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GRADIENT TUNED DENSE TRANSFER LEARNING FOR DISABLED PERSON MOVEMENT ISSUE DETECTION WITH LONG FREQUENCY RFID

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Abstract:
Disabled individuals movement monitoring is an important part in healthcare and assistive technology for guaranteeing their safety, independence, and overall well-being. The main aim is to detect abnormal movements, recognize daily activities, and identify fall events. There are diverse wireless sensing technologies such as Wi-Fi, Radio Frequency Identification (RFID), and Bluetooth (ZigBee) are used to monitor the movements of disabled individuals by detecting disturbances in electromagnetic waves. Among them, RFID is an automatic, non-contact technology aimed to detect the movement of individuals based on radio frequency tags. Conventional deep learning approaches often addressing the movement's detection of disabled individuals, but, the accuracy faced major challenging issues. This paper proposes a novel model called Gradient Tuned Dense Transfer Learning (GTDTL) model is developed. The developed GTDTL model employs deep transfer learning model for accurate movement's detection of disabled individuals with lesser time consumption. The overall structural design of transfer learning model consists of two phase's construction namely pre-trained and new model. In the beginning, transfer learning model constructs the pre-trained deep learning model called DenseCNN model with many layers, including an input layer, hidden layers and an output layer. Initially, number of RFID data samples is collected from the dataset and it given to the input layer. Consequently, data pre-processing is carried to handle missing data and outlier's removal. Followed by, the more pertinent feature selection process is carried out. Finally, activity recognition is performed with the selected features. As a final phase of transfer learning, the fine tuning process is performed to optimize the error by employing stochastic sampling squirrel search algorithm. As a final point, accurate and time efficient activity recognition results are obtained at the output layer with high accuracy and minimal time consumption using RFID data samples. Experimental assessment of proposed GTDTL model is conducted using various assessment metrics such as accuracy, precision, sensitivity, F1-score, specificity, and recognition time. The quantitatively analyzed results expose that the proposed GTDTL attains higher accuracy in recognition with minimal time consumption as well as lesser error compared to traditional deep learning methods.
Keywords: *Disabled Person movement detection, Long Frequency RFID tag, Transfer learni Gradient Tuned Dense Transfer Learning, DenseCNN model, stochastic sampling squirrel search algorithm*

1. Introduction

Monitoring the movement of disabled individuals is a significant facet of ensuring their protection and improving their quality of life. People with physical disabilities often face complexity in performing daily activities. Therefore, continuous monitoring of their activities is essential for early detection of abnormal conditions. Recently, various wireless technologies namely, wearable sensors, RFID, Bluetooth are enabled the development of smart monitoring for disabled individuals. By analyzing these sensor data, it becomes feasible to recognize irregular movement patterns and abnormal walking behavior. In the movement detection, RFID tags are efficient to track the location or movement of the individual within particular location. When the visually challenged person moves through different locations, RFID readers positioned to detect the tag and transfer the information to the monitoring system through the IoT devices. This helps to relatives or neighbors monitor the activity patterns and guarantee the safety of the person. Therefore, an effective deep learning system with RFID technology is required for disabled person's activity detection to ensure timely intervention, reduce risks associated with mobility issues, and enhance overall well-being.

A new fusion model that integrates radio frequency identification (RFID) and Radar technologies (RFiDAR system) was introduced in [1] with an LSTMvariational autoencoder (LSTM-VAE) model to improve Human activity recognition accuracy and reliability. However, the performance error rate was not reduced. Time-streaming Multiscale Transformer called TransTM was introduced in [2] for RFID-based human activity recognition (HAR) to collect the behavioral features that recognizes human activities and human-to-human interactions. However, significant reduction in human activity recognition time was not achieved. Metaheuristic optimization-driven ensemble model was introduced in [3] for disabled persons indoor activities recognition using IoT applications. Hover, the model did not may focus on incorporating more robust data preprocessing techniques and transfer learning for improving the efficiency of the model. Temporal Contrastive Learning in Human Activity Recognition approach was developed in [4] for human activity recognition based on meaningful feature representations for time-series data. However, the impact of preprocessing unlabeled data on the performance of human activity recognition was not analyzed. Temporal Convolutional Network with Augmentations and Attention model was introduced in [5] to enhance computational efficiency and accuracy. However, applicability and adaptability of the proposed method, with different subjects, and for more complex activities was not investigated. A federated learning model was developed in [6] for human activity recognition based on wearable IoT device. However, the model failed to focus on enhancing the system through selecting significant features. A novel computational radio frequency identification (RFID) system was developed in [7] for contactless activity recognition to help the blind individuals. But, the system did not utilize the machine learning approach model for accurate activity recognition.A novel Patient tracking system was introduced in [8] that utilize the RFID wristbands for real-time monitoring of patient movement activities. However, the system's adaptability and scalability of the model was not improved. An RFID-based System was introduced in [9] to guide the visually impaired people. However, time consuming was not efficiently reduced for accessibility of visually impaired people. Double tag array strategy was introduced in [10] utilizing ultra-high frequency passive RFID technology for significantly improved the recognition accuracy with minimal average error. However, it failed to reduce computational complexity and enhance real-time processing capability within large-scale scenarios.

A DeepSORT tracking algorithm was designed in [11] for human tracking system based on RFID technologies. However, the algorithm did not focus on integrating the processes to enhance the tracking accuracy of the model. Deep learning based predictive analytics was developed in [12] for contactless human physical activity monitoring based on radio frequency identification (RFID) tags. However, it failed to accurately detect indoor activities. Transparent RFID Tag Wall (TRT-Wall) system was introduced in [13] with the aim of contactless human activity monitoring based on passive ultra-high frequency (UHF) radio-frequency identification (RFID) tag array. However, the system did not developing a user identification and recognition model with minimal complexity. A novel RFID based indoor positing system was developed in [14] capable of locating and tracking activities of the persons. But, the model was not efficient in handling multiple activities of the persons. Transformer network encoder model was introduced in [15] to improve activity recognition and fall detection accuracy based on radio frequency identification (RFID). However, it failed to explore contactless real-time fall detection for multiple users using human body feature signals.

1.1 Proposal key contribution : The limitations of existing methods are overcome through the introduction of a novel GTDTL model. The major contributions of the GTDTL model are listed below,

- To design a novel model called GTDTL for accurate disabled person movement issue detection based on Long Frequency RFID tag information's collected from the dataset. In order to achieve this contribution, GTDTL model includes various processes namely data pre-processing, feature selection, classification and fine tuning.
- To minimize the time consumption of the disabled person activity recognition, data preprocessing and feature selection are carried out in GTDTL model. A Generalized regression imputation method is employed for handling the missing RFID tag data. The Rosner's test analysis is employed to detect and remove the outlier data. Moreover, the two segment regression is employed for relevant feature selection based on Soergel similarity index
- To increase the accuracy, Simple matching coefficient is employed in Dense CNN model for evaluating the different features and analyzes data samples and provides the accurate activity classification results of disabled peoples. Moreover, stochastic sampling squirrel search algorithm is employed to fine tune the hyperparameter to enhance the accuracy by minimize the error.
- At last, complete experiment is carried out to examine the performance of our GTDTL model and other deep learning methods.

1.2 Paper Organization

The rest of this paper is organized as follows. Section 2 provides an extensive review of previous works. Section 3 presents a detailed description of the proposed GTDTL model along with its architectural design. Section 4 outlines the experimental framework and offers a complete description of the datasets. Section 5 discusses the experimental outcomes and includes a comprehensive comparative assessment of the proposed GTDTL model with existing deep learning techniques using several performance metrics. Finally, Section 6 summarizes the study and highlights the major findings of the research.

2. Related works

A hardware-based RFID identification and tracking system was developed in [16]. However it failed to explore the integration of RFID data for improving efficiency. A novel behavior recognition model was introduced in [17] using RFID technology with multi-feature analysis. However it failed to enhance overall enhancing recognition performance. An integration of particle swarm optimization (PSO) and a four-stage forward neural network (4SFNN) were developed in [18] to improve the prediction accuracy. However, final prediction accuracy was not achieved with less mean absolute error rate. Deep Learning with a Snake Optimiser approach was designed in [19] for advanced smart human activity recognition with disabilities with high precision and adaptability. But the computational efficiency of the model was not addressed. Multiscale convolutional hybrid Transformer model was introduced in [20] for achieving high average recognition accuracy. However, hyperparameter settings were not analyzed. An innovative RFID (Radio-Frequency Identification)-based tracking system was developed in [21] to enhance the detection and localization. However, it failed to refine the system performance. A new cost-effective radio frequency identification (RFID)-based tracking system was introduced in [22] for robust and accuracy of human activities. However, enabling more accurate tracking system was major concern. Deep Learning-based architecture was developed in [23] for human activity recognition. However, the model did not achieve efficient trade-off between accuracy and computational cost. An ensemble of deep learning models was introduced in [24] to monitor and detect various conditions and activities within indoor spaces for disabled people. However, it failed to improve the adaptability of models for diverse disabilities peoples.An Optimised Hybrid Deep Learning Model was introduced in [25] for human activity recognition and improves the quality of life for people with disabilities. However, it did not integrating adaptive learning mechanisms to noisy inputs. An Improved Pelican Optimisation with Recurrent Neural Network model was developed in [26] to improve indoor activity detection systems for individuals with disabilities. However it failed to focus on expanding the system to handle multi-modal sensor data by integrating the transfer learning (TL) and adaptive learning strategies for improving practical usability. Binary grey wolf optimization-driven ensemble deep learning model were developed in [27] for activity recognition of disabled peoples. But it failed develop more robust data pre-processing techniques, and improve model efficiency. Deep learning based activity recognition were introduced in [28] for significantly enhances feature extraction and accuracy of human activity recognition. However, it failed to further enhance the accuracy and robustness of system. An ensemble of three different deep learning algorithms were designed in [29] for identifying human activity using sensor data. However the model was more complexity in human activity recognition. Deep learning models were developed in [30] for sensor-based human activity recognition. However, efficient deep learning models were not employed for accurate recognition.

