Evolutionary Algorithm with Deep Learning based Fall Detection on Internet of Things Environment

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Abstract

Falling is among the most threatening event proficient by the ageing population. There is a necessity for the development of the fall detection (FD) system with the increasing ageing population. FD in an Internet of Things (IoT) platform has developed as a vital application with the rapidly increasing population of aging population and the essential for continuous health monitoring. Falls among the ageing can performance in serious injuries, decreased independence, and longer recovery periods. The FD approach can constructed on deep learning (DL) approaches, especially, Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) are capable in learning difficult patterns from the sensor data. The CNNs investigate the spatial features, but the RNNs approach the temporal dependencies, allowing accurate recognition of fall events. This study presents an Evolutionary Algorithm with Deep Learning based Fall Detection and Classification (EADL-FDC) methodology in the IoT platform. The projected EADL-FDC algorithm allows the DL approaches for the effective recognition and classification of falls for disabled and ageing people. In the presented EADL-FDC technique, the span-partial structure, and attention (SPA-Net) model is utilized for feature extraction purposes. In addition, the symbiotic organism search (SOS) approach was used for the parameter selection of the SPA-Net system. The deep belief network (DBN) model is applied to classify the fall events. Lastly, the moth flame optimization (MFO) algorithm can be utilized to finetune the hyperparameters related to the DBN algorithm. The stimulation analysis of the EADL-FDC method takes place on the fall detection dataset. The experimental outcome depicts the remarkable solution of the EADL-FDC technique over other existing DL methods.

Keywords: Internet of Things; Fall detection; Elderly/disabled persons; Deep learning; Evolutionary algorithm

1. Introduction

Recently, the Internet of Things (IoTs) and mobile communication technologies were introduced for gathering human and environmental data for various smart applications and services [1]. Remote monitoring of ageing and visually impaired people living in smart home is especially difficult because of potential accidents, which may happen due to everyday activities like falls [2]. For the ageing population, fall is considered the main cause of mortality of post-traumatic complication. Thus, early recognition of older person fall in smart home is desirable to

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offer required support or improve the survival of rate of a person [3]. Currently, the emergence of Artificial Intelligence (AI) technology, smartphones, wearables IoT, etc., can enable to develop of Fall Detection (FD) system for smart homecare. Falling is a major problem handled by older people. For elderly people, a fall can be extremely dangerous and might lead to serious health problems [4]. Furthermore, a lack of balance and a fall may be indications of a dangerous disease. Despite, it is vital that when it happens, the injured person must get immediate support. Generally, people may be incapable to move up without help and need urgent medical care [5]. Falling does not only impact older persons, both amateurs and professionals, athletes, can also struggle with the harmful effects of a fall. Falling during sports activities can results in severe injuries and have disastrous impacts on an athlete's career. Consistent FD is needed for avoiding the critical effects of this fall [6]. The most commonly used technique for identifying falls are wrist-worn recognition method that estimates the accelerated force. This wrist device is gaining much attention from the population and developed progressively stronger depending on computational efficacy that applicability of AI is modest [7]. Mostly, older people seem to be attentive in using these devices while there expose privacy concerns and accurately recognize once the device can process at specific periods. In recent times, different FD approaches have been introduced [8]. This technique ranges from simple threshold-based methods to hand-crafted features-based ML methods, and finally to DL-based automatic extracting feature NN.

IoT is a more suitable candidate for this method because it has ground-breaking methods namely CC, sensing, and WSN to connect virtual object through physical object. Since the gateways can perform complicated FD approaches such as data mining or Discrete Wavelet Transform (DWT). Furthermore, a smart gateway aids to improve QoS by providing new services, for instance, local storage which stores temporary information or push notifications to notify anomalies in real-time [9]. It could be expected that IoT broadly support decreasing energy consumption of wearable devices with task allocation. Another major issue is data acquisition and transmission cause the high energy consumption in wearable sensor nodes (SNs) must be considered extensively [10]. If a wearable SN is energy inefficient, then it may reduce QoS and cause untrustworthiness.

This study progresses an Evolutionary Algorithm with Deep Learning based Fall Detection and Classification (EADL-FDC) algorithm in the IoT environment. The proposed EADL-FDC technique enables the DL approaches for the effectual detection and categorization of falls for elderly and disabled people. In the presented EADL-FDC technique, the span-partial structure, and attention module (SPA-Net) is utilized for feature extraction purposes. In addition, the symbiotic organism search (SOS) approach was used for the parameter choice of the SPA-Net algorithm. The DBN algorithm is employed to classify the fall events. Lastly, the moth flame optimization (MFO) method is applied to finetune the hyperparameter related to the DBN system. The stimulation analysis of the EADL-FDC algorithm occurs on the FD dataset.

