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Intelligent Elderly Care: Practicing Ambiguity Neutrosophic Theory for Optimization Contemporary Machine Learning Techniques in Elderly Care

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Abstract: One of the biggest challenges facing healthcare systems throughout the world is the aging population. The growing number of elderly citizens in need of specialized care is severely straining the available resources and care methods. It is sometimes difficult for traditional care techniques to address the complex and varied requirements of this expanding population. To fix these challenges, inclusion of contemporary technology is imperative and pragmatic solutions such as Internet of Thing (IoT), cloud computing (CC), and artificial intelligence (AI) techniques such as machine learning (ML), deep learning (DL). Such AI has potential role to make elderly care services (ECSs) to be intelligent ECSs (IECSs) through providing proactivity and earlier detection based on smart IoT sensors. Therefore, this study seeks to achieve two objectives. Firstly, leveraging the capabilities of ML techniques to revolutionize care delivery to be intelligent, optimize resource allocation, and proactive. Secondly, evaluating the robustness of utilized ML techniques in serving study's objectives. Accordingly, utilized ML Techniques consider alternatives (MLTs) that evaluate based on CRiteria Importance Through Inter-criteria Correlation (CRITIC) to obtain weights for criteria which alternatives evaluated based on. These weights are leveraging in Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank MLTs alternatives. For bolstering the evaluation process, we are integrating uncertainty theory of Probabilistic Simplified Neutrosophic Set (PSNS) which effectively captures the inherent uncertainty and imprecision

Keywords: intelligent elderly care services; machine learning; contemporary technology; Probabilistic Simplified Neutrosophic Set; uncertainty.

1. 1. Introduction

1.1 Context and Motivations

There is a growing need for effective and efficient elderly care solutions as the world's population ages. The United Nations estimated that the number of people 60 and over will double from 1 billion in 2020 to almost 2.1 billion by 2050, making up 26% of the world's population. For families, social services, and healthcare systems, this sharp rise poses serious difficulties [1].Economically[2], [3] the aging population has an impact on budgetary policy. Financial hardship may result from the growing load on pension funds and social security systems if they are not properly handled. Socially [4], a lack of personalized support is characteristic of traditional care models that are finding it more and more difficult to address the needs of the aging population. New methods of providing care that emphasize proactive treatments, individualized assistance, and effective resource use are required due to the growing incidence of chronic illnesses and cognitive decline.

Consequently, elder care services have been becoming an essential aspect of the strategy as they provide a more accessible way to serve the elderly, with a focus on those who are handicapped or semi-impaired. Hence, it is imperative to necessitate innovative approaches to support older adults in maintaining their health, independence, and overall quality of life.

There has been a surge in several methodologies that can be applied to improve the efficiency of elderly care practices by addressing their mental health needs. First, both research and the industrial community should exert much effort to provide clear guidance to disabled elderly individuals.

regarding the usage of intelligent systems and services in their daily lives[5].This can help alleviate the misconceptions or cognitive biases that elderly people can have regarding elderly care services.

Second, care systems require continuous development of intelligent functions that can learn the common patterns in the care requirements of a particular population, thereby becoming able to meet the real, rudimentary requirements of disabled elderly individuals [6].Third, while providing rudimentary services is imperative, enhancing the reliability of these care services and making them easy to personalize to the needs of corresponding individuals is highly recommended. This can be offered through intelligent systems that can be tailored to the explicit needs and preferences of elderly individuals [7]. For instance, intelligent services can be provided ranging from elementary detection to personalized health sustenance, which allows taking care of elderly individuals based on their exclusive conditions.

Thereby[8] provided an innovative solution to the problems of caring for the elderly. This solution is formed in Information and communication technology (ICT) which provides a wealth of chances to improve people's quality of life and services. Utilizing ICT[9] for elderly people includes a variety of uses, such as online support communities, mobile health apps, telehealth services, and systems for distant surveillance. Figure 1 showcases samples of technologies ICT and its positive roles in converting traditional elder care services into intelligent elder care services (IECSs).

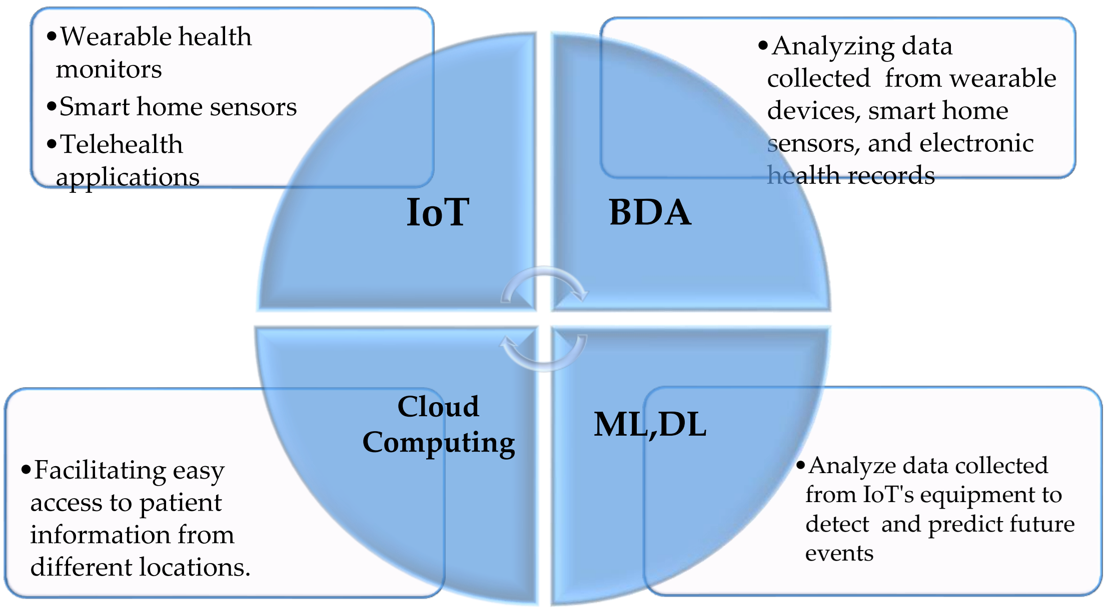

Figure 1. Role of ICT Toward Digitizing Elder Care Services

1.2 Contributions: Bolstering IECSs

We formed the provided contributions of the study into a set of hypotheses.