3. Proposal Methodology

Human Activity Recognition (HAR) for individuals with disabilities has become an increasingly significant research field in artificial intelligence (AI). The main aim of HAR systems is to detect and categorize human activities by analyzing data collected through different wireless sensing technologies. In these systems, large volumes of individuals with disabilities personal information including location data, body movements, health-related parameters, and daily behavioral patterns are collected by means of RFID technology. In this paper, a new model Gradient Tuned Dense Transfer Learning (GTDTL) model is proposed to support Human Activity Recognition specifically designed for individuals with disabilities. This proposed Gradient Tuned Transfer Learning model incorporates various processes into the transfer learning model such as data preprocessing, feature selection, classification, and fine-tuning to achieve more effective recognition. The deep learning architecture reduces errors and enhances the accuracy of classification by applying fine tuning process with the help of optimization.

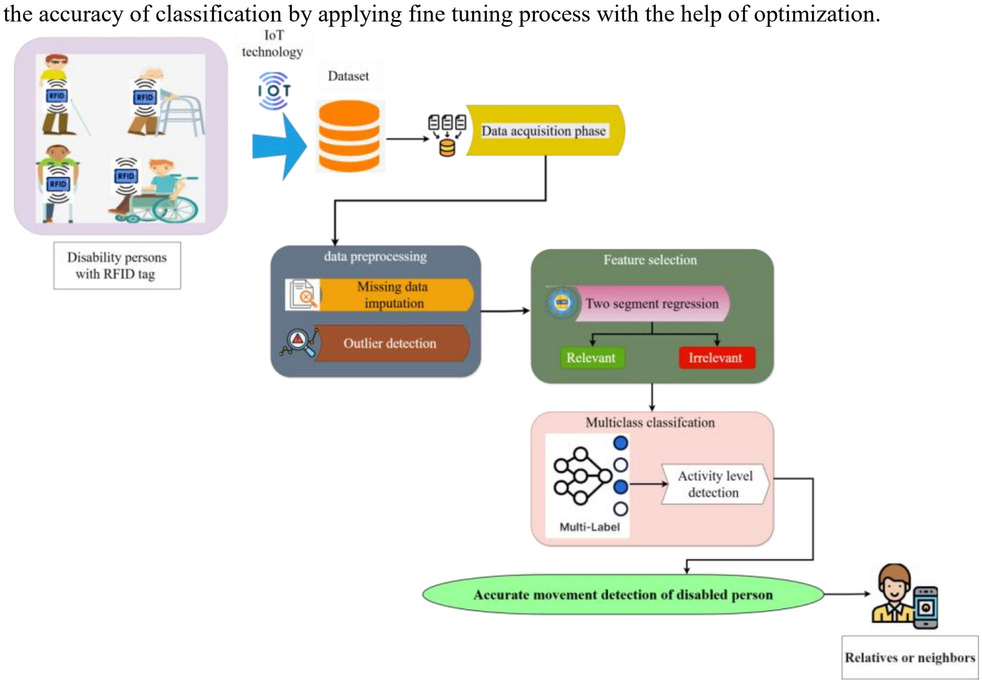

Figure 1 Architecture of the proposed GTDTL model

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Figure 1 portrays the overall structure of the proposed method for accurate activity recognition for disabled individuals effectively using RFID dataset. In GTDTL model, RFID tags are fixed to the body of disabled individuals to enable the monitoring and movement issue detection. The collected data is transmitted through Internet of Things (IoT) systems for further analysis. This process helps guarantee timely detection and improves the protection and well-being of disabled individuals. These RFID tags collect information related to body movements and physical actions performed by the person. The proposed architecture recognition diagram includes four key stages namely data acquisition, pre-processing, feature selection, classification into different classes. At first, RFID tag information's are collected from the suitable dataset for further processing. Following the data acquisition, pre-processing step is employed to smooth raw dataset into more appropriate format which comprises of two major processes namely missing data imputation and outlier data removal. Once complete the preprocessing step, the significant feature selection and removal process is carried out by employing the two segment regression analysis aimed to reduce the time complexity. As a final point, the classification step is executed in proposed GTDTL model for multi class activity detection by the means of selected relevant features attaining higher accuracy with lesser errors. When movements are detected, the system automatically sends notifications to relatives or nearby neighbor's mobile phones .to ensure the safety of the disabled person. These various processes of the proposed GTDTL model are detailed in the under subsections.

3.1 Data acquisition

The basic step of the proposed GTDTL model is a data acquisition, which involves collects large volume of data samples to provide as input for the activity recognition process. In the proposed model, RFID dataset for Device-Free Ambient Assisted Living Monitoring are gathered from https://github.com/care-group/RFID-Datasets . The RFID dataset contains a total of 25,924 snapshots of data, where snapshots were recorded at a rate of one snapshot per second. This therefore represents around 7 hours and 12 minutes of raw data. In the CSV and ARFF files of the RFID data, there are 196 targets. The data is collected from 6 different participants (i.e. disabled peoples) linearly over time. The columns include Activity, location, participant ID, and timestamp are recorded for each participants.

3.2 Transfer learning based disabled person movement detection

Once the RFID tag samples are collected from the dataset, the proposed GTDTL model utilizes the deep transfer learning approach to accurately classify disabled person movements. This transfer learning method utilizes information gained from a previously trained model and adapts it to a new prediction task. On the contrary to traditional deep learning techniques, the transfer learning model is capable of achieving higher classification performance even when datasets vary in size, while minimizing the training time as well as lower computational cost. Accordingly, the proposed transfer learning model improves both the efficiency and reliability of human activity detection using RFID tag information's. The complete architecture of the transfer learning framework is presented in Figure 2.

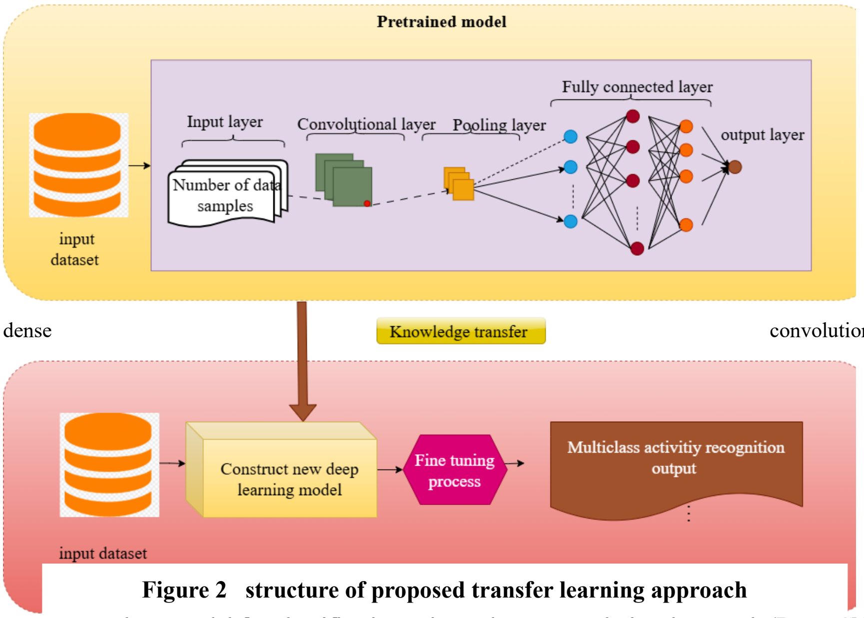

Figure 2 structure of proposed transfer learning approach

Figure 2 given above depicts the conceptual structure of the proposed deep transfer learning framework proposed for accurate activity recognition. The structure consists of two main phases namely a pre-trained model and a newly developed classification model. In the initial stage, the RFID dataset is processed using the pre-trained model i.e. dense convolutional network which performs three major steps namely data preprocessing, feature selection, and classification. The pre-trained output analyzes RFID tag information's attached to the disabled person body and produces multi-class activity recognition outputs. Followed by, new classification model is constructed using similar dense convolutional neural network (CNN) with the knowledge learned by the pre-trained network. By utilizing the knowledge previously learned model, the new model generates multi-class activity recognition results and minimizes the error and improved efficiency. As exposed in figure 2, many layers of the original pre-trained network are retained and kept freezing through the development of the new model, while selected hyperparameters are fine-tuned to improve the overall accuracy of the model.

