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A Comparison Analysis of Conventional Classifiers and Deep Learning Models for Activity Recognition in Smart Homes

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Abstract
Activity Recognition is essential for exploring human activities in smart homes in the presence of multiple sensors as residents interact with household appliances. Smart homes use intelligent IoT devices linked to residents' homes to track human behavior as humans interact with the home's equipment, which may improve healthcare and security issues for the residents. Although remarkable studies have been done for pattern recognition and prediction of human activities in smart homes based on single residents and multiple residents using wearable sensors. However, not much research has been done on using Activity Recognizing Ambient Sensing (ARAS) residents. In this paper, we suggested using the ARAS dataset and newly emerged algorithms such as Deep learning Models to predict the activities of daily living (ADL). We compared the performance of deep learning models (ANN, CNN, and RNN) with that of classification models (DT, LDA, Adaboost, GB, XGBoost, MPL, and KNN) to figure out the ADL in the smart home residents. The experimental results demonstrated that DL models outperformed with an excellent accuracy compared to conventional classifiers in houses A and B in recognizing ADL in smart homes. This work proves that Deep Learning Models perform best in analyzing ARAS datasets compared to traditional machine learning algorithms.

Keywords: Conventional Classifiers, Deep Learning Model, Activity Recognition, Smart Homes, IoT, Feature Selection.

1- Introduction

The recognition of activities contributes to the improvement of multi-quality residents and security in a smart home environment by recognizing their activities of daily living (ADL) through using both Machine Learning (ML) Algorithms and Deep Learning (DL). Due to many tragedies happening abruptly in human life, such as covid-19, many tragedies have created a need for people to take care of their health; Smart Homes have become a solution [1]. Activity identification is critical in identifying and monitoring ADL in Smart Homes, resulting in a better life for residents of smart homes. The study was carried out using the Activity Recognition with Ambient Sensing (ARAS), collected from two houses named houses A and B, using the installed sensor of different household appliances, which involved 27 various activities. This study used DL Models and popular Conventional Classifiers, i.e., DT, LDA, Adaboost, GB, XGBoost, MPL, and KNN. DL is one of the key players in facilitating data analytics and learning in the IoT field and gives more accurate results and stable predictions.

Deep Learning (DL) is an algorithm that imitates the activities of the human brain to identify associations among massive amounts of data. DL technique learns complex functions and maps input to output directly from data by automatically learning features at multiple levels of abstraction. It is used to create algorithms to predict complex patterns and problems. It can adapt to changing inputs, allowing the network to produce the best possible result without redesigning the output criteria. DL is smart enough to learn and map nonlinear and complex relations, which is essential because many of the relationship issues between actual inputs and outputs are nonlinear and complex. After gaining knowledge from the preliminary information and their interrelations, DL can assume things on the unforeseen relationship issues with testing data, allowing the model to draw conclusions and predict the

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testing data. DL differs from many other prediction methods in that it does not impose limits on the input values; additionally, several experiments have shown that DL can model better and produce better results [2, 3].
On the other hand, the selected popular Conventional Classifiers are used to create robust models in classification problems [4, 5]. The Conventional Classifier techniques have been applied successfully in human activity recognition and achieved a reasonable recognition rate after feature selection and extraction on the ARAS dataset. However, few studies were conducted to compare conventional and deep learning in classifying human activities in the multiresident environment of smart homes.

The Motivation and contributions of this paper sought to fill the void in smart homes by developing a robust model capable of extracting hidden information and insights to improve prediction accuracy by applying newly emerging techniques. The study contributes to the research community of human activity recognition in smart homes to improve different aspects of human lifestyle such as health status, security and safety, monitoring and controlling energy and water usage, reducing living expenses, and thus improving quality of life. The better the model, the better the quality of life for smart home residents, is reducing expenditures on various items at home such as electricity, and water, increasing healthcare and security for residents.

This paper is structured as follows: The second Part briefly describes the interrelated works on Conventional Classifiers and Deep Learning; Third Section, presents Research Methodology used in this research; Fourth Part presents the analysis, performance, and discussions; and Fifth Part concludes and makes recommendations for future work.

2- Literature Review

This section explains previous related works reviewed concerning activity recognition for multiresident in smart homes, and the reviewed related research are as follows:

Natani et al. [6] demonstrated human activity recognition using the ARAS dataset to identify ADL. In this study, two types of RNN, GRU and LSTM, were used to simulate the various activities of the multiple residents in House A. The outcomes for 10days of GRU obtained 76.57% accuracy. In comparison, LSTM achieved 74.82% accuracy, for 30days, GRU obtained 80.35% accuracy while LSTM reached 78% accuracy, and finally, for 50days, GRU obtained 80.5% accuracy while LSTM achieved 79.08% accuracy, while on average, the author obtained 78%.

