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DEEP LEARNING MODELS FOR HUMAN ACTIVITY RECOGNITION IN SMART HOMES USING ARAS DATASET

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ABSTRACT

Human Activity Recognition (HAR) is essential in recognizing and classifying human actions performed at home through internet of things (IoT) devices and artificial intelligence (AI) technologies. The IoT smart devices such as sensors together with AI techniques like deep learning models are used to identify activities performed by individuals, such activities include; sleeping, watching TV, walking and more. The identification of human behaviour changes helps for healthcare, security control and more. The goal of this research is to create models that can more accurately forecast the activities that occupants of smart homes will engage in deep learning models like Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). The experimental results demonstrated that ANN outperformed with an excellent accuracy of 99.4% and 99.8% in households A and B respective, compared to CNN and RNN in identifying human behavior in smart residence using the ARAS dataset.

Keywords: Human Activity Recognition, Deep Learning Models, Activity Recognition, Internet of Things, Smart Homes

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1. INTRODUCTION

The HAR algorithm predicts mortal conditioning based on data obtained by several detectors such as including portable, surveillance footage, and silence detectors (1). Recent advances in detector technology have rendered them precise, with tremendous calculation power and low cost. The wearable devices and health tracking devices are currently in employ, and their operation will not be difficult for the participants in this study. Inertial dimension unit (IMU) detectors such as accelerometers, gyroscopes, and magnetometers are widely employed in sports, health, and fitness activities (2). When compared to vision-based HAR, wearable detectors maintain a high position of sequestration. Machine intelligence and deep intelligence models are emerging.

The Deep leaning (DL) is an algorithm that mimics the conditioning processes of the mortal brain in order to identify associations among massive quantities of data. By dynamically learning characteristics at various levels of abstraction, the DL method learns complex functions and translates input to output directly from data. It is used to generate algorithms that predict complicated patterns and challenges. The DL can adapt to new inputs, allowing the network to produce the most acceptable possible output without having to rewrite the event criteria (4). The DL is intelligent enough to learn and collaborate on nonlinear and complicated relationships, which is critical because many relationship issues between factual inputs and labor are nonlinear and complex. Soon after learning from the primary data and its connections, DL can assume effects on previously unknown connections with testing data, allowing the model to make conclusions and forecast the testing data. DL differs from many other prediction methods in that it does not limit the input values; also, various trials have demonstrated that DL can model better and generate outstanding results (5).

The study was conducted using the ARAS dataset, which originated from two households, residences A and B. The data was collected using the set-up sensor into various household equipment, which involved 27 distinct activities.

The study employed ANN, CNN, and RNN due to its outstanding performance. ANNs can record detailed connections between vivid detector inputs, allowing them to complete environment and conditioning based on sensitive cues. CNNs excel at image and videotape data analysis, which is critical for visual conditioning, whereas RNNs excel at handling succession data, which aids in the recognition of temporal patterns in conditioning. When integrated into a holistic system, these neural network infrastructures provide a comprehensive and adaptive solution to exertion prediction in intelligent homes, improving convenience, effectiveness and security in the lives of the inhabitants.

Furthermore, incredible research for pattern identification and forecasting human conditions in smart homes have been conducted employing wearable detectors and vision detectors based on single and multiple residents. Still, there has been minimal research into employing Ambient sensing for numerous residents. Thus, utilizing the readily accessible Ambient sensing ARAS dataset, this study employed ANN, CNN and RNN for analyzing conditioning performed in smart homes in order to extracting hidden information and insights from human behaviors. As a result, the research leads to improvements in various elements of human existence, such as health, security, and safety.

The arrangement of this paper is as outlined below: the second part covers past work on DL models; the third part describes the research technique used in this study. The fourth part includes the analysis, performance, and discussions, and the fifth section finishes with conclusion and further works.

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:

Raihani et al. [6] used ARAS dataset and DT to detect human behavior in residence. The study attained an accuracy of 97.1% in residence A and 99.2% in residence B. It was suggested that an alternative approach should be employed to get improved outcomes.

.*Prossegger et al.* [7] utilized the ARAS dataset and DT to examine human behaviour in an intelligent home. The results show that the accuracy for residences A and B was 48.36% and 64.19%, respectively.

