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Modeling Petri Net Based Self Adaptive Childcare System

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Abstract- Humans benefit from assisted living innovations and techniques in the domains of health, education, care, monitoring, and tracking. Given that 28% of the workforce in Pakistan are women while 31.99% of the country's population is between the ages of 0 and 14, a self-adaptive child monitoring system is crucial for our society. The modeling of a childcare system that automatically controls all three main facets of childcare—child health monitoring, child activity monitoring, and child aid provision—is proposed in this study. The suggested approach involves employing motion and location sensors for activity tracking, various vital indications (blood pressure, breathing rate, body temperature, and pulse rate) for health monitoring, and help with operating various appliances in the home. The primary objective of the proposed study is to update parents about their children's health and activities as there's a pressing need to do so given the recent spike in instances of child abuse, which include harsh punishment at school, kidnapping, harassment, and health-related problems. Three types of sensors are used in this study project to collect data: mobility, physiological, and environmental. Fuzzy rules will enable the system's self-adaptive capability. Fuzzy reasoning was employed to make decisions for the benefit of behavioral variation meant to adapt to these changes, and fuzzy rules were used to simulate run-time scenario transformation. The coverability graph was used to validate the proposed Petri Nets. This study makes a significant contribution to the field that provides a novel means of meeting changing childcare needs via automated adjustment processes.

Keywords- Childcare, Intelligent/Fuzzy Petri Nets, Self-Adaptive Software Systems

I. INTRODUCTION

Childcare techniques involve standard surveillance and recording of the child's actions as they occur. These approaches also give feedback to parents and caregivers regarding the child's activities. Typically, wearable vests [1-6], waist belts [7-9], and wrist watches [10] were used for child monitoring. These systems send signals or messages to parents, caregivers, nurses, or other relevant people regarding the child's situation. The benefits of such systems include child monitoring, child safety, parent familiarity about the child at work or at home, risk prevention, and child supervision. Several applications for childcare include growth inspection of the child, energy expenditure evaluation, avoiding the child's fatness, health, security, and protection of the child [11].

Due to extreme demand, this research suggests a sample framework for children's wellness on the home grounds. Most of the time, mothers who work are unable to stay at home with their children, leaving the kids alone. For their children's health and protection, parents always want to be watching over them in various settings. The issue of preservation to satisfy observations emerges, and childcare systems are the solution for those who operate in their sectors.

The childcare facility can monitor the kids' activities and inform parents about matters pertaining to their children. In addition, there is an increase in violence against children, which includes harassment, kidnapping, and physical punishment in schools. These kinds of devices can keep an eye on a child's activities at home, at play, and at school. Such monitoring has the advantage of protecting kids against behavioral, psychological, and medical issues [12]. These systems support children's healthy development. The several aspects of youngsters that require observation were recognized by the researchers. It has been discovered that these factors—school, peer pressure, local effects, family, and friends; are connected to various forms of child monitoring [13]. The provision of childcare facilities ensures children's safety and, as a result, gives parents a mental break.

An application for self-adaptive childcare is proposed; it will employ motion and location sensors to record the child's routine and automatically monitor the child's health using vital signs. It will also help the youngster use various appliances when they are at home alone. Fuzzy rule-based Petri Nets were used in the proposed system to model the specified environment. When these rules detect contextual data from the surroundings, they will immediately be modified.

As stated in [14], a directed bi-partite graph with nodes representing transitions and conditions representing places can be used to express a Petri Net, a mathematical modeling language for distributed systems. Fig. 1 shows the Petri Net for a childcare's home setting. The details of places and transitions of this environment for Childcare are given in Table I.

$P = \{P0, P1, P2 \ldots . P8\}$
$T = \{T0, T1, T2 \ldots . T8\}$

Table I: Places & Transition Detail of Childcare Environment

Name	**Description**	**Name**	**Description**
P0	Home	T0	For watching TV
P1	TV lounge	T1	For taking meal
P2	Kitchen	T2	For freshness
P3	Bathroom	T3	For playing/towel usage
P4	Bedroom	T4	For playing/lying/ sleeping
P5	Gallery	T5	For eating/drinking
P6	Dining	T6	For computer usage
P7	Study room	T7	For going outside
P8	Exit	T8	For entering home

In terms of physical environment, Fig. 2 depicts the generalized Petri Net for Childcare. $P1$-motion values (accelerometer data), $P2$-location values (RFID readers, RFID cards, and GPRS sensor values), $P3$-brightness, $P4$-temperature, $P5$-weather, $P6$-blood pressure, $P7$-breathing rate, $P8$-pulse rate, and $P9$-body temperature are the locations covered in depth. $P10$ is a computer device, while $P11$ is a caretaker gadget.

