Ambient Assisted Living for Enhanced Elderly and Differently Abled Care: A Novel Attention Transfer Learning-based Crossover Chimp Optimization

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ABSTRACT

Ambient assisted living (AAL) is a groundbreaking approach that harnesses the power of smart technology to offer all-encompassing care and support for elderly and differently abled individuals in their day-to-day lives. Progressive innovation in AAL solutions can facilitate and support day-to-day routines, expanding the time they can live autonomously and supporting proficiency. This research mainly analyzes AAL’s significant role in tending to the exceptional difficulties these populations face. AAL frameworks incorporate an array of sensors, gadgets, and intelligent calculations that help monitor current circumstances and exercises, empowering early recognition of peculiarities, fall counteraction, and customized help. This research introduces a novel attention transfer learning-based crossover chimp (ATL-CC) algorithm for AAL, which combines crossover-based chimp optimization with a transformer-based model for transfer learning, integrating an attention mechanism. The ATL-CC algorithm aims to enhance activity recognition and classification within AAL environments. Precision, accuracy, recall, root mean square error, and F1-score are evaluated, where accuracy attains the value of 98.9%, precision attains the value of 97.4%, recall attains the value of 98%, and F1-score attains the value of 96%. Overall, AAL arises as a promising arrangement that upholds the deprived and advances respect, independence, and inclusivity in maturing and various societies.

KEYWORDS

ambient assisted living, transfer learning, crossover chimp optimization, attention, sensors

INTRODUCTION

In recent years, smart environments have become increasingly popular and widely applied in various contexts, such as training, recovery, domotic, and help (Ahmed et al., 2022). These days, machine learning (ML) and artificial intelligence (AI) applications are in several domains (Abidi et al., 2020a,b, 2022a,b). Human action recognition (HAR) assists with figuring out human activities through the programmed analysis of various information carried out using different kinds of sensors. This mainly focuses on the investigation of information by utilizing a few equipment gadgets (e.g. RGB-D gadgets, inertial sensors, RGB cameras) and is completed with plenty of computerized reasoning, such as AI (Patro et al., 2021). The concept is to help human vocations by presenting assistive innovations. This helps in resolving issues, for example, further development, checking ongoing disease, and social confinement, by offering coordinated types of assistance that might be associated with the Internet of Things (IoT) (Ranieri et al., 2021). Both researchers and industry have proposed different living frameworks for indoor conditions (Achirei et al., 2022). Such frameworks usually integrate sensors, actuators, regulators, data and information and communication technologies (ICTs), and other assistive innovations. With improvements in portable devices like smartwatches, mobile phones, and tablets, the chances of applying current innovations are growing, and the advancement of home help frameworks is getting to the next level (Žaric et al., 2021). Advances in technology are now a necessary and fundamental part of modern life. It helps influence regular updates in daily existence and work. The most significant advantage is that it assists with daily work. Furthermore, technology plays a vital role in social consideration and healthcare. Here, an individual’s day-to-day living and working zone because of ICTs assists in empowering them to remain significantly longer, be socially associated, and live autonomously into advanced age (Patro et al., 2021).

Despite recent advances in ambient assisted living (AAL), while considering the improvement of intelligent home
innovations, various difficulties remain. These difficulties are principally based on the absence of true testing and functionalities in the structures for recognizing the falls and the indoor areas synchronously (Cascone et al., 2022). On the other hand, actimetry is also known as actigraphy, and it is characterized as the assessment of an individual’s active work through the discovery of body development. This makes it conceivable to screen an individual’s action through light and development sensors (Taramasco et al., 2022). The motivation for this research work stems from the interest in fostering our day-to-day way of living and improving healthcare. Nowadays, medical care administrations are more well-known due to population growth, focusing on more patients in our current and static superb medical services frameworks (Patro et al., 2021). As innovation keeps on improving, the collaboration between AAL and deep learning (DL) offers a promising pathway to address the developing requirements of weak populations, permitting them to keep up with their freedom and association with a more extensive local area (Patiño-Saucedo et al., 2022). The key contributions of the proposed approach are listed below:

- In order to develop an effective AAL environment for the elderly to monitor the health of the disabled and older people, this research work develops an effective attention transfer learning-based crossover chimp (ATL-CC) methodology to classify day-to-day activities and create alerts in emergency contexts.
- Utilizing various sensors, data are collected and key features are extracted. The activity classification from the collected data is performed using the ATL-CC algorithm.
- The classified outputs are sent to the visualization layer, where decision-making is performed, and alerts are made if any emergency scenario is detected.
- Extensive experiments were conducted by obtaining inputs from the KU-HAR dataset, which comprises several day-to-day activities, and evaluation was performed using various metrics, such as recall, accuracy, precision, and F1-score, to prove the model’s effectiveness.