Alemdar et al. [8] examined to identify what constitutes aberrant and usual activity using the ARAS dataset and HMM classifier. The outcome in both residences was an accurate of (61%) in residence A, while in residence B was (76%).

Polat [9] applied DL classifier to extract input data variables 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. [10] compared eleven ML methods and DL for classification problems using six datasets. The comparison was conducted using different performance evaluation metrics. The results demonstrate that RF outperformed other classifiers, whereas ANN and CNN outscored DL models.

Sedky et al. [11] evaluated the performance of ML methods for ADL in intelligent homes using ARAS and OpenSSH datasets. The study employed several classifiers: AdaBoost, CLA, DT, HMM, MLP, Structured Perceptron, and SVM to address the problem. The outcomes of the research indicate the study achieved accuracy results of 53.9% and 92.3% from houses A and B using the HMM algorithm, respectively.

Zhang et al. [12] 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. [13] 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.

Yun et al. [14] 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 part explains the methodologies used in the analysis of the study for HAR using DL models and the architecture of the recommended activity detection in smart homes utilizing the ARAS dataset.

3.1. Deep Learning Models

The study employed DL models (ANN, CNN, and RNN) to improve HAR detection in smart homes. The DL models are effective neural networks that use advanced math modelling to extract insight from data in complex ways. They are composed of numerous hidden neural network layers [15]. Figures 6.1, 6.2, and 6.3 represent DL models (ANN, CNN, and RNN) architecturally proposed for recognizing human activity in multi-resident intelligent apartments.

3.1.1. Artificial Neural Network (ANN)

The ANN is a set of neurons connected to one another that function similarly to the workings of the human brain. They are made up of joined nodes known as neurons, which accept data, analyze it, and provide an output. ANNs may be deployed to perform several tasks such as categorization, regression, and recognizing patterns. They may learn from identifying patterns in data and generate predictions according to that information. ANNs are commonly organized into inputs, hidden, and output layers that are capable of learning and modelling complex, non-linear interactions [16]. In Activity recognition, ANN classifies the sensor data to recognize the ADL of the resident.

3.1.2. Convolution Neural Network (CNN)

The CNN is a sort of neural systems built from feed-forward networks in that information flows from its inputs to their outputs in only one way. CNNs extract features from input data convolution method. Convolution is performed by applying a small filter or kernel window to the input data and performing a dot product over the filter and each covering patch of the input data. This generates a feature map that clarifies regions of the input data that have particular features. The CNN stands out from other neural networks because of its better performance with image, voice, and audio inputs. The CNN architecture consists of three major layers: convolution, pooling, and completely interconnected layers [17]. The study employed CNN to recognize the ADL of the residents in the ARAS dataset.

3.1.3. Recurrent Neural Network (RNN)

The RNN is a neural systems derived from the feed-forward network that produces a predictive model using sequential data. RNNs are made up of a network of neurons, each of which is linked to each of the other neurons in the rest of the network. RNNs, on the other hand, feature recurrent connections, which imply that neurons can receive input from themselves or earlier time steps, unlike feedforward neural networks. RNNs works by calculating the output from the previous layer by assigning weight in the input training data as input to the ext layer. RNN utilize memory that can remember prior inputs and generate predictions about future inputs. They accomplish this by transmitting data from one time step to the next via recurrent connections. RNNs are helpful in modeling sequence classification, sentiment classification, and video Classification [18]. In Activity recognition, RNN was applied to classify the ADL of the residents in the ARAS dataset.

3.2. Data Preprocessing (DP)

Data preparation is an essential step in any data evaluation procedure that entails it clean, conversion, and categorizing raw data. so that it is available for analysis. The purpose is to guarantee that the data is correct, consistent, and full, as well as to remove any mistakes, duplication, or irrelevant information that could negatively affect the analysis's findings [19].

The dataset has been filtered by removing anomalies and values that are missing, as well as performing descriptive analysis and data visualization, with the purpose of decreasing unnecessary data and preparing it for model creation.