3.2.1 Pre-trained classification model construction

The proposed transfer learning framework initially constructs a base model for classification using a dense convolutional network (DenseCNN). DenseCNN is a specialized deep learning model consists of numerous organized layers that assist effective feature propagation and reuse. The main advantage of DenseCNN is to improve the efficiency by connecting each layer to other layer within a dense block. Hence it facilitates enhanced information flow throughout the entire network model. The detailed structure of the developed base network is presented in Figure 3.

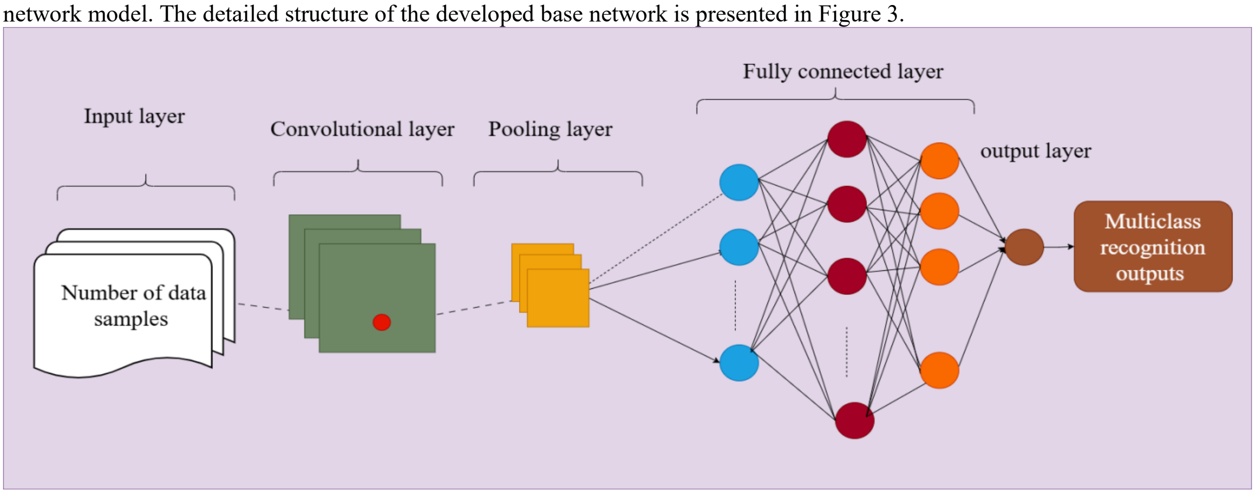

Figure 3 construction of DenseCNN

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Figure 3 given above illustrates structure of a DenseCNN architecture to perform the classification of multiple activities of disabled propels using RFID tag information. As shown in figure 3, input and output layers are always only one layer, whereas the middle layers also called as hidden layers which include three sub-layers namely convolutional layer, pooling layer and fully connected layer. Each layer in the network architecture includes small parts called artificial neurons or nodes to process the given input RFID tag information collected from the dataset. Each neuron in hidden layers receives inputs from previous layer and processes them, also generates the results to successive layers.

Let us consider the input RFID dataset 'D' which comprises of numerous samples 'S' or RFID tag information as well as features $\{A_1, A_2, \dots, A_m\}$. These input samples and features are generally arranged in the form of matrix representation. Therefore, input matrix representation of the dataset is formulated as follows,

$$Q = \begin{bmatrix} A_1 & A_2 & \dots & A_m \\ S_{11} & S_{12} & \dots & S_{1n} \\ S_{21} & S_{22} & \dots & S_{2n} \\ \vdots & \vdots & \dots & \vdots \\ S_{m1} & S_{m2} & \dots & S_{mn} \end{bmatrix} \quad m = rows, n = columns \qquad (1)$$

Where, Q represents an input matrix representation where each column represents 'm' number of features$\{A_1, A_2, \dots, A_m\}$, each row represents 'n' number of samples '$S = \{S_1, S_2, \dots, S_n\}$' respectively. This input matrix representation is given to the input layer of the DenseCNN architecture. The input layer received the data only and it did not perform any computation process. The RFID tag information is transferred to the first hidden layer of DenseCNN architecture.

- **convolutional layer (preprocessing)**

In the DenseCNN architecture, the convolutional layer acts as the first hidden layer. It consists of multiple artificial neurons that slide over the input data to capture RFID tag information of each disabled persons. By stacking several convolutional layers, the architecture progressively learns RFID tag information, enabling accurate data preprocessing and analysis of complex input data.

Data preprocessing is carried out for transforming the raw dataset into suitable format by handling the missing data and outlier data removal. Generalized regression imputation model is employed in the convolutional layers to handle the missing data samples within the dataset. Missing data refers to the value of variables is not recorded or unavailable. The Generalized regression imputation model is a machine learning technique to detect the unavailable data based on already known data samples. Therefore, the missing data imputation process is expressed as follows,

$$S_M = \beta_0 + \sum_{i=1}^{n} \beta_i S_i + e \quad (2)$$

Where, S_M denotes a missing data, β_0 and β_i represents the regression coefficient, S_i represents the known data samples, e denotes a residual or error term for the missing observation.

During the preprocessing stage, an outlier is a data point that considerably diverges from other data observations within a dataset. The proposed model utilizes the Rosner's test analysis for detecting the multiple outliers within the dataset. This test helps to distinguish outliers that are either much lesser or much larger than the rest of the samples. Rosner's test based outlier detection is then computed as follows,

$$RT = \arg\max H \quad (3)$$

$$H = \sum_{i=1}^{n} \left| \frac{S_i - \bar{S}}{\sigma} \right| \quad (4)$$

Where, RT Rosner's test analysis, S_i represents a data samples in the particular cell, $\bar{S}$ indicates a mean value of particular data samples, σ represents a mean absolute deviation. In Rosner's method for detecting outliers based on the largest standardized distance between an observation and the mean of the dataset. In this manner, the entire outlier data samples are detected within the dataset. Accordingly, the detected outlier data samples are removed from the dataset.

- **Pooling layer (feature selection)**

The next step of proposed GTDTL model is the feature selection for choosing the relevant features from the dataset to reduce the dataset's dimensionality in pooling layer. This model employs two segment regressions to recognize and maintain important features while discarding irrelevant ones. The segment regression is employed for measuring the linear relationship between input variables (features) and an output variable (target).

The proposed regression utilizes the Soergel similarity index function to analyze the linear relationship between the features and a target (i.e. activity recognition). This helps to determine the more significant features from high dimensional dataset into low dimensional space. Let us consider the set of features in the RFID dataset.

$$A_j = \{A_1, A_2, \dots, A_m\} \quad where\ j = 1,2,3 \dots m \quad (5)$$

The Soergel similarity index between the target variable and the input RFID tag features is computed by using following expression.

$$\boldsymbol{SSI} = \left[\frac{\sum_{j=1}^{m} |A_j - A_T|^2}{\sum_{j=1}^{m} \max(A_j, A_T)} \right] \quad (6)$$

Where, SSI denotes **a** Soergel similarity index which helps to measure the similarity between features A_j and other target features A_T. Based on the similarity, contextual relationship between the features and target is obtained. The output of similarity returns the values between 0 and 1. The two segment regression method is employed to differentiate the relevant and irrelevant features based on Soergel similarity index output.

$$A_{Irrelevant} = R_1.SSI + K_1, if\ SSI < T \qquad (7)$$

$$A_{Relevant} = R_2.SSI + K_2, if\ SSI > T \qquad (8)$$

Where,'$A_{Relevant}$' indicates the relevant features sets,$A_{Irrelevant}$ denotes a irrelevant features sets, SSI denotes a Soergel similarity index, regression coefficient 'R_1', 'R_2' and regression constants 'K_1', K_2' with respect to threshold (T). From the assessment results, '$A_{Relevant}$' features sets are considered for activity recognition. The selected features results are transferred into fully connected layers for analyzing the selected features and generating the activity recognition results at output layer.

