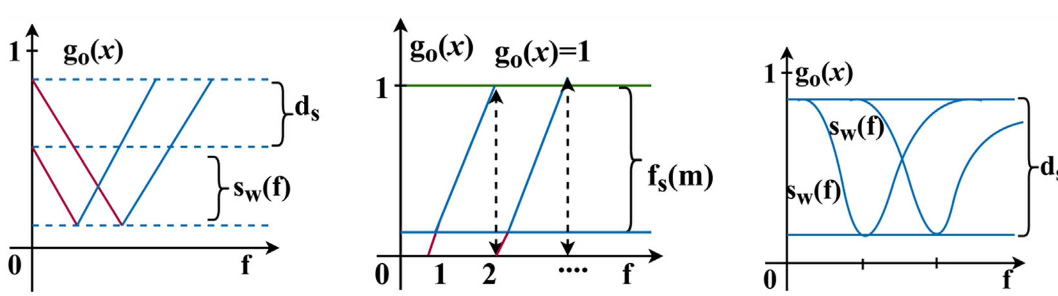

Fig. 6. (a)$\boldsymbol{f_s}$ Solution 6(b)$\boldsymbol{f_s(m)}$ Solution 6(c)$\boldsymbol{s_w(f)}$ and$\boldsymbol{d_s}$ Solution.

Table 1a
Fuzzy Outputs Post Aggregation.

f	$g_0(x) = 1$	$0 < g_0(x) < 1$	$g_0(x) = 1$	$0 < g_0(x) < 1$	$g_0(x) = 1$	$0 < g_0(x) < 1$
1	0.21	0.36	0.403	0.493	0.511	0.65
2	0	0.2	0.35	0.4	0.53	0.62
3	0.12	0	0.26	0.33	0.39	0.54
4	0.21	0	0.21	0.21	0.21	0.49
5	0.28	0.31	0.84	0	0.17	0.386
6	0.342	0.46	0.93	0.87	0	0.28
7	0.42	0.87	1	1	0.59	0
8	0.64	0.91	1	1	1	1

Table 1b
Fuzzy Output After.$\boldsymbol{d_s}$

f	$g_0(x) = 1$	$0 < g_0(x) < 1$	$g_0(x) = 1$
1	1	0.81	1
2	0.86	0.53	0.64
3	0.77	0.43	0.16
4	0.66	0.11	0.48
5	0.23	0.54	0.62
6	0.43	0.92	0.74
7	0.65	0.92	0.96
8	0.82	0.93	0.93

The output in Fig. 7a presents all the possible instances of the membership functions classified under $s_m = \partial + p_0$ and $s_m = \partial + (1 - p_0)$. The output of $g_0(x) = 0$ is not considered in the above process. This is observed for the same activity that is aggregated at different time intervals.

For the aggregated inputs, the membership function is classified using the conditions in Eq. (9) following the correlation analysis using Eq. (10). Therefore, $g_0(x)$ solution is refined from the actual count to the above, as in Fig. 7b. Therefore, the precise solution in predicting the activity for abnormality is confined to the conditions in Eq. (9) based on the linearity in Eqs. (6)–(8). This reduces the number of incorrect validations, increasing the chances for accurate prediction.

4. Performance analysis

The FDM model was analyzed using experiments performed using OpenSim [36–38]. The activities of a human subject using a treadmill as in [39] were monitored and used for analysis. The analysis was performed using FDM and was correlated with the information shared in the dataset source. The WS was operated at a frequency of 25 Hz classified into 480 segments. In this analysis, the input from 9 WS was obtained and aggregated for