2. Related Works

Alarifi and Alwadain [11] present an optimized and efficient FD model which utilizes a technique dependent upon the killer heuristics optimizer AlexNet CNN (ACNN) model. Data are accumulated from IoT-supported portable/wearable equipment for the feature extraction process and sensor data evaluation. The features that are derived are investigated by Multi-Linear Principle Component evaluation. FD is later accomplished by enforcing the intellectual ACNN model. Othmen et al. [12] proposed a new energy-efficient IoT-based construction for Message Queuing Telemetry Transport (MQTT) approach-based gateway-less surveillance for portable FD. A precise database was accumulated for offline training, whereas a real measuring set of the presented model was implemented for online validation. The approach accomplished a notable enhanced online and offline recognition achievement, surpassing the majority of the relevant studies by employing just an accelerometer. The authors [13] suggest an IoT-assisted Elderly FD technique by implementing an Optimal Deep CNN (IMEFD-ODCNN) intended for smart healthcare systems. Firstly, the video inputs taken by the IoT equipment is pre-processed in diverse manners such as augmentation, resizing, and min-max-based normalizing procedure. As well, the SqueezeNet technique's hyperparameter tuning process happens by employing the Salp Swarm Optimization (SSO) model. Last, Variational Autoencoder (VAE) with Sparrow Search Optimization Algorithm (SSOA), namely SSOA-VAE-based classifiers are utilized.

In [14], the authors construct an approach that integrates the Aggregated Heuristic Visual Features and the deep CNN in recognition of the FD. Firstly, the CNN, an Openpose method is employed for extracting from the image, the human skeleton. Then, the handcrafted spatial factors like the human shank inclination angle are combined for determining the FD. It is observed that the present FD model is incorporated into medical IoT video monitoring construction that consists of several Graphic Processing Unit ensembles for performing real-time alarming and surveillance for the needy elderly ones. Chan et al. [15] introduce a new footwear model for detecting falls and for the classification of several PA kinds based on a fusion Recurrent Neural Network (RNN) and CNN approaches.

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In [16], the authors proposed a new FD model which utilizes a non-disrupted Wave Doppler Radar Sensor for capturing elder people's activities and transmitting the information via internet to the server with the help of DL employing a CNN model that recognizes the fall. In addition, dissimilar to conventional cameras, the presented model has independency over-illumination and is atmospherically strong. This presented model attained higher precision in recognizing falls by implementing the GoogleNet CNN. Kulurkar et al. [17] introduce a new IoT-assisted model that utilizes low-power Wi-Fi sensing cloud computing, networks, big data, and smart devices for detecting elder person's falls in indoor conditions. A 3D axis accelerometer incorporated into a portable sixLowPAN equipment was employed for these needs and is responsible for collecting the information accumulated from an elder person's activities in real time. The sensor signals are processed and evaluated by implementing an ML method on a hi-tech IoT gateway for providing greater effectiveness in fall recognition.

3. The Proposed Model

This manuscript has established a new EADL-FDC method for aiding disabled and elderly persons. The proposed EADL-FDC approach enables the DL models for the effectual identification and classification of falls for elderly and disabled people. In the proposed EADL-FDC method, several stages of subprocesses include DBN classification, SPA-Net feature extractor, MFO-based parameter tuning, and SOS-based hyperparameter tuning. Fig.1 represents the working flow of the EADL-FDC technique.

A. Feature Extractor using Optimal SPA-Net Model

To derive a useful set of features, the SPA-Net model is applied. The study's purpose is to attain a mapping feature with rich gradient data [18]. Every SPA-Net block involves Conv_DWConv2D (CDW) layer on right branch and a dual span-partial structure with the stem layer on the left branch.