- **Fully connected layer (classification)**

Finally, activity recognition is performed in **fully connected layer** also known as a **dense layer** to perform the classification with the selected features. The main process of the fully connected layer is to integrate all the selected features from the previous layers (pooling layers) and perform the classification tasks to produce the desired activity recognition. In this layer, simple matching coefficient statistical method is used to determine the similarity between the training and testing data samples.

$$SMC = \left[\frac{(S_{tr} \cap S_{ts})}{\sum S_{tr} + \sum S_{ts} - (S_{tr} \cap S_{ts})} \right] \qquad (9)$$

Where, SMC indicates a simple matching coefficient,S_{tr} denotes a training samples, S_{ts} indicates testing samples, $S_{tr} \cap S_{ts}$ denotes a mutual dependence between the two samples, $\sum S_{tr}$ denotes a score value of training samples S_{tr}', $\sum S_{ts}$ denotes a score value of testing samples 'S_{ts}'.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 36 Issue 1, 2026, Pages 4773-4786

The matching coefficient (SMC) provides the output value between 0 and 1. Based on coefficient results, various activities of disabled persons are classified at the output layer.
The output of the fully connected layer is obtained at the output layer with the help of softmax activation function.

$$Y_c = \tau\,(w_{ho} * h_t) \quad (10)$$

$$\tau = \frac{\exp(Y_c)}{\sum_{c=1}^{k}\exp(Y_c)} \quad (11)$$

Where, τ represents a softmax activation function, Y_c indicates an output of the model for multiple class 'k'. The softmax activation function produces outputs in the range [0, 1]. Using this activation output, the network generates multiple activities classification results at the output layer. The algorithm of pre-trained model is described as follows,

// Algorithm 1: Pre-trained classification model construction

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \dots . S_m\}$', Features '$A_1, A_2, \dots, A_m$'
Output: Activity recognition

Begin
Step 1: Collect number of number of Samples '$S = \{S_1, S_2, \dots . S_m\}$', Features '$A_1, A_2, \dots, A_m$' from input dataset 'DS'
Step 2: Samples given to input layer of dense convolutional network
Step 3: Transfer the input samples to Convolutional layer
Step 4: **For each** samples S_i
Step 5: Handle missing data using (2)
Step 6: Find the outlier data using (3)
Step 7: **If** ($\arg\max H$) **then**
Step 8: Samples is identified as outlier
Step 9: **else**
Step 10: Samples is identified as normal
Step 11: **End if**
Step 12: **For each preprocessed dataset**
Step 13: Compute the similarity between the features using (6)
Step 14: **Apply the segment regression**
Step 15: **if** ($SSI < T$) **then**
Step 16: features is said to be irrelevant
Step 17: **else**
Step 18: features is said to be relevant
Step 19: **End if**
Step 20: Select the relevant features and removed others
Step 21: **End for**
Step 22: **For each** selected features and training samples----- **fully connected layer**
Step 23: Compute the simple matching coefficient using (10)
Step 24: Obtain classification **results** with softmax activation function using (17)
Step 25: Return final classification output
Step 26: **End for**
End

Algorithm 1 given above depicts the various process involved for constructing a pre-trained classification model for human activity recognition. The pre-trained model considers the RFID input samples and features collected from the dataset and it given to the input layer. The input samples and features are then transferred to the convolutional layer. In this layer, preprocessing is carried out which includes missing data handling and outlier removal. The pre-processed dataset is then proceeds to the max pooling layer, which used for retaining the more revenant features and removing the others based on similarity index output. In the fully connected layer, selected features with training samples are processed using matching coefficient for classification purposes. At last, output layer applies a softmax activation function to generate the multi class classification outcomes. By following this structured Dense CNN, the pre-trained classifier model is able to accurately detect the different movements of disabled persons.

3.3 Construct new classification model based activity recognition

The proposed transfer learning approach construct the new model using a number of input RFID tag information's by utilizing the knowledge obtained from preceding pre-trained network architecture. As shown in Figure 2, many layers in new classification model typically referred to as frozen layers that are preserved from the pre-trained model, and their process also remain unaltered. However, only the fine-tuning tasks is employed to refine the total architecture of pre-trained model

In the first frozen hidden layer (i.e. convolutional layer), the proposed transfer learning model performs the data preprocessing which involves missing data handling and outlier data removal. First, the missing data handling process is carried out in the convolutional layer of new classification model using generalized regression imputation model according to the equation (2). The outlier removal process is done by employing Rosner's test analysis along with the equation (3).

In the second hidden layer (i.e. pooling layer), the new classification model performs similarity using (6) (7) (8) allowing it to preserve the more relevant features.

The fully connected layer utilizes the matching coefficient to analyze the training and testing data samples using (9). Based on the matching coefficient outcomes, the multiple classes of activity recognitions are observed. For each result, the recognition error is calculated as based on squared difference between the actual and predicted output.

$$RE = \left(Y_{act} - Y_{pre}\right)^2 \quad (12)$$

In order to minimize the recognition error, the hyperparameters (weights) gets updated using gradient function as follows,

$$w_{new} = w_{old} - \eta\left[\frac{\partial RE}{\partial w}\right] \quad (13)$$

Where, w_{new} indicates an updated weights, w_{old} represents a current weight, η denotes a learning rate, $\frac{\partial RE}{\partial w}$ represents the first-order derivative function regarding recognition error 'RE' and weight 'w'. From the above analysis, multiple weight values are computed. The fine

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Vol. 36 Issue 1, 2026, Pages 4773-4786

tuning phase of the DenseCNN helps to improve the accuracy by decreasing the error. In order to perform the fine tuning process, stochastic sampling squirrel search algorithm is employed. The squirrel search algorithm is a meta-heuristic technique inspired by the behavior of food source searching of flying squirrels. In this fine tuning process, squirrels represent candidate hyperparameter solutions i.e. number of updated weights, while the food sources correspond to the fitness function to evaluate result quality. At first, a population of squirrels is randomly created within the search space. These candidate solutions are then iteratively updated to identify the optimal one. The population initialization process is executed as follows,

$$w_k = w_1, w_2, w_3, \ldots. w_k \quad (14)$$

Where, w_k denotes a 'k' number of weights updated using gradient function. For each weight, the fitness is calculated depends on the recognition error.

$$fitness(w_k) = arg\,min\ RE \quad (15)$$

Where $fitness(w_k)$ represents a fitness for each weight, $arg\,min$ represents an argument minimal function, RE indicates a recognition error. Among the population, the current best weight is chosen based on the fitness estimation. The current best is chosen based on stochastic universal sampling method. The selection of current best is detected based on probability estimation as given below,

$$P_s = \frac{fitness(w_k)}{\sum_{k=1}^{r} fitness(w_k)} \quad (16)$$

Where, P_s indicates a selection probability calculated depends on ratio of every individual weight fitness '$fitness(w_k)$' to the average fitness of the population in r^{th} individual '$\sum_{k=1}^{r} fitness(w_k)$ '. Therefore high probabilities of weight are selected as currents best. Followed by, the different behaviors of squirrels are executed along with the best fitness function.

- **Generate New Locations through Gliding**

The gliding process is one of the behaviors of squirrels for generating the new locations from the previous locations. In this process, new locations generation is obtained as follows,

$$X^{new} = X_i + r\ \varphi_C * 0.5\ |X_i - X_{best}| \quad (17)$$

Where, $X_i{}^n$ denotes a new location of the squirrels, X_i represents old location of the squirrel, r indicates a random gliding distance, φ_C represents a gliding constant, $0.5|X_i - X_{best}|$ denotes a variance between the current position of squirrel 'X_i' and best position of the squirrel 'X_{best}'.

- **Check Seasonal Monitoring Condition:**

The next behavior is a seasonal monitoring mechanism. The foraging behavior of flying squirrels is considerably influenced by changing the seasonal conditions. In this process, the flying squirrels changed from active to inactive modes in winter season to escape local optima.

$$\delta = \sqrt{\left(X_i^t - X_{best}\right)^2} \quad (18)$$

Where, δ represents a seasonal constant, X_i^t denotes a current solution, X_{best} indicates a current best solution.

$$\delta_{min} = \frac{10*\exp(-6)}{365^{(t/t_{max})*2.5}} \quad (19)$$

Where δ_{min} represents a minimum seasonal constant, 't' indicates an iteration, t_{max} represents a maximum iteration. The seasonal monitoring behavior indicating that the flying squirrels drop the ability to efficiently explore for food sources. This condition persists until the algorithm reaches the maximum number of iterations. If the seasonal constant did not fall below the threshold, the algorithm continues by generating new candidate positions and updating the new seasonal state. Through this iterative procedure, the optimal weight is determined. These optimized parameters contribute to minimize the errors during the activity recognition stage. As a result, accurate human activity recognition results are observed at the output layer with softmax activation function.

$$Y_{new} = \tau\,(w_{ho} * h_t) \quad (20)$$

Where, τ represents a softmax activation function, Y_{new} indicates an output of the new classifier model. The algorithm process of new classification model based activity recognition is given below,

// Algorithm 2: New classifier model based activity recognition
Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \ldots. S_m\}$', Features '$A_1, A_2, \ldots, A_m$' **Output:** Accurate activity recognition
Begin **Step 1: Collect n**umber of number of Samples '$S = \{S_1, S_2, \ldots. S_m\}$', Features '$A_1, A_2, \ldots, A_m$' from input dataset 'DS' --- **input layer** **Step 2:** Samples given to input layer of dense convolutional network **Step 3:** Transfer the input samples to Convolutional layer **Step 4:** **For each** samples S_i **Step 5:** Handle missing data using (2) **Step 6:** Find the outlier data using (3) **Step 7**: **End for** **Step 8**: **For each pre**-processed outcomes –**pooling layer** **Step 9:** Select relevant features using (8) **Step 10:** **Remove** relevant features using (7) **Step 11:** **End for** **Step 12:** **For each** training samples----- **Fully connected layer** **Step 13:** Measure the matching coefficient using (9) **Step 14:** Obtain classification **results** **Step 14:** **End for** **Step 15:** **For each** classification result **Step 16:** Measure the recognition error ' RE using (12) **Step 17:** Update the weights using (13) **Step 18:** **End for** **Step 19:** Initialize the population of the weights using (14) **Step 20:** **for each** weight ' w_k'