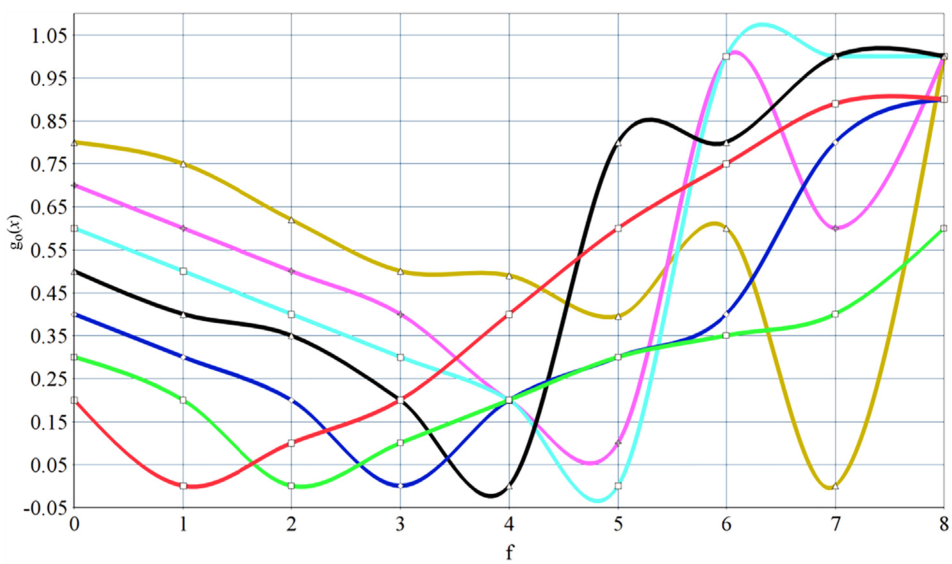

Fig. 7a. Observed$\mathbf{g}_0(\boldsymbol{x})$ for different.$\boldsymbol{f}$

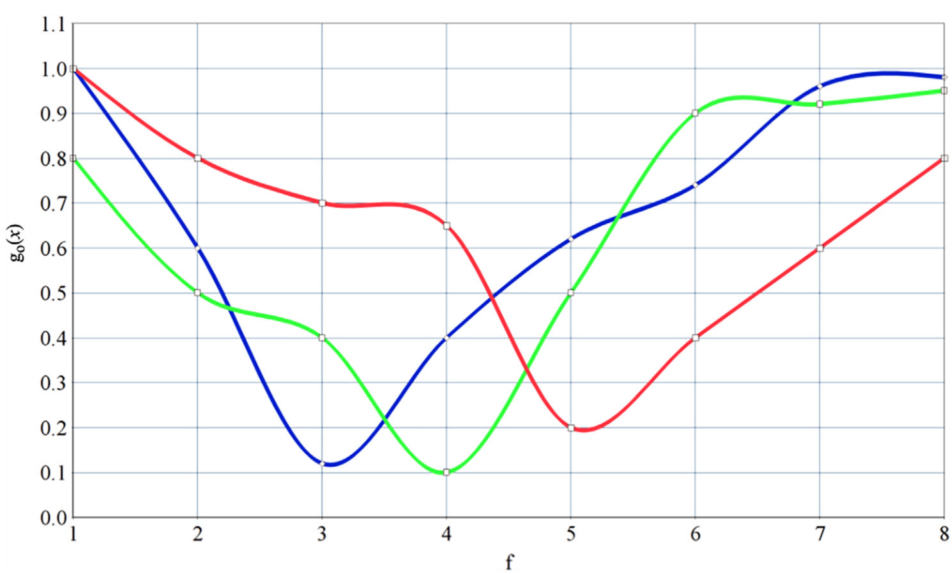

Fig. 7b. Classified$\mathbf{g}_0(\boldsymbol{x})$ after.$\boldsymbol{d_s}$

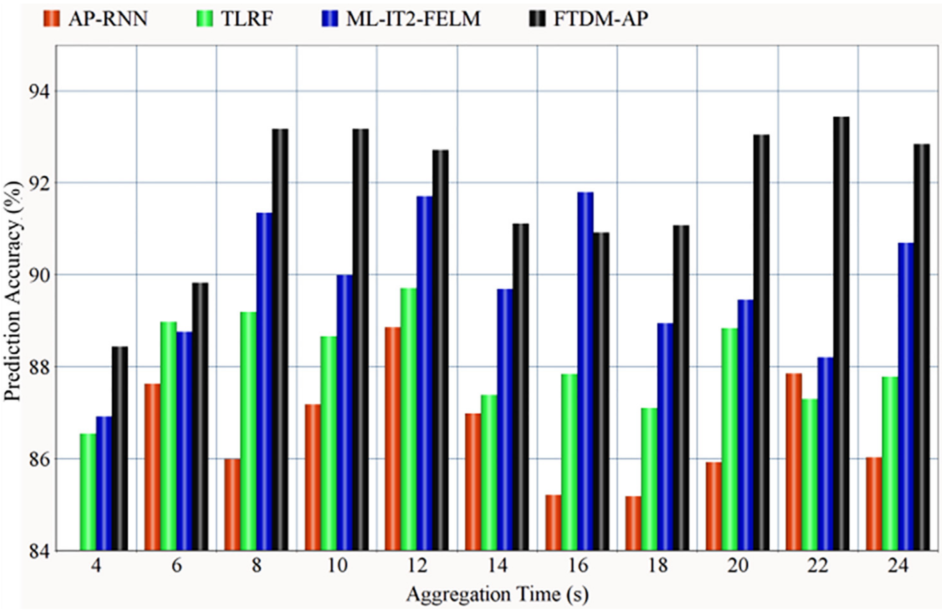

Fig. 8a. Prediction Accuracy versus Aggregation Time.

an interval of 5 s to 20 s. The dataset consisted of 19 activities from 8 subjects out of which the treadmill activity was selected for analysis. This dataset contained 124 samples of sensor data for the above activity with 45 columns of classification [40,41]. In this analysis, a comparative study was performed using the metrics prediction accuracy, decision error, and detection time for varying inputs and aggregation time. For comparison, the existing methods AR-RNN, TLRF, and ML-IT2-FELM are considered.

5. Prediction accuracy

Figs. 8a and 8b presents the comparison of detection accuracy for the varying aggregation time and inputs. The sensor data in t_m for s, m_n and z us first segregated based on$l_m(t)$. Following the segregation process, the membership function was formulated to identify all the possible members in$f$ classification. For different instances of time and input, $f_s(m)$ was defined to identify the grade of input processing f_{s_m}. From this identified processing, the prediction was performed; the information was correlated to the outcome of the previously stored information to verify its accuracy. The diverse stages in classification using $h = 0$ and $h = 1$ condition, the decisions were performed to detect precise abnormality. The timed model verifies $\left[e_d - \frac{a}{p_o}\right] < \alpha$ and $\left[e_d - \frac{a}{p_o}\right] > \alpha$ condition in handling different inputs in different aggregation time intervals. Therefore, d_s satisfies either of the above conditions in identifying precise abnormality due to the varying activity pattern, In particular, $l_m(t)$ and $f_s(m)$ classification at the initial stage helps to identify the data and the time sequence for generating appropriate membership functions and obtaining precise outputs.

