Whale Optimization Algorithm with Deep Learning based Indoor Monitoring of Elderly and Disabled People

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Abstract

Social isolation and loneliness are subjective measures related to the feeling of distress and discomfort for disabled and elderly people. Currently, computing platform offers a smart healthcare observing technique for earlier fall detection. Internet of Things (IoT) based health system had a crucial role in the healthcare service and assists in improving data processing and its prediction. Transmitting data or reports takes more energy and time, as well as causes energy issues and higher latency. These study concentrations on the development of Whale Optimization Algorithm with Deep Learning based Indoor Monitoring System (WOADL-IMS) for Elderly and Disabled People. The presented WOADL-IMS system purposes to identify the presence of indoor activity by elderly people. In the presented WOADL-IMS technique, NASNetMobile model is applied to produce feature vectors. In addition, the WOADL-IMS technique uses WOA based hyperparameter selection approach. Finally, triplet neural network (TNN) model can be employed for automated classification and recognition of indoor activity. The simulation result of the WOADL-IMS approach can be examined on indoor activity dataset. The outcomes of the experimentation highlighted that the WOADL-IMS technique reaches better results than other recent approaches

Keywords: Indoor activity monitoring; Elderly and disabled person; Deep learning; Whale optimization algorithm

1. Introduction

Technology is becoming an integral and indispensable element in contemporary day living. Technology has positive effect as its aids us to control and manage our daily habits [1]. Still, contemporary day technology has a significant part to play in other fields like overpowering the many difficulties fronting social and health care. Ambient Assistive Living (AAL) refers to the idea of generating novel living places that integrate social surroundings with modern technology for producing services and products that pointedly boost the standard of life of the inhabitant [2]. Several parts of study pay interest to assistive solutions, with several trials started to evaluate their possibility. The use of various fields was used to increase and enable the utility of technologies in the household [3]. The integration and collection of these technologies are denoted as AAL or Ambient Intelligence that targets back persons by allowing them to attain their everyday points. AML is not just considered as the incorporation of different technologies and relevant fields (i.e. medicine, computer science, social sciences, and engineering) but emphases on applicability and amalgamation of these technologies [4]. The core task of any method is the capability to find human actions from the assimilated sensory dataset [5]. This can be attained by implementing meaning (that is typically in the usage of medicinal vision) to comments.

In a conventional health care mechanism, transmission between patients and health care providers would be unconstrained by obstacles like geographical or organizational place [6]. It must boost the evolution of safe stages and apps to share health information. This can aid physicians make superior analyses and provide better care. In the out-of-date medical system, specialists do inspections and record their results on paper tables or in the clinic's main database utilizing manual entry [7]. Realtime identification was impossible, as the local structure is not connected to the smartphone of user. The clinical centre can gain the medical histories of patients from one central

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place. However, data integrity, privacy, and openness are all lost which makes it tough for individuals to have control over their own health data [8]. Machine learning (ML) and Artificial intelligence (AI) approaches have the ability for enhancing diagnostics and predictive modelling and decision-making to convert health care services [9]. AI methods were employed in an increasing number of health care applications in recent times, because of the deep learning (DL) approaches [10]. DL refers to a class of ML methods that enables clinicians in superior decision making to analyse the illness with precise precision and offer superior treatment. DL methods offer to ensure that patient care is appropriate and more personalized.

This study focuses on the development of Whale Optimization Algorithm with Deep Learning based Indoor Monitoring System (WOADL-IMS) for Elderly and Disabled People. The presented WOADL-IMS approach drives to identify the presence of indoor activity by elderly people. In the presented WOADL-IMS technique, NASNetMobile model is applied to produce feature vectors. In addition, the WOADL-IMS technique uses WOA based hyperparameter selection approach. Finally, triplet neural network (TNN) model can be employed for automated detection and classification of indoor activity. The simulation result of the WOADL-IMS systen can be tested on indoor activity dataset. The outcomes of the experimentation highlighted that the WOADL-IMS technique reaches better results than other recent approaches. The key contribution of the paper is summarized as:

- The study introduces a novel technique called WOADL-IMS technique to identify the presence of indoor activities performed by elderly people. This is a critical aspect of providing care and assistance to this demographic.
- Utilizes the NASNetMobile deep learning model to extract feature vectors from the data. This step is essential for understanding and representing the indoor activities accurately.
- The WOADL-IMS employs the WOA based approach for hyperparameter selection. This helps optimize the solution of the deep learning model and improve the accuracy of activity detection.
- Employs TNN model for automated detection and classification of indoor activities. TNNs are commonly used in tasks involving similarity and dissimilarity comparisons, which can be useful for activity recognition.