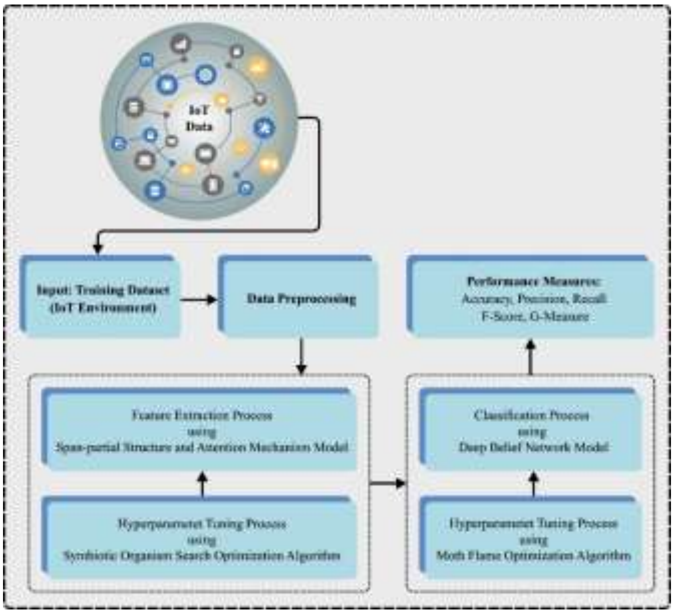

Figure 1: Working flow of the EADL-FDC system

We use concatenate layer for combining both branches, and the classical layer that has an activation function, convolutional layer, and BN are utilized for further extracting the feature maps. All the SPA-Net Blocks exploit a concatenate layer because of the mapping feature of the similar dimensional to combine the feature map from the right and left channel sizes. The 256x256x64 mapping feature in the pre-processing layer can be divided into 2 mapping features, every comprising a dimensional 256x256x32. One mapping feature exploits stem layer-I, whereas the CDW for extracting the feature, every comprising a dimensional of 128x128x64 that is later interconnected through concatenation. The split and merge strategy could efficiently decrease the probability of the duplication during data integration process and thereby considerably enhance the learning capability of networks. One branch stem layer has several convolution layers and residual structures and later it increases the gradient value of BP among layers and prevents the gradient vanishing produced by deepening, such that fine-grained feature was extracted, without concerning network degradation. The additional branch CDW layer contains the typical 3x3 kernels and depthwise convolution (DWConv2D) with 3x3 kernels for reducing the size and improving the channels, correspondingly. The output of the stem layer is 128x128x 64, 64x 64x128, 32x 32 x256, and 32x32x256, correspondingly, in the succeeding four blocks and similar to the output of the CDW layer.

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The SOS system was used for tuning the hyperparameter related to SPA-Net model. The SOS was stimulated by symbiotic relationships: mutualism, commensalism, and parasitism define the biological relationships between organisms [19]. This technique is both simple and effective, and it exploits a population-based search technique for guiding a possible answer by continually searching for the best possible region until the global best solutions.

The mutual survival benefit of both organisms included in the mutualism stage will rise in the environment. Once the individual communicates in the mutualism stage, a mutual vector is produced that shows the relationships between both species along with the useful aspect of all the individuals. This stage will generate two new organisms, as given in Eqs. (1), & (2). In this stage, all the organisms x_i, an organism x_j is selected randomly from the environment to be engaged with x_i (where x_i and x_j are not equivalent) for creating a mutual relationship.

$$X_{inew} = X_i + rand(0,1) \times (X_{best} - X_{mutual} \times BF_1), \quad if\ fitness(X_{inew}) > fitness(X_i) \tag{1}$$

$$X_{jnew} = X_j + rand(0,1) \times (X_{best} - X_{mutual} \times BF_2), \quad if\ fitness\left(X_{jnew}\right) > fitness\left(X_j\right) \tag{2}$$

Where X_{mutual} is equivalent to the average of x_i and x_j. $rand\ (0, l)$ denotes the random number in [0,1]. Eq. (3) is used for obtaining the values of BF_l and BF_2 benefit factors. Such parameters represent all the organisms is benefitted from the relationship. The study highlighted that an update is performed only if the newly evaluated fitness function value was better than the older fitness function.

$$BF_{1,2} = 1 + round\left(rand(0,1)\right) \tag{3}$$

To stimulate the commensalism relationships between X_i and X_j, A solution X_j is selected randomly. In this stage, different from the mutualism stage, X_j is used for updating X_i. It is used for computing X_{inew}. The benefits that X_i receives from X_j are characterized by the segment of the equation $(X_{best} - X_j)$. There is no new solution for X_j because they get nothing from the exchange. The objective is to obtain X_i as nearer to X_{best} as possible, with some assistance from X_j.

$$X_{inew} = X_i + rand(-1,1) \times (X_{best} - X_j), if\ fitness(X_{inew}) > fitness(X_i) \tag{4}$$

A parasitic relationship, different from mutualism and commensalism, causes harm to the other creatures which act as a host. A solution X_j is selected randomly for mimicking the parasitism communication with X_i. The modified solution, otherwise called $X_{imutated}$, is produced randomly by changing more than one parameter of X_i. The number of parameters changed is selected randomly. When the parasitism stage doesn't exist, this process gets caught at a local minimum since the mutualism and commensalism stage store only the higher fitness values. $F(X)$ indicates the objective function, N is the population size, X_{best} represents the final optimum solution of the population and D shows the dimension of the problems.

B. Fall Detection Model

For FD, the DBN model is used. DBN is a kind of NN that consists of three different models namely a backpropagation neural network (BPNN), DNN and cascading RBMs. RBM is commonly used for extraction, collaborative feature filtering, and dimensionality reduction before feeding into BPNN [20]. By employing the greedy layer-wise unsupervised training model as a training algorithm, the DNN can be trained quickly using DBN in this work. Similar to other NNs, the DBN is dependent upon the basic principles of initialized FFNN with unsupervised pretraining on unlabelled datasets before fine-tuning with labelled datasets. The initial RBM was trained for using contrastive divergence (CD). The weight of each RBM was trained layer-wise still the final RBM. The RBM in the low layer of the stacked RBM learns low-level features, and the RBM in the high layer learns high-level features of a trained dataset. Fig. 2 demonstrates the structure of DBN.

The Bernoulli random value hidden unit $(m\ nodes)$, a primary constrictor of RBM is visible $(n\ nodes)$, and the weighted matrix connection among them with $(m \times n)$ is dimensional.