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4773-4786

Step 21: Compute the fitness '$fitness(w_k)$' using (15)
Step 22: **End for**
Step 23: Select current best using (16)
Step 24: While (t < Max_t) **do**
Step 25: Generate new location using (17)
Step 26: Check Seasonal Monitoring Condition using (18)
Step 27: $\boldsymbol{if}$ ($\delta < \delta_{min}$) **then**
Step 28: Relocate the search space
Step 29: Obtain the optimal weight
Step 30: **else**
Step 31: $t = t + 1$
Step 32: go to step 24
Step 33: **End if**
Step 34: **End while**
Step 35: Return (optimal solution)
Step 36: Process the entire structures
Step 37: **Obtain** final classification results at output layer **using (20)**
End

Algorithm 2 describes a step by step process of transfer learning–based model designed to enhance human activity recognition accuracy while minimizing error rate. The proposed method initiates by selecting a set of training samples, which are provided as inputs to the new denseCNN model. For each input data sample, data preprocessing is carried to clean the raw dataset. Followed by, significant features are selected for accurate classification. Finally, the matching coefficient is employed for classifying the various activities of disabled peoples. For each classified results, recognition error is computed. Based on error, the weight values get updated. To enhance accuracy and reduce restoration error, a squirrel search algorithm is utilized. This algorithm determines an optimal weight values based on fitness evaluation. Followed by, different behavioral mechanisms are evaluated. This process gets iterated and refined until reaches the predefined maximum number of iterations. Finally, optimal weight is then applied to improve the accuracy of human activity recognition for disabled persons.

4. Experimental Setup

An experimental analysis of the proposed GTDTL model and baseline deep learning methods, namely RFiDAR system [1] and TransTM [2] are implemented using the Python programming high level programming language with RFID-Datasets taken from https://github.com/care-group/RFID-Datasets. The RFID dataset contains a total of 25,924 snapshots of data, where snapshots were recorded at a rate of one snapshot per second. This therefore represents around 7 hours and 12 minutes of raw data. In the CSV and ARFF files of the RFID data, there are 196 features and other features such as activity, location, participant ID, and timestamp for each participant. The data is collected from 6 different participants (i.e. disabled peoples) linearly over time.

4.1 Implementation results

The GTDTL model is extensively analyzed to estimate its efficiency in analyzing disabled person movement issue detection. The evaluation includes several key stages, including RFID tag data acquisition, preprocessing, feature selection, and classification, utilizing the RFID-Datasets taken from github repository. Initially, the numbers of RFID tag data are collected from the dataset as shown in figure 4.

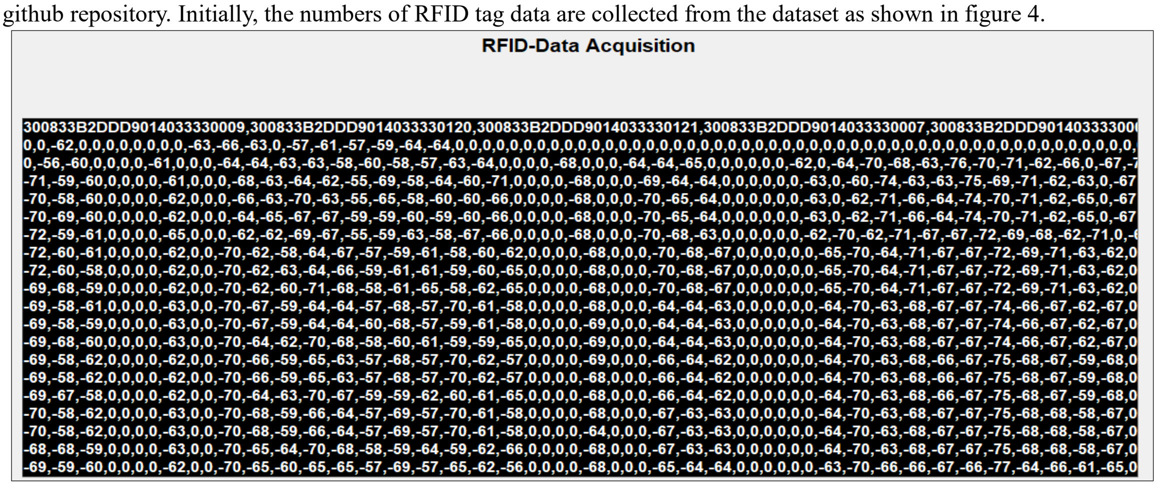

Figure 4 RFID tag data acquisition

The dataset consists of 12 different activities and includes a total of 25,924 data snapshots as shown in figure 5.

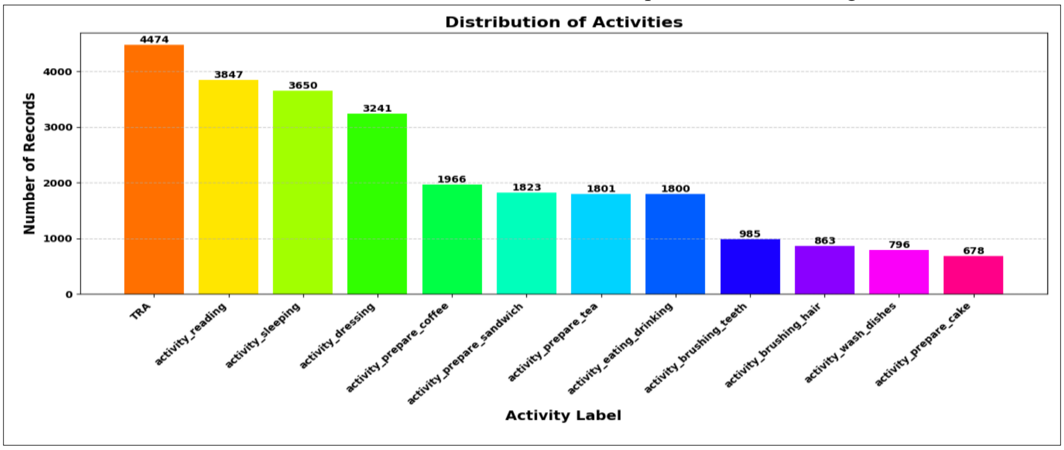

Figure 5 class activity distributions

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4773-4786

The figure 5 illustrates the distribution of activity labels in the dataset. Following RFID tag data acquisition, preprocessing step is carried out, including missing values handing and outlier's removal. The dataset size after missing data imputation was 16,999KB, which was reduced to 14,102KB after outlier removal. The preprocessing results are shown in figure 5.

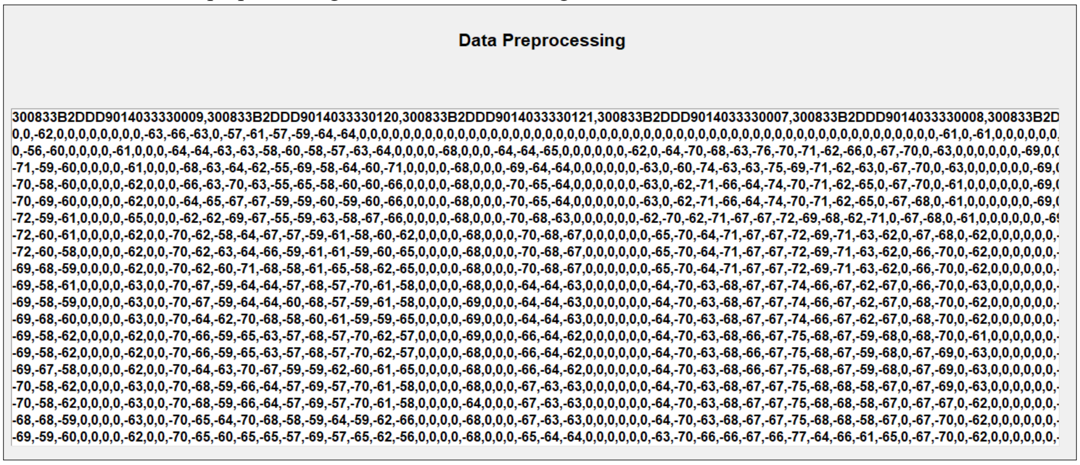

Figure 6 data preprocessing

After the RFID tag data preprocessing, the GTDTL model performs the dimensionality reduction process using the two segment regression algorithm to discover and preserve the most pertinent features while discarding others. Based on calculated similarity values, the model selects 103 key features from 200 attributes for accurate classification. In the final stage, the GTDTL model performs the activity detection of disabled peoples using RFID tag information's using simple matching coefficient with selected features.

