OCCUPANCY DETECTION THROUGH LIGHT, TEMPERATURE, HUMIDITY AND CO_2 SENSORS USING ANN

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Abstract- Previous studies showed that knowing occupancy certainly can save energy in the control system of building. In this regard, occupancy detection has a significant role in many smart building applications such as heating, cooling, ventilation (HVAC) and lighting system. In this paper, various Artificial Neural Network algorithms were applied to the dataset composed by samples obtained from light, temperature, humidity and CO2 sensors. When the results were compared, it was seen that Limited Memory Quasi-Newton algorithm has the highest accuracy rate with 99.061%. The lowest accuracy rate was obtained from Batch Back algorithm with 80.324%.

Keywords- Occupancy Detection, Classification, Artificial Neural Network

I. INTRODUCTION

A recent literature review [1] shows that when occupancy is known certainly and it is applied to the control system of building, the energy/money can be saved by 20%-50%. The accurate occupancy detection in buildings has been recently predicted to save energy in the order of 30% to 42% [2–4]. Experimental measurements reported that energy savings was 37% in [5] and between 29% and 80% [6] when occupancy data was used as an input for HVAC (Heating, Ventilating and Air Conditioning) control algorithms [7-8].

This research has used dataset composed by samples obtained from light, temperature, humidity CO2 sensors and a digital camera to establish ground occupancy for supervised classification model training. The trained and tested algorithms are Quick Propagation, Conjugate Gradient Descent, Quasi-Newton, Limited Memory Quasi-Newton, Levenberg-Marquardt, Online Back Propagation, Batch Back Propagation.
The paper is organized as follow. In section 2, a literature survey is given briefly. In section 3, the dataset is introduced and information about artificial neural network and ROC curve is given. In section 4, Further information about the study and the results of the study are given. In section 5, short summary of the study is given.

II. THEORETICAL BACKGROUND

In [9], Real time occupancy detection using decision trees was presented. The accuracy was 97.9% when using data from a passive infrared motion sensor.
In [10], The number of occupants in a room was modelled using SVM (Support Vector Machine). The reported accuracy rate was 88%.
In [3], the number of occupants in a room monitored by a wireless sensor and a model was developed. The researchers reported that the energy can be saved by 42%.
In [11], the researchers studied on detecting occupancy using Hidden Markov Models and 73% accuracy was reported.
In [12], the authors used RFID (Radio-frequency identification) to monitor occupancy and they reported 62%-88% accuracy in detecting occupancy.
In [13], the authors reported occupancy detection accuracy between 92.2% and 98.2%.
In [14], a neural network model was used for occupancy detection. They benefited from CO2, sound, humidity, motion and temperature sensor. The reported accuracy was between 75% and 84.5%.
In [15], a model of occupancy was introduced. The model used data of digital video cameras, passive infrared detection and CO2sensors. The model used Bayesian statistics to account for the role of previous information. The authors reported that the introduced model reduced the average error from 70% to 11%
In [2], the researchers used data was gathered from a wireless sensor network for occupancy detection and they predicted that it is possible to save 42% of annual energy consumption.
In [16], to detecting the number of occupants a model that used temperature, CO2, humidity, light, motion and sound sensors was introduced. They used neural network in MATLAB. The accuracy was 64.8%.

III. MATERIALS AND METHODS

3.1. Dataset Description

The data was received from UCI Machine Learning Repository. The information about the dataset is below. (UCI Machine Learning Repository, 2016) [17].
The provided dataset comprises of data from light, temperature, humidity and CO2 sensors. The dataset consists of 3 parts. They were used, one for training, one for validation and one for testing. The dataset contains 20390 samples, 8146 of them were used for

training task, 2664 of them were used for validation task and the rest ,9580, were used for testing network. [18]

