An Improved ANN Approach for Occupancy Detection of a Smart Building

Mitali Ray[1], Padarbinda Samal[2], Chinmoy Kumar Panigrahi[3]
[1, 2, 3] School of Electrical Engineering, KIIT Deemed to be University,
Bhubaneswar, Odisha, India

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ABSTRACT

Building energy performance can be improved with a reduction in energy consumption. The heating and cooling loads of a building are important factors to consider in the field of energy conservation. It is possible to estimate energy consumption by predicting the presence of occupants in a room based on information provided by the HVAC (Heating, Ventilation, and Air Conditioning) system using standard information. Temperature, humidity, light, and CO_2 levels from various sensors are taken as input parameters. In addition, the output of the network is programmed to be "0" when the building is not occupied and "1" when the building is occupied for the purpose of occupant detection. Pattern recognition using an Elman back propagation network is being proposed for occupancy detection. The data sets were used for training and testing (with the office door open and closed) the models during occupancy. The proposed ANN-based method is trained and tested and was found to be more effective, with an accuracy of 98.5% and 97.5% in cases of closed and opened doors, respectively.

Corresponding Author:

Mitali Ray,
School of Electrical Engineering, KIIT Deemed to be University,
Bhubaneswar, Odisha, India,
Email: mitaliray87@gmail.com

1. INTRODUCTION

The consumption of energy in buildings is a significant source of concern. One-third of total energy is generally consumed by buildings [1]. In addition, the majority of opportunities for energy savings lie in the proper load management of existing buildings. Among these loads, the HVAC (heating, cooling, and air conditioning), system has a great significance in influencing the energy consumption in buildings. Many factors are responsible for proper load management of the HVAC system. Advance control techniques have been developed to provide a promising solution in the field of energy management to deal with an issue [2]. The most important of these factors is occupancy, which affects the heating and cooling loads of buildings.As people spend most of their time inside the rooms, occupants' behaviour plays an important role in the control system [3]. This indoor occupancy estimation is done by using temperature, humidity, motion, and gas sensors [4].

In this paper, occupancy detection is used to control HVAC load in a building. However, doing so reliably is difficult due to technical challenges, sensor requirements, and privacy considerations. Factors including indoor air temperature, relative humidity, solar heat gain coefficient, occupancy behaviour, and energy usage data can help with accurate occupancy detection. HVAC systems can track occupant location in multiple spaces using RFID-based occupancy tracking [5].It estimates the inhabitants in each thermal zone for an actual time interval. [6] Also, detection of occupants can be classified as explicit or implicit. Explicit methods rely on sensors and CO2 levels to determine occupant count, while implicit systems rely on patterns of usage of building equipment like computers, printers, and other similar devices. The measurement of CO2 in a space determines occupancy [7]. PIR detection systems use PIR sensors to detect radiation from objects or individuals, and ultrasonic detection devices detect occupants by analysing changes in signal echoes' transmission intensities [8]. Some of the most commonly used methods for predicting occupancy include linear discriminant analysis (LDA), random forest (RF), classification and regression trees (CART), and Bayesian statistics [9]. The thermal characteristics of the building, occupant behaviour parameters, and annual load intensity of the HVAC system data simulated with Energy Plus software [10] are used to test performance prediction methods using various artificial neural networks (ANNs). With the proper analysis in this paper, it has been established that the ANNs are giving better results than the conventional methods.

Artificial neural networks can solve complex tasks. Occupancy also affects building energy conservation. So, this research proposes an ANN technique for building occupancy detection. In a free operating state, optimising energy consumption by HVAC loads through accurate level prediction or occupancy detection of the room is dependent on CO2 concentration inside the room and outside air temperature. In free running, taking into account both indoor and outdoor temperatures can affect the performance analysis. So, the effect of occupancy on HVAC demand is presented separately when the door is closed and opened. So, along with the ANN approach, section 2 highlights the suggested method, section 3 specifies the data used, sections 4 and 5 provide results analysis and comparative analysis, and section 6 concludes and discusses future scope.