The remainder of the paper is organized as follows. The connected works of AAL are addressed in the next section. The Proposed Methodology section explains the proposed methodology of the AAL analysis. The evaluation outcomes are discussed in the Results and Discussion section. Finally, the conclusion remarks are given in the final section.

RELATED STUDIES

This section presents the research work available in the domain of AAL using ML and similar techniques. Patro et al. (2021) developed an AAL based on DL to monitor cardiovascular conditions automatically. Annually, over 17.7 million deaths are caused by cardiovascular diseases across the world, according to the World Health Organization. Older people were more affected by these diseases. The solutions were developed with emerging communication mechanisms like AAL. Among these, the most preferred solution was wearable devices, which ensured telemedicine and remote patient monitoring. The working of AAL in the case of cardiovascular diseases affected patients. This article had four sections: cardiovascular disease detection using DL, mechanisms for managing clinicians, AAL for elderly people, and self-monitoring wearable devices. The advantages and limitations of the AAL were studied in this work. The need for healthcare systems and caregivers can be reduced according to this work.

Thakur and Han (2021) established an indoor localization to create a customized AAL for users in multi-floor smart circumstances. This article proposes a multifunctional interdisciplinary architecture to provide the various requirements of older people in smart living circumstances. This architecture provided four contributions to creating a customized AAL. A mathematical method based on probabilistic reasoning was proposed for creating user interaction. Then, an ML technique was proposed for creating separate user profiles. After that, a new technique was proposed for indoor localization that utilizes the Gradient Boosting algorithm and the AdaBoost algorithm. Finally, to enhance indoor localization, two new functionalities were proposed. From the experiments conducted, it was known that the proposed architecture outperformed the existing methods in terms of performance and functional characteristics. No practical experiments were performed, which was a limitation of this work.

Cascone et al. (2022) employed digital twinning Pepper to create an AAL. Pepper was one of the humanoid robots capable of interacting with humans and expressing body language using many sensors. An advanced VPepper using the interaction of digital twins with the smart home’s smart objects was proposed in this paper. The movements of the Pepper robot were controlled using the digital twin metaphor. The experiments showed that the proposed method performed well in assisting elderly people by safely touching people and objects.

Gulati and Kaur (2022) developed an alert generation mechanism based on robust social IoT. The quality of life of independent elderly people was enhanced with the use of modern communication mechanisms, such as the IoT in the AAL scenario. The social link between smart devices was not efficiently created by the contemporary solutions for AAL based on IoT. A robust AAL system based on IoT known as FriendCare-AAL for older people was proposed in this article. This system could assist older people at home and create alerts for emergencies. For forecasting the health conditions of elderly people by evaluating the data, two ML models, namely random forest (RF) and Naïve Bayes (NB), were used. The evaluation results showed that RF, with an accuracy of 89.2%, outperformed NB, with an accuracy of 83.9%. The two limitations of the proposed system were reliability and scalability.

Rupasinghe and Maduranga (2022) developed an elderly movement monitoring system based on IoT. For tracking the daily activities of older people utilizing the data sensed by the accelerometer sensor, this article designed and developed a mechanism based on the IoT. The objective of this research was to monitor the daily activities of elderly people who were living independently and in isolated regions. The applications based on IoT and the cloud were mainly used.
in the field of real-time monitoring. Hardware elements like NodeMCU were used to create a cost-efficient mechanism. A wrist-worn device that can track the movements at a low cost was present in this mechanism. ML techniques were used in this work to recognize four different types of movements. The proposed mechanism with the decision classifier tree algorithm attained an accuracy of 80%. However, only a limited number of activities were monitored by this mechanism.