3.2. Artificial Neural Network

Artificial Neural Networks have emerged as the simulation of the biological nervous system. A mode of operation of a computer by assimilating to the mode of operation of a brain, neural network model was developed. Learning in artificial neural network algorithms depend on previously acquired experiences. After removing the properties of a system even if an algorithm based on solution of system or it has a complex solution analysis, artificial neural networks can be applied to this system. Artificial neural networks are composed of neurons. These neurons can be connected into each other, even in a very complex way as in real nervous system. Each neuron has entries in the different weight and one output. For this purpose, total of inputs in the different weights is defined as follows [19-20].

$$n = \sum_{i=1}^{P} W_i X_i + b \tag{1}$$

Here; P is the number of inputs, w is the input weight, x is input, b is the value of the bias and neural network. The weighted inputs and sum of each neuron together with the bias are passed through the activation function and consequently output depend on that neuron is obtained. If we indicate activation function with "f", it is expressed as follows.

$$f(n) = f\left(\sum_{i=1}^{P} W_i X_i + b\right) \tag{2}$$

The activation function (activity function, φ) may be sigmoid function, threshold function or a hyperbolic tangent function according to the structure of the system. After the output has obtained if the system is multilayer, the output of a neuron (y) may be an input (x) of a neuron. In this way, a multilayer neural network model is generated [21].

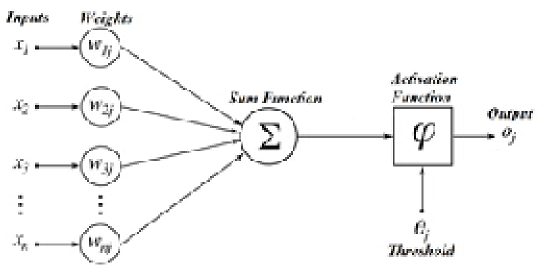

Fig. 1. Artificial Neuron Network Model

Artificial neural network model usually consists of three parts: the input layer, hidden layer and output layer. Each layer may consist of a lot of neurons. After information transmits from the input layer, it transmits activation function. Outputs of the input layer continues as the entry of the hidden layer. After this process, in result function once again evaluating the hidden output layer of activation functions, final output is obtained. The first step of learning in neural networks can be characterized as activation. Signals which enter nerve cell may activate cell signal. If total signal is as high as to fire the cell and get over threshold then the cell is active, but it is passive if not so. According to being active or passive of nerve cell, can be extrapolated if it can make classification or not. An artificial neural network cell which is capable of making classification for input patterns as 1 or 0, it is deemed to have decided setting value to pattern 1 or 0. "Making decision" "and" classifying ", are the cornerstones of the learning process [22].

3.3. Network Confusion Matrix and ROC Curve

A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The following table shows the confusion matrix for a two-class classifier. [23]

The entries in the confusion matrix have the following meaning in the context of our study:

- a is the number of correct predictions that an instance is negative,
- b is the number of incorrect predictions that an instance is positive,
- c is the number of incorrect of predictions that an instance negative, and
- d is the number of correct predictions that an instance is positive.

Table 1: Confusion Matrix

		Predicted	
		Negative	*Positive*
Actual	*Negative*	**a**	**b**
	Positive	**c**	**d**

Correctly Classified Ratio (CCR)) is the proportion of the total number of predictions that were correct. It is determined using the equation:

$$\%CCR = \frac{a+d}{a+b+c+d} * 100$$

ROC graphs are another way besides confusion matrices to examine the performance of classifiers.A ROC graph is a plot with the false positive rate on the X axis and the true positive rate on the Y axis. The point (0,1) is the perfect classifier: it classifies all positive cases and negative cases correctly. It is (0,1) because the false positive rate is 0 (none), and the true positive rate is 1 (all). The point (0,0) represents a classifier that predicts all cases to be negative, while the point (1,1) corresponds to a classifier that predicts every case to be positive. Point (1,0) is the classifier that is incorrect for all classifications. In many cases, a classifier has a parameter that can be adjusted to increase TP at the cost of an increased FP or decrease FP at the cost of a decrease in TP. Each parameter setting provides a (FP, TP) pair and a series of such pairs can be used to plot an ROC curve. A non-parametric classifier is represented by a single ROC point, corresponding to its (FP,TP) pair[24].