2. Related Works

Li et al. [11] present a novel HEL system for indoor acoustic FD. Primarily, the author pre-processed an indoor fall acoustic in data and abstract the fall-like sound signal by short-time energy. Next, the spectrogram and MFCC are gained as features. Eventually, the author adopted the HEL system for categorizing the actual human fall and daily fall-like signals that use stacking method and bagging ensemble selection approach for combining 3 independent base classifiers. Chen et al. [12] offer a combined structure for elderly first aid mechanism in an indoor atmosphere by means of CV and building information model (BIM) methods that has 3 primary elements: a BIM-based module, a vision-related module for FD, and a cloud server for rescue routing.

Khraief et al. [13] introduce a new vision-related approach for FD in smart home settings. Firstly, the author mine person's efficacy constructed on background deduction technique and active outline. Then, shape features and motion are mined from individual body parts and examined for classifying falls from other daily actions with rule-related classification. The authors [14] develop an IMEFD-ODCNN (IoT-enabled elderly FD method via optimal deep CNN) for smart homecare. Mainly, input video seized by the IoT gadgets was pre-processed in diverse methods such as min-max based normalization, resizing, and augmentation. Moreover, to descend appropriate feature vectors for FD SqueezeNet methodology has been employed as a feature extraction process. As well, employing the salp swarm optimizer (SSO) method the parameter tuning of SqueezeNet technique occurs. Eventually, SSO method (SSOA) with VAE called as SSOA-VAE related classifier was exploited to categorize fall and non-fall events.

Kavya et al. [15] modelled a realtime vision-related FD method to back the aging persons by examining the rate of change of motion in terms of the ground point. The aim of this study is to offer a potential approach to identify falls, without wearing any physical gadgets. The presented approach refers to an amalgamation of ground point estimation related to texture segmentation by means of Gabor filter and computes the rate of change of angle. Long et al. [16] developed the image-based FD system that combined the YOLO object recognition approach with the Image-related FD mechanism in identifying fall events. The structure will get person track in the video frames with the FD algorithm object and detection method will be utilized to get track the height of an individual and to distinguish fall event precisely and immediately to inform the caregivers.

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3. The Proposed Model

In this study, we have established an automated activity monitoring technique, named WOADL-IMS technique for Elderly and Disabled People. The presented WOADL-IMS technique aims to identify the presence of indoor activity by elderly people. It comprises three stages of operations: NASNetMobile feature extraction, WOA based hyperparameter tuning, and TNN based classification. Fig. 1 illustrates the workflow of WOADL-IMS method.

This article gives linear model, which is the direct simplex method using neutrosophic logic, the logic that is the new vision of modelling and is designed to effectively address the uncertainties inherent in the real world founded by the Romanian mathematician Florentine Smarandache [1, 2]. In addition to that, Ahmed A. Salama presented the theory of neutrosophic classical categories as a generalization of the theory of classical categories [12,20], also, he developed, introduced, and formulated new concepts in the various disciplinary of mathematics, statistics, computer science by neutrosophic theory [17,18,19,22,28].