3.2.1. Feature Scaling

Feature scaling convert numerical characteristics to a common scale. The values of the characteristics are scaled in this manner such that they fall inside a certain range, generally between 0 and 1. To ensure that we attain the best accuracy with the specified DL models, the datasets were sparsely divided into zeros (0) and ones (1) using MinMaxScaler [20].

$$X = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

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

3.2.2. Imbalanced Dataset

The dataset was skewed, thus the SMOTE technique was used to balance it. For this reason, the imblearn class was applied to cater to the imbalanced problem. The dataset was then split into the testing and training sets at an 8:2 ratio, and DL models were employed to build the models [21].

4. RESULTS AND DISCUSSIONS

This section explains the ARAS dataset, the findings, and discussions of the suggested methods for activity identification in multiple residents using the ARAS dataset. This study experimented with both DL and Conventional Classifiers using the ARAS dataset.

4.1. Experimental Setup

The dataset involved smart households A and B which includes a total of 5,184,000 occurrences from each residential and involves 27 distinct sorts of activity [22].

4.2. Evaluation Matrices

The study involved four evaluation measures to analyze the created models' accuracy, including Classification Accuracy, recall, precision, and F1-measure. The purpose of evaluation matrices was to provide a quantifiable evaluation of how well the model predicts the outcome variable on new, unknown data [23].

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

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{2}$$

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

$$\mathrm{P}recision = \frac{(TP)}{(TP + FP)} \tag{3}$$

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

$$\text{Recall}\frac{(TP)}{(TP+FN)} \quad (4)$$

F-1 Measure: Mean of Precision and Recall

$$F1-Score = 2*\frac{(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})} \quad (5)$$

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 describes analysis implemented for the proposed approaches in developing a predictive HAR models for activity detection in smart homes settings using deep learning models. At first the ARAS dataset was loaded and followed with the basic libraries.

- **ANN Analysis**

We created ANN for houses A and B by creating the sequence model with dense layers. The research developed a powerful prediction HAR model using hyper-parameters of ANN architectures.

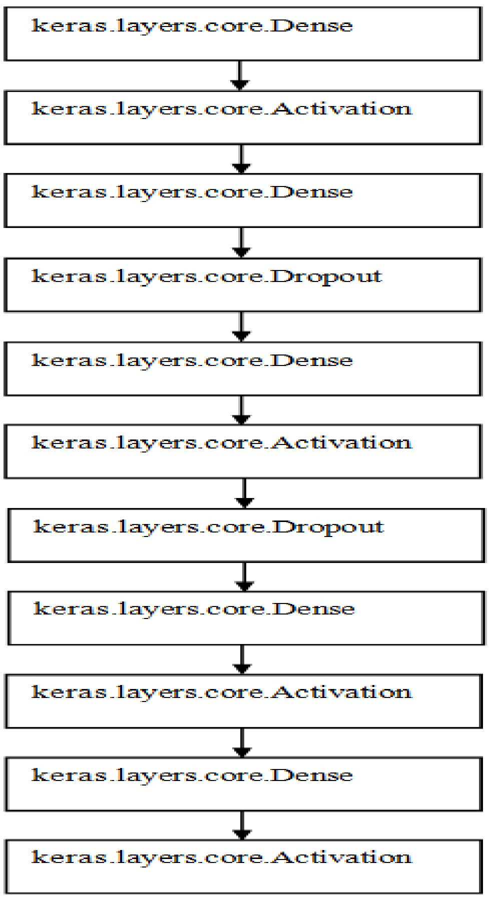

Fig.1. ANN Architecture

Next, we compiled the model, and since this is a multiclass classification, we used categorical cross-entropy as the loss function and Adam as an optimizer. Next, we trained the model using epochs=300 and batch_size=256; after that, we assessed our model using a test dataset, and the model achieved an excellent accuracy.

- **CNNs Analysis**

We created CNN for houses A and B by creating the sequence model with convolution, maxpooling, and fully connected layers. The study deployed Relu activation function, batch_normalization, dropout and at the end Softmax activation function. The research utilized hyper-parameters of CNN architectures to develop a robust HAR model for prediction by applying one-dimensional convolution neural network (1D-CNN) to perform multiclass classification tasks.