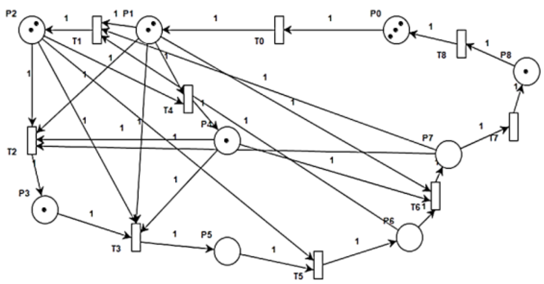

Fig. 1. Home Environment Petri Net for Childcare

$p1$ through $p9$ are part of the child device and are separated into three categories: $p1$ and $p2$ are related to the activity monitoring process, $p3 – p9$ are related to the provision of help, and $p6 – p9$ are related to child health monitoring. Data fusion for activity monitoring is done at $t1$, data fusion for health monitoring is done at $t3$, and data fusion for assistance relevance is done at $t2$. Every computing decision is made at $p10$ and is relayed to $p11$ as well.

According to a motion in [14], fuzzy logic is a type of many-valued logic where variables' truth values might be any real number between 0 and 1. In situations where the truth value could vary from fully true to false, it is used to manage the idea of partial truth. Originating from fuzzy set theory, it is the opposite of Boolean logic." A generic fuzzy technique is shown in Fig. 3, and some sample rules of our proposed work are provided in Table II. Fuzzy rules are defined as rules that are based on fuzzy values.

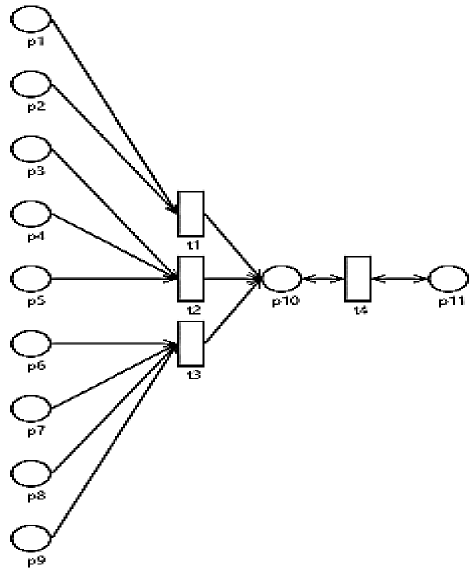

Fig. 2. Generalized Petri Net for Childcare

As seen in Fig. 3, fuzzy logic consists of three primary components: the fuzzifier, the inference engine, and the de-fuzzifier. The sample details are provided in Figs. 4 (brightness), 5 (temperature), and 6 (blood pressure), and the membership values are fuzzified in the proposed work utilizing scalar vector, trapezoidal curve, and symmetric Gaussian functions. The following provides more information about fuzzy inputs:

- *Child (True & False)*
- *Brightness (Ultra-High, High, Medium, Low & Ultra-Low)*
- *Temperature (Ultra-High, High, Medium, Low & Ultra-Low)*
- *Weather (Sunny, Rainy, Cloudy)*
- *Blood Pressure (Ultra-High, High, Normal, Low & Ultra-Low)*
- *Body Temperature (Normal, High & Ultra-High)*
- *Breathing Rate (Ultra-Slow, Slow, Normal, Fast & Ultra-Fast)*
- *Pulse Rate (Ultra-Slow, Slow, Normal, Fast & Ultra-Fast)*

The first function used was $'trimf'$ and this function belongs to a vector x, that determined on three parameters. These are parameters scalar i.e. a, b, c as shown in equation-1;

$$f(x;a,b,c) = f(x) = \begin{cases} 0, & x < 0 \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases}$$

Or, further trimly, by

$$f(x;a,b,c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b},\right), 0\right)$$

The second used function trapezoidal curve (trapmf), is a function of a vector, x, and determined on four scalar parameters a, b, c, & d, as shown in equation 2.

$$f(x;a,b,c,d) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases}$$

Or, further concisely, by

$$f(x;a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{c-x}{c-b},\right), 0\right)$$

The parameters a & d locate the "feet" of the trapezoid and the parameters b and c locate the "shoulders." The third used function, symmetric Gaussian function $(gausmf)$ trusted on two parameters as given by equation 3.