Figure 1: ASPG logo

Table 1: the available quantities of the raw materials, and the profit returned from one unit of both products in the Classical Context

Products / Raw Materials	Required quantity per unit		Available quantities of the raw materials
	A	B	
F_1	2	3	19
F_2	2	1	13
F_3	0	3	15
F_4	3	0	18
Profit Returned per unit	7	5	

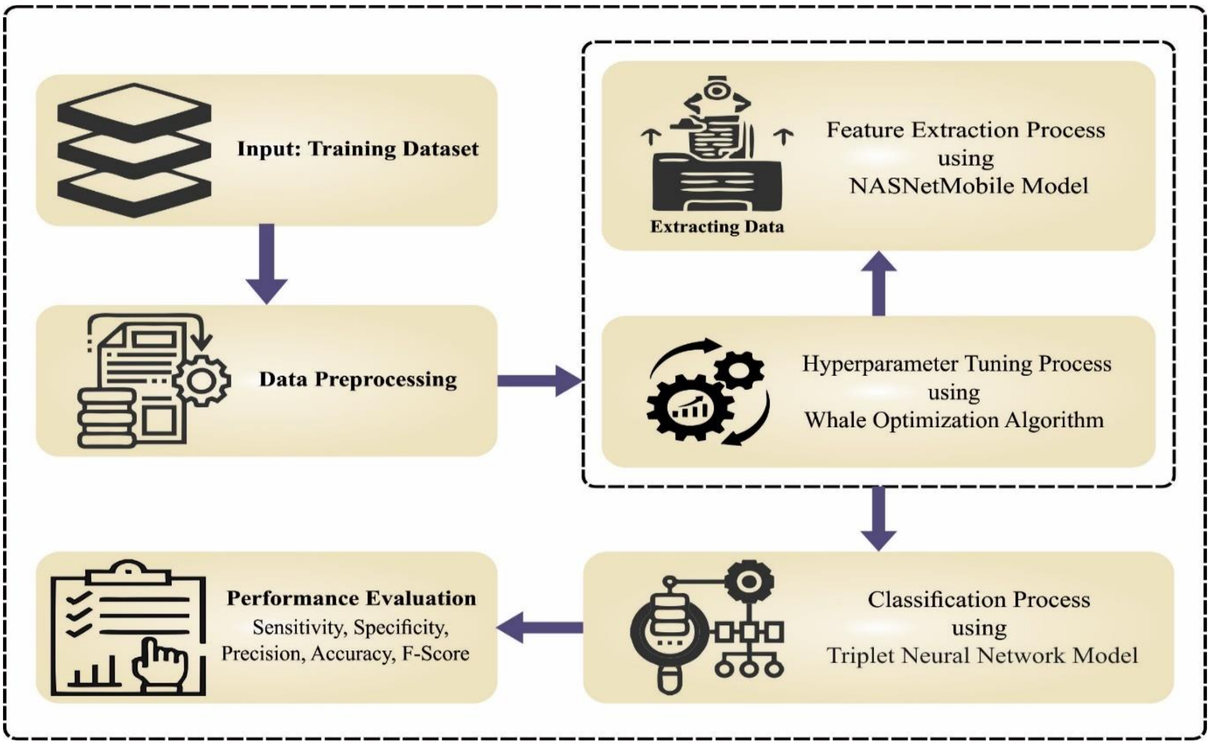

Figure 1: Workflow of WOADL-IMS method

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A. Optimal Feature Extraction

In the presented WOADL-IMS technique, NASNetMobile model is applied to produce feature vectors. NASNet refers to a scalable CNN structure (built by neural architecture search) which has fundamental components (cells) boosted with the use of reinforcement learning (RL) [17]. A cell includes some processes (numerous pooling and separable convolutions) and can be repeated more than once as per the network capacity. The NASNet-Mobile (mobile version) contains 12 cells includes 564 million multiple accumulates (MACs) and 5.3 million parameters. The two lightweight CNN structures are NASNet-Mobile and MobileNetV2.

In addition, the WOADL-IMS technique uses WOA based hyperparameter selection approach. The WOA mimics random searching, shrinkage encircling and bubble-net attacking to perform exploration and exploitation [18]. The WOA has good optimization ability, straightforward structure, easy implementation, and stronger stability. In this work, every whale represents a searching agent, and the humpback whale updates its location for hunting the prey.