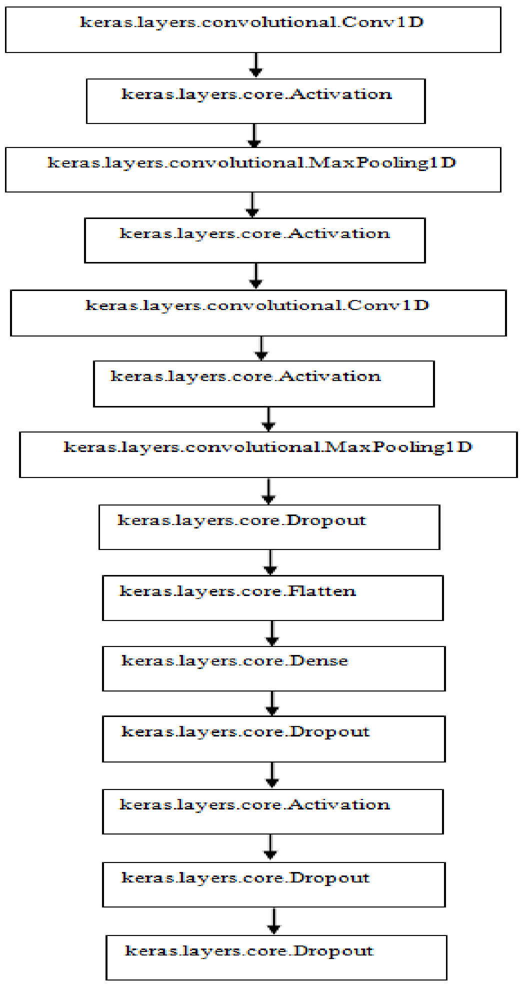

Fig.2. CNN Architecture

Next, we compiled the model, and since this is a multiclass classification, we used categorical cross-entropy as the loss function and Adam as an optimizer. Next, we trained the model using epochs=300 and batch_size=256; after that, we estimated our model using a testing set, and the model achieved better result.

- **RNN Analysis**

Finally, we created RNN for houses A and B by creating the sequence model with dense layers. In this research, hyper-parameters of RNN architectures were employed to develop a robust HAR model for prediction using a SimpleRNN layer, tanh was applied as activation function for hidden layers and a Softmax at output layer.

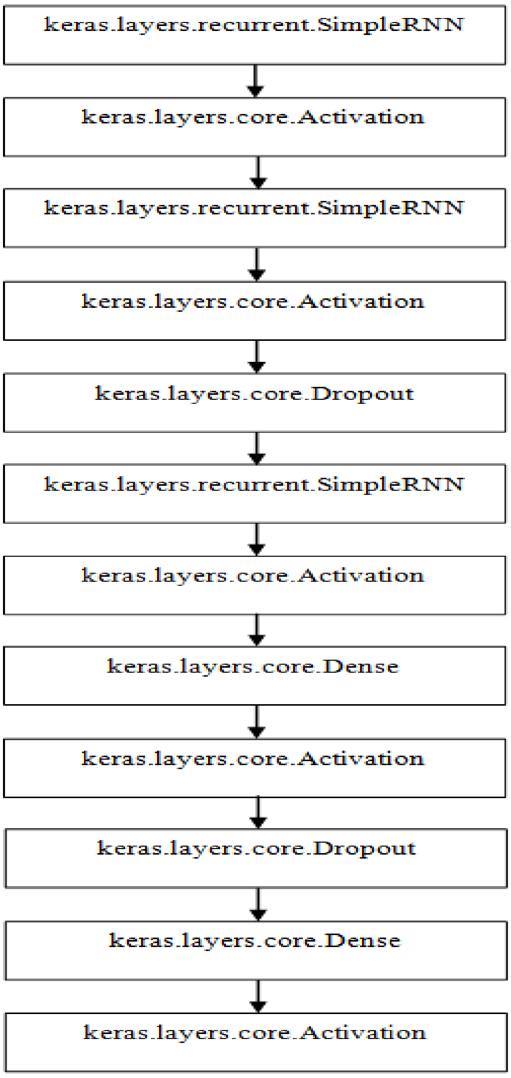

Fig.3. RNN Architecture

Next, we compiled the model, and since this is a multiclass classification, we used categorical cross-entropy as the loss function and Adam as an optimizer. Next, we trained the model using epochs=300 and batch_size=256; after that, we assessed our model using a testing set, and the model achieved the outcome. Finally, we cross-checked the correctness of the predicted and expected values using the loop function and plotted model accuracy and model loss curves.