Bhattacharjee et al. [7] studied human activity classification to recognize different human activities using PNN, SVM, BPNN, and RNN techniques. The study identified other ADLs, and the experimental results were 94.10%, 59.11%, 97.40%, and 97.55% accuracy, respectively. The RNN outperformed the rest of the model by achieving 97.55% accuracy, predicting ADL.
Wang et al. [8] researched activity recognition using a deep learning algorithm based on the sensor. The authors suggested Deep Learning Algorithms used in identifying activities of daily living (ADLs) in smart homes because they have been proved to give better accuracy in model prediction.
Liciotti et al. [9] proposed using DL applications to identify human activities in Home Automation. An experimental outcome indicates that the LSTM method outperforms the existing DL and ML methods, producing better results than the current literature. The authors suggest more research to test other similar data sets for comparative analysis on activity detection.
Polat [10] developed a deep learning model to extract input data features automatically. In this regard, the researchers used LSTM, CNN, DBN, and RNN to test and train the models. The outcomes show that the suggested DL obtained an accuracy of 82.41%. The researcher recommends different human activity datasets and deep learning models and classifiers to enhance the model's efficiency.
Vakili et al. [11] compared eleven ML methods and DL for classification problems using six datasets. The comparison was conducted using different performance evaluation metrics. The experimental results show that RF performed better than other classifiers while ANN and CNN outperformed DL models.
Alshammari et al. [12] evaluated the performance of machine learning methods for ADL in Smart Homes; for this matter, the researchers employed several classifiers: DT, SVM, HMM, MPL, and Adaboost to address the problem. The experimental results demonstrate that the NN approach outperforms the other machine learning methods.
Tran et al. [13] proposed using edge intelligence in recognizing human activity in Smart Homes. For this case, they used both ML and DL algorithms to address the problem. Thus, CNN and SVM were adopted for activity recognition. The experiments were done, and DL outperformed ML techniques; the model achieved an accuracy of 95% in activity recognition. The authors suggested that other neural models be investigated in future work to improve the accuracy.
Park et al. [14] employed several deep neural networks to analyze residents' activities in a smart home using the MIT dataset. The experimental findings demonstrate that LSTM and GRU outshone other DL models; however, the dataset was too small to determine the best accuracy.

Akour et al. [15] performed a comparative study between standard traditional classifiers and deep learning to address ADL's effectiveness for older people. The CNN provided promising results in predicting ADL compared to ordinary conventional machine classifiers.

Igwe et al. [16] established a supervised learning algorithm known as a margin setting algorithm (MSA). They used ARAS as a data set to recognize patterns in the activity of daily living ADL) for both two residents in the smart home. Researchers obtained an average activity accuracy of 68.85% for house A and 96.24% for house B from the experiments. Despite the models outperforming researcher suggested conducting a comparative study between supervised learning algorithms with other different ML classifiers in a larger dataset scale.

Yun et al. [17] conducted a comparative analysis between classical machine classifiers (RF, SVM, IBL, and BayesNet). Deep learning algorithms were performed to detect human movements in smart homes using accuracy, precision, and recall evaluation metrics. Deep Learning outperformed with an accuracy of 90% compared to classical machine classifiers, which demonstrated poor performance.

3- Methodology

This section explains the methods deployed in this study, including the selected classifiers and the architecture of the activity recognition method.

3-1- Deep Learning Algorithm

Deep Learning (DL) was deployed in this study to identify human activities in smart homes using the ARAS dataset. The DL is a powerful NN formed by sophisticated mathematical modeling of various hidden layers in the NN and analyzing the data in a complex manner. In IoT data analytics, the DL Model is the most successful, produces the best results, and has been better than the conventional classifier [18, 19].

The DL is the most powerful among ML algorithms that process the input data to extract hidden insights from the dataset using dense layers, improving model accuracy. DL trains use massive amounts of data, eliminating the need to do a feature extraction manual as per conventional classifiers. Figure1 shows the Deep learning architecture model whereby the input layers receive binary data from observations. The binary data must be normalized or standardized to minimize the model's error and achieve the best model accuracy. The hidden layers use mathematical calculations on input data and nonlinear processing units to extract and transform features, while the output layers produce the desired results [20, 21]

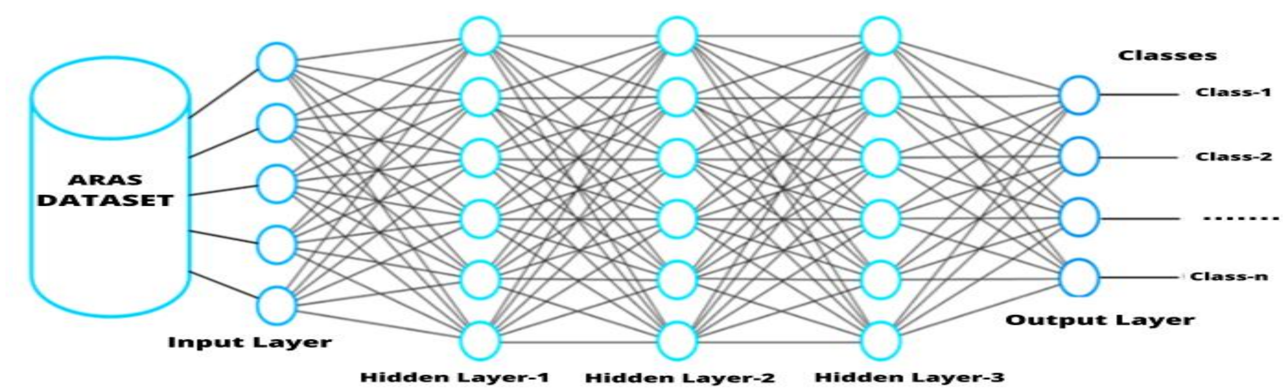

Fig.1 Structure of Deep Learning Model

1-1- Figure 2 shows the architecture of the Activation Function with inputs (X1, X2, X3, X4, + …….Xn), where f(s) is a nonlinear function known as the activation function Oj as an output value of the current neuron. The primary role of the Activation Function is that it is used to calculate and decide the output of a neural network.