H1: What are deployed methodologies for bolstering ECSs to be IECSs?

Herein, we are exploiting the ability of ML [10] to proactive and individualized care for elders by analyzing large, composite data, discovering, learning patterns, and performing predictions with no or negligible human intervention. As well as [11] stated that ML has the potential to personalize the solutions for activity monitoring, fall detection, and early diagnosis of age-related settings. Scholars of [12]are settling ML as a cornerstone of modern elder care technologies. Due to its ability to process real-time data from wearable sensors, ML algorithms became able to forecast possible anomalies and deliver timely alerts, which can ensure proactive safety and quality of life for elder people.

H2: Evaluating the ability of ML techniques for Predicting future occurrences based on data collected from smart equipment.

Neutrosophic theory, entrenched in handling uncertainty, indeterminacy, and imprecision, represents a vigorous framework for decision-making in a broad range of complex applications with uncertain environments [13].It represents an extension to fuzzy logic, in which neutrosophic sets introduce nuanced data representation, which accommodates contradictory, incomplete, or vague information [14]. With this representational ability, neutrosophic sets come to be valuable to elder care, in which decision-making always includes many criteria and uncertain settings. whereinc the integration of neutrosophic theory into healthcare makes it easy to accurately assess risk by considering the inherent uncertainties daily activities of elder people. Leveraged neutrosophic theory can improve decision-making abilities by offering reliable and adaptive solutions that can effectively meet the complex requirements of elderly individuals[15].

H3: What are utilized methodologies for evaluating and prioritizing ML techniques?

Multi-attribute decision-making (MADM) refers to the practice of decision-making that prioritizes solutions in alignment with existing information through specific methodologies [16]–[18] . Its theories and models are extensively utilized across various domains such as venture-capital decision-making, project evaluation, and industrial sector development evaluation [19], [20] . In recent decades, MADM has seen broad applications in different fields[21], [22] . The evaluation of community home-based elderly care services quality for disabled elderly individuals constitutes a MADM. Recently, the TOPSIS model [23] has been employed to rank alternatives and obtaining the optimal. As an extension of the traditional neutrosophic set, the Probabilistic Simplified Neutrosophic Set (PSNS) was presented to handle uncertainty, imprecision, and indeterminacy in a more organized and probabilistic way[24] . Like neutrosophic sets, PSNS represents an element with three components: truth membership (T), indeterminacy membership (I), and falsity membership (F), however, it assigns each of these components with probabilistic value, which allows a more flexible representation of information by integrating randomness as well as indeterminacy concurrently. This makes PSNS ease its practical implementation while preserving the competence to model uncertainty in real-world problems., making them an active tool for improving MADM.

Generally, we are leveraging ML techniques in this study to early detect of falls of elderly people in indoor environments. The performance of various ML algorithms is evaluated using PSNNs to capture uncertainty, imprecision, and indeterminacy in the evaluation process. wherein the evaluation is conducted based on a set of criteria. Hence, MCDM techniques of CRITIC and TOPSIS are used to obtain weights for utilized criteria and utilize the obtained weights from CRITIC in TOPSIS to rank alternatives of ML algorithms. The findings and discussions of proof-of-concept experiments have demonstrated our framework's capacity to guarantee a thorough and reliable ranking, hence enhancing the decision-making process in elder care systems.

The structure of study is organized as follows. First, we discuss definitions and essential concepts Sect. 2. The, methodology procedures are described in Sect. 3. Next, we discuss Valdity of elderly care and related setups as given in Sect 4. Sect. 5 reports the comparative analysis. Sect. 5 concludes the work.

2. Preliminaries

The objective of this section is to exhibit the basic concepts of utilized techniques.

Definition 1: Wang et al. described Single Value Neutrosophic Sets (SVNSs) in [25] and formed as:

$$CC = \{(\theta, CT(\theta), CI(\theta), CF(\theta)) | \theta \in \Theta\} \quad (1)$$

where $CT(\theta), CI(\theta), CF(\theta)$ is membership, indeterminacy-membership and falsity-membership, $CT(\theta), CI(\theta), CF(\theta) \in [0,1]$, $0 \le CT(\theta) + CI(\theta) + CF(\theta) \le 3$.

Definition 2: PSNSs have been clarified in c as:

$$PSNS = \left\{\left(\theta, CT(\theta)(PCT(\theta)), CI(\theta)(PCI(\theta)), CF(\theta)(PCF(\theta))\right) | \theta \in \Theta\right\} \quad (2)$$

where $PCT(\theta), PCI(\theta), PCF(\theta)$ is possibility values of $CT(\theta), CI(\theta), CF(\theta)$. The probabilistic simplified neutrosophic number (PSNN) is listed as $PC = (CT(PCT), CI(PCI), CF(PCF))$.

Definition 3: Let two $PSNNs\ sets$, [24] clarified these sets as $PSNN_1 = (CT_1(PCT_1), CI_1(PCI_1), CF_1(PCF_1))$, $PSNN_2 = (CT_2(PCT_2), CI_2(PCI_2), CF_2(PCF_2))$, the basic operations are put forward:

$$(1)\ PSNN_1 \oplus PSNN_2 = \begin{pmatrix} CT_1 + CT_2 - CT_1 \cdot CT_2 \left(2! \frac{PCT_1 \cdot PCT_2}{PCT_1 + PCT_2}\right), \\ CI_1 \cdot CI_2 \left(2! \frac{PCI_1 \cdot PCI_2}{PCI_1 + PCI_2}\right), CF_1 \cdot CF_2 \left(2! \frac{PCF_1 \cdot PCF_2}{PCF_1 + PCF_2}\right) \end{pmatrix};$$

$$(2)\ PSNN_1 \otimes PSNN_2 = \begin{pmatrix} CT_1 \cdot CT_2 \left(2! \frac{PCT_1 \cdot PCT_2}{PCT_1 + PCT_2}\right), \\ CI_1 + CI_2 - CI_1 \cdot CI_2 \left(2! \frac{PCI_1 \cdot PCI_2}{PCI_1 + PCI_2}\right), \\ CF_1 + CF_2 - CF_1 \cdot CF_2 \left(2! \frac{PCF_1 \cdot PCF_2}{PCF_1 + PCF_2}\right) \end{pmatrix};$$

$$(3)\ \lambda\, PSNN = \left(1 - (1 - CT)^{\lambda}(PCT), (CI)^{\lambda}(PCI), (CF)^{\lambda}(PCF)\right), \lambda > 0;$$

$$(4)\ (PSNN)^{\lambda} = \left((CT)^{\lambda}(PCT), 1 - (1 - CI)^{\lambda}(PCI), 1 - (1 - CF)^{\lambda}(PCF)\right), \lambda > 0$$