2. PROPOSED METHOD

The literature shows complex networks can be solved by neural networks with a faster solution. In Elman back propagation, neural network feedback reorganisation is done by feeding the output of each hidden layer back to the corresponding input layer. The major difference between the proposed network and other types of static and dynamic neural networks like feed-forward networks, feed-forward with back propagation networks, and recurrent networks is that these networks can perform well with more neurons in the hidden layers as per the complexity of the problem. The Elman network uses back propagation techniques that can resort to minimal error sequences during training. The Elman back propagation network is a two-layer back propagation network in which a recurrent connection exists from the output of the hidden layer to its input. So an Elman back propagation neural network exhibits good approximation and generalisation [16]. Back-propagation, on the other hand, is quick, simple to understand, and easy to program, with no parameters to tune other than the number of inputs. In this paper, we have analysed the data by considering an Elman back propagation network with three layered 20-20-20-1 neurons and the Levenberg-Marquardt training algorithm. Because it is more efficient in small and medium-sized networks and patterns, the Levenberg-Marquardt training algorithm is used here [9]. The transfer function taken in each method has been fixed to tansig - tansig - tansig - purelin and the performance goal has been fixed to 10e(-7). This combination is considered here because, after several tests, this combination of neurons and transfer function is giving better results. The training model is shown in Figure 1. During training of the dataset, it was observed that the Elman back propagation network took 415 iterations and 6154 seconds to train.

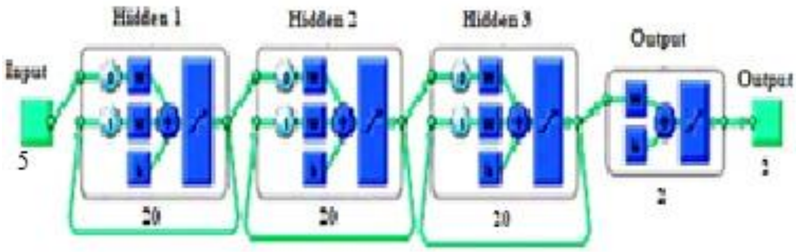


Figure 1. Elman back propagation network developed

3. DATASET USED

There is a machine-learning repository at the University of California, Irvine (UCI). Sensors and microcontrollers are used to collect and store data such as temperature, humidity, light, CO_2 levels, and humidity ratio in an office room with dimensions of 5.85 m x 3.50 m x 3.53 m [11]. A smart motion detector camera is used to determine how many people are in the room. For unoccupied space, the output is set to "0", while for occupied space, it is set to "1". Different neural networks are used for occupancy detection based on sensor data. The data was taken in February in Mons, Belgium, during the winter months. With the help of hot water radiators, the room's temperature was kept at or above 19 degrees Celsius. Testing the data sets when the office door is open and closed gives an indication of the correctness of the proposed models. The data was collected at 14-second intervals.

4. METHODOLOGY

After getting the sensor data, it is fed to the network, which consists of three hidden layers with 20 neurons in each layer and is trained using the Levenberg-Marquardt algorithm. The output of the network is set to "0," either for not occupied or "1," for occupied. The performance of a classification model on a set of test data for which the actual values are known is described here by a N*N confusion matrix. where "N" is the number of classes to target. In order to compare actual target values to the anticipated values predicted by the suggested models, the confusion matrices for training and testing data sets for each network are constructed. Figure 2 shows the training data's confusion matrix, and Table 1 shows the significance of each row and column.

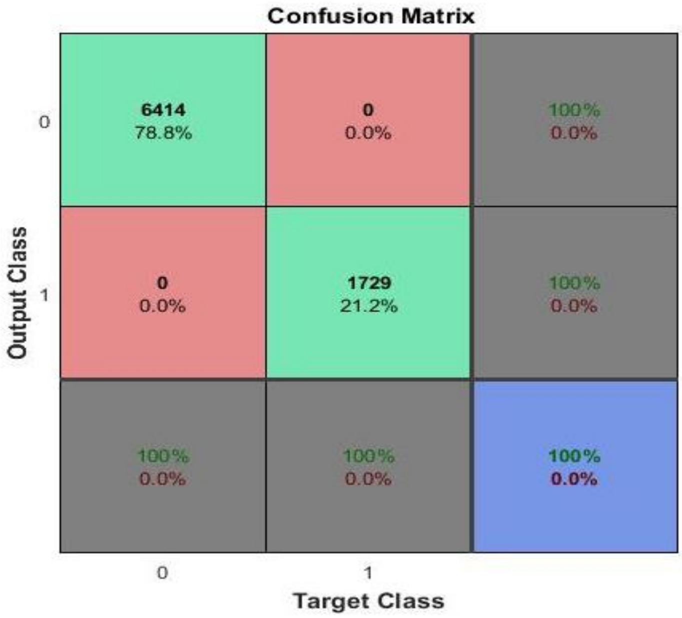


Figure 2. Training of dataset

Table 1. Confusion matrix

	TARGET 0 (Absence of occupants)	TARGET 1 (Presence of occupants)
OUTPUT 0 (Absence of occupants)	P	Q
OUTPUT 1 (Presence of occupants)	R	S

The accuracy of the model can be determined as follows:

$$\text{Accuracy} = (P + S) / (P + Q + R + S) \tag{1}$$

where, P is the predicted true positives, S is the predicted true negatives, and (P+Q+R+S) is the total number of predictions.