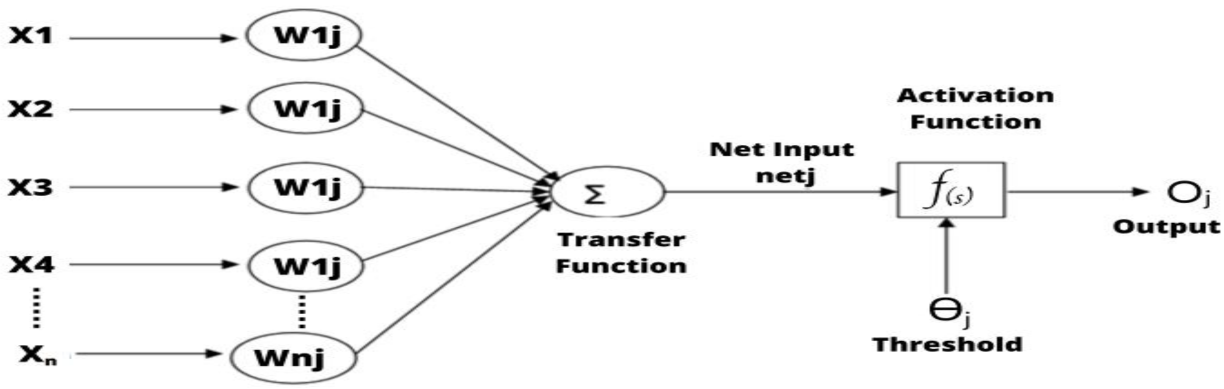

Fig. 2 Activation functions in neural networks

Figure 3 shows the suggested architecture for human activity recognition in multiresident based on smart homes using Deep learning and the ARAS dataset [22]. Before using Deep Learning to train the model, the ARAS data preprocessing was used to clean the dataset, perform feature scaling, and compute the sample size. Feature scaling was utilized to reduce model complexity while also increasing model accuracy. To ensure that we managed to achieve our goal, we used MinMaxScaler to sparse the datasets into zeros (0) and ones (1)