Definition 4 [24] **:** Given $PSNN_1 = \left(CT_1(PCT_1), CI_1(PCI_1), CF_1(PCF_1)\right)$ and $PSNN_2 = \left(CT_2(PCT_2), CI_2(PCI_2), CF_2(PCF_2)\right)$, the PSNN Logarithmic distance (LD_{PSNN}) between PC_1 and PC_2 is constructed:

$$\boldsymbol{LD_{PSNN}(PSNN_1, PSNN_2) = \frac{1}{3}\left(\begin{array}{l}(CT_1 \times PCT_1)\, log \dfrac{(CT_1 \times PCT_1)}{\frac{(CT_1 \times PCT_1) + (CT_2 \times PCT_2)}{2}} \\ +(CT_2 \times PCT_2)\, log \dfrac{(CT_2 \times PCT_2)}{\frac{(CT_1 \times PCT_1) + (CT_2 \times PCT_2)}{2}} \\ +(CI_1 \times PCI_1)\, log \dfrac{(CI_1 \times PCI_1)}{\frac{(CI_1 \times PCI_1) + (CI_2 \times PCI_2)}{2}} \\ +(CI_2 \times PCI_2)\, log \dfrac{(CI_2 \times PCI_2)}{\frac{(CI_1 \times PCI_1) + (CI_2 \times PCI_2)}{2}} \\ +(CF_1 \times PCF_1)\, log \dfrac{(CF_1 \times PCF_1)}{\frac{(CF_1 \times PCF_1) + (CF_2 \times PCF_2)}{2}} \\ +(CF_2 \times PCF_2)\, log \dfrac{(CF_2 \times PCF_2)}{\frac{(CF_1 \times PCF_1) + (CF_2 \times PCF_2)}{2}}\end{array}\right)} \quad (3)$$

3. Methodology: Deployment and Evaluation Procedures

Herein, we are clarifying the procedures for implementing ML techniques to serve the study objectives. As well AS modeling the complex patterns from sensory information about elder people. After that, the role of PSNSs begins to promote harnessed MADM to prioritize alternatives of utilized ML techniques implemented in an uncertain environment**.**

Generally speaking, the utilized ML techniques in our study are illustrated in Table 3. The procedures for deploying these techniques are implemented as follows:

Step 1: we normalize all sensor measurements into a similar scale using min-max normalization, which prevents features with large ranges from dominating the model.

Step 2: we input the missing samples with mean values to maintain dataset integrity.

Step 3: we apply z-score to remove outliers

Step 4: we choose appropriate ML models to classify different older people's activities.

Step 5: we train these models under k-fold cross-validation strategy to ensure robust model evaluation.

Step 6: Evaluation Process

Evaluating the harnessed ML techniques using MADM techniques that work under the authority of PSNSs. Hence, the basic aspects of the evaluation process are determined as:

- Let $A = \{MLT_1, MLT_2, \cdots, MLT_m\}$ be alternatives, and $C = \{C_1, C_2, \cdots, C_n\}$Be attributes with weight w_c, where $w_c^j \in [0,1], \sum_{j=1}^{n} w_c^j = 1$.

- Suppose that the evaluated data is represented with PSNN-based decision matrix Đ. Then, the PSNN-TOPSIS technique is applied in conjunction with the CRITIC technique's weights to select the best alternative
- Construct PSNN-matrix $Đ = (Đ_{ij})_{m\times n} = \left(CT_{ij}(PCT_{ij}), CI_{ij}(PCI_{ij}), CF_{ij}(PCF_{ij})\right)_{m\times n}$
- Put forward the normalized matrix $Đ^{normalized} = \left[Đ_{ij}^{normalized}\right]_{m\times n}$ based on $Đ = (Đ_{ij})_{m\times n}$.

$$Đ_{ij}^{normalized} = \left(CT_{ij}^{N}(PCT_{ij}^{N}), CI_{ij}^{N}(PCI_{ij}^{N}), CF_{ij}^{N}(PCF_{ij}^{N})\right) = \begin{cases} \left(CT_{ij}(PCT_{ij}), CI_{ij}(PCI_{ij}), CF_{ij}(PCF_{ij})\right) \\ \left(CF_{ij}(PCF_{ij}), 1 - CI_{ij}(1 - PCI_{ij}), CT_{ij}(PCT_{ij})\right) \end{cases} \quad (4)$$

6.1. Generating criteria weight based on PSNN-CRITIC

The CRITIC technique[26] is utilized to put forward the weight. The decision steps of CRITIC technique are constructed

1. From the PSNN-matrix $Đ^{normalized} = \left[Đ_{ij}^{normalized}\right]_{m\times n}$, the PSNN correlation coefficient (r^{PSNN}) for attributes is put forward.

$$r_{jt}^{PSNN} = \frac{\sum_{i=1}^{m}\left(SV(Đ_{ij}^{normalized}) - SV(Đ_{j}^{normalized})\right)\left(SV(Đ_{it}^{normalized}) - SV(Đ_{t}^{normalized})\right)}{\sqrt{\sum_{i=1}^{m}\left(SV(Đ_{ij}^{normalized}) - SV(Đ_{j}^{normalized})\right)^2}\sqrt{\sum_{i=1}^{m}\left(SV(Đ_{it}^{normalized}) - SV(Đ_{t}^{normalized})\right)^2}},$$

for all $j, t = 1,2, \dots, n,$ (5)

$$SV(Đ_{j}^{normalized}) = \frac{1}{m}\sum_{i=1}^{m} SV(Đ_{ij}^{normalized}) = \frac{CT_{ij}^{N} \cdot PCT_{ij}^{N} + CI_{ij}^{N} \cdot PCI_{ij}^{N} + CF_{ij}^{N} \cdot PCF_{ij}^{N}}{3m}$$

and

$$SV(Đ_{it}^{normalized}) = \frac{1}{m}\sum_{i=1}^{m} SV(Đ_{it}^{normalized}) = \frac{CT_{it}^{N} \cdot PCT_{it}^{N} + CI_{it}^{N} \cdot PCI_{it}^{N} + CF_{it}^{N} \cdot PCF_{it}^{N}}{3m}$$

2. Computing standard deviation (PSNNSD) based on Eq.(6).

$$SD_{j}^{PSNN} = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(SV(Đ_{ij}^{normalized}) - SV(Đ_{j}^{normalized})\right)^2} \quad (6)$$

where $SV(Đ_{j}^{normalized}) = \frac{1}{m}\sum_{i=1}^{m} SV(Đ_{ij}^{normalized})$.