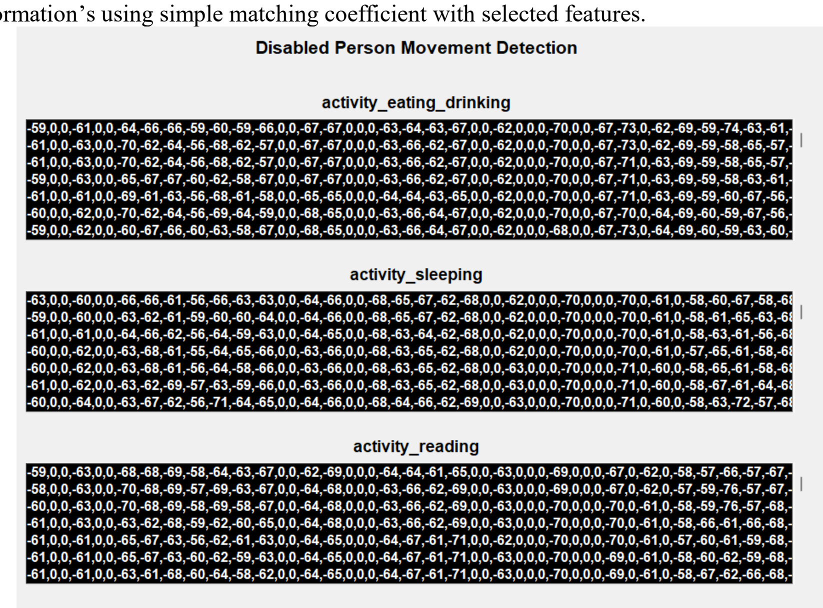

Figure 7 disabled people's movement detection

5. **Performance analyses of different methods**

This section presents a relative performance examination of different approaches, including the proposed GTDTL model and existing methods referenced in RFiDAR system [1] and TransTM [2]. The assessment is conducted using numerous performance metrics, such as accuracy, precision, sensitivity, F1-score, and recognition time. These metrics are used to comprehensively evaluate the efficiency of each method. The results of the analysis are presented with the help of both tabular data and graphical visualizations to provide a clear assessment and better explanation of the different approaches.

Accuracy: It measures a performance of model correctly classify activities of disabled persons based on collected data (e.g., from RFID tag). It refers to the ratio of correctly predicted labels to the total number of data samples collected from the RFID tag dataset. It is calculated using the following formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} * 100 \qquad (21)$$

Where, TP (True Positive) indicates correctly recognized activities of disabled persons, TN (True Negative) indicates correctly recognized that a certain activity was not occurrence, FP (False Positive) represents an incorrectly recognized an activity, FN (False Negative) represents the system fails to distinguish an activity that truly take place.

Precision: it is a key performance metric that measures the quality of positive detection made by the recognition model. It refers to the proportion of correct positive predictions out of all positive predictions. The overall precision is formulated as follows,

$$Precision = \frac{TP}{TP+FP} \qquad (22)$$

Where, TP (True Positive) indicates correctly recognized activity, FP (False Positive) denotes an incorrectly recognized activity.

Sensitivity: it also measures the system's capability to distinguish all actual data samples of a particular activity. The overall sensitivity of the model is mathematically expressed as follows,

$$Sensitivity = \frac{TP}{TP+FN} \qquad (23)$$

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4773-4786

Where, Re TP (True Positive) indicates correctly recognized, FN (False negative) denotes the system failed to detect the activity that truly happened.

F1 score: it is a metric that incorporates both precision as well as recall into a single value providing a reasonable measure of a model's performance.

$$F1\ score = 2 * \left[\frac{Precision*Sensitivity}{Precision+Sensitivity}\right] \quad (24)$$

Specificity: It computes the model's ability to efficiently distinguish negative. It measures the capacity of the model to correctly recognize negative instances and is calculated as the ratio of true negatives to the sum of true negatives and false positives.

$$Specificity = \frac{TN}{TN+FP} \quad (25)$$

Where, 'TN denotes a true negative and'FP' indicates a false positive.

Recognition time: it refers to the amount of time consumed by algorithm to perform movement detection of disabled people. It includes the overall time consumption is mathematically expressed as follows

$$RT = \sum_{i=1}^{n} S_i * TME[AD] \quad (26)$$

Where, RT indicates a Recognition time, S indciates a number of data samples, $TME[AD]$ indicates a activity detection of time consumption of disabled peoples. It is measured in terms of seconds (sec).

Table 1 Comparison of Accuracy

Number of RFID data samples	Accuracy (%)		
	Proposed GTDTL	Existing RFiDAR system [1]	Existing TransTM [2]
2500	97.2	94	92.4
5000	97.33	93.85	92.28
7500	97.58	93.86	92.33
10000	98.02	94.03	92.45
12500	97.41	94.23	92.63
15000	97.85	93.65	92.54
17500	97.22	93.44	92.77
20000	97.67	93.85	92.74
22500	97.58	94.08	93.03
25000	97.68	94.12	92.74

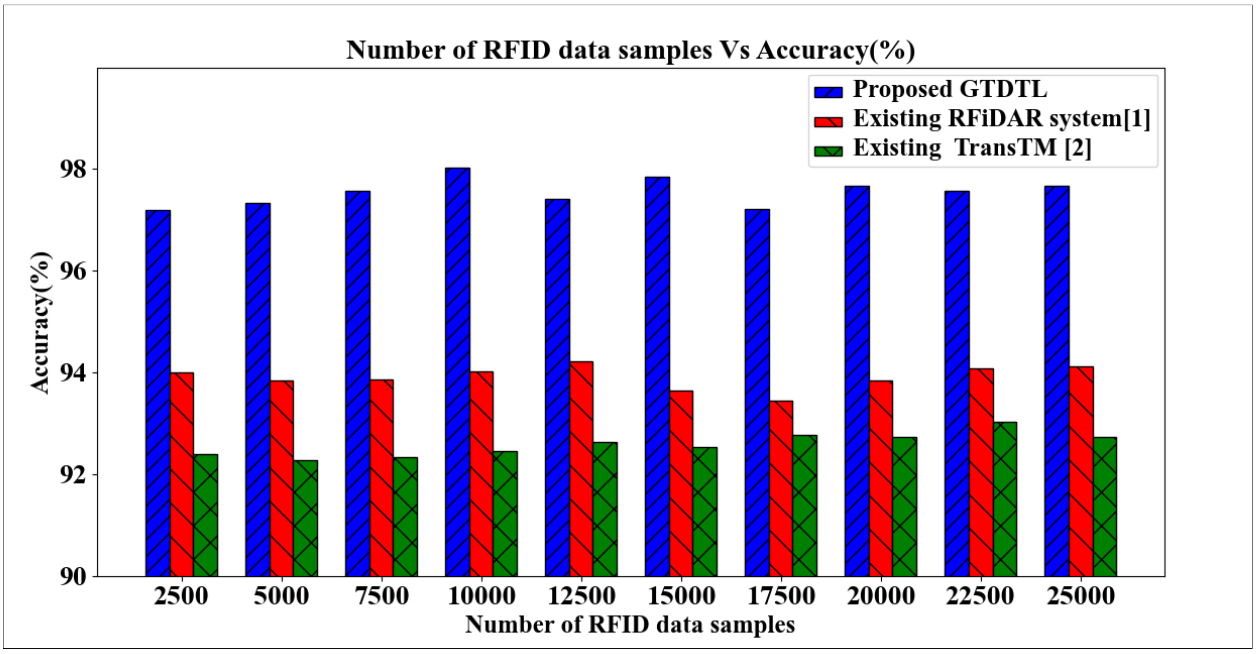

Figure 8 graphical chart of accuracy comparison

Figure 8 reveals the accuracy of detecting the accuracy versus number of RFID data samples about the disabled peoples varying from 2500 to 25000, as collected from the dataset. As revealed in figure 8, the number of sample data represented in horizontal direction, while the vertical axis demonstrates the corresponding accuracy of movement detection. The graph illustrates that the proposed GTDTL model outperforms the existing approaches namely RFiDAR system [1] and TransTM [2] respectively. Let us consider the input RFID data samples of 2500 in the first iteration. By applying the GTDTL model, enhanced accuracy of activity detection is found to be 97.2%. In comparison, the accuracy of the existing methods [1] and [2] are observed to be 94% and 92.4%, respectively. Similarly, ten different outcomes are observed and compared. This improved performance is achieved owing to the application of a deep transfer learning approach. This model analyzes both training and testing data samples by applying the Dense CNN model using simple matching coefficient. By transferring the knowledge from a pre-trained model of deep transfer learning approach, Dense CNN model efficiently processes RFID tag feature vectors, leading to improved accuracy in detecting the activities of the disabled peoples in various locations at different time instance's. The fine tuning process of Dense CNN model minimizes the false positive and false negative performance results in activity detection. Therefore, average of these ten evaluation results illustrate that the accuracy of the GTDTL model improved approximately by 4% and 5% when compared to existing methods [1] and [2], respectively.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4773-4786

Table 2 Comparison of precision

Number of RFID data samples	precision		
	Proposed GTDTL	Existing RFiDAR system [1]	Existing TransTM [2]
2500	0.967	0.935	0.922
5000	0.965	0.933	0.92
7500	0.966	0.935	0.921
10000	0.97	0.942	0.925
12500	0.963	0.946	0.928
15000	0.974	0.939	0.922
17500	0.977	0.936	0.926
20000	0.976	0.935	0.924
22500	0.968	0.944	0.921
25000	0.966	0.943	0.922