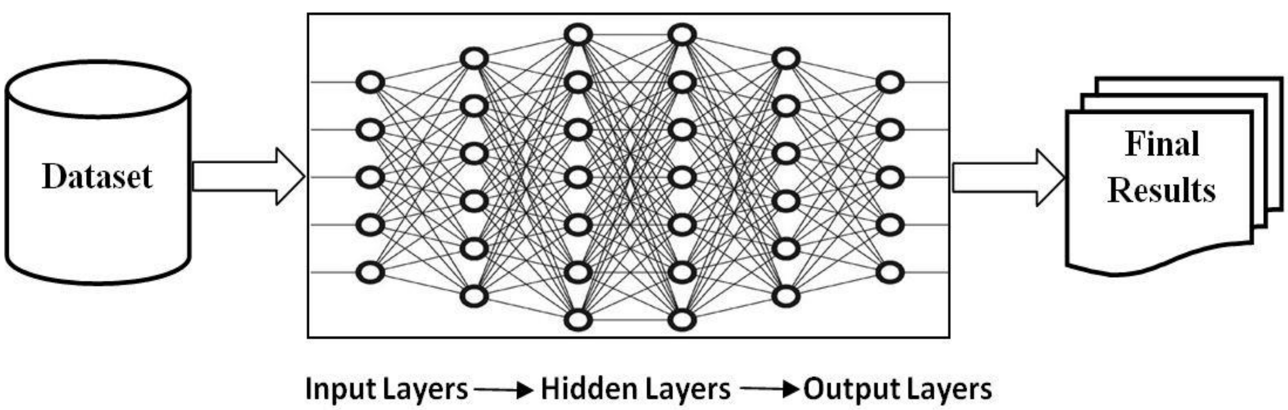

Fig.3 Proposed Deep Learning Architecture

3-2- Conventional Classifiers

On the other hand, the study employed several popular conventional classifiers to recognize human activities in the Smart Homes using the ARAS dataset. This study employed a popular conventional classifier for comparative research with DL, which includes; DT-is the method used for solving classification problems, which uses internal nodes to represent a predictor variable. In this tree-structured classifier, each leaf node represents the outcome of the majority voting, and it is applied to and utilized in more than one classification [23]. LDA - is a statistical technique for binary and multiclass classification that reduces the number of features to a more manageable number before classification by assigning objects to one group among several groups. Hence, increasing the model accuracy [24]. Adaboost is a method used as an ensemble technique to build multiple models of the type using a sequential set of algorithms, reduce bias and variance, and convert weak learners into strong ones to create a robust model to improve the performance [25]. Gradient boosting (GB) is an ensemble strategy for enhancing the model's prediction performance using ensembles. Decision trees are often used because they combine multiple weak classifier models to create a robust predictive model employing a set of classifiers [26]. XGBoost method is a type of ensemble method that uses the framework of gradient boosted the decision tree to tackle classification tasks. It uses enhanced regularization (L1 & L2) and parallel computation [27]. Multi-layer perceptrons (MLP) are often used for training input-output pairs for problem classifying and predicting input-output relationships. Training entails fine-tuning model parameters to reduce errors and thus improve model performance [28]. KNN- is the most straightforward algorithm used to classify a new data point into a target class depending on the features of its neighboring data points. The KNN algorithm believes that identical items are close to each other, and for better accuracy, it uses turning parameters to select the correct value of 'k' [29].

The reasons for selecting the above-mentioned conventional classifiers are suitable for the multiclassification problem, simple to implement, fast to train and overcome overfitting, ability to compress the dataset into a manageable size, and ability to produce a robust model. Activity recognition plays a vital role in Smart homes by maintaining the residents' well-being and making life more meaningful. It helps enhance multiresidents quality of life and health in a smart home neighborhood

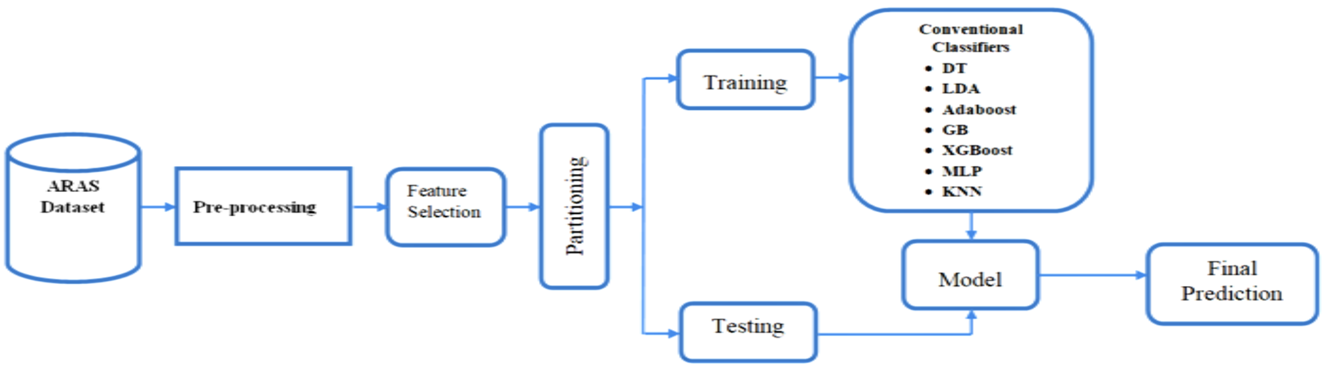

Fig.4 Proposed Approach for conventional classifiers

3-3- Data Preprocessing

Data preprocessing is a data mining technique that transforms raw data into an understandable format. For this reason, we employed feature selection, and feature scaling. We calculated the sample size before creating models using DL and conventional classifiers in multiclass classification problems using the ARAS dataset.

3-3-1 Feature Selection

Feature Selection: A secret to the performance of any algorithm is the selection of relevant features; removing irrelevant features in the dataset reduces the computing complexity of the model, which in turn leads to outstanding accuracy. Feature selection was done to minimize overfitting, speed up training time, and improve the model accuracy. Univariate feature selection was employed to select randomly the 10 best features that have a strong relationship with the target variables. For this matter, we employed the sklearn library that provides the SelectKBest class that uses the chi-squared (chi2) statistical test to select the 10 best features from the ARAS dataset that are strongly dependent on the response [30].

$$X_C{}^2 = \sum \frac{(O_i - E_i)}{E_i} \tag{1}$$

Where; c – is the degree of freedom; O – is the observed value(s) and E–is the expected value(s)

3-3-2 Feature Scaling

Feature scaling was used to scale all values into the range of 0 and 1 to reduce model complexity and increase the model's accuracy. It was carried out using MinMaxScaler to sparse the datasets into zeros (0) and ones (1) to make sure that we achieve the best accuracy with the selected Conventional Classifiers and DL [31].

$$X = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

Where; X – is the normalized data, X_i – is the original feature value, X_{min} – is the minimum value, and X_{max} – is the maximum value in the original dataset before scaling.

3-3-3 Imbalanced Dataset

The ARAS dataset is imbalanced, so the SMOTE technique was applied to balance the dataset to solve this problem. Then, the dataset was divided into training and testing sets; for this reason, the imbalanced Learn library that provides the imblearn class was applied to cater to the imbalanced problem. After that, models were built using Conventional Classifiers and DL (DT, LDA, Adaboost, GB, XGBoost, MPL, KNN, and DL). Hence, a comparison between Deep learning and Conventional Classifiers was performed; DL was outshone compared by Conventional Classifiers [32, 33].