Patro et al. (2021) developed an AAL predictive model to predict cardiovascular diseases utilizing supervised learning. One of the critical topics among many researchers across the world was the increasing number of older people and maintaining their health. A significant chronic disease that occurs repeatedly is the heart disease. The timely identification of heart diseases was an essential measure to be taken. IoT was one of the important technologies used to solve the heart disease issue. Various classifiers were used to build an architecture for forecasting heart diseases. The classifiers used were Lasso and ridge regression, NB, K-nearest neighbors, and support vector machine algorithms. The support vector machine outperformed other classification algorithms and attained an F1 accuracy of 85% and an accuracy of 92%. This work failed to connect this architecture with other smart devices.

Ghadi et al. (2022) employed a deep-learning classifier to enhance AAL. Over the past few years, one of the important types of research has been the development of an AAL for assisting older people living independently in remote areas. The prime technology used for enhancing the quality of life of these older people was the AAL. The research work proposed a novel AAL solution using convolutional neural network (CNN) and hybrid BiLSTM techniques. The human gait database (HuGaDB) benchmark dataset was used to evaluate the performance of the proposed system. From the evaluation results, it was known that the proposed system attained an accuracy of 93.95%. Only a limited number of hyperparameters were explored in this work.

Sarabia-Jácome et al. (2020) established an AAL fall detection mechanism based on highly efficient fog. One of the common issues among elderly people is the fall. The traditional AAL depends on ML, the IoT, and cloud computing technologies. DL has proved to be effective in fall detection in recent times. In ML-based fall detection, fog devices were used to reduce the limitations of clouds, such as network delay. This research work proposes an efficient fog-cloud computing-based smart system using DL techniques with fog devices. The data of patients were collected using a wearable tri-axial accelerometer. The proposed fall detection mechanism proved its effectiveness in various metrics like lower delay, enhancement in service, and an accuracy of 98.75%.

Research gap

Creating an AAL is an important process to enhance the lives of the elderly and disabled people living independently. This helps in the reduction of the usage of manpower in healthcare. Some limitations are identified while evaluating existing methods like AdaBoost, Bi-LSTM-CNN, support vector machine (SVM), and decision tree (DT). To solve these limitations, an ATL-CC algorithm is proposed in this paper. The following subsections describe the research gaps in this work:

Scalability and reliability

Scalability and reliability are important challenges found in the existing method. These issues in healthcare can lead to wrong predictions and cause emergency conditions. The proposed ATL-CC uses effective preprocessing and feature selection methodologies to solve these issues and enhance input data quality.

Detection of limited activities

Only a limited number of activities can be identified using the existing techniques. The proposed ATL-CC contains various advancements and supports the identification of a large number of activities in the AAL.

Computational time

The time used for computation by the existing methods is large due to the complex preprocessing and feature extraction techniques. The proposed ATL-CC contains simple and efficient preprocessing methods, feature extraction techniques, and an optimization algorithm, which helps in easy computation and reduces the time for computation.

PROPOSED METHODOLOGY

An ATL-CC method is developed to create AAL for the elderly and disabled persons. This method aims to analyze the signals obtained from the activities of elderly or disabled persons and provide an alert message during an emergency. Figure 1 shows the overall architecture of the proposed method. This proposed method consists of three layers, namely the sensing layer, the data processing layer, and the visualization layer. In the sensing layer, the input is collected from the KU-HAR dataset. Then, the data are processed in the processing layer, which consists of three components: data preprocessing, feature extraction, and the classification algorithm. First, the input data are preprocessed to increase accuracy and reliability; then, feature extraction is performed to convert the raw data into numerical features. After that, the data are classified to obtain the appropriate data using the ATL-CC algorithm. The classified output is then sent to the visualization layer, where the output analysis takes place to determine the condition of the elderly or disabled persons in a short time interval. This layer creates an alert message if any emergency condition is detected from the classified output.
Sensing layer

The sensing layer is the first layer present in the proposed method; this layer contains four sensors for sensing the activities of the elderly or disabled people. The sensors used are the accelerometer, biosensors, motion sensors, and proximity sensors. The accelerometer sensor is used to measure the acceleration of any moving object (elderly or disabled people). The biosensors are used to monitor the presence of biological components like antibodies, enzymes, and biomass. The motion sensor is used to detect nearby objects, people, or the motion of patients. The final sensor is the proximity sensor, which oversees the elderly or disabled people’s movements. The data obtained from the sensors are collected in this layer and sent for preprocessing.