3. Put forward the weight information.

$$w_c^j = \frac{SD_j^{PSNN}\sum_{t=1}^{n}(1 - r_{jt}^{PSNN})}{\sum_{j=1}^{n}\left(SD_j^{PSNN}\sum_{t=1}^{n}(1 - r_{jt}^{PSNN})\right)} \quad (7)$$

where $w_c^j \in [0,1]$ and $\sum_{j=1}^{n} w_c^j = 1$.

6.2: Ranking ML alternatives based on PSNN-TOPSIS

Put forward the PSNN positive ideal decision alternative ($PIDA_{PSNN}$) and PSNN negative ideal decision alternative ($NIDA_{PSNN}$) :

$$PIDA_{PSNN} = \{PIDA^{j}_{PSNN}\}, for\ all\ j = 1,2, \dots, n. \quad (8)$$

$$NIDA_{PSNN} = NIDA^{j}_{PSNN}, for\ all\ j = 1,2, \dots, n. \quad (9)$$

$$PIDA^{j}_{PSNN} = \begin{pmatrix} CT_j^{+N}(PCT_j^{+N}), \\ CI_j^{+N}(PCI_j^{+N}), CF_j^{+N}(PCF_j^{+N}) \end{pmatrix} \quad (10)$$

$$NIDA^{j}_{PSNN} = \begin{pmatrix} CT_j^{-N}(PCT_j^{-N}), \\ CI_j^{-N}(PCI_j^{-N}), VC_j^{-N}(PCF_j^{-N}) \end{pmatrix} \quad (11)$$

$$SV\left(CT_j^{+N}(PCT_j^{+N}), CI_j^{+N}(PCI_j^{+N}), CF_j^{+N}(PCF_j^{+N})\right) = \max_i SV\left(CT_{ij}^{N}(PCT_{ij}^{N}), CI_{ij}^{N}(PCI_{ij}^{N}), CF_{ij}^{N}(PCF_{ij}^{N})\right) \quad (12)$$

$$SV\left(CT_j^{-N}(PCT_j^{-N}), CI_j^{-N}(PCI_j^{-N}), VC_j^{-N}(PCF_j^{-N})\right) = \min_i SV\left(CT_{ij}^{N}(PCT_{ij}^{N}), CI_{ij}^{N}(PCI_{ij}^{N}), CF_{ij}^{N}(PCF_{ij}^{N})\right) \quad (13)$$

where

$$SV\left(CT_j^{+N}(PCT_j^{+N}), CI_j^{+N}(PCI_j^{+N}), CF_j^{+N}(PCF_j^{+N})\right) = \frac{CT_j^{+N} \cdot PCT_j^{+N} + CI_j^{+N} \cdot PCI_j^{+N} + CF_j^{+N} \cdot PCF_j^{+N}}{3} \quad (14)$$

$$SV\left(CT_j^{-N}(PCT_j^{-N}), CI_j^{-N}(PCI_j^{-N}), VC_j^{-N}(PCF_j^{-N})\right) = \frac{CT_j^{-N} \cdot PCT_j^{-N} + CI_j^{-N} \cdot PCI_j^{-N} + CF_j^{-N} \cdot PCF_j^{-N}}{3} \quad (15)$$

$$SV\left(CT_{ij}^{N}(PCT_{ij}^{N}), CI_{ij}^{N}(PCI_{ij}^{N}), CF_{ij}^{N}(PCF_{ij}^{N})\right) = \frac{CT_{ij}^{N} \cdot PCT_{ij}^{N} + CI_{ij}^{N} \cdot PCI_{ij}^{N} + CF_{ij}^{N} \cdot PCF_{ij}^{N}}{3} \quad (16)$$

1. Put forward the PSNN positive Logarithmic distance (PLD_{PSNN}) from $PIDA_{PSNN}$ and PSNN negative Logarithmic distance (NLD_{PSNN}) from $NIDA_{PSNN}$:

$$PLD_{PSNN}(A_i, PIDA_{PSNN}) = \sum_{j=1}^{n} cw_j\left(PLD_{PSNN}(A_i, PIDA^{j}_{PSNN})\right)$$

$$= \sum_{j=1}^{n} cw_j \begin{pmatrix} \left(CT_{ij}^{N} \times PCT_{ij}^{N}\right) \log \left(\frac{\left(CT_{ij}^{N} \times PCT_{ij}^{N}\right)}{avg\left(\left(CT_{ij}^{N} \times PCT_{ij}^{N}\right), \left(CT_{j}^{+N} \times PCT_{j}^{+N}\right)\right)}\right) \\ +\left(CT_{j}^{+N} \times PCT_{j}^{+N}\right) log\left(\frac{\left(CT_{j}^{+N} \times PCT_{j}^{+N}\right)}{avg\left(\left(CT_{ij}^{N} \times PCT_{ij}^{N}\right), \left(CT_{j}^{+N} \times PCT_{j}^{+N}\right)\right)}\right) \\ +\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right) log\left(\frac{\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right)}{avg\left(\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right), \left(CI_{j}^{+N} \times PCI_{j}^{+N}\right)\right)}\right) \\ +\left(CI_{j}^{+N} \times PCI_{j}^{+N}\right) log\left(\frac{\left(CI_{j}^{+N} \times PCI_{j}^{+N}\right)}{avg\left(\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right), \left(CI_{j}^{+N} \times PCI_{j}^{+N}\right)\right)}\right) \\ +\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right) log\left(\frac{\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right)}{Avg\left(\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right), \left(CF_{j}^{+N} \times PCF_{j}^{+N}\right)\right)}\right) \\ +\left(CF_{j}^{+N} \times PCF_{j}^{+N}\right) log\left(\frac{\left(CF_{j}^{+N} \times PCF_{j}^{+N}\right)}{Avg\left(\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right), \left(CF_{j}^{+N} \times PCF_{j}^{+N}\right)\right)}\right) \end{pmatrix} \tag{17}$$