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$$

The vector's parameters σ and c, stated in sequence, are represented by the parameters for the "$gaussmf$" function. The LilyPad Arduino and Adafruit Flora platform, along with hardware like an ARM7, Xbee radio, Raspberry Pi network gateway, RFID tags, RFID reader, Android phone, and sensors like light, barometer, temperature, accelerometer, and gyroscope, have been the mainstays of childcare systems.

These included adhesive patches, wrist bands, belts, watches, vests, and bracelets that were prototypes. Fig.-7 provides a detailed description of these activities. The most difficult problem is classifying children's typical activities into safe and harmful categories. These technologies alert the person in question to a potentially harmful situation when they identify one involving children.

Each of these sophisticated systems gathers and provides information (alerts) on the child's position, location, health, and safety [8] and [9]. These units transmit alerts, the movement of a child to specific area.

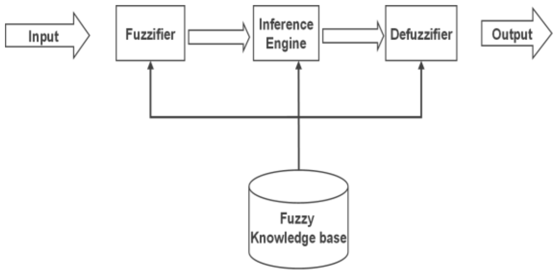

Fig. 3. Generalized Fuzzy System

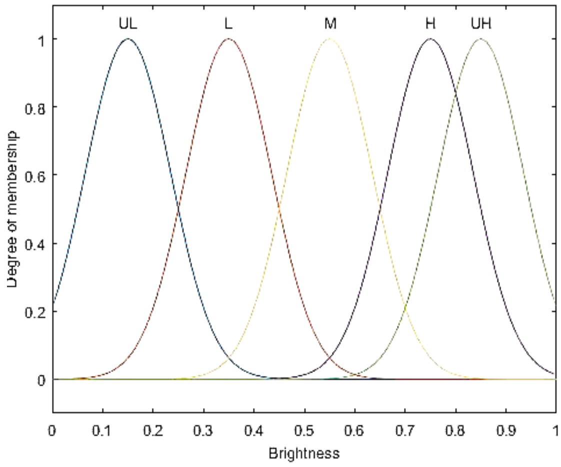

Fig. 4. Fuzzy Membership Values for Brightness

Table II: Rules for General Childcare System

No.	Rules
1.	If (Child is true) and (Brightness is UL) then (light is On)
2.	If (Child is true) and (Brightness is L) then (light is On)
3.	If (Child is true) and (Temperature is UH) then (Fan is On)
4.	If (Child is true) and (Temperature is H) then (Fan is On)
5.	If (Child is true) and (Temperature is UL) then (Heater is On)
6.	If (Child is true) and (Weather is Sunny) then (Window is Open)
7.	If (Child is true) and (BP is H) then (Inform CT)
8.	If (Child is true) and (BT is High) then (Inform CT)
9.	If (Child is true) and (BP is UH) then (Inform CT)
10.	If (Child is true) and (BP is UL) then (Inform CT)
11.	If (Child is true) and (Falling is True) then (Inform CT)
12.	If (Child is true) and (Taking Medicine is False) then (Inform CT)
13.	If (Child is true) and (Doing Exercise is False) then (Inform CT)
14.	If (Human is true) and (Sleeping is False) then (Inform CT)

That can be outdoor or indoor and their health situation. Some of these can control through web. Wireless data transfer to mobile computing devices was used in certain systems. This communication's goal was to analyze the signal that was received and identify human behavior. Most of the time, the guardian's apps were Android-based [10].