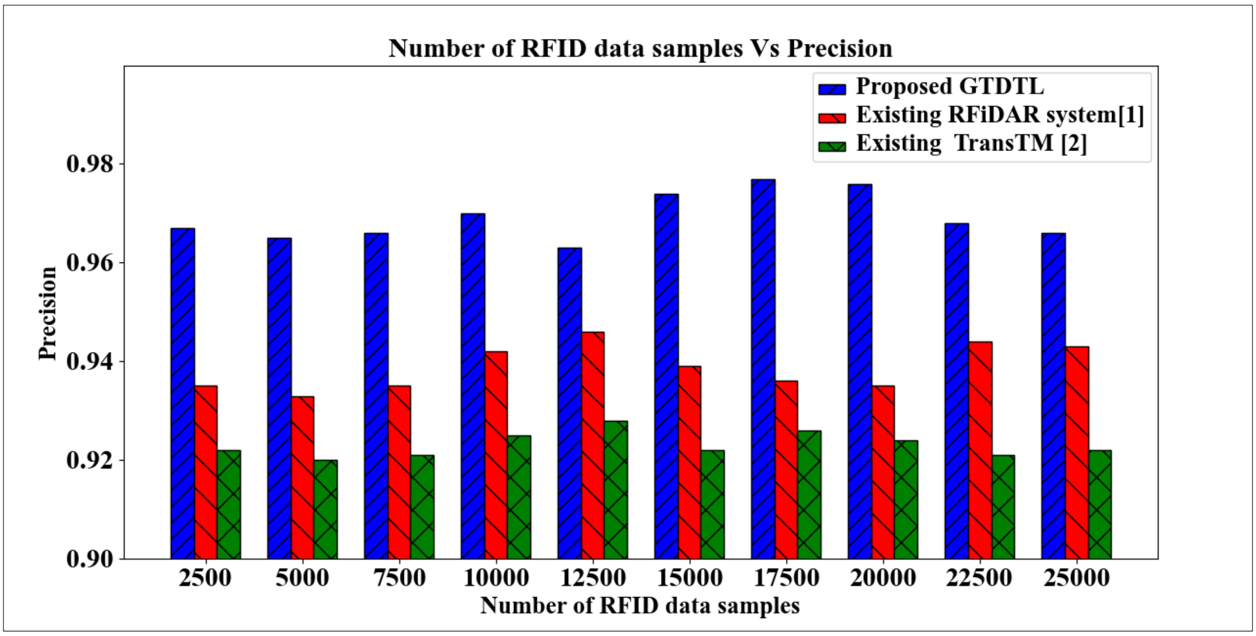

Figure 9 graphical chart of precision comparison

Figure 9 symbolizes the graphical chart consequences of the precision in activity detection using three various deep learning methods namely GTDTL model outperforms the existing approaches namely RFiDAR system [1] and TransTM [2] based on a dataset of RFID tag information. In the chart, the horizontal axis indicates the number of data samples, while the vertical axis specifies the precision output. The overall upshots reveal that the precision performance of GTDTL model outperforms is better than that of existing methods [1] and [2]. Considering RFID tag data samples of 2500, the GTDTL model achieved a precision of 0.967%. The other two conventional methods [1] and [2] observed the precision of 0.935 and 0.922 respectively. . This upgrading performance is achieved by applying a GTDTL model to effectively investigate the RFID tag features vectors in the hidden layer of DenseCNN by employing matching coefficient and offer superior results. In addition, the squirrel search algorithm is employed to refine the DenseCNN layers, aiming to decreasing the errors during activity detection. This approach considerably enhances accuracy by achieving high true positive rate and decrease false positive, thereby increasing the precision. Therefore, the comparison of these results demonstrates that GTDTL model increases the precision approximately by 3% and 5% when compared to existing methods [1] and [2], respectively.

Table 3 Comparison of sensitivity

Number of RFID data samples	sensitivity		
	Proposed GTDTL	Existing RFiDAR system [1]	Existing TransTM [2]
2500	0.986	0.966	0.953
5000	0.984	0.965	0.952
7500	0.983	0.97	0.95
10000	0.985	0.968	0.949
12500	0.983	0.965	0.946
15000	0.988	0.962	0.948
17500	0.984	0.963	0.947
20000	0.988	0.967	0.944
22500	0.989	0.968	0.945
25000	0.988	0.969	0.952

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4773-4786

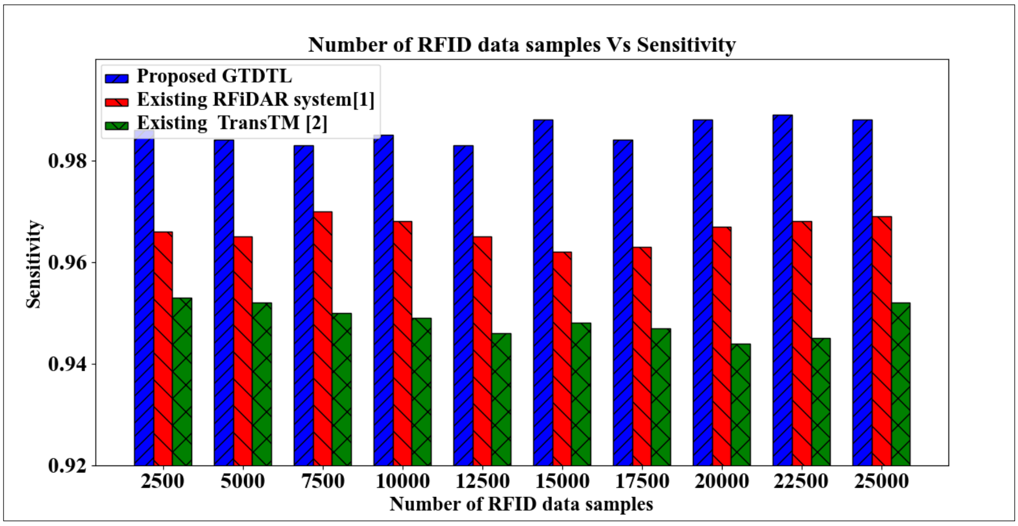

Figure 10 graphical chart of sensitivity comparison

Figure 10 reveals the performance effects of sensitivity regarding number of data samples ranges from 2500 to 25000 collected from the RFID tag dataset. The performance analysis of the sensitivity is examined through three dissimilar deep learning methods namely GTDTL model existing approaches namely RFiDAR system [1] and TransTM [2]. Among three different methods, the GTDTL model displays a visible development in sensitivity performance compared to existing methods [1] and [2]. For instance, 2500 RFID tag data samples are considered in first iteration, the performance of sensitivity using GTDTL model is found to be 0.986, the recall values of 0.966 and 0.953 are recorded using [1] and [2], respectively. For each method, dissimilar performance results are observed about different numbers of input RFID tag data samples. The overall observed results of the GTDTL model are compared to the existing methods. This development is achieved by applying robust fine-tuning process in deep transfer learning model. By employing a DenseCNN, the model reduces the squared error between predicted and actual outcomes through optimal hyperparameter selection using squirrel search optimization. This iterative process continues until attained minimal error, directing to reduce in false-negative rates and enhance in true positive outcomes for increasing the accuracy. The comparison consequences shows that the performance of the sensitivity using GTDTL model is considerably improved by 2% and 4% compared to [1] and [2], respectively.

Table 4 Comparison of F1 score

Number of RFID data samples	F1 score		
	Proposed GTDTL	Existing RFiDAR system [1]	Existing TransTM [2]
2500	0.976	0.950	0.937
5000	0.974	0.948	0.935
7500	0.974	0.952	0.935
10000	0.977	0.954	0.936
12500	0.972	0.955	0.936
15000	0.980	0.950	0.934
17500	0.980	0.949	0.936
20000	0.981	0.950	0.933
22500	0.978	0.955	0.932
25000	0.976	0.955	0.936

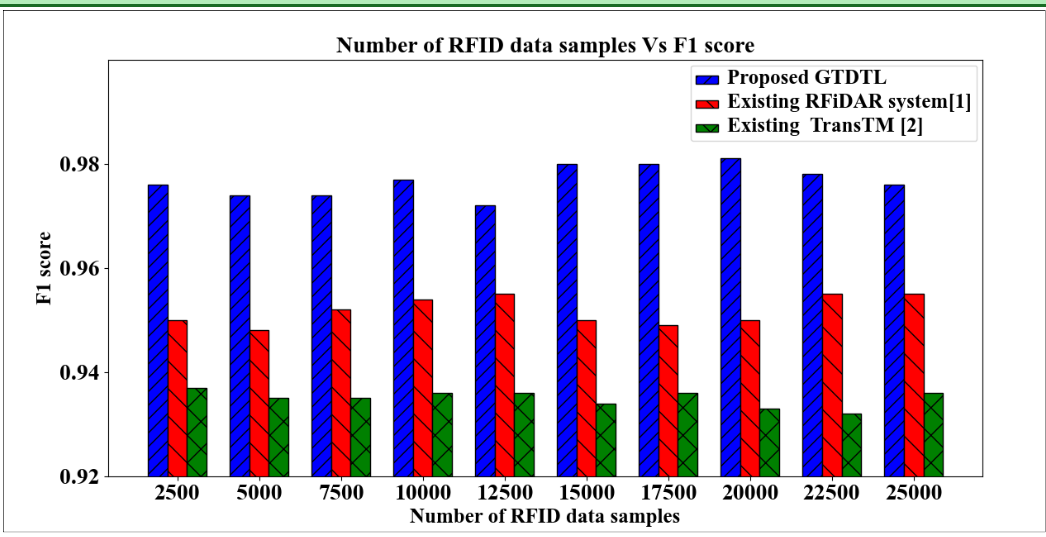

Figure 11 graphical chart of F1 score comparison

Figure 11 illustrates the performance of graphical chart of F1-score by varying numbers of data samples ranges from 2500 to 25000 by implementing three models namely the proposed GTDTL model existing approaches namely RFiDAR system [1] and TransTM [2]. The F1-score offers as a harmonic mean of precision as well as recall, providing a reasonable evaluation of the model's efficiency. The improved performance of the GTDTL model is accomplished due to the integration of a deep transfer learning strategy, which precisely performs the activity recognition. Overall, the relative results emphasize that the GTDTL model achieves an improvement in F1-score of approximately 3% compared to [1] and 4% compared to [2].