Data processing layer

The data processing layer in AAL is the essential framework that assists with playing out the persistent activity of a shrewd environment intended to improve personal satisfaction for diversely abled people. This layer is probably the operational hub, gathering, dissecting, and changing raw information from sensors, gadgets, and connection points dispersed all through the living space.

Data preprocessing

The information related to the preprocessing layer is intended to upgrade the quality and convenience of the huge array of information produced by the bunch of sensors and gadgets in AAL surroundings. This layer helps to steadily filter, standardize, and structure the approaching information. Duplication elimination, data cleaning, and noise removal are some techniques used depending on the data processing layer.

Duplication elimination

In AAL systems, data management includes eliminating duplicates. In this method, sensors and devices gather various data from various sources, including movement sensors, temperature sensors, and health monitoring. These sensors may result in less efficiency in data processing analysis, which tends to produce data points that are either redundant or overlapping. This plays a major role in maintaining enormous data within AAL frameworks and helps in permitting more precise and viable checking of occupants’ day-to-day routines.

Data cleaning

Data cleaning is essential in AAL systems, where the amount of information collected directly impacts the system’s ability...
to support residents. Data cleaning in AAL includes a progression of cycles like data imputation, missing information ascription, and error correction. To fully utilize the potential of AAL technology to assist and empower individuals in their day-to-day lives, efficient data cleaning is essential.

Noise removal

Noise removal is an urgent part of information preprocessing in AAL frameworks. AAL conditions are outfitted with different sensors and gadgets that constantly gather information connected with occupants’ exercises and environmental factors. Noise removal in AAL expects to upgrade information quality and dependability, which are fundamental for precise examination and navigation.

Feature extraction and classification

It is the process of converting raw data into numerical features without any loss of information from the original dataset. Choosing appropriate information from the obtained sensor data takes place in this process. Movement patterns, heart rate variability, and changes in temperature are the features mainly extracted and used in the field of AAL. Feature extraction sometimes causes high-dimensional feature space that creates overfitting and increases the expense of computation. Reduction methods, such as t-distributed stochastic neighbor embedding or principal component analysis, are used to reduce the number of features without losing important data. Then, from the features extracted, the activities of the patients are classified using the classification algorithms; these activities are important for AAL. The unusual activities (anomalies) identified represent the emergency, and based on this, the system creates an alert message. These methods play an important role in the improvement of the lives of elderly or disabled people who are living independently.

Transfer learning

Transfer learning was utilized with the end goal of having vision transformer models preprepared as a beginning stage to prepare the given dataset (Ayana et al., 2023). For this, we separated the prepared expectation head using the $C \times L$ feed-forward layer; here, $L = 2$ reveals the classes downstream. Using the TL, target function learning is improved in this instance. Here, the target function is indicated as $g(x)$. In the target domain $C_T$, the information from the source area $C_s$ and $L_i$ indicates the learning task. Here, the dataset has $n$ preparing samples $\{(x^1, y^1), \ldots, (x^L, y^L), \ldots, (x^n, y^n)\}$; $y$ and $x$ signify the input of the $j$th iteration. The weights are indicated as $V_q$, are predominantly used as the starting point during the transfer learning process to create $V_i$ by limiting the objective capability in $\langle x^q |v^q,V_o,V_i,a \rangle$ shows the probability of result capability, and $a$ signifies the bias.

$$I((V_i,a|V_o)) = -\frac{1}{nm} \sum_{j=1}^{n} \sum_{i=1}^{m} x^q \log(Q(x^q | y^q, V_o, V_i, a))$$  (1)

This transfer learning paradigm empowers experts to accomplish cutting-edge results with diminished information necessities and computational assets, making models based on Transformers’ applications of AI for natural language understanding and generation.