Children under the age of twelve who require special care will be covered under the proposed system for both health and safety. The authors of [14] proposed that fracture injuries primarily affect people in the 25–36 month and 37+ month age groups. The injuries in children in primary school are expressed by the research in [15]. Due to their inability to move around the house alone, these age groups also need health and security-related measures. The proposed system can be used in home, at primary school, at daycare center and other such places where children are playing.

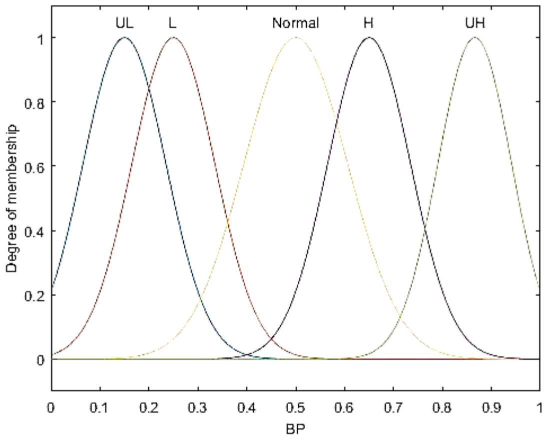

Fig. 5. Fuzzy Membership Values for Blood Pressure

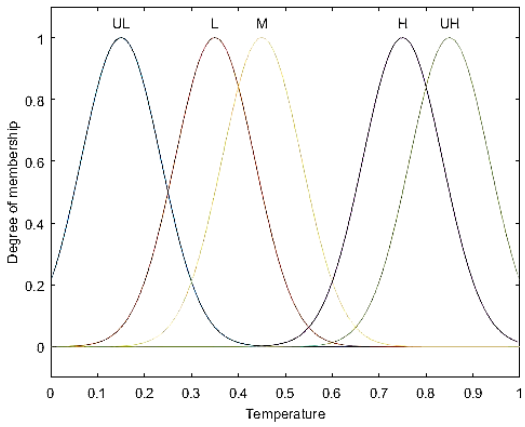

Fig. 6. Fuzzy Membership Values for Temperature

The system notifies the Care-Taker and makes recommendations for preventing harmful situations once it has identified them. The risk factors include fever, extremely high or low blood pressure, falls, fires, medication poisoning, knife wounds and choking, strangulation when climbing stairs, drowning while descending steps, and burns [16]. Additionally, regular behaviors like eating, sleeping, walking, and drinking will be detected by the system. The goal is to support women who work by selecting this age group and issue. This childcare strategy is what we advocated, and the following paragraphs describe it. Childcare techniques are provided in [6,8–10], yet they have drawbacks such as the necessity for data for training, quick modification to changes in routine or environment, and appropriate performance in a dynamic setting. The ongoing removal or replacement of sensors because of human mobility, sensor malfunction, and low battery are other frequent issues. The necessity for updated training is another problem with these systems.

As far as we are aware, there isn't a childcare system that is self-adaptive by nature. According to [17], a self-adaptive software system is one that can independently change its behavior during operation in response to changes in the environment and the system. Like [18], the authors implemented an ontological technique-based Smart-Home environment and provided an activity recognition strategy for ADL in [19], which also used an ontological technique. These kinds of systems face challenges including knowledge engineering skill requirements and high language competency requirements for knowledge representation, expressiveness constraints in OWL-DL (Ontology Web Language Description Logic), and computationally costly reasoning.

Mamdani method for fuzzy inferencing is being used in this study. This method was introduced by [19]. And we use Smallest of Maximum (SOM) de-fuzzifying method for de-fuzzification. It is performed using Activity recognition, intends to differentiate different actions and activities of concern human or object from sequence of results from the sensors attached to the objects and surroundings. However, activity monitoring is to ensure the progress of concerned on the scheduled time and on the decided targets and goals. There are two techniques for activity recognition; data driven and knowledge driven and we may use the emergent of both. Data driven technique produces models of user activity from previously recorded data set of humans and these models was being used to perform the recognition of activities. For generation of model's data mining and machine learning techniques are being practiced. It is very tough to apply these models to all persons as most of these models are subject dependent. In the knowledge driven approach, the prior field knowledge is being used for creation of models. Hybrid techniques syndicate knowledge driven and machine learning to construct activity models [20].