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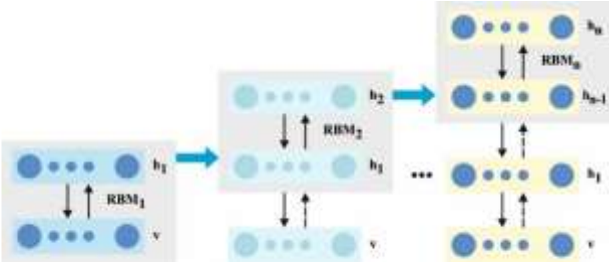

Figure 2: Architecture of DBN

The RBM train the sample values of (v) for computing the probability of hidden unit (h) based on the contrastive divergence (CD) algorithm. The energy function $E(v,h)$ of the joint configuration$\{v,h\}$ is computed by Eq. (5):

$$E(v,h) = -\sum_{i=1}^{m} b_i\, v_i - \sum_{j=1}^{n} c_j\, h_j - \sum_{j=1}^{n}\sum_{i=1}^{m} v_i\, w_{ij} h_j \tag{5}$$

In Eq. (5), w shows the weighted matrix which links the visible unit to the hidden one. b and c denote the bias values of visible and hidden units, and the joint probability of the (v,h) pair can be evaluated using the following expression:

$$p(v,h) = \frac{e^{-E(v,h)}}{\Sigma_{v,h} e^{-E(v,h)}} \tag{6}$$

Subsequently, the unit in the visible and hidden states aren't interconnected, the activation possibility of i^{th} visible units and j^{th} hidden units are shown below:

$$p(v_i = 1|h) = \sigma\left(\sum_{j=1}^{m} h_j\, w_{ij} + a_i\right) \tag{7}$$

$$p(h_j = 1|v) = \sigma\left(\sum_{i=1}^{n} v_i\, w_{ij} + b_i\right) \tag{8}$$

Where σ refers to the sigmoid logistics function.

$$\Delta W = \alpha v h^T - v' h'^T \tag{9}$$

C. Hyperparameter Optimization Process

The hyperparameter selection of the DBN approach was performed utilizing the MFO system. MFO is a population-based meta-heuristic system dependent upon the natural performance of the moth, primarily the sloping movement [21]. The MFO technique acts as moth and flames, in which moth location represents the problem parameter. Presently, the moth represents the search mediator that attempts to discover the schedule during the search space. The collection of moths might search different locations within the searching space by notifying the position. The MFO technique exploits 4 arrays to stimulate the moths and flames:

An array with 1D, called OM aims to keep the fitness values of all the moths.

An array with a 2D termed M, is designed to preserve the group of moths. The amount of moths that is initial size, is represented as n and the job counts from the searching problem, which is second dimension of the array, is characterized as d.

An array with 1D, called OF, to save the corresponding fitness rate for every best location.

An array with 2D, called F, to preserve the flames that are the same as the M array.

The three characteristic features of the MFO algorithm are initialization (I), searching process (P), and termination (T). During the initialization stage, the solution has been arbitrarily created as a population based on Eq. (6), whereas the arbitrary trial of jobs can be produced by an arbitrary set of jobs.

$$M(i) = randomSequenceofJobs(0, d-1). \tag{10}$$

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Whereas d denotes the job counts, OM shows the moth objective function that is equivalent to the fitness function (FF) (viz., OM =FF (M)). Then, the makespan can be evaluated from FF.

In the local search, the algorithm continues to search for the solution until the termination condition (T) is satisfied. The performance with minimal value is returned during the termination stage. But the moth position has been updated by the $M_i = S(M_i, F_j)$, whereas i^{th} and j^{th} are indices, M_i shows the moth, F_j denotes the flame, and S refers to the spiral process.

$$S(M_i, F_j) = D_i * e^{bt} * \cos(2\pi t) + F_j. \tag{11}$$

Here Di denotes the distance from a moth to a flame, where $Di = |F_j - M_i|$, b indicates a constant procedure of the logarithmic spiral, and t shows the arbitrary integer whose value falls among r and 1. The r value dropped linearly from -1 to -2.

The discrete optimizer problems is recommended by moving location of tasks with the move operator. Eq. (11) was utilized to characterize the novel position for the task. The term S stimulates the moth for moving towards the flames. The flame number ($Flame\_no$) is estimated as follows:

$$Flame\_no = round\left(N - l * \frac{N-1}{T}\right). \tag{12}$$

Here l shows the current iteration count, T shows the iteration counts, and N indicates the highest number of flames.

Fitness choice is a primary factor in the MFO technique. An encoder outcome was executed to measure the better of the candidate performance. The accuracy values are the main condition used to develop a FF.

$$Fitness = \max(P) \tag{13}$$

$$P = \frac{TP}{TP + FP} \tag{14}$$

Where TP and FP are the true and false positive values.

4. Results and Discussion

The fall detection outcomes of the EADL-FDC system are tested utilizing the Multiple cameras' fall (MCF) database [22] with frontal sequence and the URFD database [23] with overhead sequence. Table 1 illustrates a comprehensive description of datasets. Fig. 3 represents the falls and no falls images.