1. Shrinkage Encircling

The WOA exploits every foraging behavior of whales to perform a targeted search that is helpful for learning the best solution and modifying the position. The humpback whales exploits a $9'$ shaped pathway to capture and observe the target prey. This route uses echolocation technology to effectively transfer location and perform global search. Assume that a targeted location of prey and a best whale were the best solutions to optimized problems, the residual humpback whales directly condense and enclose target, and location can be updated as:

$$D = |C \cdot X^{*}(t) - X(t)| \quad (1)$$

$$X(t+1) = X^{*}(t) - A \cdot D \quad (2)$$

Here A and C denote two adjustable parameters, t demonstrated the iteration, X^{*} symbolizes the optimum location of prey and X indicates the place of prey and are formulated below:

$$A = 2a \cdot r - a \quad (3)$$

$$C = 2 \cdot r \quad (4)$$

$$a = 2 - \frac{2t}{T} \quad (5)$$

Here r signifies stochastic value within zero and one, a can be decreased from two to $zero$ and T represents the maximal iteration.

2. BubbleNet Attacking

The BubbleNet attack has BubbleNet predator-prey strategy, logarithmic spiral, and rocks nearby predator-prey strategy. By utilizing Eq. (5), the rocking surrounding the predator-prey strategy was performed. The A can be affected by a. The A was a randomly generated value between $-a$ and a, where a was reduced from 2 to 0. If A is within $[-1,1]$, whale vigorously finds the position:

$$D' = |X^{*}(t) - X(t)| \quad (6)$$

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^{*}(t) \quad (7)$$

Where b shows a logarithmic spiral number, D' signifies distance, and l defines a stochastic value in [1, 1]. Fig. 2 demonstrates the flowchart of WOA.

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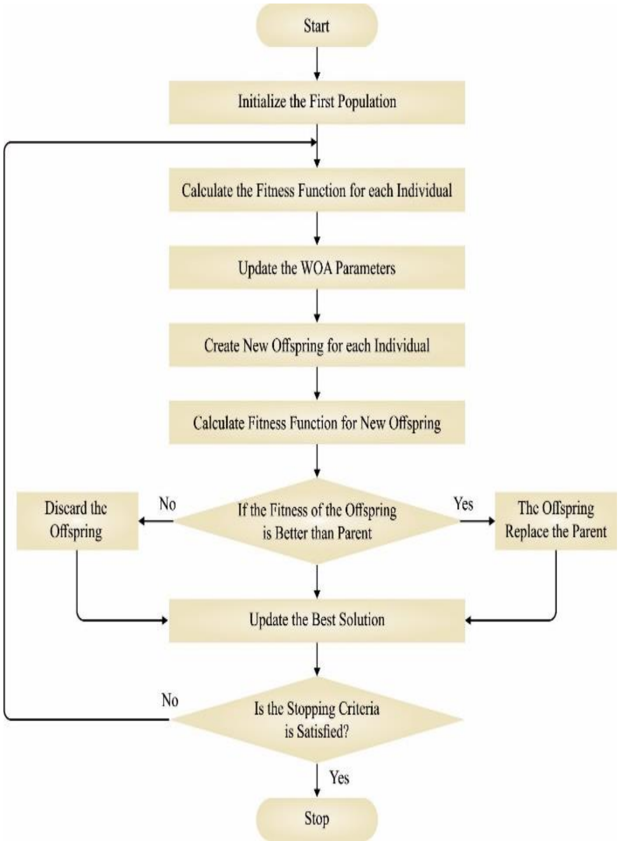

Figure 2: Flowchart of WOA

In this work, Bubble-Net predator prey approach, the logarithmic spiral made an individual whale spit bubbles, spiral motion and estimate distances to chase the targeted prey and the astounding neighbouring the predator-prey strategy made whale shrink, enclose and overcome the targeted prey:

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D & if\ p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & if\ p \geq 0.5 \end{cases} \quad (8)$$

In Eq. (8), p represents stochastic value within zero and one.

3. Random Searching

When$|A|$>1, the whale swim beyond shrinking, encircle circle of BubbleNet, and the humpback whales fails to choose the targeted prey to update its location. The humpback whales randomly find their prey based on sharing of position data amongst humpback whales. The WOA expands search space, optimizes the optimization capability, and evades search stagnation:

$$D = |C \cdot X_{rand}(t) - X(t)| \quad (9)$$

$$X(t+1) = X_{rand}(t) - A \cdot D \quad (10)$$

Where X_{rand} signifies random location vector of humpback whales.