This study makes a significant contribution to the field by proposing a self-adaptive childcare system based on a new Petri Net that provides a novel means of meeting changing childcare needs via automated adjustment processes. The driving force is the growing need for adaptable and responsive childcare options, underscoring the potential of Petri Net modeling to improve flexibility and effectiveness in childcare provision.

II. RELATED WORK

An intelligent system, as defined in the introduction, is one that, upon receiving signals from the environment or from within the system itself, may independently modify its activities during operation [21]. These days, the design of such a system is an area of concentrated research and a difficult model to create. An Intelligent Petri net for simulating a self-adaptive system in a manufacturing setting was presented by Ding et al. in [21]. This fuzzy rule-based intelligent Petri Net has several advantages, including the ability to adjust variable behavior at runtime, support for multiple languages for these nets, and the ability to make adaptive judgments on its own.

The researchers employed smartphones with sensors to identify human activity [17] or wearable technology [16-17]. There are several issues with wearable sensors, including: 1) "privacy," 2) "difficulty placing sensors on different body parts for patients," and 3) "expensive sensing circuits, etc." Most of these issues were resolved by using sensor-based smartphones in research. Using smartphones with sensor capabilities, the problem of "difficulty in wearing devices" was fixed. With the widespread availability of smartphones, the problem of "expensive circuits" has also been resolved [22] & [23]. Additionally, smartphones can be used for interactive apps, control-based video analysis, security and surveillance, monitoring, behavioral biometrics, and monitoring [23]. Smartphone-based systems do, however, have several drawbacks, such as concerns with battery, orientation, and processing speed [22]. Systems and tools for keeping an eye on and limiting children within a specific region were created by some researchers [24]. When a youngster is in the restricted area or getting close to the boundary, the object wears a device that can record, generate, and transmit signals to the controlling unit. Another element (the transmitter in the monitoring section) is used to facilitate parent-child communication [21].

Developed a fuzzy rule-based decision support system in [24] for analyzing vital sign data from various devices to detect abnormal health conditions. This system compares the data with standard data that has already been stored as an example for everyday living activities. He used data collected in labs and simulated environments to do evaluation. The fuzzy logic-based approach that was suggested was put into practice and tested on a dummy dataset to identify the various topic states. Vital signs were used to determine whether the subject's checked states were normal or abnormal. The outcomes demonstrated promising outcomes and provided assurance for applying this strategy in real-world clinical settings with similar cases. The three postural status conditions: Static, Raising, and Lowering, that were identified by a tilt table on a human subject were also verified by the authors using actual data.

There are a few wearable devices, developed by different researchers for monitoring of children. One of them is wearable vest proposed in [6]. Their target audience was children of nurseries, daycare centers and primary schools. Another wearable was security shirt proposed in [12].

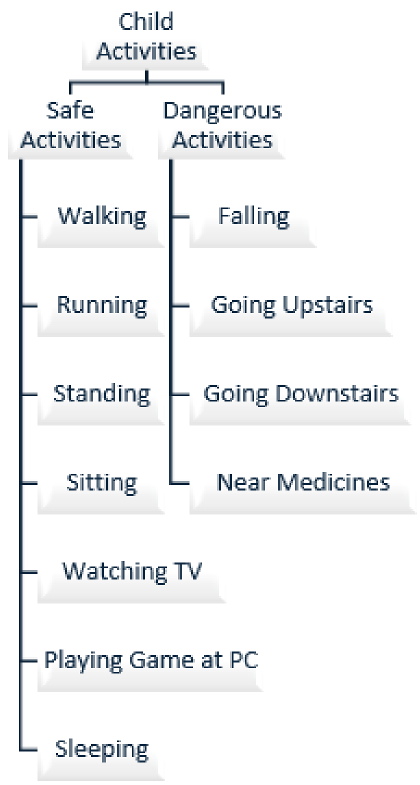

Fig. 7. Classification of Activities

That shirt comprises of 3axis accelerometer for recognition of activities and a radio frequency communication module. The wearable safety shirt automatically provides information regarding position of the child from their location. There is another module after wearable system that is a guardian system installed on PC/laptop. They use LilyPad Arduino, which is used for e-textiles and wearables. That had two parts; one was wearable sensor node for measuring movement and height from the ground by using 3-axis accelerometer. And the second one was wireless receiver that receives the measured data and transmits it to the processer. The alarming system generated emergency alerts to the parents. The same type of device was presented in [5]. They use accelerometer within wrist bands, bracelets, adhesive patches and belts.