This analysis follows the flow chart presented in Figure 3. The flow chart follows the following steps: Data pre-processing is executed by loading and segregating the dataset into inputs and outputs in the initialization stage; training, testing, and validation of the dataset are done in the ratio of 90:5:5. Performance analysis is done with 10-fold cross validation in the training and cross-validation stages; using the dataset, the trained model is run, the tested model's performance is evaluated in the testing phase, and the computation of accuracy in terms of the confusion matrix is done in the last stage, i.e., displaying the performance.

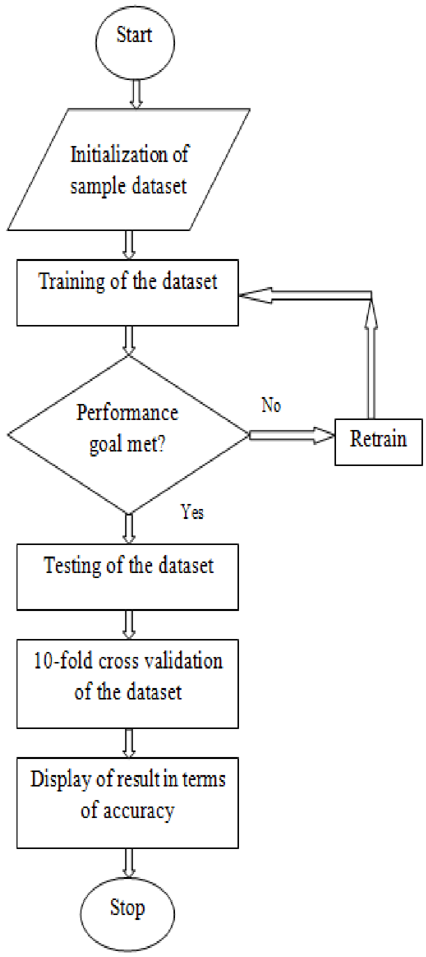


Figure 3. Flow chart for classification of confusion matrix

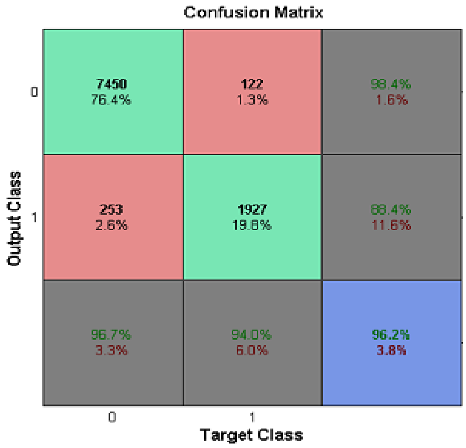
5. RESULT ANALYSIS

5.1. Varying number of neurons

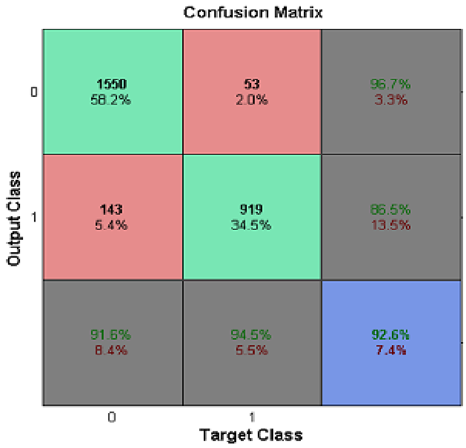
The performance evaluation is carried out by a variable number of neurons. Neurons are mathematical functions in artificial neural networks that carry the weighted sum of their inputs and alter their outcomes with the activation function before passing them on to the other layers or the output layer, respectively. In this case, 20 neurons and 10 neurons in each layer are represented by the numbers 20-20-20 and 10-10-10, respectively. In all cases, the training algorithm is tansig-tansig-tansig-purelin with an activation function trainlm, a performance target of 10e (-7), and a learning rate of 0.01. Individually, the results are collected for open door and closed door conditions in the cases of 20–20–20 neurons, 10–10–10 neurons and 5-5-5 neurons, respectively. The details of the result analysis are provided in Table 2, and the corresponding confusion matrices are presented in Figures 4, 5 and 6. Here we can see that the accuracy of an open door is 96.2 percent and that of a closed door is 92.6 percent in 20-20-20 neurons, whereas the accuracy of an open door is 98.1 percent and that of a closed door is 97.1 percent in 10-10-10 neurons, as shown in the table. As a result of this finding, it can be argued that the network with 10-10-10-neurons has more accuracy. As a result, this network is used for a more in-depth performance study.