The pseudocode for the WOA can be shown in Algorithm 1.

Algorithm 1: Pseudocode of WOA
Initialized the whale population $X, \cdots$ Calculate the fitness values of all the whales; Achieve X^*,

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While (t<T) , do;
For every whale, do;
Change p, l, a, A and C, ...
If (p<0.5) , then;
If (|A|<1) , then;
Change the location based on Eq. (2) using shrinkage surrounding;
Else (|A|≥1)
Select a stochastic whale X_{rand};
Change the location based on Eq. (10) using random searching;
End;
Else (p≥0.5),
Change the location based on Eq. (7) using Bubble-Net attacking;
End;
End;
Authenticate if any whale surpasses searching region;
Calculate the fitness values of all the whales;
Change X^* if a better choice is available;
Then, $t = t + 1$,
End;
Achieve X^*.

B. ctivity Classification

Finally, the TNN model can be employed for automated detection and classification of indoor activity. TNN is kind of SNN due to the cohesive structure with similar parameter and the learning method that attempt to train method for minimizing and maximizing intra-and inter-class distance between object classes [19]. But the Triple Loss function (Eq. (11)) is utilized for learning how to produce an embedding space $g(x)$ via calculating distance among triplets of samples.

$$TLOSS = \sum_{a,p,n y_p = y_a, y_n \neq y_0} , \max\{d(x_a, x_p) + \alpha - d(x_a, x_n), 0\}_+ \tag{11}$$

A triplet can be formulated based on the negative x_n, anchor x_a and a positive x_p samples, each with their corresponding labels (y_a, y_p, y_n), under the condition that $y_p = y_a$ and $y_n \neq y_a$, where Euclidean distance (d) is evaluated by the $en \uparrow bedd\dot{m}gs$ produced by the neural network. During the training, Different from SNNs, NN was directly trained by the random pair of samples. TNN requires a triplet selection stage because training a network using each potential triplet from the dataset denotes the inefficient and high cubic computation difficulty $O(n)^3$, and not each triplet contributes to the effective learning. To comprehend the essential of choosing the right triplet to be fed into a NN is to consider that a method, like humans, learns optimum to find various objects from learning hard samples where the diverse classes have near identical or similar attributes.

Furthermore, it is essential to remark that TNN is utilized as feature extraction model, different from SNNs where classification and feature extraction are implemented by a similar architecture. The NN might have optimized parameters under training to generate a novel embedding space where other metric learning models (KNN) would implement the multiclass classification phase.

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4. Results and Discussion

The indoor activity monitoring outcomes of the WOADL-IMS method can be examined briefly. In Table 1 and Fig. 3, the fall detection outcomes of the WOADL-IMS technique is clearly demonstrated under several runs. The results depicted that the WOADL-IMS technique properly categorizes fall and non-fall events. On run-1, the WOADL-IMS approach attains average $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.69%, 98.17%, 98.36%, and 98.1% respectively. Meanwhile, on run-2, the WOADL-IMS method attains average$accu_y$, $prec_n$, $reca_l$, and F_{score} of 98.56%, 98.55%, 98.59%, and 98.30% respectively. Then, on run-3, the WOADL-IMS method gains average$accu_y$, $prec_n$, $reca_l$, and F_{score} of 97.19%, 97.02%, 96.68%, and 97.25% correspondingly.

Table 1: Fall detection outcome of WOADL-IMS approach under various runs

Run1	Accuracy	Precision	Recall	F-Score
Fall	99.71	98.36	98.79	98.31
Non-Fall	99.67	97.99	97.93	97.89
Average	99.69	98.17	98.36	98.10
Run2	Accuracy	Precision	Recall	F-Score
Fall	98.84	98.19	98.41	97.80
Non-Fall	98.28	98.90	98.76	98.79
Average	98.56	98.55	98.59	98.30
Run3	Accuracy	Precision	Recall	F-Score
Fall	96.86	97.89	96.42	96.86
Non-Fall	97.51	96.14	96.94	97.63
Average	97.19	97.02	96.68	97.25