III. METHODOLOGY

To comprehend the childcare issue, we are looking at this situation. *"Mr. X is a child; he is studying in Grade 3 in a school (his age is 9 years old). His mother is also a working lady as his father is a teacher. Most of the time Mr. X is alone at home and no one from his parents are with him after the school. Most of the time his parents are worried about him."* We got motivation from the scenario that will help us in understanding and developing the system and also show the need for observing the children.

Fig. 8 presents the suggested framework graphically. Context reasoning, data collecting, and recognition, sensors, and monitoring are the four levels that make up this framework. Several sensors were employed in the first layer to collect data. The sensor fusion module will fuse the input from many sensors after data collecting through sensors. The second layer contains the child's personal data as well as domain knowledge, which includes the child's regular activities, physical environment, contents, rules, properties, and other pertinent information. The results of these procedures were stored in a database or data center for use in making decisions later. This module additionally handles context recognition. Sensor data was handled in the following three steps: segmentation, classification, and data processing. Next two steps model the activities and perform reasoning. The result of all these steps forwarded to reasoning layer.

The reasoner uses information from the location server, rule base, and preceding layer to prepare the judgment. This module's output is routed to the services layer or monitoring layer. The communication is initially transmitted to parents, caregivers, physicians, nurses, or educators in this layer. Using the network provider service, they keep an eye on and mentor the child. Modules of the framework are organized as follows:

Knowledge-base: this module contains personal information and domain knowledge. In user profile the personal data of a child; gender, age, preferences, and habits are given. The second sub-module domain knowledge contains the routines activities of child contents, rules, properties and other relevant things. The sample diagram of the module is given in Fig. 9.

Sensors and Sensor Data Fusion: These modules include environment sensors and body worn (worn at the body of child) or Smartphone sensors. These sensors provide signals/data such as accelerometer signals, RFID readings, and Physiological sensors reading. The fusion of readings of different sensors performed in this part. We are performing sensor fusion using Kalman filter and is used for estimation of internal state of a process given for removing noise from the input. For the purpose we specify the matrices given below:

$Ek, evolution\ model$

$Ik, inspection\ model$

$Ok, Covariance\ of\ the\ basic\ clatter$

$Rk, Covariance\ of\ the\ inspected\ clatter$

$Ck, Control\ input\ model$

This filter methodology presumes the factual state at the given time K, and this time is chosen using the state (K-1) by:

$$X_k = E_k X_{k-1} + C_k u_k + W_k$$

On the preceding state x_{k-1}, the evolution model E_k is pertained. The control vector u_k is gained by applying the control input (C_k).

For assumption of process noise we use zero mean multivariate normal distribution, N with covariance, Ok: $wk\ N\ (0, Ok)$. The inspection i_k of the true state at time k is accomplished as per, $ik = Ikxk + vk,$ where first Ik is the Inspection model and $\boldsymbol{v_k}$ is the inspection noise.

Data Center/Database: this module contains information about previous results for modeling of activities. All data collected from different sensors was stored in database.

Location Server: this module is in charge of providing location information; GSM system, GPS System or RFID system.

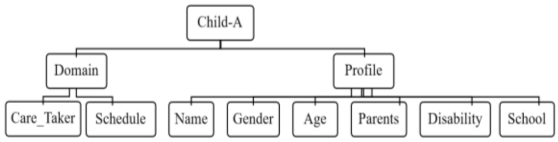

Fig. 8. Knowledge Base

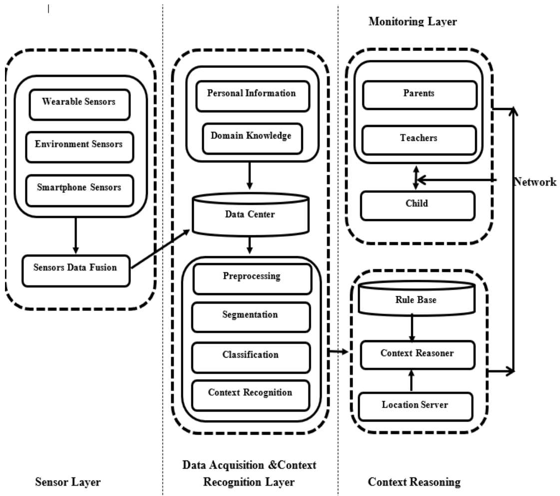

Fig. 9. Activity Recognition Framework for Childcare

Context Representation: this module represents contextual information (environmental data and basic activities selected by child monitoring module) to the reasoner.