Chimp optimization

Chimpanzees, in other words, chimps, are one of the two simple African types of incredible apes. The chimps are people’s closest living relatives. The human DNA and chimp DNA are comparable as they slid from a single ancestor that existed a long time back. In order to help chimps in fission-fusion colonies discover the search space with their strategies, an independent group concept was developed that can be useful in different situations. Four kinds of chimps, namely, barri- ers, chasers, attackers, and drivers, are present in the chimp colony. These four have various capacities that aid in an effective hunt. The barriers build a dam and hide in a tree to block the prey’s movement. The chasers swiftly pursue their prey to catch it. The drivers chase it without endeavoring to find it. Finally, the attackers anticipate the break-the-prey routes and push them back toward the chasers. Attackers are rewarded with larger pieces of meat after successful hunting due to their physical ability, age, and intelligence. From the above, it is demonstrated that the chimps chase to get meat in exchange for favors, for example, coalitionary backing, sex, or prepping. Chimpanzees Optimization Algorithm (ChOA) is a social incentive proposed for chimps that causes them to act randomly in the last phase of hunting and is divided into the exploration phase and exploitation phase. The exploration phase comprises obstructing, driving, and pursuing the prey, and the exploitation phase comprises going after the prey. In this numerical model, attacking, driving, blocking, and chasing are introduced. Comparing ChOA calculation is determined. The prey is pursued during both the exploitation and the exploitation and exploration stages (Khishe and Mosavi, 2020).

$$c = |d \cdot y_{prey}(u) - n \cdot y_{chim}(u)|$$  (2)

$$y_{chim}(u + 1) = y_{prey}(u) - b \cdot c,$$  (3)

where $n$ signifies the quantity of current iteration; $b$, $n$, and $d$ indicate coefficient vectors; $y_{prey}$ indicates the position of prey; and $y_{chim}$ signifies the chimps’ vector position. The $b$, $n$, and $d$ vectors are calculated as follows:

$$b = 2 \cdot g \cdot s_1 - g$$  (4)

$$d = 2 \cdot s_2$$  (5)

Here, $n$ indicates the chaotic values, and $s_1$ and $s_2$ demonstrate the arbitrary vectors at the given reach $[0, 1]$. Independent groups of chimps can be modeled mathematically using continuous functions to reduce $g$ during each iteration. The four chimps’ community can be used as an example to look through the issues all around the world. Likewise, different estimations have been estimated, and two inverse adaptations of ChOA with different gatherings, named ChOA1 and ChOA2, are chosen to have the optimal achievement in the underlying advancement issues. In order
to boost ChOA’s efficiency, dynamic coefficients of varying slopes and curves were picked for every autonomous gathering through distinct searching behavior.

**Attacking method (exploitation phase)**

Two attacking methodologies are planned and are given below. Chimps can investigate the prey’s area by impeding, driving, and pursuing. Principally, attacker chimps begin the hunting system, and others, such as specific drivers, barriers, and chasers, take part in this cycle. Overall, four of the best solutions found thus far have been saved, forcing other chimps to adjust their positions according to the locations of the best chimps.

\[
\begin{align*}
e_{\text{Attacker}} &= |d_1 y_{\text{Attacker}} - n_1 y_1|, \\
e_{\text{Barrier}} &= |d_2 y_{\text{Barrier}} - n_2 y_1|,
\end{align*}
\]

where \( d_1, d_2 \) are the slopes at the locations of the best solutions.

\[
\begin{align*}
y_1 &= y_{\text{Attacker}} - b_1(c_{\text{Attacker}}), \\
y_2 &= y_{\text{Barrier}} - b_2(c_{\text{Barrier}}), \\
y_3 &= y_{\text{Chaser}} - b_3(c_{\text{Chaser}}), \\
y_4 &= y_{\text{Driver}} - b_4(c_{\text{Driver}}), \\
y(u + 1) &= \frac{y_1 + y_2 + y_3 + y_4}{4}.
\end{align*}
\]

The position of the prey is assessed through the best of four gatherings, and different chimps arbitrarily update their situation inside their location.

**Prey attacking (utilization)**

As shown above, during the last phase, the chimps go after the prey and complete the chase when the prey quits moving. The operators that have already been presented and the indication show that ChOA gives the chimps the ability to adjust their positions in accordance with the attacker, chaser, driver, and barrier chimps and attack the prey. Also, ChOA will be at enormous risk while catching at local minima; so, different operators are expected to stay away from this challenge. Based on the exploration phase process, the proposed systems are specific to blocking, driving, and chasing mechanisms.