4- Experimental Results and Discussions

This section explains the ARAS dataset, the findings, and discussions of the suggested methods for activity detection in multiresidents based on the ARAS dataset's smart homes. This study experimented with both DL and Conventional Classifiers using the ARAS dataset.

4-1-Experimental Setup

The data used during this research was collected by the ARAS (Activity Recognition with Ambient Sensing) dataset for multiresidents in smart homes to detect activity. The ARAS dataset was collected from two different real houses for two months in Turkey in 2013. The dataset involved 27 different types of activities and contained a total of 5,184,000 instances from each house which is a large dataset [34]. In this regard, both conventional classifiers and Deep Learning were employed to draw significant insight from Activities of Daily Living (ADL).

4-2- Evaluation Matrices

The study used four evaluation methods to examine the performance of our model, including Classification Accuracy (CA), recall, precision, and F1-measure. These metrics were used to evaluate the model's performance because accuracy alone is not enough to infer a model's performance.

Accuracy: Is the value of the forecast divided by the total forecasting value

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{3}$$

Precision: Is the actual positive value divided by the positive class value and false positive value.

$$\Pr ecision = \frac{(TP)}{(TP+FP)} \tag{4}$$

Recall: It is called the True Positive rate. The positive truth value is divided by the actual positive and false negative values

$$\mathrm{Re}call \frac{(TP)}{(TP+FN)} \tag{5}$$

F-1 Measure: Mean of Precision and Recall

$$F1-Score = 2 * \frac{(\Pr ecision * \mathrm{Re}call)}{(\Pr ecision + \mathrm{Re}call)} \tag{6}$$

Whereas TP represents True Positive values, TN is a True Negatives value, FP is a False Positive, and FN is a False Negatives value.

4-3- Analysis

This section provides a comparative analysis obtained while implementing the proposed approach in developing a predictive model for activity recognition in multiresidents in a smart home environment using both Deep Learning and conventional classifiers. We first loaded the ARAS dataset and then loaded the basic libraries; we created the sequence model with dense layers. First, we constructed the dense layer with 128 neurons, and like the first, we had to specify the number of input dimensions (20), and ReLU was used as an activation function, the next layer was the dense layer with 256 neurons, and ReLU was used as an activation function; then a dropout layer with 0.2% as the techniques used to overcome the issue of overfitting during the training of the model. After that, we had another dense layer with 64 neurons, and ReLU was used as an activation function. Finally, we had a dense output layer, and softmax was used as an activation function; it converts the results in probability values. Next, we compiled the model, and since this is a multiclass classification, we used categorical cross entropy as the loss function and softmax as an optimizer. We also used categorical accuracy as a metric. Next, we trained the model using epochs=300 and batch_size=128; after that, we evaluated our model using a test dataset, and the model achieved an excellent accuracy compared to the conventional classifier. Finally, we cross checked the correctness of the predicted and expected values using the loop function and plotted model accuracy and model loss curves.

On the other hand, conventional classifiers: The models were created using the sklearn library; in the preprocessing data stage, we applied feature scaling in the input values before developing a model for predictions to reduce the scatteredness of the data. For this matter, we used

MinMaxScaler to carter for feature scaling in conventional classifiers. The ARAS dataset was divided into training and testing sets; then, models were developed using DT, LDA, Adaboost, GB, XGBoost, MLP, and KNN. The performance metrics such as accuracy, precision, recall, f1-score, and correlation matrix were applied to evaluate the performance of the model. Hence, the model prediction was done to cross-check the correctness of the predicted and expected values using the loop function.

4-4- Findings and Discussion

This part describes the findings of the experimental tests and discussions for multiresident activity detection in a smart home using both the Deep learning (DL) method and seven conventional classifiers (DT, LDA, Adaboost, GB, XGBoost, MLP, and KNN) together with performance metrics such as accuracy, precision, recall, f1-score and correlation matrix. The results show that DL outshone seven conventional classifiers in both houses A and B for activity identification for multiresidents. Furthermore, DL performed best in house B compared to house A, and conventional classifiers performed best in house B compared to house A. Table 1 and Table 2 show the outcomes achieved by Deep learning compared to the seven conventional classifiers used in this study aligned with the discussion.

Table 1: Classification performance comparison in House A

Classifiers	**Evaluation Metrics**			
	Acc (%)	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
DT	0.6999	0.685	0.683	0.667
LDA	0.6349	0.634	0.624	0.596
Adaboost	0.5951	0.562	0.567	0.515
GB	0.6960	0.673	0.655	0.594
XGBoost	0.6969	0.685	0.687	0.634
MLP	0.6945	0.687	0.696	0.603
KNN	0.6921	0.676	0.675	0.684
ANN	0.9944	1.00	0.993	0.993
CNN	0.9916	0.9921	0.991	0.993
RNN	0.9898	0.989	0.989	0.989

As shown in Table 1, the experimental results for both conventional classifiers and Deep learning models regarding the accuracy, precision, recall, and F1 score. The deep learning model outscored with precision accuracy of 100% compared to conventional classifiers, which performed moderately. The conventional classifier's performance was DT 69.99% accuracy, followed by MLP - 69.45%, XGBoost-69.69%, GB-69.60%, KNN-69.21%, and LDA-63.49%, while Adaboost performed moderately compared to the rest classifiers with an accuracy of 59.51%. In addition, the results from Table 1 are demonstrated in figure 5 below.