Table 2. Performance by varying number of neurons

Number of neurons	Accuracy in case of Door opened	Accuracy in case of Door closed
20-20-20	96.2%	92.6%
10-10-10	98.1%	97.1%
5-5-5	98.0%	95.2%

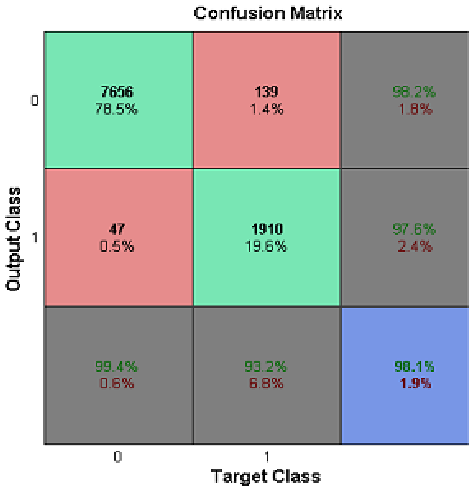


(a) Open door

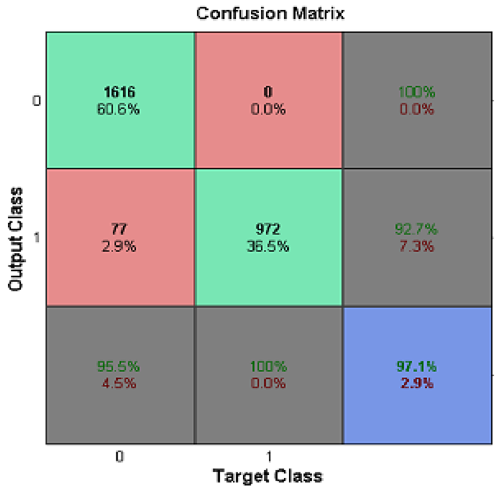


(b) Closed door

Figure 4. 20-20-20 neurons

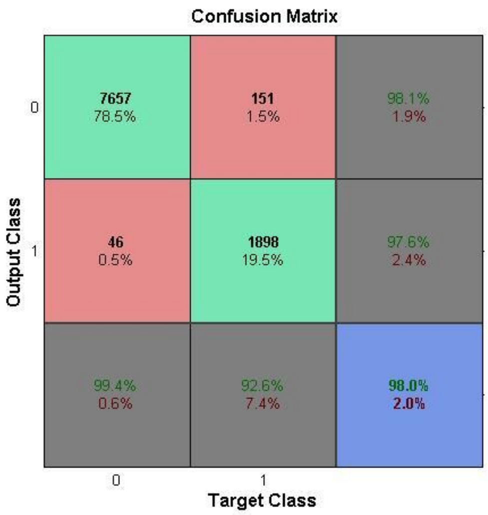


(a)Open door

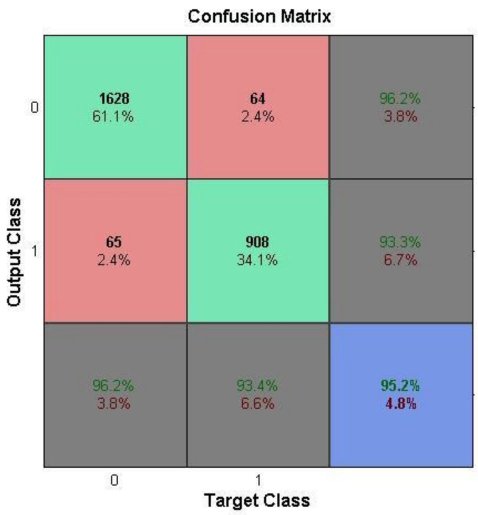


(b) Closed door

Figure 5. 10-10-10 neurons



(a)open door



(b) Closed door

Figure 6. 5-5-5 neurons

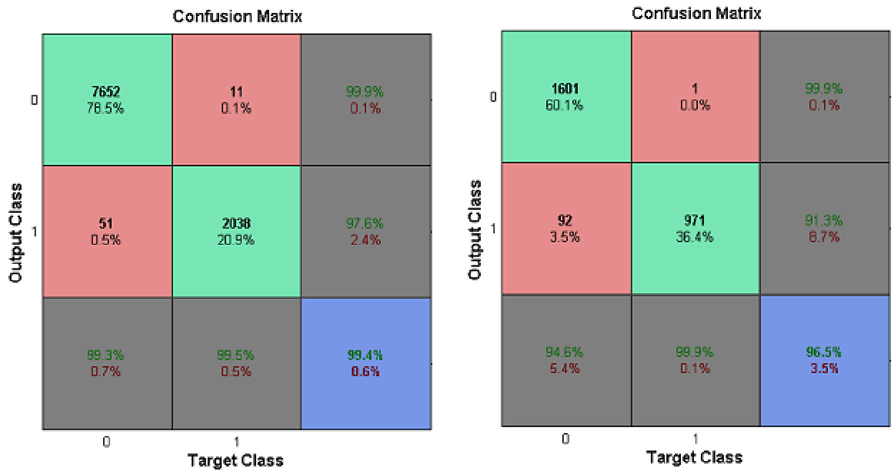
5.2. Varying number of hidden layers

The number of hidden layers in the proposed network can be varied to further test the network's performance. In order to split the function of a neural network into distinct transformations of data, hidden layers must be used. Every hidden layer has a certain specialisation that allows it to produce a specific output. They identified the features in the input data and used them to establish a link between the input and the output data.

The analysis is carried out for networks with three hidden layers and two hidden layers, i.e., networks with 10-10-10-10, 10-10-10 and 10-10 networks, respectively. Moreover, it has been noted that in the 10-10 network, we are getting 99.4 percent accuracy for the open door system and 96.5 percent accuracy for the closed door system, also for 10-10-10-10 network, we are getting 95.8 percent accuracy for the open door system and 89.2 percent accuracy for the closed door system, as indicated in Figure 7 and 8 for the closed door system and separately for the open door system. We are getting an average accuracy of 97.95 percent, which is higher than the previously considered 10-10-10 network, which had an average accuracy of 97.6 percent. Table 3 depicts the results of the comparison investigation. The performance of this 10-10 network using a Tansig-Tansig-Purelin transfer function and Trainlm as the training method with parameters.

Table 3. Performance by varying number of hidden layers

Number of neurons	Accuracy in case of Door opened	Accuracy in case of Door closed