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 DL models and thereafter performance metrics were applied. The findings indicate that ANN outshone other CNN and RNN in both houses A and B for activity identification for multiresidents in smart homes using ARAS dataset. Table 2 and Table 3 show the outcomes achieved by DL models in this study aligned with the discussion.

Table 2: Classification performance comparison in House A

Classifiers	Evaluation Metrics			
	Accuracy (%)	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
ANN	0.994	0.994	0.995	0.994
CNN	0.993	0.993	0.994	0.992
RNN	0.993	0.993	0.994	0.993

The above Table 1, the experimental outcomes indicate that ANN outperformed with an accuracy of 99.4% in house A compared to CNN and RNN. CNN and RNN achieved the same outcome with an accuracy of 99.3% each. This implies that ANN model fit best with the ARAS dataset for activity identification in intelligent home settings.

Table 3: Classification performance comparison in House B

Classifiers	Evaluation Metrics			
	Accuracy (%)	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
ANN	0.998	0.997	0.998	0.997
CNN	0.997	0.995	0.997	0.996
RNN	0.996	0.995	0.996	0.996

In Table 3 the outcomes of the experiments conducted at House B shows that again ANN still performs best compared with CNN and RNN DL models using the ARAS dataset for activity identification in smart home environment. The ANN outshone with an accuracy of 99.8% for activity recognition, followed with CNN and RNN with an accuracy of 99.7% and 99.6%, respectively.

4.5. Comparative Analysis

Table 4 demonstrates the comparison between the prior study and the proposed approach. This study outperformed the previous studies in activity recognition using DL models. The earlier research by Alemdar et al. [6] the owner of the dataset achieved 61% and 76% in houses A and B, respectively, using HMM. Another study by Natani et al. [7] obtained an accuracy of 79.25%, and 88.75% using CNN. Another research by Igwe et al. [8] achieved an accuracy of 67.32% and 95.43% in home A and B, respectively, using ANN. As a result, the proposed approach outperformed the earlier experiments in identifying human activity in the intelligent home using the ARAS dataset as shown in Table4.

Table 4: A comparison of Forecast Performance from ARAS Dataset

Research Study	Method	Accuracy House A	Accuracy House B
Alemdar et al. [6]	HMM	61%	76%
Natani et al. [7]	CNN	79.25%,	88.75%
Igwe et al. [8]	ANN	67.32%,	95.43%
The proposed approach	ANN, CNN, RNN	99.4%, 99.3%, 99.3%	99.8%, 99.7%, 99.6%

5. CONCLUSIONS AND FUTURE DIRECTIONS

This study presents a novel of HAR in smart home using DL models (ANN, CNN and RNN). The experimental outcomes prove that ANN outscored in both residence A and B contrast to CNN and RNN models. The ANN achieved accuracy of 99.4% and 99.8% in home A and B; in forecasting human conducts. The results prove that the ANN analyzes ARAS datasets better than CNN and RNN models. In future work, we suggest that different DL models be employed on the ARAS dataset to improve the prediction accuracy.