$$NLD_{PSNN}(A_i, NIDA_{PSNN}) = \sum_{j=1}^{n} cw_j \left(NLD_{PSNN}\left(A_i, NIDA_{PSNN}^{j}\right)\right)$$

$$= \sum_{j=1}^{n} cw_j \begin{pmatrix} \left(CT_{ij}^{N} \times PCT_{ij}^{N}\right) \log \left(\frac{\left(CT_{ij}^{N} \times PCT_{ij}^{N}\right)}{avg\left(\left(CT_{ij}^{N} \times PCT_{ij}^{N}\right), \left(CT_{j}^{-N} \times PCT_{j}^{-N}\right)\right)}\right) \\ +\left(CT_{j}^{-N} \times PCT_{j}^{-N}\right) log\left(\frac{\left(CT_{j}^{-N} \times PCT_{j}^{-N}\right)}{avg\left(\left(CT_{ij}^{N} \times PCT_{ij}^{N}\right), \left(CT_{j}^{-N} \times PCT_{j}^{-N}\right)\right)}\right) \\ +\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right) log\left(\frac{\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right)}{avg\left(\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right), \left(CI_{j}^{-N} \times PCI_{j}^{-N}\right)\right)}\right) \\ +\left(CI_{j}^{-N} \times PCI_{j}^{-N}\right) log\left(\frac{\left(CI_{j}^{-N} \times PCI_{j}^{-N}\right)}{avg\left(\left(CI_{ij}^{N} \times PCI_{ij}^{N}\right), \left(CI_{j}^{-N} \times PCI_{j}^{-N}\right)\right)}\right) \\ +\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right) log\left(\frac{\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right)}{Avg\left(\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right), \left(CF_{j}^{-N} \times PCF_{j}^{-N}\right)\right)}\right) \\ +\left(CF_{j}^{-N} \times PCF_{j}^{-N}\right) log\left(\frac{\left(CF_{j}^{-N} \times PCF_{j}^{-N}\right)}{Avg\left(\left(CF_{ij}^{N} \times PCF_{ij}^{N}\right), \left(CF_{j}^{-N} \times PCF_{j}^{-N}\right)\right)}\right) \end{pmatrix} \tag{18}$$

2. Put forward the PSNN close degree values (PSNNCDV) from PSNNPIDA.

$$PSNNCDV(CA_i, PIDA_{PSNN}) = \frac{PLD_{PSNN}(A_i, PIDA_{PSNN})}{\left(NLD_{PSNN}(A_i, NIDA_{PSNN}) + PLD_{PSNN}(A_i, PIDA_{PSNN})\right)} \tag{19}$$

3. According to $PSNNCDV(A_i, NIDA_{PSNN})$. The lower $PSNNCDV(A_i, PIDA_{PSNN})$ is selected as the better alternative.

4. Validation Procedures

To demonstrate the efficacy of the proposed research methodology, a public case study is carefully chosen, in which healthy older people are monitored and recorded based on battery less wearable sensors.

4.1 Description of Required Aspects

The data of this case study was labeled for multi-class activity recognition tasks. In particular, the motion data was collected by 14 healthy elderly individuals in age intervals from 66 and 86 years old, each was wearing batteryless wearable sensors on top of their clothing at sternum level. The data was inherently and noisy because of the reliance on a passive sensor. This reflects the appropriateness of our experiments as it reflects uncertainty settings. The data contained nine variables namely 'Time in seconds', 'Acceleration reading in G for frontal axis', 'Acceleration reading in G for vertical axis', 'Acceleration reading in G for lateral axis', 'Id of antenna reading sensor', 'Received signal strength indicator (RSSI)', 'Phase', 'Frequency', and 'Label'. The sensory data was labeled with three distinct labels namely 1: sit on bed, 2: sit on chair, 3: lying, 4: ambulating. To get useful insights about the sensory data, we present a concise summary of descriptive statistics in Table 1. The data contains a total of 52482 observations. It could be noted that the RSSI values span from -70 to -38.5, with a mean of -58.431, which indicates signal strength distribution.

The ranges of constituting variables diverge expressively, with some (e.g., time and frequency) spanning large intervals, while others (e.g., frontal axis and vertical axis) are limited to slighter scales. This necessitates scaling or normalization of values to guarantee uniformity across variables for ML models. Additionally, there are no missing values, as evidenced by the consistent count for all variables. The data is well-structured, making it suitable for preprocessing and further analysis, such as predictive modeling and classification tasks.

Table 1. Summarized descriptive statistics for elder people care case study

	Time	frontal axis	vertical axis	lateral axis	antenna ID	RSSI	Phase	Frequency	Label
count	52482	52482	52482	52482	52482	52482	52482	52482	52482
mean	235.002	0.80504	0.3778	0.00771	2.36075	-58.431	3.27591	922.762	2.376
std	148.257	0.39636	0.4689	0.18067	1.26154	4.61122	2.24034	1.69377	0.9418
min	0	-0.7481	-0.5535	-0.4812	1	-70	0	920.25	1
25%	117.98	0.42446	-0.0253	-0.0935	1	-61.5	0.95107	921.25	1
50%	227.665	0.9521	0.1355	-0.0251	3	-57.5	4.0727	922.75	3
75%	325.75	1.128	0.91636	0.06614	4	-56.5	5.4257	924.25	3
max	730.25	1.5032	2.0302	1.2178	4	-38.5	6.2817	925.75	4

Proof-of-concept experimentations are conducted on a Dell workstation operated by Windows 10 64-bit. This workstation was equipped with 64 G RAM and Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz 2.71 GHz. To facilitate the reproducibility of ML experimental results, we provide a summary of training settings, as shown in Table 2.

Table 2. Summary of implementation setups.