Table 1: Description of databases

Classes	No. of Samples in Each Dataset	
	Frontal Sequence	Overhead Sequence
Falls	74	75
No Falls	240	227
Total Samples	314	302

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Figure 3: a) Fall Images b) No Fall Images

The classifier outcomes of EADL-FDC methodology on the frontal sequence database is given in Fig. 4. The confusion matrix offered by the EADL-FDC techniques on 70:30 of the TR set (TRS)/TS set (TSS) is shown in Figs. 4a-4b. The outcome represented that the EADL-FDC algorithm has recognized and categorized all 2 classes. Similarly, the PR curve of the EADL-FDC algorithm is exhibited in Fig. 4c. The outcome revealed that the EADL-FDC system has gained highest PR outcome on 2 classes. Lastly, the ROC analysis of EADL-FDC technique is established in Fig. 4d. The outcome represented that the EADL-FDC model has resulted in promising outcome with high ROC values under 2 classes.

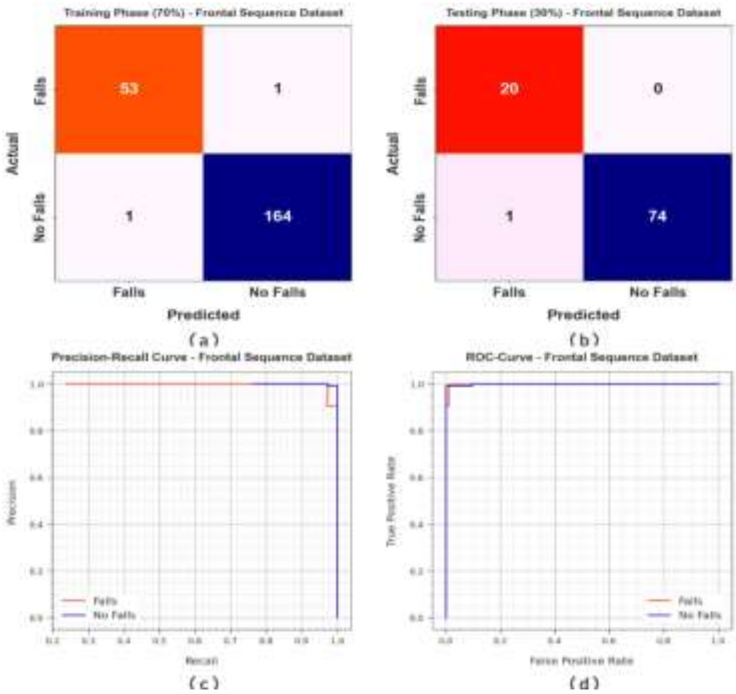

Figure 4: Performance on frontal sequence dataset (a-b) 70% of TRS /30% of TSS, (c) PR_curve, and (d) ROC_curve

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The fall detection results of the EADL-FDC approach on the frontal sequence database are depicted in Table 2 and Fig. 5. The outcomes indicate that the EADL-FDC technique properly categorizes falls and no falls classes proficiently. On 70% of the TRS, the EADL-FDC methodology provides an average $accu_y$ of 98.77%, $prec_n$ of 98.77%, $reca_l$ of 98.77%, F_{score} of 98.77%, and $G_{measure}$ of 98.77%. Moreover, on 30% of TSS, the EADL-FDC algorithm provides average $accu_y$ of 99.33%, $prec_n$ of 97.62%, $reca_l$ of 99.33%, F_{score} of 98.44%, and $G_{measure}$ of 98.46%.

Table 2: Fall detection outcomes of EADL-FDC approach on frontal sequence dataset

Frontal Sequence Database					
Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
TRS (70%)					
Falls	98.15	98.15	98.15	98.15	98.15
No Falls	99.39	99.39	99.39	99.39	99.39
Average	98.77	98.77	98.77	98.77	98.77
TRS (30%)					
Falls	100.00	95.24	100.00	97.56	97.59
No Falls	98.67	100.00	98.67	99.33	99.33
Average	99.33	97.62	99.33	98.44	98.46