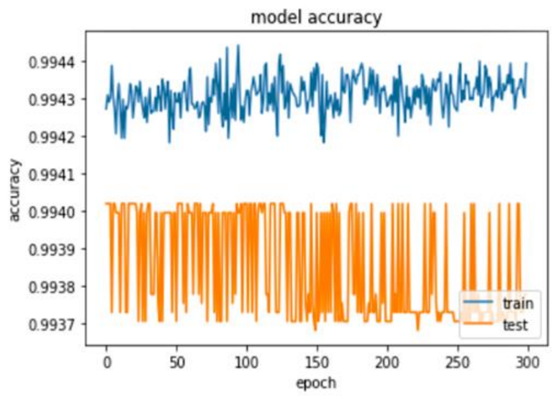

Fig. 4 Model Accuracy of ANN in House A

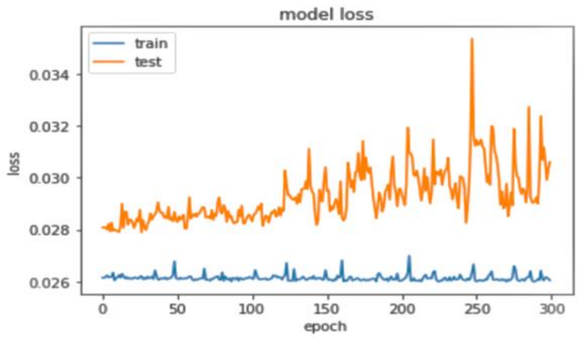

Fig.5 Model Loss of ANN in House A

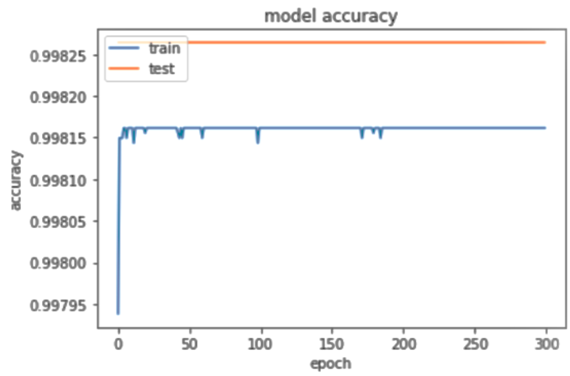

Fig.6 Model Accuracy of ANN in House B

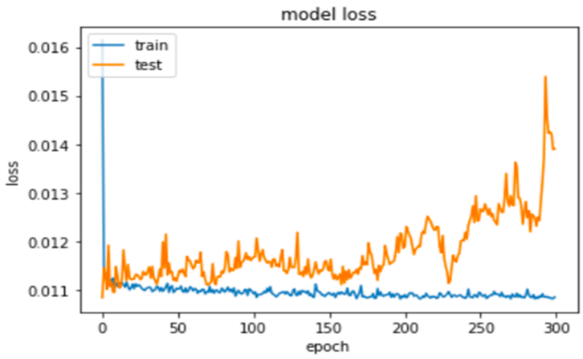

Fig. 7 Model Loss of ANN in House B

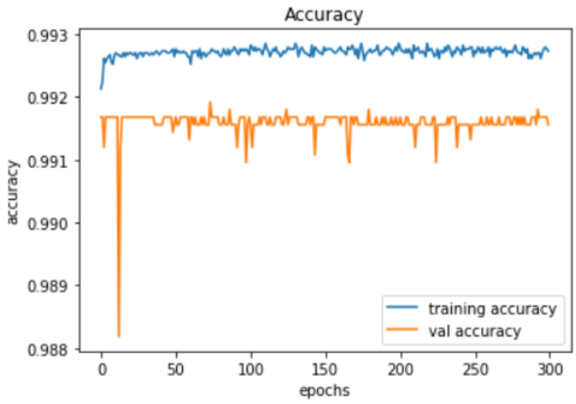

Fig.8 Model Accuracy of CNN in House A

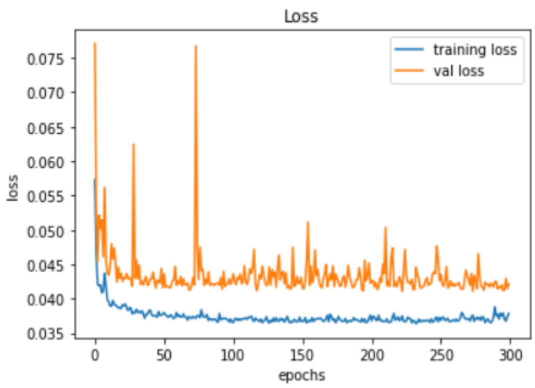

Fig. 9 Model Loss of CNN in House A

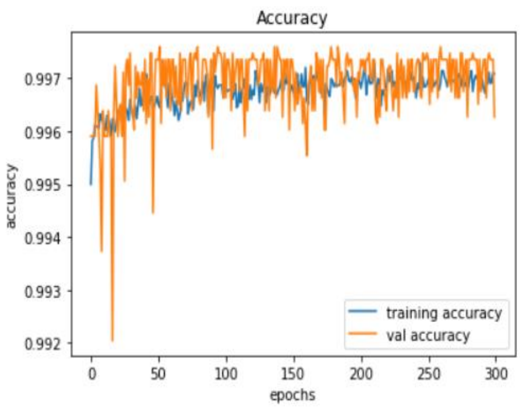