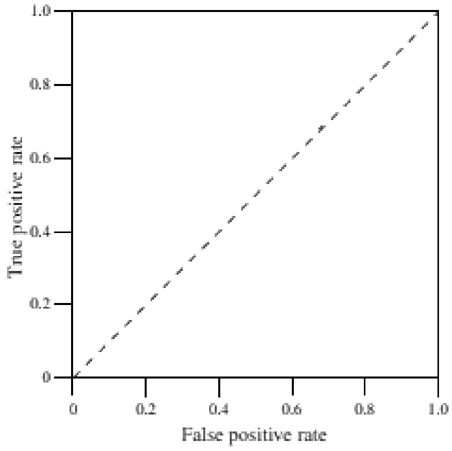

Fig. 2. A basic ROC graph [25]

It has been suggested that the area beneath an ROC curve can be used as a measure of accuracy in many applications [24]. Provost and Fawcett (1997) argue that using classification accuracy to compare classifiers is not adequate unless cost and class distributions are completely unknown and a single classifier must be chosen to handle any situation. They propose a method of evaluating classifiers using a ROC graph and imprecise cost and class distribution information [26].

IV. EXPERIMENTAL STUDY

Our system consists of 1 input layer, a hidden layer consists of 6 neurons and 1 output layer.

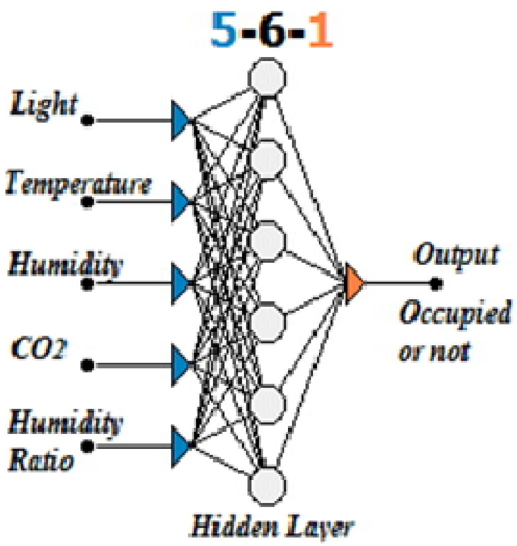

Fig. 3. Our artificial neuron network model

Seven different algorithm namely Quick Propagation, Conjugate Gradient Descent, Quasi-Newton, Limited Memory Quasi-Newton, Levenberg-Marquardt, Online Back Propagation, Batch Back Propagation were applied to dataset and obtained results are shown in Table 2. As can be seen from Table 2 Limited Memory Quasi-Newton algorithm has the highest CCR ratio.

Table 2: Correctly Classified Ratio of Seven Different Algorithm Applied To The Dataset

Algorithm	Correctly Classified Ratio (% CCR)			
	Trainin g	Validatio n	Test	All
Quick Propagation	98,895%	97,748%	96,033 %	97,401 %
Conjugate Gradient Descent	98,944%	97,823%	98,038 %	98,372 %
Quasi-Newton	98,932%	96,959%	96,524 %	97,543 %
Limited Memory Quasi-Newton	98,846%	97,748%	99,061 %	98,803 %
Levenberg - Marquardt	80,739%	97,745%	95,741 %	90,010 %
Online Back Propagation	98,625%	97,785%	98,382 %	98,401 %
Batch Back Propagation	78,701%	63,664%	80,324 %	77,499 %

Table 3: Confusion Matrix of Training Task

n=8146	***FN***	***FP***
TN	1730	5
TP	89	6322

As can be seen in Table 3, in training task, 8052 of 8146 samples were classified correctly.