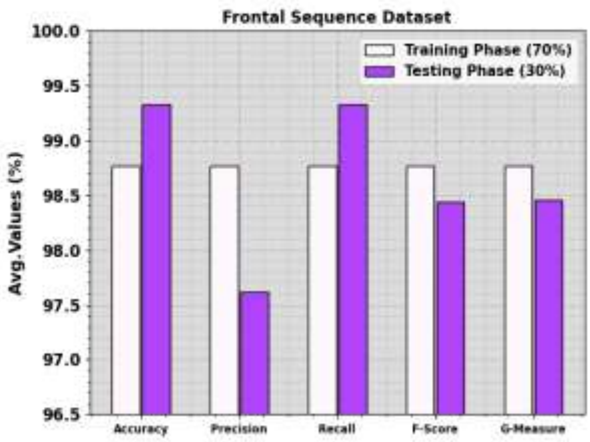

Figure 5: Average outcome of EADL-FDC approach on frontal sequence dataset

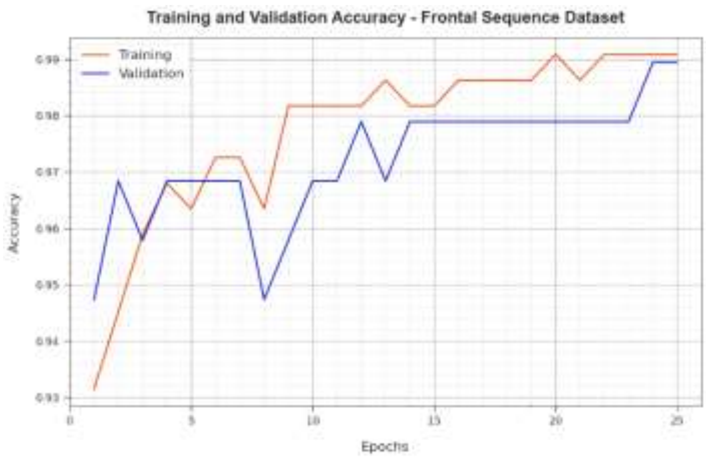

Figure 6: $Accu_y$ curve of EADL-FDC approach on frontal sequence dataset

The TR_accu_y and VL_accu_y of EADL-FDC system on the frontal sequence dataset illustrated in Fig. 6. The TL_accu_y is evaluated by measuring the EADL-FDC algorithm on TR dataset while VL_accu_y is evaluated by computing the outcome on TS data. The outcome exhibits that TR_accu_y and VL_accu_y increased with maximum

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epoch count. Therefore, the performance of EADL-FDC model acquires enhancement on the TR and TS dataset with increased epoch count.

The TR_loss and VR_loss analysis of EADL-FDC system on the frontal sequence dataset is demonstrated in Fig. 7. The TR_loss represent the error among the new and predictive outcome values on the TR dataset. The VR_loss reveals the performance measure of EADL-FDC approach on validation data. The outcome denotes that TR_loss and VR_loss tend to minimize with maximum epoch count. It stated the better outcome of EADL-FDC model and its ability to make correct classification. The reduced values of TR_loss and VR_loss reveals the greater outcomes of EADL-FDC model in capturing connections and designs.

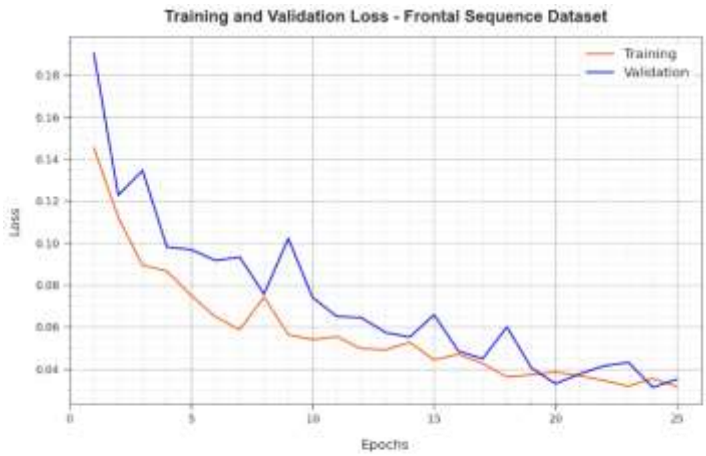

Figure 7: Loss curve of EADL-FDC algorithm on frontal sequence dataset

The comparative analysis of the EADL-FDC methodology is assessed on the frontal sequence database is exposed in Table 3 and Fig. 8 [24]. The outcomes exhibit that the EADL-FDC technique achieves a maximum $accu_y$ of 99.33%. On the other hand, the IWODL-FDDP, VGG16, VGG19, 1D-CNN, 2D-CNN, ResNet50, and ResNet101 systems accomplish minimal $accu_y$ values with 99.04%, 97.66%, 98.25%, 94.31%, 95.63%, 95.68%, and 96.33% correspondingly.

Table 3: $Accu_y$ outcome of EADL-FDC algorithm with existing techniques on frontal sequence dataset

Frontal Sequence Dataset	
Methods	Accuracy (%)
EADL-FDC	99.33
IWODL-FDDP	99.04
VGG16	97.66
VGG19	98.25
1D-CNN	94.31
2D-CNN	95.63
ResNet50	95.68
ResNet101	96.33

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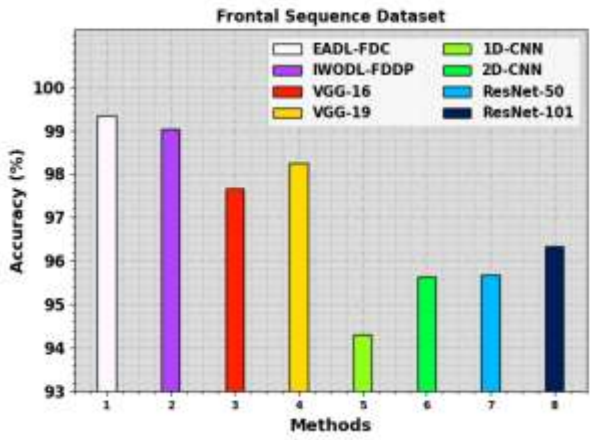

Figure 8: $Accu_y$ outcome of EADL-FDC algorithm on frontal sequence dataset

The classifier outcomes of EADL-FDC model on the Overhead sequence dataset is illustrate in Fig. 9. The confusion matrices offered by the EADL-FDC system at 70:30 of the TRS /TSS is portrayed in Figs. 9a-9b. The outcome shows that the EADL-FDC model has detected and categorized all 2 classes. Similarly, the PR investigation of the EADL-FDC model is revealed in Fig. 9c. The experimental outcome showed that the EADL-FDC method has gained high PR outcomes on 2 classes. Lastly, the ROC examination of EADL-FDC system is demonstrated Fig. 9d. The outcome inferred that the EADL-FDC model has resulted in efficient outcome with high ROC value on 2 classes.