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4773-4786

Table 5 Comparison of specificity

Number of RFID data samples	specificity		
	Proposed GTDTL	Existing RFiDAR system [1]	Existing TransTM [2]
2500	0.95	0.9	0.88
5000	0.945	0.896	0.875
7500	0.944	0.898	0.874
10000	0.942	0.902	0.882
12500	0.94	0.906	0.884
15000	0.938	0.905	0.887
17500	0.936	0.904	0.885
20000	0.935	0.901	0.888
22500	0.937	0.899	0.887
25000	0.938	0.898	0.886

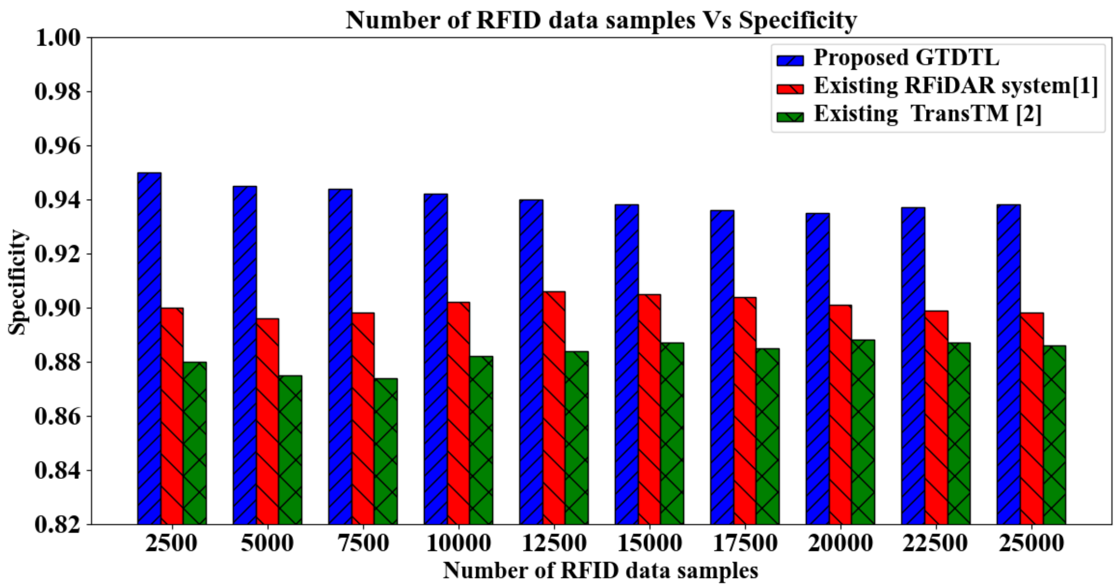

Figure 12 graphical chart of specificity comparison

Figure 12 exhibits a chart analysis of specificity performance against different samples sizes, ranging from 2500 to 25000. The specificity values are estimated using the proposed GTDTL model and compared with two existing methods, [1] and [2]. In this chart, the horizontal direction designates the number of different samples obtained from the dataset, while the vertical axis reflects the equivalent specificity. The experimental consequences disclose that GTDTL model delivers higher specificity than the other two approaches. For example, in the initial evaluation with 2500 RFID tag data samples, the GTDTL model achieved a specificity of 0.95, while methods [1] and [2] recorded 0.9 and 0.88, respectively. This development is achieved due to model's advanced feature analysis capabilities enabled by the transfer learning, which enhances the activity detection of true negatives and reduces false positives, thereby increasing the overall accuracy. At last, the average across ten runs, the GTDTL model demonstrated an improvement in specificity of approximately by 4% than [1] and 7% than [2].

Table 6 Comparison of recognition time

Number of RFID data samples	Recognition time (seconds)		
	Proposed GTDTL	Existing RFiDAR system [1]	Existing TransTM [2]
2500	57.5	65	72.5
5000	60.3	68.3	75.9
7500	65.2	70.5	80.4
10000	68.2	75.2	90.7
12500	72.8	78.6	92.6
15000	80.6	89.4	95.6
17500	88.3	95.4	106.5
20000	92.1	103.5	112.4
22500	105.6	116.4	126.8
25000	116.5	127.9	133.7

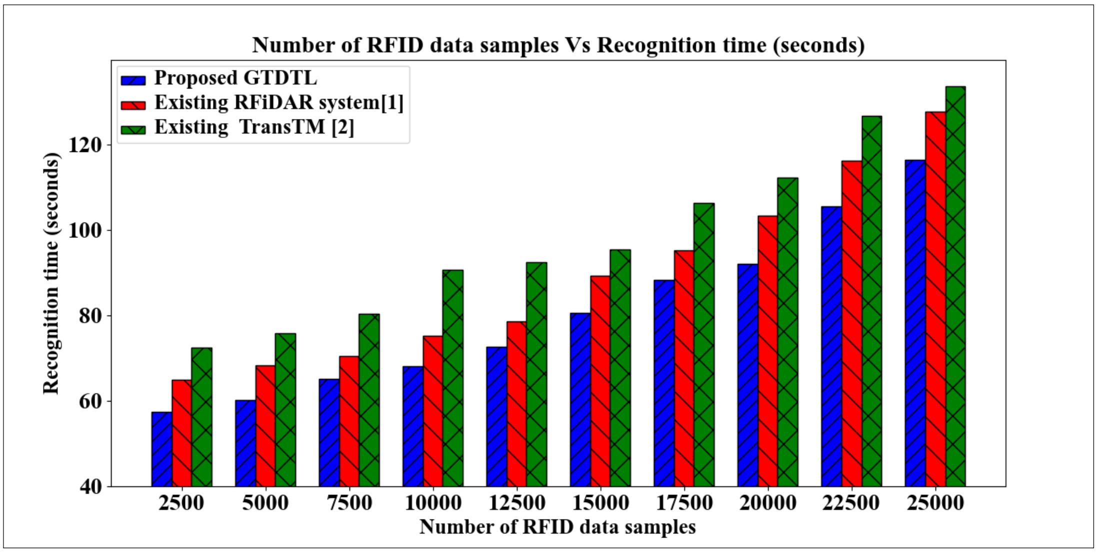

Figure 13 graphical chart of recognition time comparison

Figure 13 demonstrates the performance outcomes of recognition time using three models namely the proposed GTDTL model existing approaches namely RFiDAR system [1] and TransTM [2]. Each model is estimated over ten experiment runs, using a data of 25000 unique RFID tag data samples. As disclosed in the figure 13, recognition time of all three methods gets increased while enhancing the number of data samples. However, in a specific trial with 25000 RFID tag data samples, the GTDTL model consumed only $57.5sec$, while [1] and [2] consumed $65sec$ and $72.5sec$, respectively. The efficiency of the GTDTL model is achieved due to its integrated data preprocessing and important feature selection method. Specifically, it employs the two segment regressions to determine and preserve the more significant features while removing the irrelevant features. This efficient reduction in feature space significantly reduces the activity recognition time. Finally, the overall result emphasize that the GTDTL model reduced the performance of recognition time by 9% and 19% when compared to the existing approaches.

6. Conclusion

This paper proposed a disabled person movement issue detection task of collecting RFID data with the help of IoHT device through the GTDTL model. The proposed deep learning GTDTL model is employed for accurate multi-classification of disabled person activity detection. In GTDTL model, the transfer learning model initiates the data preprocessing and the selection of important features from the RFID dataset, aiming to minimizing the overall time required for activity detection. This GTDTL model employs the model's capability to transfer learned knowledge, enabling efficient analysis of RFID tag features using matching coefficient to enhance the accuracy of the model. Moreover, error rate is further minimized through fine-tuning process related with activity detection. A comprehensive statistical assessment is carried out using several performance metrics, such as accuracy, precision, sensitivity, F1-score, specificity, and time. The experimental outcomes expose that the GTDTL model consistently outperforms conventional deep learning approaches by achieving higher accuracy, faster times, and lesser error rates.

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