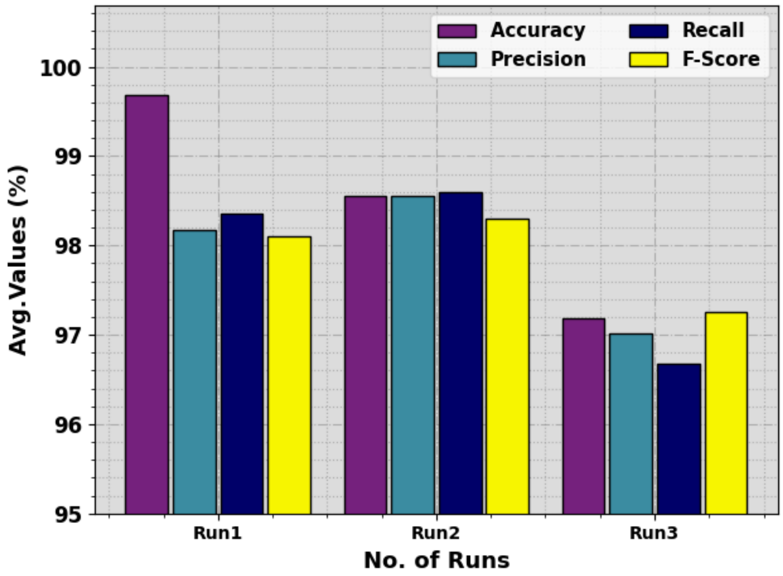

Figure 3: Average outcome of WOADL-IMS methodology under various runs

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Fig. 4 inspects the $accu_y$ of the WOADL-IMS methodology under the training and validation on test database. The outcome specifies that the WOADL-IMS method have higher $accu_y$ performances over greater epochs. Likewise, the maximal validation $accu_y$ with training $accu_y$ demonstrations that the WOADL-IMS algorithm acquires productively on test database.

Figure 4: Accuracy curve of the WOADL-IMS system

The loss curve of the WOADL-IMS methodology in the training and validation is shown on test database in Fig. 5. The performances specify that the WOADL-IMS system have adjacent outcomes of training and validation losses. The WOADL-IMS system effectively on test database.

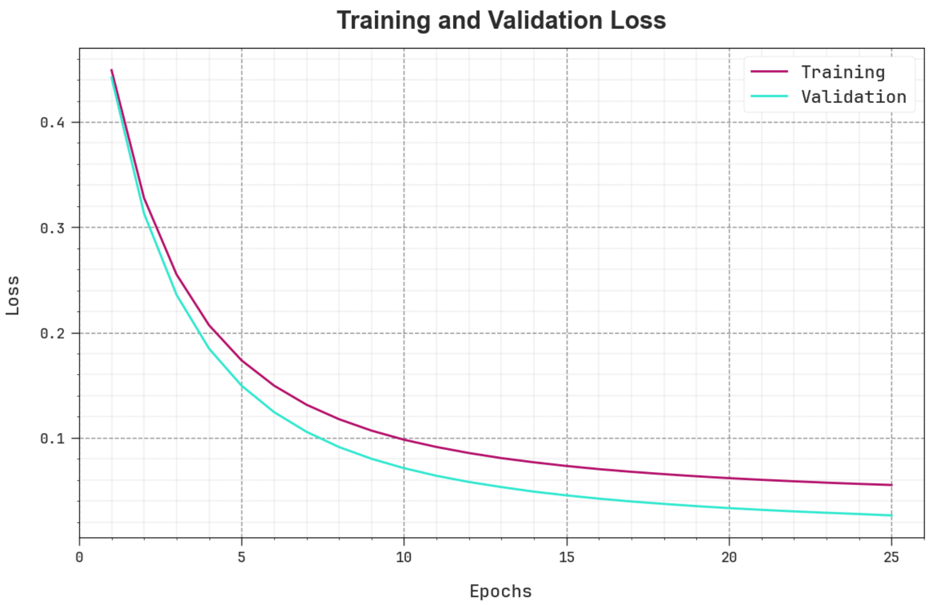

Figure 5: Loss curve of the WOADL-IMS methodology

Table 2: Comparative outcome of WOADL-IMS algorithm with recent systems

Techniques	Accuracy	Precision	Recall	F-Score
KNN Algorithm	97.80	94.66	95.55	94.55