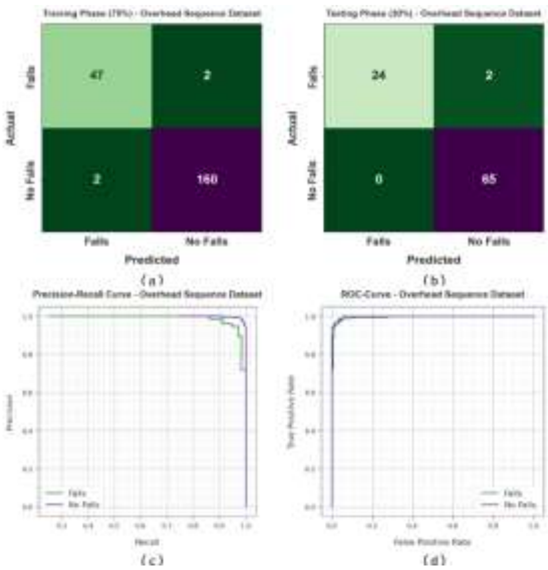

Figure 9: Performance on Overhead sequence dataset (a-b) 70% of TRS /30% of TSS, (c) PR_curve, and (d) ROC_curve

The fall detection analysis of the EADL-FDC approach on the Overhead sequence database is depicted in Table 4 and Fig. 10. The outcome indicated that the EADL-FDC system properly categorizes falls and no falls class labels proficiently. On 70% of the TRS, the EADL-FDC model provides an average $accu_y$ of 97.34%, $prec_n$ of 97.34%, $reca_l$ of 97.34%, F_{score} of 97.34%, and $G_{measure}$ of 97.34%. Also, on 30% of TSS, the EADL-FDC method provides average $accu_y$ of 96.15%, $prec_n$ of 98.51%, $reca_l$ of 96.15%, F_{score} of 97.24%, and $G_{measure}$ of 97.29%.

Table 4: Fall detection outcome of EADL-FDC approach on Overhead sequence dataset

Overhead Sequence Dataset					
Classes	$\boldsymbol{Accu_y}$	$\boldsymbol{Prec_n}$	$\boldsymbol{Reca_l}$	$\boldsymbol{F_{Score}}$	$\boldsymbol{G_{Measure}}$
TRS (70%)					

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Falls	95.92	95.92	95.92	95.92	95.92
No Falls	98.77	98.77	98.77	98.77	98.77
Average	97.34	97.34	97.34	97.34	97.34
TSS (30%)					
Falls	92.31	100.00	92.31	96.00	96.08
No Falls	100.00	97.01	100.00	98.48	98.50
Average	96.15	98.51	96.15	97.24	97.29

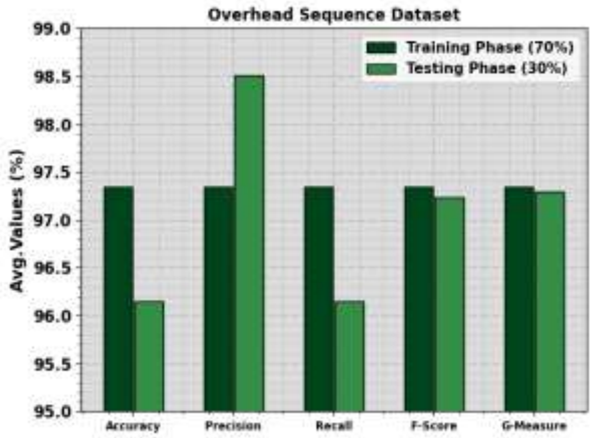

Figure 10: Average outcome of EADL-FDC approach on Overhead sequence dataset

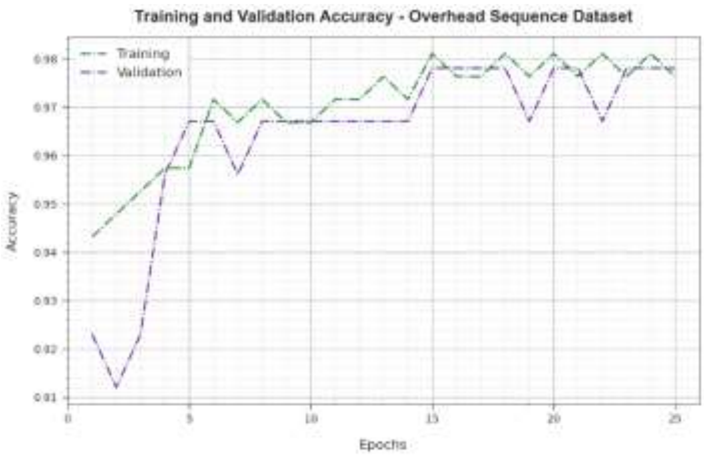

Figure 11: $Accu_y$ curve of EADL-FDC approach on Overhead sequence dataset

The TR_accu_y and VL_accu_y of the EADL-FDC method on the Overhead sequence dataset is portrayed in Fig. 11. The TL_accu_y is evaluated by measuring the EADL-FDC methodology on the TR dataset while the VL_accu_y is defined by assessing the outcome on TS data. The stimulation value exhibits that TR_accu_y and VL_accu_y increased with maximum epoch count. Thus, the performance of EADL-FDC methodology attains enhancements on TR and TS data with increased epoch count.