10-10	99.4%	96.5%
10-10-10	98.1%	97.1%
10-10-10-10	95.8%	89.2%



(a) Open door (b) Closed door

Figure 7. 10-10 neurons

(a) Open door (b) Closed door

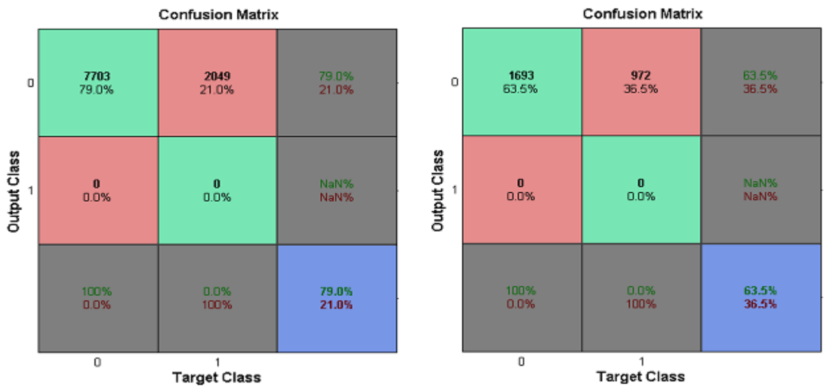
Figure 8. 10-10-10-10 neurons

5.3. Varying training algorithm

By altering the training algorithm, it is possible to further investigate the proposed network. In an iterative process, the neural network learns from the input by altering the weights and biases of the network. There are specific rules to follow in a systematic procedure, and the selection of a training algorithm is essential in order to complete this operation. Trainlm is a training method that changes the outcome by taking into account weight and bias in accordance with Levenberg-Marquardt optimization principles. It is widely regarded as the fastest back propagation algorithm available in the mathematics toolkit. With the help of the Bayesian regularisation optimization technique, the Trainbr algorithm reduces squared errors and identifies the most correct combination of datasets possible. The weights and bias are updated according to the gradient descent momentum optimization technique used by Traingdx. As demonstrated in Figure 7, the outcome obtained by using training as the activation function is displayed in this case. Consequently, by altering the activation function for trainbr and traingdx, the outcome is given in Figures 9 and 10, respectively, for the open door and for the closed door, as illustrated in Figure 8. The accuracy of the network with training algorithm trainlm is 99.4 percent and 96.5 percent for open door and closed door, respectively, while the accuracy of the network with training algorithm trainbr is 79.0 percent and 63.5 percent, and the accuracy of the network with training algorithm traingdx is 98.4 percent and 94.3 percent for open door and closed door, respectively. According to the results analysis, the network with the training algorithm has a higher accuracy than the other networks tested. The results of the analysis are clearly displayed in Table 4.