Description	Value	Description	Value

Session id	42	Imputation type	simple
Target	Decision	Numeric imputation	mean
Target type	Multiclass	Categorical imputation	mode
Original data shape	(41985, 9)	Fold Generator	StratifiedKFold
Transformed data shape	(41985, 9)	Fold Number	10
Transformed train set shape	(33588, 9)	CPU Jobs	-1
Transformed test set shape	(8397, 9)	Use GPU	FALSE
Numeric features	8	Log Experiment	FALSE
Preprocess	TRUE	Experiment Name	clf-default-name

4.2 *Metrics of Validation*

The process of evaluating the classification performance of different ML algorithms is conducted based on a popular set of evaluation metrics, which are computed based on the elementary components of the confusion matrix: True positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

$$\mathbf{Accuracy} = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}} \tag{20}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{21}$$

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \tag{22}$$

$$\mathbf{F_1 - score} = \mathbf{2}\,\frac{\mathbf{precision \times recall}}{\mathbf{precision + recall}} \tag{23}$$

$$\mathbf{Matthews\ Correlation\ Coefficient\ (MCC)} = \frac{\mathbf{TP \times TN - FP \times FN}}{\sqrt{\mathbf{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}} \tag{24}$$

$$\text{cohen kappa score} = \frac{p_o \times p_e}{1 - P_e} \tag{25}$$

where Po symbolizes the relative observed agreement among raters. Pe symbolizes the hypothetical possibility of agreement occurring by chance.

5. Comparative Analysis and Discussion

In Table 3, we introduce and compare the classification performance of various ML algorithms involved in our framework, according to different evaluation metrics as mentioned before. These metrics aim to detect the strengths and weaknesses of each algorithm for monitoring and caring for elderly people's activities. Also, they give the decision-makers valuable insights into the trade-offs between different performance aspects. With these tabulated results, we aren't only highlighting the erraticism in algorithm performance, but we are informing the decision-makers to select the ML algorithms that can satisfy the needs of elder people's healthcare.

Table 3. Quantitative comparison of the performance of ML for elder people activity recognition

ML algorithms	Accuracy	Recall	Prec.	F1-score	Kappa	MCC
Extreme Gradient Boosting	0.9932	0.9932	0.9932	0.9931	0.9879	0.9879
Light Gradient Boosting Machine	0.9927	0.9927	0.9926	0.9925	0.9869	0.9870
Random Forest Classifier	0.9919	0.9919	0.9919	0.9917	0.9856	0.9856
Extra Trees Classifier	0.9915	0.9915	0.9916	0.9912	0.9848	0.9849
Decision Tree Classifier	0.9883	0.9883	0.9883	0.9883	0.9791	0.9791
Gradient Boosting Classifier	0.9845	0.9845	0.9842	0.9835	0.9723	0.9725
K Neighbors Classifier	0.9820	0.9820	0.9816	0.9814	0.9678	0.9679
Quadratic Discriminant Analysis	0.9548	0.9548	0.9540	0.9541	0.9188	0.9190
Naive Bayes	0.9345	0.9345	0.9360	0.9294	0.8807	0.8833
Logistic Regression	0.9029	0.9029	0.9027	0.8851	0.8213	0.8294
Linear Discriminant Analysis	0.8955	0.8955	0.8883	0.8831	0.8088	0.8131
SVM - Linear Kernel	0.8896	0.8896	0.8759	0.8548	0.7949	0.8087
Ridge Classifier	0.8730	0.8730	0.7860	0.8227	0.7613	0.7795
Ada Boost Classifier	0.7579	0.7579	0.8380	0.7672	0.6042	0.6412

To formulate the above results as a MADM problem, in which healthcare stockholders can rank and select ML algorithms according to their needs, we consider ML algorithms as alternatives, while the performance metrics are considered as the criteria for evaluation. This approach enables a systematic comparison of the models based on multiple performance dimensions simultaneously. With the inherent uncertainty and variability in model performance, we employ TOPSIS based on PSNN- methodology. This enhanced TOPSIS framework leverages neutrosophic logic to effectively handle indeterminacy and imprecision in the criteria evaluations. Based on these comparisons, we have many ML systems for elderly care. Wherein Table 4 provides a concise mapping and definition of both system alternatives and evaluation criteria driven by ML results, which can be later used for our MADM problem.

Table 4. Formulation of alternatives and criteria in MADM

Metrics	Accuracy	Recall	Prec.	F1-score	Kappa	MCC
Criteria	C1	C2	C3	C4	C5	C6

ML algorithms →	Alternatives
Extreme Gradient Boosting	MLT1
Light Gradient Boosting Machine	MLT2
Random Forest Classifier	MLT3
Extra Trees Classifier	MLT4
Decision Tree Classifier	MLT5
Gradient Boosting Classifier	MLT6
K Neighbors Classifier	MLT7
Quadratic Discriminant Analysis	MLT8
Naive Bayes	MLT9
Logistic Regression	MLT10
Linear Discriminant Analysis	MLT11
SVM - Linear Kernel	MLT12
Ridge Classifier	MLT13
Ada Boost Classifier	MLT14

Following, quantitative results from Table 3 are encoded into PSNN representation with three components for each criterion, as shown in Table 5. This encoding process involved insights of many ML experts to assess the reliability of each evaluation metric concerning each algorithm, which helped ensure that reliability is determined according to a mixture of expert judgment, and consistency across different criteria. Doing so, the indeterminacy for each metric is calculated as the accompaniment of reliability, using the relationship $I = 1 - Reliability$. The tabulated values can effectively encode and capture the certainty as well as the ambiguity associated with the performance of various ML models, which offer a nuanced framework for decision-making. Given that ML results are inherently normalized, we can refer to Table 5, as the normalized matrix $NCR = [NCR_{ij}]_{11\times 6}$.