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SVM Algorithm	92.30	94.55	95.71	96.56
ANN Algorithm	96.01	92.24	95.57	95.51
PHM-DLEC	99.03	93.63	96.13	94.63
WOADL-IMS	99.69	98.17	98.36	98.10

In Table 2 and Fig. 6, the overall comparison analysis of the WOADL-IMS method is provided. The performances imply that the WOADL-IMS method gains enhanced outcomes under all measures. Based on $accu_y$, the WOADL-IMS system gains increased $accu_y$ of 99.69% while the KNN, SVM, ANN, and PHM-DLEC models offer decreased $accu_y$ of 97.80%, 92.30%, 96.01%, and 99.03%. Also, based on $prec_n$, the WOADL-IMS method gains increased $prec_n$ of 98.17% while the KNN, SVM, ANN, and PHM-DLEC approaches offer decreased $prec_n$ of 94.66%, 94.55%, 92.24%, and 93.63%. Moreover, based on $reca_l$, the WOADL-IMS algorithm gains increased $reca_l$ of 98.36 % while the KNN, SVM, ANN, and PHM-DLEC methods offer decreased $reca_l$ of 95.55%, 95.71%, 95.57%, and 96.13%. At last, based on F_{score}, the WOADL-IMS algorithm gains increased F_{score} of 98.10% while the KNN, SVM, ANN, and PHM-DLEC methods offer decreased F_{score} of 94.55%, 96.56%, 95.51%, and 94.63%.

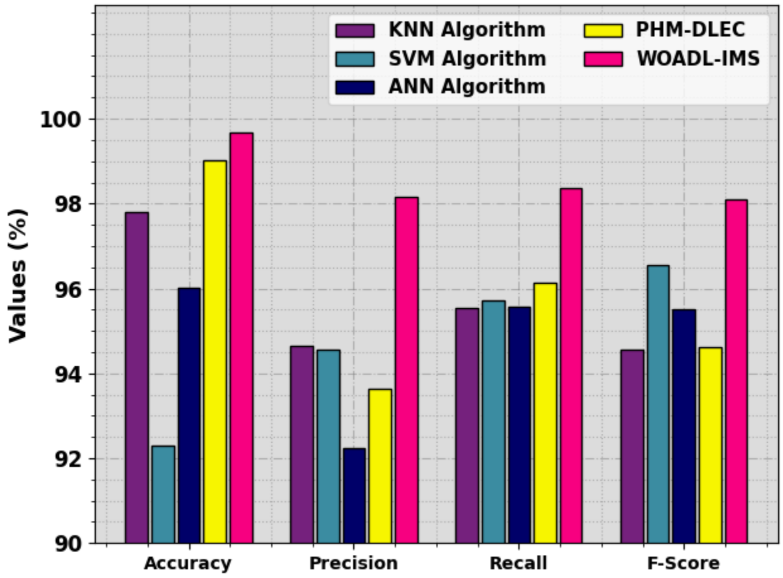

Figure 6: Comparative outcome of WOADL-IMS algorithm with recent systems

5. Conclusion

In this article, we have established an automated activity monitoring approach called as WOADL-IMS technique for Elderly and Disabled People. The presented WOADL-IMS technique aims to identify the presence of indoor activity by elderly people. It comprises three stages of operations: NASNetMobile feature extraction, WOA based hyperparameter tuning, and TNN based classification. In the presented WOADL-IMS technique, NASNetMobile model is applied to produce feature vectors. In addition, the WOADL-IMS technique uses WOA based hyperparameter selection approach. Finally, the TNN model can be employed for automated classification and recognition of indoor activity. The experimental result of the WOADL-IMS methodology has been tested on indoor activity database. The performances of the experimentation highlighted that the WOADL-IMS technique reaches better results than other recent approaches.

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