Table 2: Classification performance comparison in House B

Classifiers	**Evaluation Metrics**			
	Acc (%)	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
DT	0.9193	0.912	0.935	0.914
LDA	0.8343	0.810	0.836	0.815
Adaboost	0.9036	0.898	0.903	0.905
GB	0.9084	0.914	0.921	0.913
XGBoost	0.9147	0.913	0.902	0.925
MLP	0.9113	0.924	0.913	0.905
KNN	0.9034	0.905	0.923	0.914
ANN	0.9983	1.00	1.00	1.00
CNN	0.9963	0.9963	0.995	0.995
RNN	0.9965	0.9965	0.997	0.996

Table 2 displays the experimental comparison results in house B for both conventional classifiers and deep learning models regarding the accuracy, precision, recall, and F1 score. The DL model outshone conventional classifiers in every measure with the precision, recall, and f1-score of 100% for activity recognition in house B. DT, XGBoost, and MLP came in second, with an accuracy of 91.93%, 91.47%, and 91.13%, respectively, approximately 6% lower than Deep learning. However, when compared to the other classifiers, LDA scored less, with an accuracy of 83.43%.

4-5- Comparative Analysis

Table 3 demonstrates the comparison between the prior study and the proposed approach. This study outperformed the previous studies in activity recognition using ANN by achieving an average precision, recall, and f1-score of 100%. In comparison, the earlier research by Natani et al. [6] achieved an accuracy of 81.7%, 79.25%, 70.9%, 83.61%, and 85.94%, 88.75%,90.85%, 88.87% in houses A and B, by using RNN, CNN, MLP, and GRU, respectively. Tran et al. [13] achieved 95% in house B using CNN, while Igwe et al. [16] obtained 67.32%, 68.85%, and 67.32%, 68.85% accuracy by using ANN and MSA. As a result, the proposed approach outperformed the earlier experiments in activity recognition by achieving an accuracy of 99.4%, 99.16%, 98.98%, 69.45%, and 99.83%, 99.63%, 99.65%, 91.132% in houses A and B, respectively using ANN, CNN, RNN, and MLP.

Table 3: Classification with Previous Research

Research Study	Method	Accuracy House A	Accuracy House B
Natani et al. [6]	ANN, MSA	67.32%, 68.85%	95.43%, 96.24%
Tran et al. [13]	CNN	-	95%
Igwe, et al. [16]	RNN, CNN , MLP, GRU	81.7%, 79.25%, 83.61%, 70.9%	85.94%, 88.75%, 88.87%, 90.85%
The proposed approach	**ANN, CNN, RNN, MLP**	**99.4%, 99.16%, 98.98%, 69.45%**	**99.83%, 99.63%, 99.65%, 91.132%**

5- Conclusions and Future Directions

This study presents a novel comparative analysis study between conventional classifiers and deep learning (DL) models. The experimental results show that Deep learning models outperformed in both houses A and B compared to conventional classifiers. The ANN outperformed other DL models and all ML classifiers with an average score of 100% for precision, recall, and f1-score in house B; in predicting human activities using the ARAS dataset. However, conventional classifiers performed best in house B compared to house A. The experimental results prove that the Deep learning methods analyze ARAS datasets better than conventional classifiers. In comparison between the prior study and the proposed approach, this study outperformed the previous studies in activity recognition using ANN by achieving an average precision, recall, and f1-score of 100%.

In future work, we suggest that different traditional machine learning classifiers to be employed on the ARAS dataset compared with Deep learning models.