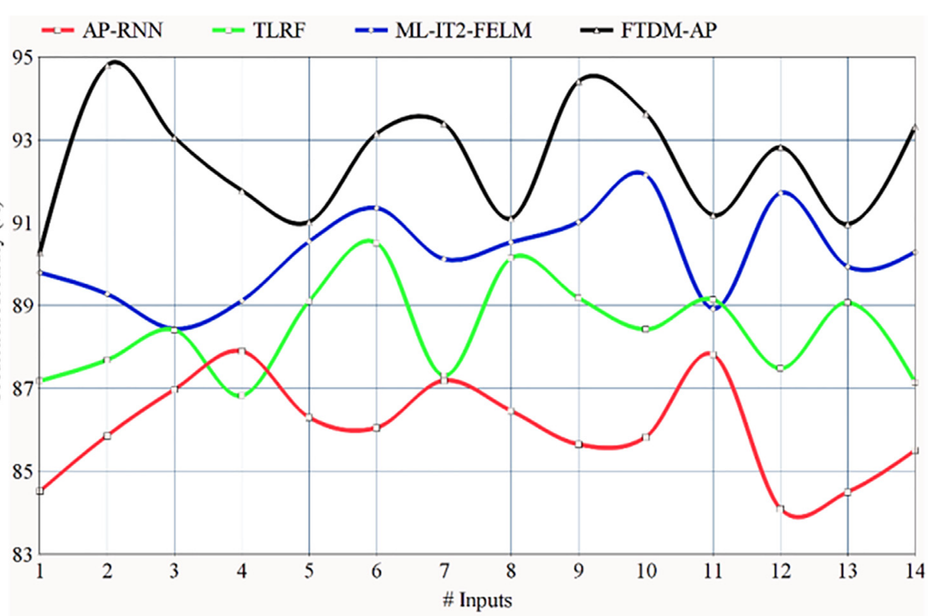

Fig. 8b. Prediction Accuracy versus Inputs.

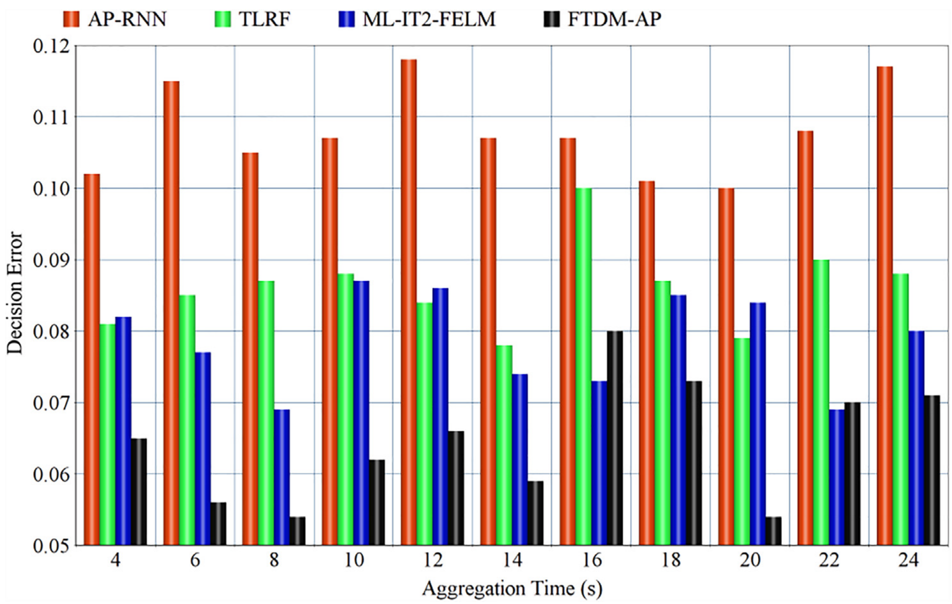

Fig. 9a. Decision Error versus Aggregation Time.

6. Decision error

The proposed FDM model provides granular analysis of$s$, m_n, and δ both independently and linearly. The linearity in the activities was observed using the aggregation time metric. This time metric generates a continuous sequence for identifying the actions and helps to improve the accuracy of prediction. The nonmembers of the fuzzy function as classified using Eq. (6) are identified and excluded from the validation process. Therefore, $f_s(m)$ for $g_o(x) = 1$ and $o < g_o(x) < 1$ are the identified members (Unanimous for s, m_n and ∂). This like process of estimating data is alone analyzed for its grade of output using Eq. (8). Finally, based on α, the fuzzy output is modeled such that existing fine-grained analysis is performed for both $l = 1$ and $b_o = 1$ for any number of inputs and varying aggregation time. The correlation analysis of d_s is performed by validating $< \alpha, > \alpha$,and $= \alpha$ conditions refraining the errors in decision-making. The membership function $g_o(x) = 0$ if present in the validating sequence, causes an error and is less in the proposed FDM (Figs. 9(a) and 9(b)).