Table 4: Confusion Matrix of Validation Task

n=2664	***FN***	***FP***
TN	966	2
TP	58	1638

As can be seen in Table 4, in validation task, 2604 of 2664 samples were classified correctly.

Table 5:Confusion Matrix of Test Task

n=9580	***FN***	***FP***
TN	1876	9
TP	81	7614

As can be seen in Table 5, in testing task, 9490 of 9580 samples were classified correctly.

Table 6: Confusion Matrix of All Tasks

n=20390	***FN***	***FP***
TN	4572	16
TP	228	15574

As can be seen in Table 6, in whole dataset, 20146 of 20390 samples were classified correctly.

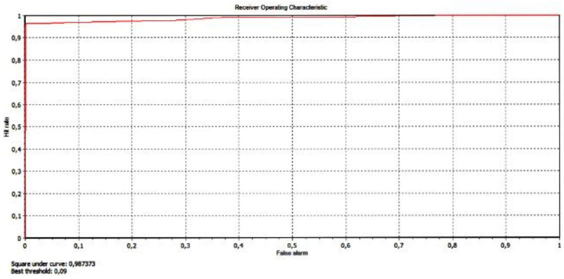

Fig. 4. ROC curve of training

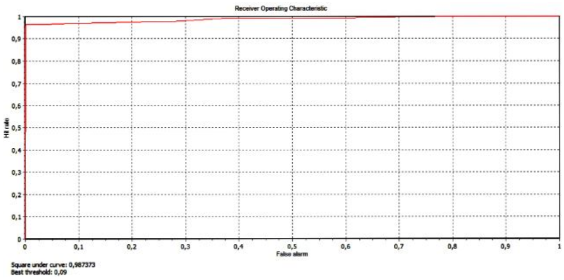

Fig. 5. ROC curve of validation

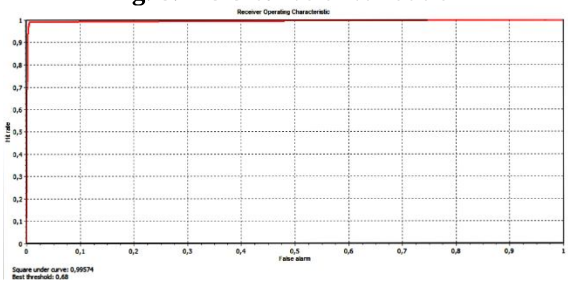

Fig. 6. ROC curve of testing

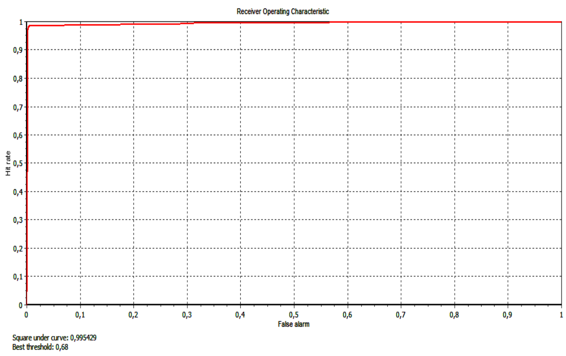

Fig. 7. ROC curve of all samples

ROC curves of training, validation, testing and all samples were given in Figure 4,5,6 and 7 respectively. As can be seen in Figure 4,5,6 and 7, The squares under ROC curves are 0.987373 in training and validation task, 0.99574 in testing task and 0.995429 in all samples.

CONCLUSIONS

In this work, various classification algorithms were applied to the dataset that was received from UCI Machine Learning Repository. For this classification task, seven different Artificial Neural Network algorithms namely Quick Propagation, Conjugate Gradient Descent, Quasi-Newton, Limited Memory Quasi-Newton, Levenberg-Marquardt, Online Back Propagation, Batch Back Propagation were used. When the results were compared, it was seen that Limited Memory Quasi-Newton algorithm has the highest accuracy rate with 99.061%. The lowest accuracy rate was obtained from Batch Back algorithm with 80.324%.

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