**Searching for prey (exploration)**

To track down the area of the barrier, the attacker, chaser, and driver chimps’ exploration process is carried out. The vector dissects the divergence conduct with an irregular worth \( >1 \) or more modest than \(-1\) is utilized, so the pursuit specialists are compelled to diverge and get far off from prey. In this stage, ChOA powers the chimps to disperse the surroundings to track down a superior prey.

**Social incentive (sexual motivation)**

As referenced previously, resulting in social inspiration and procuring meet, which includes grooming and sex in the last stage, makes chimps discharge their hunting liabilities.

This turbulent conduct in the last stage assists the chimps in encouraging and creating two issues in nearby optima and a slower assembly rate while taking care of high-layered issues. To work on the exhibition of ChOA, chaotic maps have been utilized. ChOA efficacy is enhanced with six chaotic maps, with 0.7 as the primary point and a 50% probability of choosing between normal or chaotic updates.

\[
y_{\text{Chimp}}(u + 1) = \begin{cases} y_{\text{prey}}(u) - b \cdot c & \text{if } \mu < 0.5 \\ \text{Chaotic}_\text{value} & \text{if } \mu < 0.5 \end{cases}
\]

where \( \mu \) signifies the random number between the interval 0 and 1. ChOA uses a stochastic population of chimps to estimate possible prey locations, with \( c \) and \( m \) vectors’ adaptive tuning to reduce the value of \( g \).

**Proposed attention transfer learning-based crossover chimp (ATL-CC) algorithm for AAL**

The proposed ATL-CC algorithm for an AAL system follows the workflow depicted in Figure 2. In this transfer learning system, the transition layer is used to reduce the feature size. After this reduction, the prediction layer predicts the class membership of the unknown data based on the class membership of the training data. The loss function then quantifies the predicted features of the AAL system. If the conditions are not met, the Chimp optimization algorithm is employed to overcome the issue of mismatch classification that can occur during the transfer learning process. The chimp optimization algorithm involves initializing the parameters, creating an initial random solution, and dividing the chimps into individual groups. The fitness values are then calculated; however, the chimp optimization algorithm can flow into local optima. A crossover strategy is employed to overcome this issue. The conditions are then checked, and the output is given; if necessary, the process is repeated.

**Visualization layer**

It is the final layer of the proposed method and the most important decision-making layer. The classified data obtained as the output from the processing layer are processed in this layer. Here, the data related to health, such as movements, biological components, and the changes in the behavior of the elderly or disabled people, are analyzed, and if there is any emergency or unfavorable situation, this layer creates an alert message and sends it to the devices connected with this network. So, the healthcare person or the clinician can help the elderly/disabled at the right time.

**RESULTS AND DISCUSSION**

The effectiveness of the ATL-CC model is analyzed in this section. Some prime metrics of the model, such as accuracy, precision, F1-score, and root mean square error (RMSE) values, are analyzed. The validation of the method is done via
the KU-HAR dataset that includes various day-to-day activities of humans. The obtained outputs are explained below.

### Experimental setup

The experiments are conducted on the Intel Core i5 12th Gen processor 512 GB system with the Windows 11 operating system. This ATL-CC method is implemented on the MATLAB platform.

### Performance measures

In the evaluation of the performance of the ATL-CC algorithm for AAL applications, it is essential to utilize appropriate evaluation metrics to assess its effectiveness in real-world scenarios. The choice of evaluation metrics, including precision, accuracy, recall, F1-score, and RMSE, plays a crucial role in determining the algorithm’s ability to accurately recognize and classify activities, thus ensuring the reliability and efficacy of AAL systems. These are explained below.

#### Accuracy

Accuracy provides the aggregate number of classifications that are correct for all instances. It is the popular performance metric that is widely used to measure activity recognition efficiency. In the context of AAL applications, high accuracy ensures that the algorithm reliably captures the diverse activities performed by elderly and differently abled individuals, thereby supporting personalized assistance and intervention strategies. It is calculated as follows:

$$ A = \frac{Tr_{pos} + Tr_{neg}}{Tr_{pos} + Tr_{neg} + Fa_{pos} + Fa_{neg}} $$

where $Tr_{pos}$ denotes the occurrence of the events that are correctly classified, $Tr_{neg}$ denotes the events that are correctly classified as not occurred, $Fa_{pos}$ denotes the false
classification of the events, and \( Fa_{neg} \) denotes the events that are incorrectly classified as not occurred.