7. Decision time

A conventional decision-making process relies on the quantity of data and the number of processing instances. In FDM, time is the deciding factor as the activities in precise time help to identify the reason and prediction of abnormality. The different aggregation instances increase the quantity of data and multiple inputs. Therefore, to avoid complex processing, the data were segregated on its linearity based on$f$ and$g_o(x)$. This classification identifies members and nonmembers functions for precise validations. The

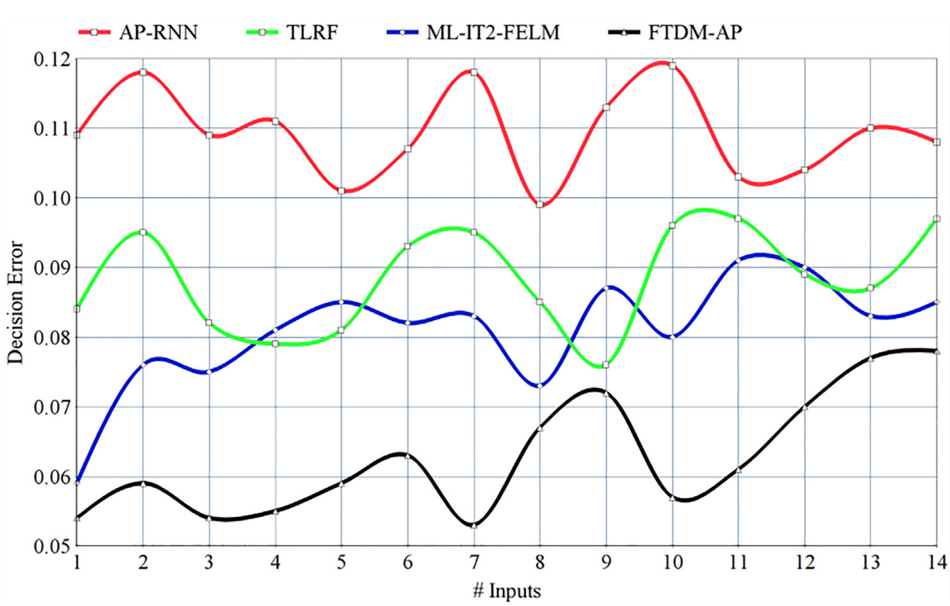

Fig. 9b. Decision Error versus Inputs.

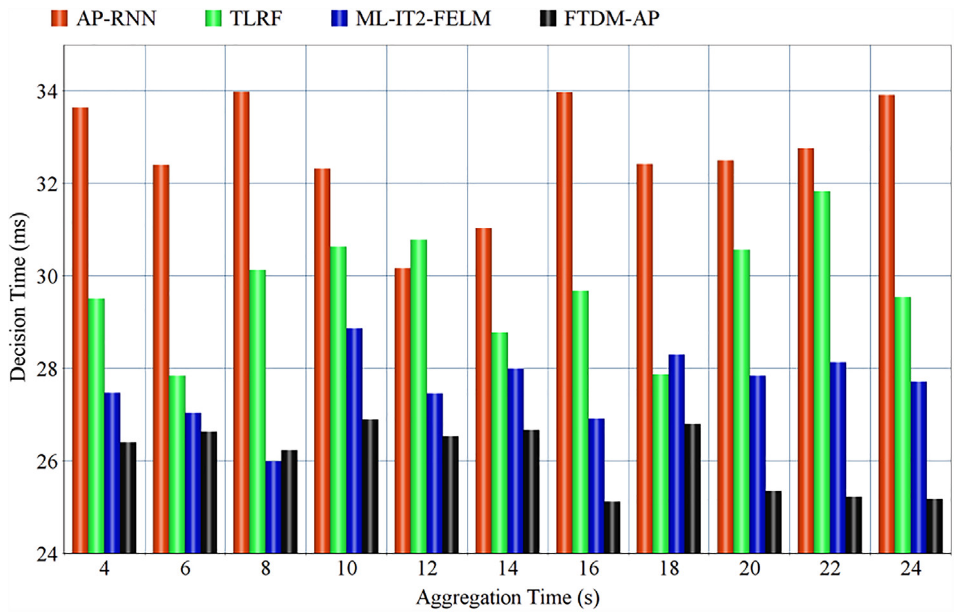

Fig. 10a. Decision Time versus Aggregation Time.