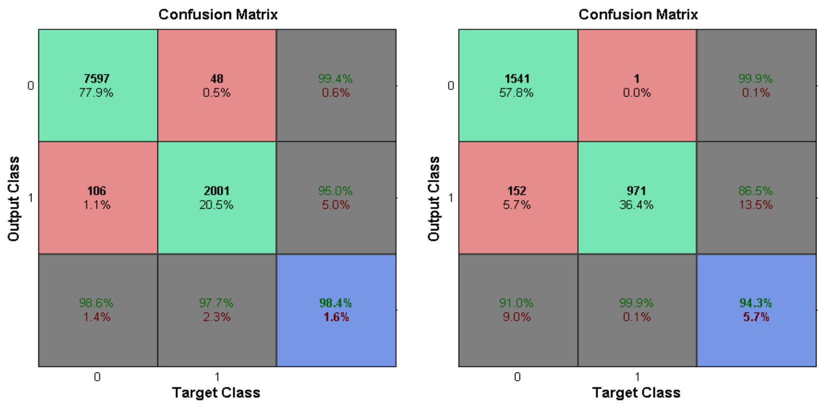
Table 4. Performance by varying training algorithm

Training algorithm	Accuracy in case of Door opened	Accuracy in case of Door closed
Trainlm	99.4%	96.5%
Trainbr	79.0%	63.5%
Traingdx	98.4%	94.3%



(a) Open door (b) Closed door

Figure 9. 10-10 neurons with trainbr training algorithm



(b) Open door (b) Closed door

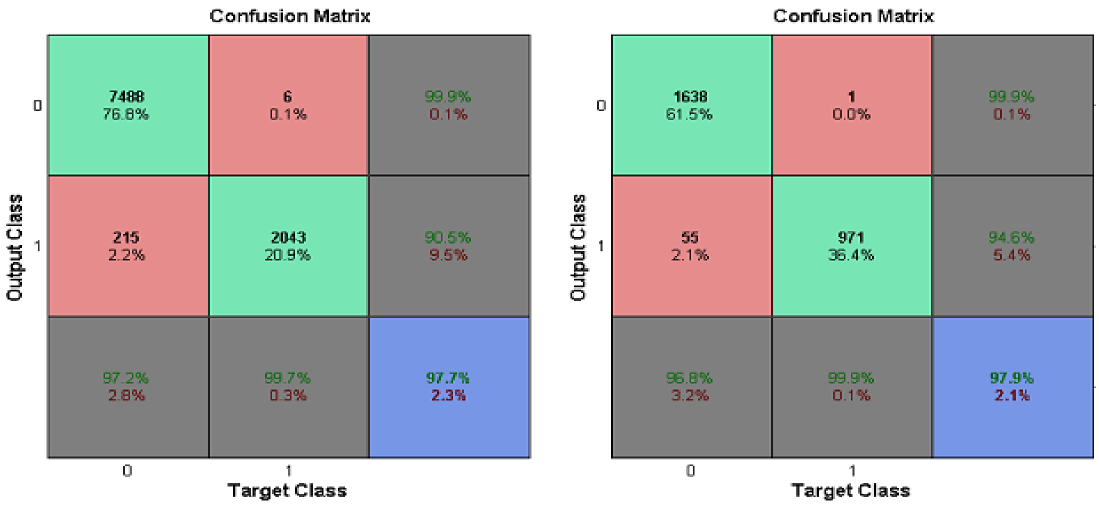
Figure 10. 10-10 neurons with traingdx training algorithm

5.4. Varying transfer function

The suggested network can be further tested by varying the transfer function. The transfer function models the input to output by processing a set of inputs with respect to the target output. Figure 6 depicts the result of considering Tansig-tansig-purelin, TR. Now, by considering tansig as the output layer transfer function, the result is found to be 97.7% for an open door and 97.9% for a closed door, which is shown in Figure 11 in terms of the confusion matrix. Tansig-tansig-purelin has higher accuracy than Tansig-tansig-tansig, according to the results analysis. It shows an accuracy of 99.4% with the door open and 96.5% with the door closed. The results of the analysis are clearly shown in Table 5.