Pre-processing, Segmentation and Classification: In next three steps (data processing, segmentation and classification) sensor data is processed. The classification is performed using algorithm-1. The detail of these attributes is given in Table V.

We use core and reduct methods of rough set theory [28] for attributes/rules reduction. The attributes that conserved the indiscernibility relation and consequently, set approximation were kept. There are usually several such subsets of attributes and those which are minimal are called reducts. The set of attributes is called a reduct of C, if $T' = (U, R, D)$ is independent and

$POS_R(D) = POS_C(D)$.

The set of all the condition attributes indispensable in T is denoted by CORE(C).

$CORE(C) = \cap RED(C)$
$R \subseteq C$Where RED(C) is the set of all reducts of C. Core = {Child, Brightness} for Turning on Light as in next table.

Table III: Attributes after Reduction

U	Child	Brightness	Light
U1	True	Ultra Low	ON
U2	True	Low	ON
U3	True	Medium	OFF
U4	True	High	OFF
U5	True	Ultra-High	OFF

Algorithm 1: Activity Classification Algorithm

1: Procedure Activity Classification
2: Input: Sensor Values
3: Output: Classified Activities
4: Features extraction from raw signals using computation of different statistical features
5: Features selection using fuzzy c-means algorithm:

$$\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \left\|x_i - c_j\right\|, 1 \le m < \infty$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left[\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right]^{\frac{2}{m-1}}}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

6: Attaining frequent patterns through fuzzy membership options selected in 5th step
7: Performing activity classification using proposed fuzzy rules
8: Classify
9: end procedure

IV. RESULTS & DISUSSIONS

This section contains the simulation findings. First, we give a description of the values of the fuzzy input and output membership functions. The membership values for the inputs of temperature, blood pressure, and brightness are displayed in Figs. 4–6. The trapezoidal curve illustrates the brightness, with values ranging from ultra-low to low, medium, high, and ultra-high. Triangular shape membership functions display the values of the other two inputs, blood pressure and temperature, which are ultra-low, low, normal, high, and ultra-high. Fig. 11 shows the coverability graph for a child's general Smart home environment. Coverability graphs are utilized because they are a computationally less expensive option and because they may be used to display the coverage of specific petri net attributes.
There are endless runs in most of these graphs, but this diagram covers the majority of the space. Figures 11 and 12 show the output membership functions for blood pressure and lowering, respectively, together with the pertinent rules. The likelihood of turning on a light increases when there are people around and the brightness is low or ultra-low. The values in Figs. 12 and 13 are self-explanatory, and their presence triggers the service.
To verify the result, we used both coverability graph and simulation tools. The general environment of a child's Smart home is depicted in the coverability graph shown in Fig. 11. Coverability graphs are used because they are a less costly solution in terms of computation and because these same structure may be useful to depict the coverage of some characteristics of Place/Transition Petri nets. Most of these graphs contain unlimited runs, depending on the number of measurements, but this diagram takes most of the area. This helps the model to be able to achieve the best capability when tested against a range of real-world scenarios that are likely to be encountered.
The Petri nets used in the paper were imitated in PIPE2 and algorithm is simulated in Matlab 2018a and got the result as shown in Table IV:

Table IV: Algorithm Simulation Results

Time stamp	Sensor1 Value	Sensor2 Value	Accuracy (%)	Activity
1	0.7	0.8	75	Sleeping
2	0.65	0.85	75	Playing
3	0.6	0.8	70	Eating
4	0.7	0.9	80	Running
5	0.9	0.85	87.5	Walking
6	9.0	0.94	92	Standing