**Precision**

This metric shows the proportion of activities that are correctly classified over all the activities predicted as positive values for every physical activity under consideration. It is defined as the ratio of true-positive predictions to the total predicted positive instances and is particularly relevant in the context of AAL as it measures the algorithm's ability to correctly identify relevant activities while minimizing false alarms. A high precision value indicates a low rate of false positives, which is essential for maintaining user trust and minimizing unnecessary interventions in AAL environments. It is computed using the following equation:

\[
P_r = \frac{TP_{pos}}{TP_{pos} + FP_{pos}}.
\]  

(13)

**Recall**

It is the ratio of activities correctly predicted to the real-positive values for every activity under consideration. In AAL systems, high recall is crucial for ensuring comprehensive monitoring and timely detection of activities, especially those related to emergency situations or changes in health status. It is defined as follows:

\[
R_r = \frac{TP_{pos}}{TP_{pos} + FN_{pos}}.
\]  

(14)

**F1-score**

This measure is utilized to measure an algorithm's classification efficiency despite these activities being distributed in an uneven format. It computes the weighted harmonic mean of precision and recall. A high F1-score indicates a well-rounded performance, which is desirable for AAL systems aiming to provide reliable support and assistance to users. It takes false-positive and false-negative values and is computed using the following equation:

\[
F_{1s} = \frac{2 \times (P_r \times R_r)}{P_r + R_r}.
\]  

(15)

**Root mean square error**

This specifies the variation between the predicted activity class and the measured class. In the context of AAL, RMSE can be used to quantify the accuracy of activity duration predictions or other continuous variables, thereby facilitating more precise monitoring and intervention strategies. It is computed using the following equation:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (A_{predicted,i} - A_{measured,i})^2}.
\]  

(16)

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**Dataset description**

**KU-HAR dataset**

The human action perception capability of the machines is referred to as HAR (Sikder and Nahid, 2021). This dataset includes data about eighteen activities gathered from 75 male and 15 female participants. A total of 90 participants were included in the data collection process, and the actions were collected via the accelerometer and gyroscopic sensors in the smartphone. It comprises 9445 original activities gathered straight from the participators and around 9185 subsamples extracted from the original activities. The collected actions and their details are described below. Sit (sit for 1 minute), stand (stand for 1-minute duration), stand-talking (standing and talking with hand movements for 1 minute), talk-sit (sitting and talking with hand movements for 1 minute), stand-sit (sitting and standing recursively five times), lay-stand (standing up and laying down actions five times repeatedly), lay (laying for 1 minute), pick (picking up an object from the floor ten times), push-up (performing push-ups five times), jump (jumping ten times), walk (walking nearly 20 meters), sit-up (do sit-ups five times), walk-circle (circular path walking), walk-backward (walking in the backward direction for nearly 20 meters), run (running for 20 meters), stair-up, stair-down, and playing table-tennis for 1 minute.

**Performance analysis**

Figure 3 illustrates the comparison output of the accuracy of the proposed ATL-CC model and other existing methods, such as AdaBoost, BiLSTM-CNN, SVM, and DT methods. The proposed method achieved 98.9% accuracy, which is greater than that of all other competent models. Thus, this figure confirms the highest activity recognition capacity of the ATL-CC model. Activities are recognized and classified precisely, and alerts are sent if required.

The precision value of the proposed ATL-CC model is analyzed and shown in Figure 4. The figure shows that the
The proposed model attains 97.4% precision, which is higher than that of all other existing methods taken for comparison. The existing AdaBoost algorithm achieves a 91% precision rate, and the BiLSTM-CNN method achieves the second-highest value of 94% precision. SVM and DT achieved 88 and 82% precision scores, respectively. It again guarantees how precisely the method recognizes and classifies the activities.

The graphical representation of recall scores achieved by the proposed ATL-CC and the existing methods is shown in Figure 5. The proposed model achieves a 98% recall rate, higher than that of all other underlying models. However, the DT method achieves the lowest value, an 86% recall score. The proposed model improved its recall rate by nearly 12% from the DT method and 11.4% from the AdaBoost method.

The F1-score values of the proposed ATL-CC and the four other existing activity recognition methods are demonstrated in Figure 6. The mean values of recall and precision are represented in terms of the F1-score value. The F1-score value shows the highest value if the precision and recall values are high. The proposed method achieves the highest F1-score value, which is 96%.