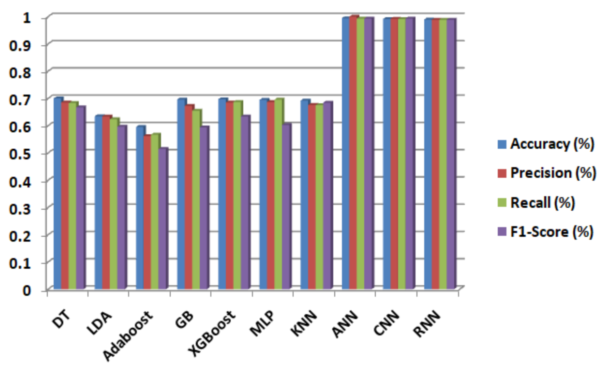

Fig. 5 Classification comparison in house A

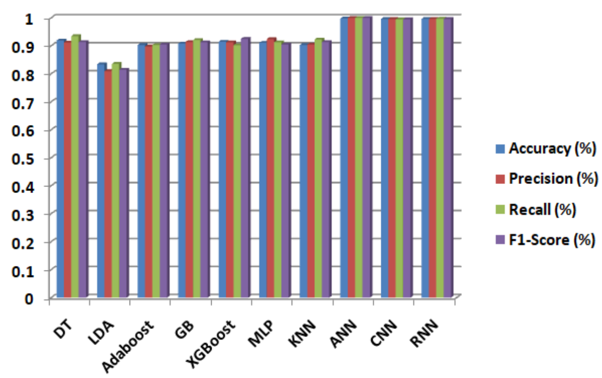

Fig. 6 Classification Comparison in House B

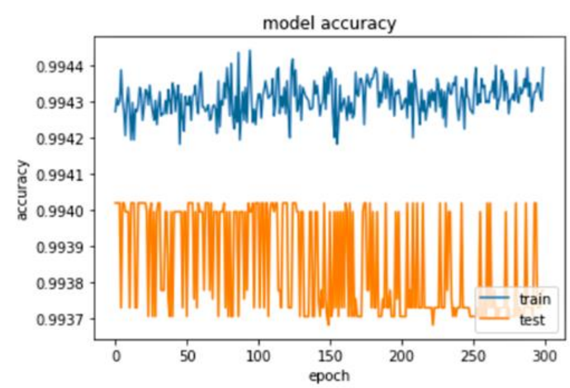

Fig. 7 Model Accuracy in House A using ANN

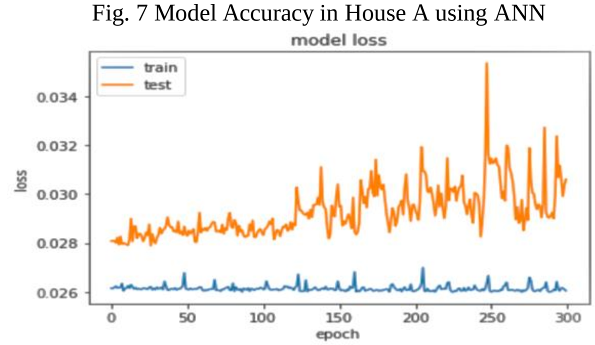

Fig.8 Model Loss in House A using ANN

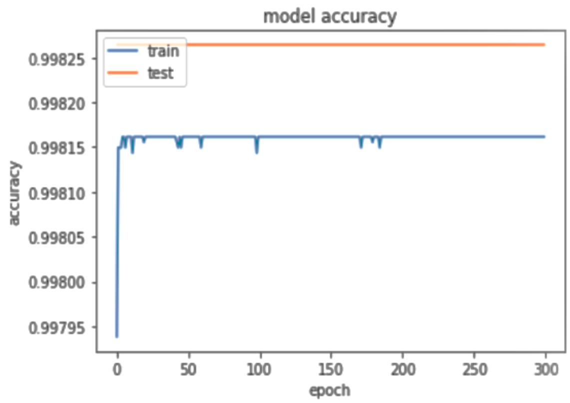

Fig.9. Model Accuracy in House B using ANN

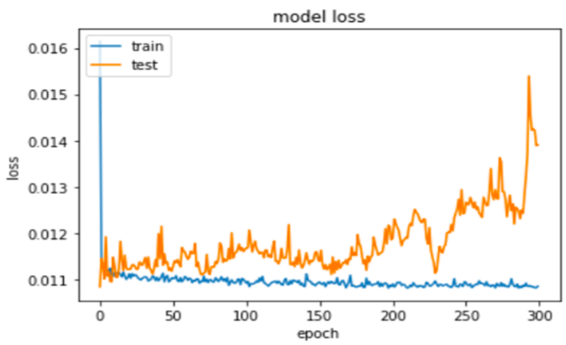

Fig. 10 Model Loss in House B using ANN

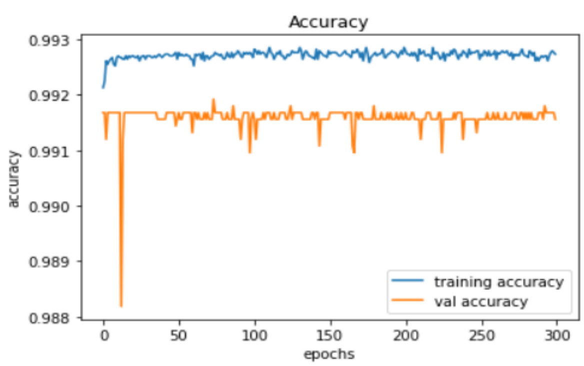

Fig.11 Model Accuracy in house A using CNN

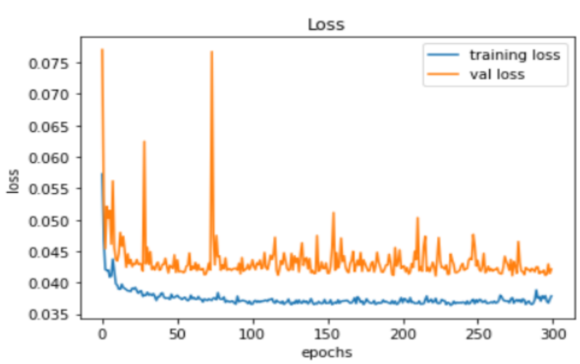

Fig. 12 Model Loss in House A using CNN