Fig.10 Model Accuracy of CNN in House B

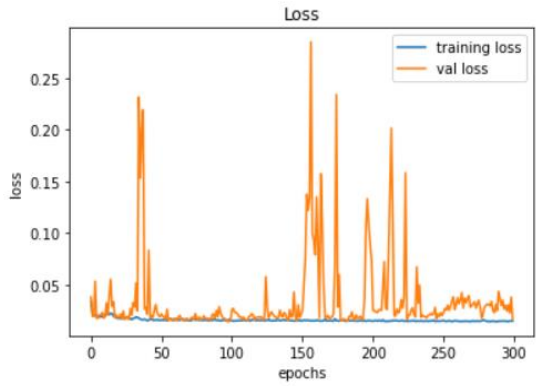

Fig. 11 Model Loss of CNN in House B

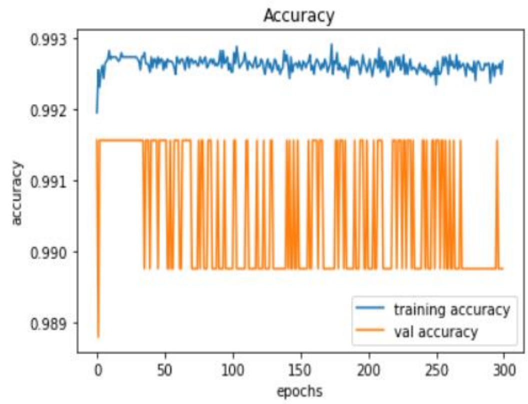

Fig.12 Model Accuracy of RNN in House A

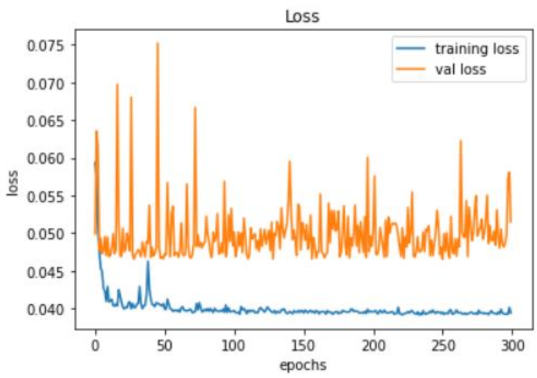

Fig.13 Model Loss of RNN in House A

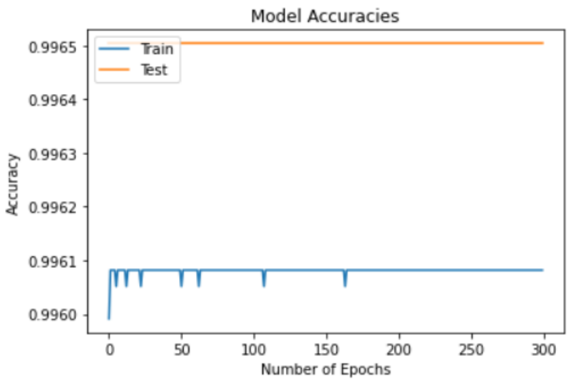

Fig.14 Model Accuracy of RNN in House B

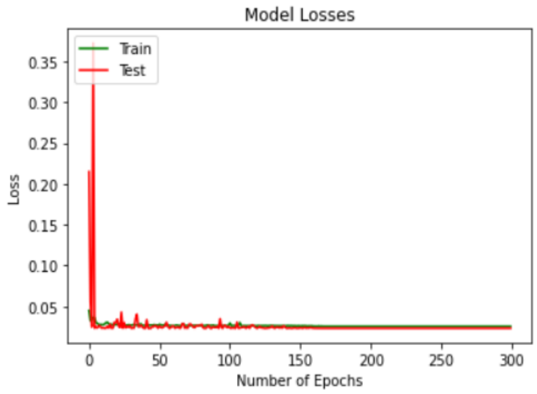

Fig.15 Model Loss of RNN in House B

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