Table 5. Performance by varying transfer function

Transfer function	Accuracy with Door opened	Accuracy with Door closed
Tansig-tansig-purelin	99.4%	96.5%
Tansig-tansig-tansig	97.7%	97.9%



(a) Open door (b) Closed door

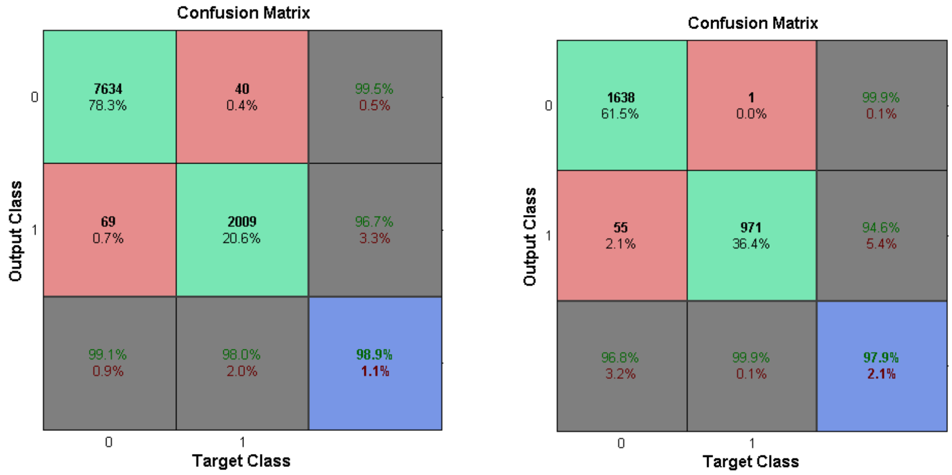
Figure 11. 10-10 neurons with transfer function tansig-tansig-tansig

5.5. Varying performance goal

Now that the suggested network has been tested, it may be evaluated against several performance goals, such as 10e (-7) and 10e (-5). Rather than concentrating on the output of the network, the performance target concentrates on the effectiveness with which the desired output is achieved. The accuracy of the network with a performance goal of 10e(-7) has previously been evaluated, and the results have shown that it is 99.4 percent accurate for open doors and 96.5 percent accurate for closed doors. According to Figure 11, when the network is tested with a performance goal of 10e(-5), the accuracy is found to be 97.7 percent for open doors and 97.9 percent for closed doors, respectively, as shown in Figure 12. This is demonstrated in Table 6, where it can be determined that the network with performance goal 10e (-7) has greater accuracy than the network with performance goal 10e (-5).

Table 6. Performance by varying performance goal

Performance goal	Accuracy with Door opened	Accuracy with Door closed
10e(-7)	99.4%	96.5%
10e(-5)	98.9%	97.9%



(a) Open door (b) Closed door

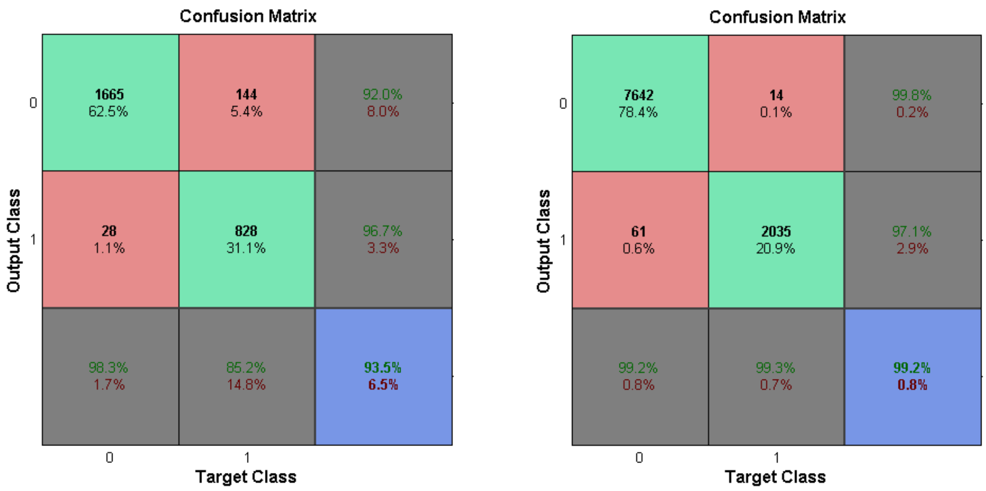
Figure 12. 10-10 neurons with performance goal 10e (-5)

5.6. Varying learning rate

The proposed network is now tested once more with learning rates of 0.01 and 0.001, respectively. The learning rate is what affects how soon the model converges to local minima. Because of this, adjustments may be performed quickly and efficiently with fewer epochs, allowing the training to be finished in less time. Figure 13 shows that with learning rate 0.01 we get an accuracy of 99.4 percent for open door and 96.5 percent for closed door, respectively; however, with learning rate 0.001 we get an accuracy of 93.5 percent and 99.2 percent for open door and closed door, respectively. Based on the results of the performance analysis shown in Table 7, we can conclude that the network with a learning rate of 0.01 provides superior accuracy.