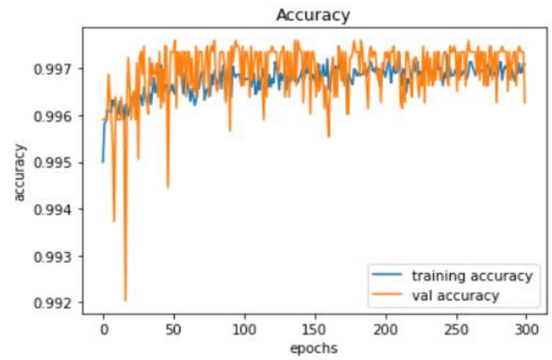

Fig. 13 Model Accuracy in House B using CNN

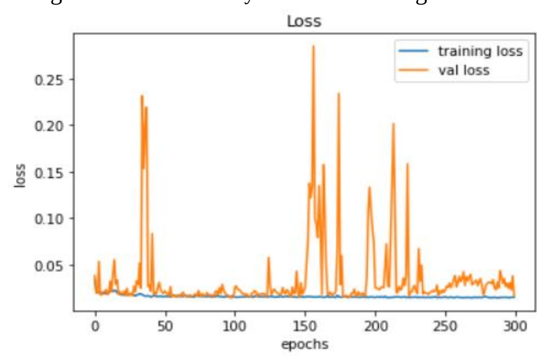

Fig. 14 Model Loss in House B using CNN

Fig. 15 Model Accuracy in House A using RNN

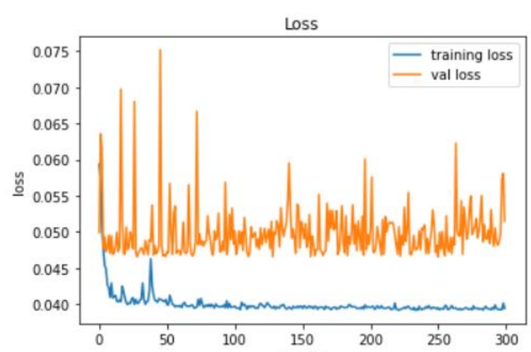

Fig.16 Model Loss in House A using RNN

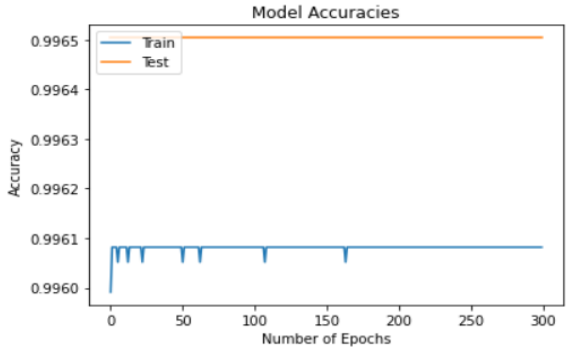

Fig. 17 Model Accuracy in House B using RNN

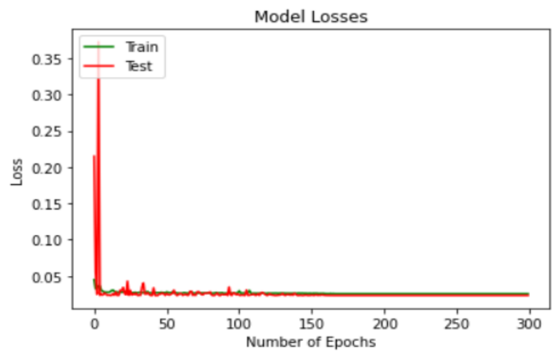

Fig. 18 Model Loss in House B using RNN

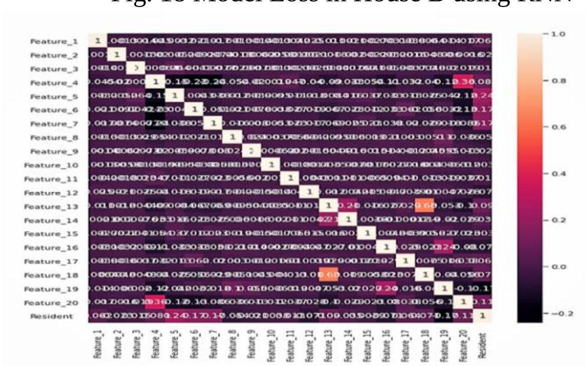

Fig. 19 Correlation Matrix with Heatmap for House A

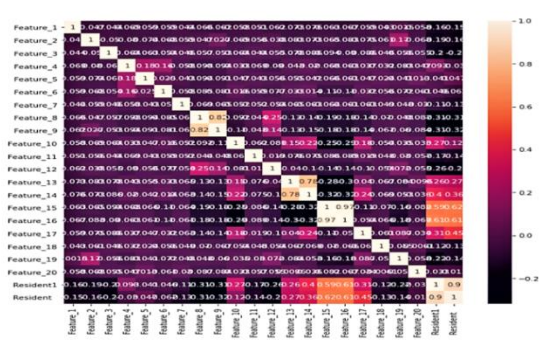

Fig. 20 Correlation Matrix with Heatmap for House B

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