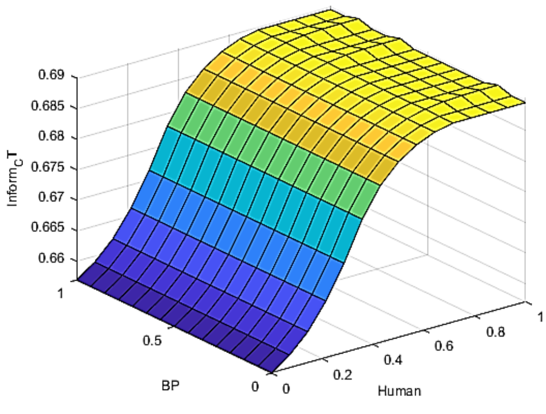

Fig. 10. Output for Bood Pressure

Table V: Attributes for Assistance Provision

U	Child	Brightness	Temper ature	Weather	Light
U1	True	Ultra Low	Ultra-High	Sunny	ON
U2	True	Low	High	Rainy	ON
U3	True	Medium	Medium	Cloudy	OFF
U4	True	High	Low	Sunny	OFF
U5	True	Ultra-High	Ultra Low	Rainy	OFF

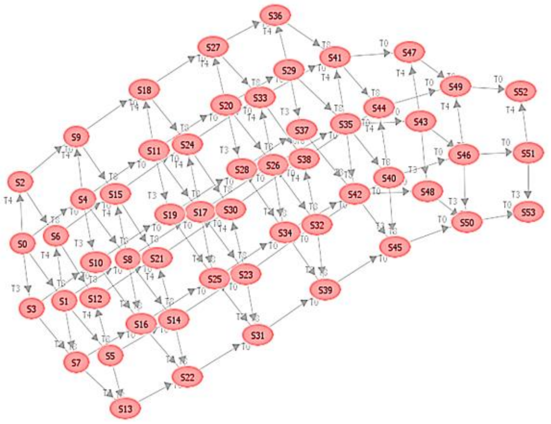

Fig. 11. Coverability Graph of Home Environment for Child

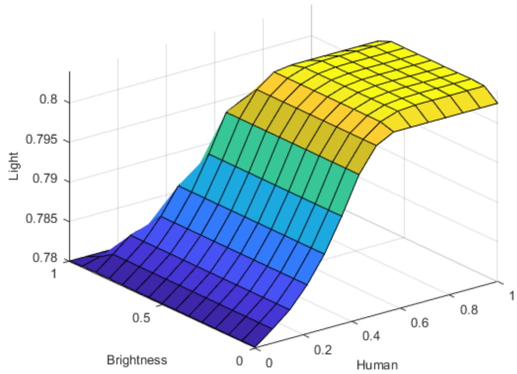

Fig. 12. Output for Falling

V. Conclusion

In this study, we presented a childcare framework and modeled it with Petri nets based on fuzzy rules. The study makes a significant contribution to the field by providing a novel means of meeting changing childcare needs via automated adjustment processes. The system automatically completes three primary tasks associated with childcare: providing kid assistance, monitoring child activity, and monitoring child health. We utilized mobility, physiological, and environmental sensors to gather data for our work. However, it's essential to acknowledge the limitations of the study, including the complexity of integrating multiple sensor inputs and the potential challenges in real-world implementation due to technological constraints and ethical considerations. Fuzzy rules were employed to obtain the system's self-adaptive capabilities, allowing for dynamic adjustments in response to changing childcare requirements. Fuzzy reasoning was utilized to make decisions about behavioral variations in response to these changes, and fuzzy rules were applied to simulate runtime scenario modification. While the fuzzy rules approach offers flexibility and adaptability, it's crucial to recognize the potential disadvantages, such as the need for expert knowledge in crafting effective rule sets and the computational overhead involved in real-time decision-making. Furthermore, coverability graphs were used to validate the suggested Petri Nets, ensuring the correctness and reliability of the proposed modeling approach. However, it's important to acknowledge that the validation process may have limitations in capturing the full complexity of real-world childcare environments and may not fully account for unpredictable interactions between system components. In the future, we aim to extend this research by addressing these limitations and exploring additional avenues for improvement. Specifically, we plan to delve deeper into the integration of advanced machine learning techniques to enhance the system's predictive capabilities and improve its ability to adapt to diverse childcare scenarios. Additionally, we aspire to conduct extensive user studies and field trials to validate the effectiveness and usability of the proposed system in real-world settings. Ultimately, our long-term goal is to develop a fully functional smart-home environment tailored specifically for childcare, leveraging the latest advancements in technology and incorporating feedback.

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