Table 7. Performance by varying learning rate

Learning rate	Accuracy with Door opened	Accuracy with Door closed
0.01	99.4%	96.5%
0.001	93.5%	99.2%



(a) Open door (b) Closed door

Figure 13. 10-10 neurons With learning rate 0.001

6. COMPARISON WITH OTHER METHODS

A number of academics have devised a variety of ways for determining whether or not a space is occupied. For example, in [9], CART models are utilised with 95 percent accuracy because they are straightforward to comprehend and interpret. The genetic algorithm (GA) is used in classification and regression [12], among other applications. The implementation of genetic algorithms can also be used to generate high predictive power while using high-frequency smart meters. In this instance, it is discovered that the accuracy is 90 percent. SVM makes use of the kernel trick to its advantage. The SVM is capable of coping with problems that have multiple dimensions. Kernels are used to convert nonlinear separation issues into separable separation issues when dealing with nonlinear separation challenges. Kernels are frequently employed in the solution of nonlinear separation issues. [13] The K Nearest Neighbors (k-NN) approach is yet another means of categorising information. Having this tool available while dealing with huge and dynamic databases is a useful thing to have. With an accuracy of between 80 and 88 percent, it saves time while simultaneously increasing efficiency and effectiveness. Reportedly, the accuracy of back propagation NN is 95.6 percent, in agreement with [14]. Similarlly Markov based feedback recurrent neural network [17] method is giving an accuracy of 80.9% by collecting the data from the PIR sensors fitted in the test areas. Also, LSTM neural network technique [18] is used for occupancy detection in a building. And the experimental results has shown that the proposed long short-term memory neural network (LSTM) is well suited to account for occupancy detection at the current state and occupancy prediction at the future state, respectively, with an overall detection rate of 99.5% and 92.6% with an average value of 96.08% accurracy . Table 8 compares a number of different models and provides a summary of the comparison. By using the proposed Elman back propagation network, it is possible to attain an accuracy rate of 99.4% for open doors and 96.5% for closed doors, which is higher than the accuracy rate produced by another technique under discussion.

Table 8. Comparison with other models

Method Used	Accuracy
Classification and regression tree (CART) [9]	95%
GA [12]	90%
SVM, k-NN [13]	80% to 88%
Feed forward back propagation [14]	95.6%
Markov based feedback recurrent neural network [17]	80.9%
LSTM neural network technique [18]	96.08%
Proposed method	96.5% – 99.4%

7. CONCLUSION AND FUTURE SCOPE

According to this paper, an Elman back propagation network is proposed for detecting building occupancy using data from several sensors, such as light, temperature, humidity, and carbon dioxide. According to the results of the comparison, the proposed network design, which includes two hidden layers of ten neurons each and Levenberg-Marquardt as the training algorithm, is the most accurate. The learning rate is 0.01 and the transfer function is tansig-tansig-purelin. The accuracy of this model in predicting occupancy is 99.4% for an open door condition and 96.5% for a closed door condition. In the future, it will be possible to identify optimal features with good performance and an appropriate occupancy model, and improved algorithms will be able to analyse hidden patterns.

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BIOGRAPHY OF AUTHORS

Mitali Ray was born in 1987. She got her bachelor degree and master degree from BPUT, Odisha in the year of 2009 and 2015. Now she is continuing her PhD at KIIT Deemed to be University, Bhubaneswar in the department of Electrical engineering.

Samal, Padarbinda, was born in 1987, and he graduated from the S.I.T, Bhubaneswar (Orissa) in 2009 with a Bachelor of Technology degree in electrical engineering and he got a Master of Technology degree from V.S.S University of Technology, Burla (Orissa). as well as he was awarded a Ph.D. in electrical engineering from the National Institute of Technology (NIT), Rourkela (Orissa). At SOA University in Bhubaneswar, Odisha, he served as an assistant professor in the electrical engineering department from 2010 to 2011 and now he is continuing at KIIT Deemed to be University in Bhubaneswar, Odisha. Distribution system planning and soft computing applications to power systems are his research areas.

Chinmoy Kumar Panigrahi was born in Orissa in 1967. In the years 1990 and 1997, he earned his Bachelor of Technology and Master of Technology Degrees from Sambalpur University, Orissa. In the year of 2007, he earned his Ph.D. from Jadavpur University, Kolkata. e has 23 years of experience in teaching and 5 years of experience in the field of research. His resume has a long list of honors and recognitions. Power system control, renewable energy systems, and soft computing techniques are his areas of interest.