The TR_loss and VR_loss analysis of EADL-FDC method on the Overhead sequence dataset is shown in Fig. 12. The TR_loss evaluates the error among the original and predictive solutions values on the TR dataset. The VR_loss denotes the performance measure of EADL-FDC method on validation data. The outcome indicates that TR_loss and VR_loss tend to minimize with maximum epoch count. It showed the better outcome of the EADL-FDC algorithm and its ability to produce correct classification. The diminished value of TR_loss and VR_loss exhibits the superior outcome of the EADL-FDC approach in capturing designs and connection.

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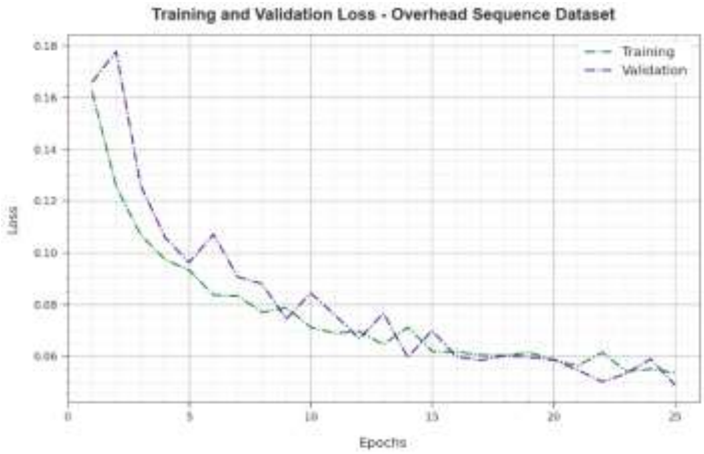

Figure 12: Loss curve of EADL-FDC approach on Overhead sequence dataset

In Table 5 and Fig. 13, the comparison analysis of EADL-FDC system is assessed on the Overhead sequence dataset. The outcomes revealed that the EADL-FDC algorithm achieves a maximal $accu_y$ of 97.34%. Alternatively, the IWODL-FDDP, VGG16, VGG19, 1D-CNN, 2D-CNN, ResNet50, and ResNet101 techniques obtain minimum $accu_y$ values with 97.02%, 95.16%, 96.56%, 92.69%, 95.48%, 95.58%, and 96.69% correspondingly. Thus, the EADL-FDC technique was found useful for accurate fall detection.

Table 5: $Accu_y$ outcome of EADL-FDC algorithm with recent approaches on Overhead sequence dataset

Overhead Sequence Dataset	
Methods	Accuracy (%)
EADL-FDC	97.34
IWODL-FDDP	97.02
VGG16	95.16
VGG19	96.56
1D-CNN	92.69
2D-CNN	95.48
ResNet50	95.58
ResNet101	96.69

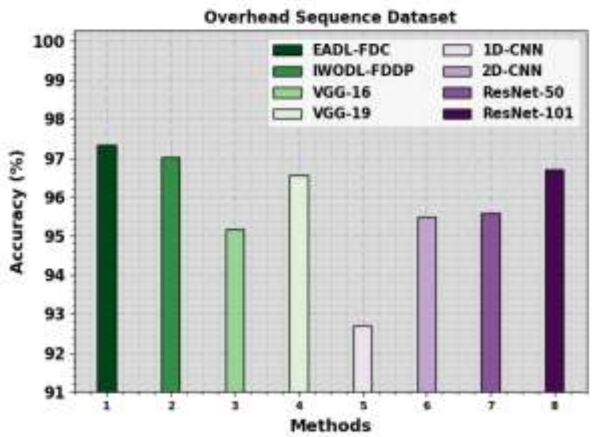

Figure 13: $Accu_y$ outcome of EADL-FDC algorithm on Overhead sequence dataset

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5. Conclusion

This manuscript has presented a new EADL-FDC method for aiding disabled and elderly persons. The presented EADL-FDC technique enables the DL models for the effectual identification and classification of falls for elderly and disabled people. In the proposed EADL-FDC method, several stages of subprocesses includes SPA-Net feature extractor, SOS-based hyperparameter tuning, DBN classification, and MFO-based parameter tuning. Here, the SOS system can be used for the parameter choice of the SPA-Net methodology and the MFO approach is exploited to finetune the hyperparameter related to the DBN algorithm. The performance analysis of the EADL-FDC approach takes place on the FD dataset. The stimulation outcome indicates the remarkable performance of EADL-FDC system over other DL algorithms. The study focus on the development of feature fusion method to enhance the detection performance of the EADL-FDC method.

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