Table 5. The normalized decision in the form of PSNNs

Model	C1	C2	C3	C4	C5	C6
MLT1	{0.993 (0.634), 0.567 (0.362), 0.007 (0.004)}	{0.993 (0.822), 0.209 (0.173), 0.007 (0.006)}	{0.993 (0.806), 0.233 (0.189), 0.007 (0.006)}	{0.993 (0.757), 0.311 (0.237), 0.007 (0.005)}	{0.988 (0.812), 0.217 (0.178), 0.012 (0.01)}	{0.988 (0.814), 0.213 (0.176), 0.012 (0.01)}

MLT2	{0.993 (0.648), 0.531 (0.347), 0.007 (0.005)}	{0.993 (0.799), 0.243 (0.195), 0.007 (0.006)}	{0.993 (0.818), 0.214 (0.176), 0.007 (0.006)}	{0.993 (0.764), 0.299 (0.23), 0.007 (0.006)}	{0.987 (0.799), 0.235 (0.19), 0.013 (0.011)}	{0.987 (0.803), 0.229 (0.186), 0.013 (0.011)}
ML3	{0.992 (0.653), 0.52 (0.342), 0.008 (0.005)}	{0.992 (0.797), 0.245 (0.197), 0.008 (0.007)}	{0.992 (0.806), 0.23 (0.187), 0.008 (0.007)}	{0.992 (0.793), 0.251 (0.201), 0.008 (0.007)}	{0.986 (0.784), 0.256 (0.204), 0.014 (0.011)}	{0.986 (0.796), 0.239 (0.193), 0.014 (0.012)}
MLT4	{0.992 (0.662), 0.498 (0.332), 0.008 (0.006)}	{0.992 (0.741), 0.338 (0.252), 0.008 (0.006)}	{0.992 (0.658), 0.508 (0.337), 0.008 (0.006)}	{0.991 (0.71), 0.395 (0.283), 0.009 (0.006)}	{0.985 (0.823), 0.197 (0.164), 0.015 (0.013)}	{0.985 (0.779), 0.265 (0.21), 0.015 (0.012)}
MLT5	{0.988 (0.705), 0.401 (0.286), 0.012 (0.008)}	{0.988 (0.624), 0.583 (0.368), 0.012 (0.007)}	{0.988 (0.698), 0.416 (0.294), 0.012 (0.008)}	{0.988 (0.678), 0.458 (0.314), 0.012 (0.008)}	{0.979 (0.669), 0.463 (0.317), 0.021 (0.014)}	{0.979 (0.656), 0.492 (0.33), 0.021 (0.014)}
MLT6	{0.985 (0.674), 0.462 (0.316), 0.015 (0.011)}	{0.985 (0.635), 0.551 (0.355), 0.015 (0.01)}	{0.984 (0.673), 0.462 (0.316), 0.016 (0.011)}	{0.984 (0.616), 0.598 (0.374), 0.016 (0.01)}	{0.972 (0.644), 0.51 (0.338), 0.028 (0.018)}	{0.973 (0.664), 0.464 (0.317), 0.027 (0.019)}
MLT7	{0.982 (0.666), 0.474 (0.321), 0.018 (0.012)}	{0.982 (0.628), 0.564 (0.361), 0.018 (0.012)}	{0.982 (0.666), 0.474 (0.322), 0.018 (0.012)}	{0.981 (0.634), 0.548 (0.354), 0.019 (0.012)}	{0.968 (0.614), 0.576 (0.365), 0.032 (0.02)}	{0.968 (0.665), 0.456 (0.313), 0.032 (0.022)}
MLT8	{0.955 (0.649), 0.471 (0.32), 0.045 (0.031)}	{0.955 (0.613), 0.558 (0.358), 0.045 (0.029)}	{0.954 (0.616), 0.55 (0.355), 0.046 (0.03)}	{0.954 (0.623), 0.53 (0.347), 0.046 (0.03)}	{0.919 (0.596), 0.542 (0.351), 0.081 (0.053)}	{0.919 (0.62), 0.483 (0.326), 0.081 (0.055)}
MLT9	{0.935 (0.628), 0.488 (0.328), 0.066 (0.044)}	{0.935 (0.605), 0.545 (0.353), 0.066 (0.042)}	{0.936 (0.593), 0.579 (0.367), 0.064 (0.041)}	{0.929 (0.605), 0.537 (0.349), 0.071 (0.046)}	{0.881 (0.57), 0.545 (0.353), 0.119 (0.077)}	{0.883 (0.587), 0.504 (0.335), 0.117 (0.078)}
MLT10	{0.903 (0.616), 0.467 (0.318), 0.097 (0.066)}	{0.903 (0.587), 0.538 (0.35), 0.097 (0.063)}	{0.903 (0.572), 0.577 (0.366), 0.097 (0.062)}	{0.885 (0.589), 0.502 (0.334), 0.115 (0.076)}	{0.821 (0.528), 0.557 (0.358), 0.179 (0.115)}	{0.829 (0.547), 0.516 (0.34), 0.171 (0.113)}
MLT11	{0.896 (0.582), 0.539 (0.35), 0.105 (0.068)}	{0.896 (0.574), 0.561 (0.359), 0.105 (0.067)}	{0.888 (0.589), 0.507 (0.336), 0.112 (0.074)}	{0.883 (0.555), 0.593 (0.372), 0.117 (0.073)}	{0.809 (0.532), 0.519 (0.342), 0.191 (0.126)}	{0.813 (0.542), 0.501 (0.334), 0.187 (0.125)}
MLT12	{0.89 (0.608), 0.463 (0.317), 0.11 (0.075)}	{0.89 (0.592), 0.503 (0.335), 0.11 (0.073)}	{0.876 (0.555), 0.578 (0.366), 0.124 (0.079)}	{0.855 (0.566), 0.509 (0.337), 0.145 (0.096)}	{0.795 (0.523), 0.52 (0.342), 0.205 (0.135)}	{0.809 (0.532), 0.52 (0.342), 0.191 (0.126)}
MLT13	{0.873 (0.65), 0.343 (0.256), 0.127 (0.095)}	{0.873 (0.544), 0.604 (0.376), 0.127 (0.079)}	{0.786 (0.502), 0.566 (0.361), 0.214 (0.137)}	{0.823 (0.576), 0.428 (0.3), 0.177 (0.124)}	{0.761 (0.495), 0.538 (0.35), 0.239 (0.155)}	{0.78 (0.494), 0.579 (0.367), 0.221 (0.14)}
MLT14	{0.758 (0.437), 0.735 (0.424), 0.242 (0.14)}	{0.758 (0.399), 0.899 (0.473), 0.242 (0.127)}	{0.838 (0.556), 0.507 (0.337), 0.162 (0.107)}	{0.767 (0.457), 0.68 (0.405), 0.233 (0.139)}	{0.604 (0.355), 0.702 (0.412), 0.396 (0.233)}	{0.641 (0.402), 0.595 (0.373), 0.359 (0.225)}