The RMSE values of the proposed ATL-CC method are illustrated in Figure 7. The figure concludes that the proposed method performs better with a lower RMSE value. Lower RMSE values resulted in the highest performance. The RMSE value of certain activities is shown in Figure 8. Each activity has a varying RMSE value, which ranges between 0.0042 and 0.0045, and has an average value of 0.004.

The performance (accuracy, F1-score, recall, and precision) of activities selected from the input dataset is illustrated in Table 1. A few numbers of activities, such as stand, sit, lay, pick, jump, walk, and run, are selected from the 18 activities present in the dataset. The mean values from the table showed that all activities have a higher percentage of all metrics, such as F1-score, precision, accuracy, and recall values.
The confusion matrix of the proposed ATL-CC model is shown in Figure 9. The true-positive values are plotted against the predicted values. Here, 7 activities from the total of 18 are selected for comparison. The confusion matrix summarizes the correct and incorrect classifications in a tabular format. Here, four key components are utilized: true positive, true negative, false positive, and false negative. The true-positive and true-negative values show the effective classification performance of the classifier, and the false-negative and false-positive values illustrate the misclassification percentages. The figure showed that all the activities have a precise classification value of higher than 97%, automatically resulting in better performance.

A detailed comparison of the performance of the ATL-CC algorithm with that of the existing models, namely AdaBoost, BiLSTM-CNN, SVM, and DT, in the context of AAL applications is presented here.

### Feature representation

One of the key advantages of the ATL-CC algorithm lies in its ability to extract meaningful features from preprocessed input data collected from elderly and differently abled individuals. Unlike traditional feature extraction methods used in AdaBoost, SVM, and DT, ATL-CC leverages attention-based transfer learning techniques, enabling it to capture complex patterns and nuances in activity data more effectively.

### Model architecture

The ATL-CC algorithm employs a hybrid approach that integrates crossover-based chimp optimization with a transformer-based model for transfer learning. This unique architecture allows ATL-CC to adaptively learn from diverse activity data sources, resulting in improved generalization and robustness across different AAL environments compared to the single-model approaches used in BiLSTM-CNN, SVM, and DT.

### Attention mechanism

Incorporating an attention mechanism in the ATL-CC algorithm facilitates dynamic weighting of input features based on their relevance to the activity recognition task. This attention mechanism enhances ATL-CC’s ability to focus on salient aspects of activity data, leading to more accurate and context-aware predictions compared to models like BiLSTM-CNN, which may struggle with capturing long-range dependencies.

### Performance metrics

The performance of the ATL-CC algorithm was evaluated using a comprehensive set of metrics, including precision, accuracy, recall, F1-score, and RMSE. Our results demonstrate that ATL-CC consistently outperforms the existing models across all evaluation metrics, achieving higher accuracy, precision, recall, and F1-score values.

### Limitations and challenges

It is important to acknowledge potential limitations or challenges in the comparison with existing models, including dataset bias, parameter tuning, and computational complexity. While our study has endeavored to address these factors to the best of our ability, further research is needed to explore the robustness of the ATL-CC algorithm in diverse AAL scenarios.
CONCLUSIONS
For developing a high-quality AAL environment for all people to offer a positive influence on the health and quality of life of people, specifically the elderly and disabled people, this research work presents the ATL-CC method, which is an effective activity recognition and classification system and generates alerts in emergency scenarios. The mandatory features extracted from the preprocessed input data, which are collected from elderly people, contain daily activities, and the classification is performed via the ATL-CC classification algorithm. Then, alerts are sent if any emergency situation is detected. The inputs are collected from the KU-HAR dataset, which includes 18 activities. The activity classification performance is evaluated with precision, accuracy, recall, F1-score, and RMSE metrics and compared with four existing models: AdaBoost, BiLSTM-CNN, SVM, and DT. The evaluation concluded that it offers the highest accuracy (98.9%), precision (97.4%), recall (98%), and F1-score (96%) values. In the future, this model will be extended to end-to-end models to minimize the risk for people affected by Parkinson’s disease and other multiple mental disorders. Besides, the method will be evaluated with multiple imbalanced datasets to ensure its effectiveness.

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