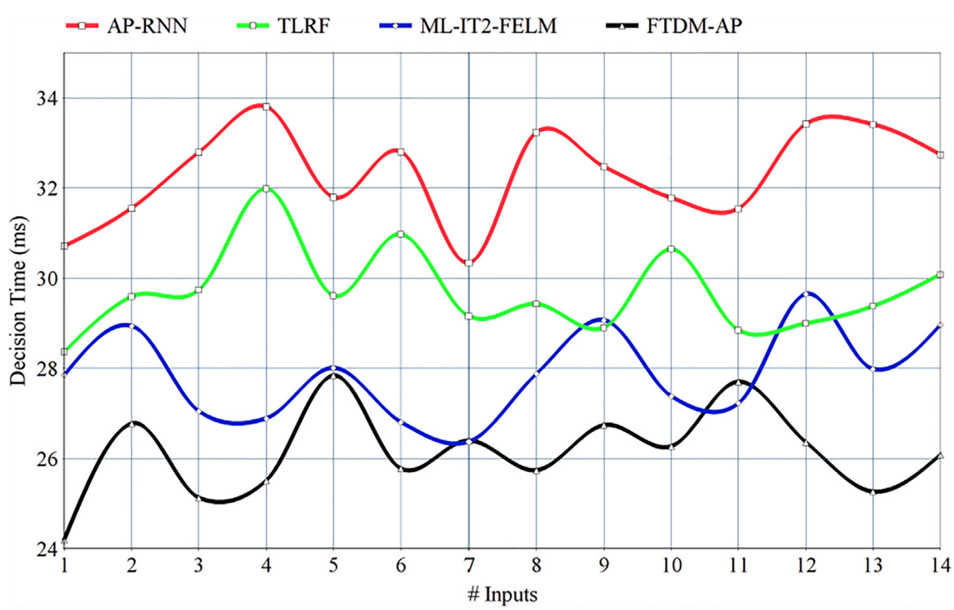

Fig. 10b. Decision Time versus Inputs.

Table 2
Comparative Analysis Results.

Metrics	AP-RNN	TLRF	ML-IT2-FELM	FTDM-AP
Varying Aggregation Time				
Prediction Accuracy (%)	86.03	87.79	90.7	92.84
Decision Error	0.117	0.088	0.08	0.071
Decision Time (ms)	33.917	29.544	27.722	25.184
Varying Inputs				
Prediction Accuracy (%)	85.506	87.142	90.29	93.317
Decision Error	0.1073	0.097	0.085	0.078
Decision Time (ms)	32.731	30.181	28.962	26.081

conditional case of$h$ for all the $f_s(m)$ and $l_m(t)$ is used for analyzing d_s for the varying inputs. This helps to reduce the required decision time for the valid members other than the available members, for varying aggregation time and inputs (Figs. 10(a) and 10(b)). In Table 2, the comparative analysis is presented concerning the varying aggregation time and inputs.

From the above comparative analysis, it can be seen that the proposed decision-making model achieves 4.67% high prediction accuracy, 2.4% less decision error, and 17.14% less decision time for the varying aggregation time. In concern to the varying input, the proposed method achieves 5.67% high prediction accuracy, 1.87% less decision error, and 14.84% less decision time, respectively.

8. Conclusion

In this paper, an activity-based abnormality prediction for sportspersons using a FDM model is introduced. This model is useful in identifying the abnormalities through seamless monitoring and analysis of sports activities. In this decision-making model, fuzzy membership functions are designed for inputs that are classified linearly based on different aggregation intervals. Membership functions are then classified based on the available activity sequence from which the abnormality is detected. In the detection process, conditional correlation is implied for improving the prediction accuracy for the different inputs and aggregation time. The timed decision-making helps to identify linear fuzzy sets without additional time, and hence, instantaneous solutions of the fuzzy process reduce decision errors.

CRediT authorship contribution statement

Amr Tolba: Conceptualization, Methodology, Software, Writing - original draft. **Zafer Al-Makhadmeh:** Visualization, Investigation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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