Figure 2 represents the results of the PSNS-CRTIC computed to assign weight to each evaluation criterion, which reflects the relative importance of each criterion in causative decision-making according to its variability and impact. Wherein C3 recorded highest value otherwise C4 recorded lowest value

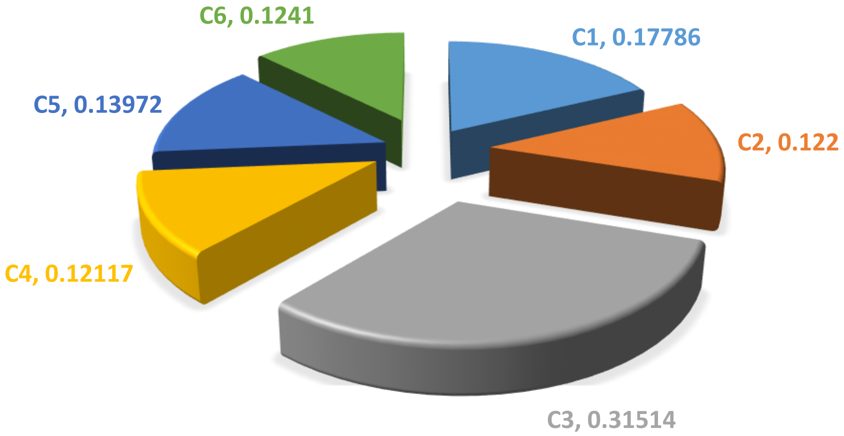

Figure 2. Final Criteria Weights

Table 6 presents the PSNNPIDA and PSNNNIDA derived as part of the decision-making framework. The former represents the optimal values for each criterion, which serve as benchmarks for alternatives. Conversely, the latter signifies the least needed performance values, which provide a reference for the lower bounds of acceptability.

Table 6. The $PIDA_{PSNN}$ and $NIDA_{PSNN}$

	$\mathbf{PIDA_{PSNN}}$	$\mathbf{NIDA_{PSNN}}$
C1	{0.993 (0.634), 0.567 (0.362), 0.007 (0.004)}	{0.758 (0.437), 0.735 (0.424), 0.242 (0.14)}
C2	{0.993 (0.799), 0.243 (0.195), 0.007 (0.006)}	{0.89 (0.592), 0.503 (0.335), 0.11 (0.073)}
C3	{0.993 (0.806), 0.233 (0.189), 0.007 (0.006)}	{0.786 (0.502), 0.566 (0.361), 0.214 (0.137)}
C4	{0.992 (0.793), 0.251 (0.201), 0.008 (0.007)}	{0.823 (0.576), 0.428 (0.3), 0.177 (0.124)}
C5	{0.988 (0.812), 0.217 (0.178), 0.012 (0.01)}	{0.604 (0.355), 0.702 (0.412), 0.396 (0.233)}
C6	{0.988 (0.814), 0.213 (0.176), 0.012 (0.01)}	{0.641 (0.402), 0.595 (0.373), 0.359 (0.225)}

Following, we make use of $PIDA_{PSNN}$ and $NIDA_{PSNN}$ to calculate the $PLD_{PSNN}(MLT_i, PIDA_{PSNN})$ and $NLD_{PSNN}(MLT_i, PIDA_{PSNN})$ presented in Table 7.

Table 7. The $\mathrm{NLD_{PSNN}(MLT_i, NIDA_{PSNN})andPLD_{PSNN}(MLT_i, PIDA_{PSNN})}$

Alternatives	$\boldsymbol{NLD_{PSNN}(MLT_i, PIDA_{PSNN})}$	$\boldsymbol{PLD_{PSNN}(MLT_i, PIDA_{PSNN})}$

MLT_1	0.232005	0.000621
MLT_2	0.231966	0.000672
MLT_3	0.226083	0.000653
MLT_4	0.179804	0.026402
MLT_5	0.141492	0.048833
MLT_6	0.125629	0.059494
MLT_7	0.117359	0.063446
MLT_8	0.090704	0.081505
MLT_9	0.071575	0.096659
MLT_{10}	0.049688	0.116274
MLT_{11}	0.044957	0.113560
MLT_{12}	0.041897	0.125661
MLT_{13}	0.041074	0.168411
MLT_{14}	0.026084	0.273210

The ranking of ML alternatives process require compute PSNNCDV based on $PLD_{PSNN}(MLT_i, PIDA_{PSNN})$and $NLD_{PSNN}(MLT_i, PIDA_{PSNN})$, as shown in Table 8. Based on the findings of this Table MLT_1 is the optimal solution for elderly care monitoring.

5.Conclusion

In this study, a robust framework is introduced to take advantage of ML techniques as well as the PSNS to develop a comprehensive methodology for elderly care service while considering the uncertainty and variability of the environment. In this framework, a broad range of ML algorithms evaluated according to different sets of evaluation criteria, in which their results are encoded into the PSNS domain. Then, valuable insight into the importance of each evaluation criterion is obtained by the CRITIC approach to computing the weights of each criterion. Followingly, a customized TOPSIS approach is introduced to select the best alternative in a PSNS-driven MADM methods. Quantitative analysis of public case study sensor-based elderly caring services is performed to legalize the proposed approach. The results demonstrate the promise of our solution, which might have valuable managerial implications for improving the decision-making process.

Table 8. The PSNNCDV based on PSNNPIDA

Alternatives	PSNNCDV	Rank
MLT_1	0.0026701	1
MLT_2	0.0028872	3
MLT_3	0.0028814	2
MLT_4	0.1280348	4
MLT_5	0.2565759	5
MLT_6	0.3213774	6
MLT_7	0.3509097	7
MLT_8	0.473291	8
MLT_9	0.5745505	9
MLT_{10}	0.7006051	10
MLT_{11}	0.7163919	11
MLT_{12}	0.7499547	12
MLT_{13}	0.8039296	13
MLT_{14}	0.9128486	14

Data Availability:

deployed data is available at: https://archive.ics.uci.edu/dataset/427/activity+recognition+with+healthy+older+people+using+a+batteryless+wearable+sensor.

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