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An ANN based Classification Algorithm for Swine Flu Diagnosis

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Abstract

Machine learning technology adds a new potential to medical diagnosis systems. This paper presents an Artificial Neural Network (ANN) based swine flu diagnosis model. The proposed model selects significant features for swine flu diagnosis by a feature selection algorithm using k- Nearest Neighbour (k-NN) classifier, which reduces the size of data to be used for training the ANN model with an objective of making the training more efficient and accurate. A threshold value is determined by ANN to identify positive and negative cases and the model classifies the test cases either positive or negative based on the threshold value. The results obtained with the proposed model demonstrate the ability of the model to provide high level of accuracy for swine flu diagnosis. The assessment (classification) ability of the proposed ANN based model is compared with that of Case Based Reasoning (CBR) approaches and is observed that the proposed model is superior to others.

Keywords: Artificial Neural Network, Back-propagation, Pattern, Pattern Classification, CBR

Introduction

Swine flu is a type of flu which is highly contagious and has potential of rapid spread. The disease generally spreads through air and water. The swine flu, more properly called the H1N1, is a new strain of the common influenza virus. The influenza virus is a very significant zoonotic pathogen and it causes recurrent outbreaks at the local or global scale, resulting in potentially severe consequences for human health as well as for the global economy. The 2009 flu pandemic is a global outbreak of a new strain, which was first identified in April 2009. The outbreak began in Mexico, with the evidence that Mexico was already in the midst of an epidemic for months before the outbreak was recognised. Swine influenza virus infections in humans have been reported in the United States, Canada, Europe and Asia (Rajoura, Roy, Agarwal & Kannan, 2011). Swine flu is on the rise at present. There are thousands of people dying of it and the most common cause of death from the virus is respiratory failure. Therefore in this paper, an artificial neural network (ANN) based model is proposed in order to solve the classification and prediction problem and to develop a swine flu prediction system that decreases the cost of authentic tests and also time.

With the advent of internet and efficient communication, medical science industry collects a huge amount of relevant and invaluable data, which is not properly mined and not organized for optimum use. Discovery of these hidden patterns and their relationships often goes unexploited and un-known. Due to this reason, clinical decisions are often made based on doctor's intuition and experiences rather than on the knowledge about data hidden in the database. Sometimes, this approach leads to unnecessary errors and increase in medical costs, which affects the quality of services provided to the patients. So, ANN can be used to diagnose the case of a patient to decide whether the patient has swine flu or not immediately without doing pathological tests. Thus, the proposed model aims

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at assisting the medical practitioner in the diagnosis process for a newly arrived case with reduced amount of information, obtained through a feature selection process. It will save time and money and provide ample time in hand for treatment, which is very important for a patient.

Swine flu prediction is a problem that involves determining whether an individual has Swine Flu or not, aimed for medical facilitation purposes. This is a binary classification problem in which an outcome of prediction has to be determined with a decision of 'Yes' or 'No'. The proposed model uses neural network technique that is to be applied to classification problems.

Artificial neural network (ANN) is a technique that mimics the learning capability of human brain from experiences. It means that if a neural network is trained from past data, it will be able to generate outputs based on the knowledge extracted from the data. ANN can adapt itself to the data without making prior assumption of the functions. ANN could be used as a nonlinear model to solve complex real world applications.

Artificial neural networks (ANNs) are most often chosen for its ability to generalize results from unseen data. ANNs are parallel computational models comprised of densely interconnected processing units that have the ability to respond to input stimuli and to learn to adapt to the environment. ANN includes two working phases, the phase of learning and phase of recall. During the learning phase, known data sets are commonly used as a training signal in input and output layers to obtain updated weights. The recall phase is performed by one pass using the weight obtained in the learning phase. Back propagation neural network (BPNN) is the most popular neural network and is used in numerous applications. It is the most commonly used neural network in classification.

The ANN approach demonstrates better results than techniques like CBR for classification problems in medical domain. The ANN model is based on the concept of generalized knowledge. In this concept, data patterns used in developing the model are disregarded afterwards and the model is used independently. On the other hand, the CBR model is based on the concept of specialized knowledge. The CBR model specifies exactly the cases that are retrieved and allows the user to track these cases, their circumstances, and solutions. Even though CBR selects the closest value, it definitely would never be able to predict better than what exists as the solution of the closest case in its case-base. A key aspect of ANN models is that they are able to learn, and their behaviour may improve with training and experience. This advantage of ANN provides superior prediction results over CBR (Dogan, Arditi & Gunaydin, 2006).

In this paper, the artificial neural network is trained using the back propagation algorithm with a training set and then is validated with a validating set (test set). The validating set is used to check the generalisation ability of the trained network. The back propagation learning algorithm performs a gradient descent optimisation on the weights linking the nodes in each layer. While BPNN has shortcomings such as long training time and the possibility of over training, it is nevertheless simple to use and has shown to be robust and gives good results in most cases in our experiment. It is therefore taken as the benchmark of solving classification problem using neural network.

Related Work

Neural network was proved to be a universal approximator. The idea of prediction using neural networks is to find an approximation of mapping between the input and output data through training. The trained neural network is then used to predict the values for the future. The main advantages of ANN are that, depending on the activation function they can perform non-linear classification tasks, and that, due to their parallel nature, they can be efficient and even operate if part of the network fails.

The training step for an ANN may be completed by using one of the several available training paradigms. The training paradigm of our choice is back propagation, which is the most widely used algorithm to train neural networks. The training is based on a simple concept, i.e., if the network gives a wrong answer, then the weights are corrected so that the error is lessened and as a result, future responses of the network are more likely to be correct (Khoa, Sakakibara & Nishikawa, 2006). It corresponds to a propagation of errors backwards through the network. It involves an iterative procedure for minimisation of an error function, with adjustments to the weights. In order to achieve a realistic training time, a learning rate parameter, which represents the percentage of the step taken towards minimum error must be specified. If this quantity is too small, training will take too long, and if it is too large, the gradient descent will degenerate and the error will increase (Paola & Schowengerdt, 1995).

The basic building block for ANN is an artificial neuron or a node (Hashemiand & Stafford, 1993). Nodes in the neural network are organised into layers. Every node in one layer has weighted connections to nodes in the next layer. A node receives inputs x_l, x_2, ...,x_n through its n input connections. If the associated weights to these connections are w_1, w_2, ...,w_n then the sum of weighted inputs (Net) for the node is given by the equation 1.

$$\text{Net} = \sum_{i=1}^{n} w_i x_i \qquad (1)$$

To determine whether the sum is large enough to excite the node, an activation function is applied on the weighted sum of inputs to generate an output value that represents the excitement or activation level of the node. For the backpropagation training algorithm, the activation function must be differentiable (Paola & Schowengerdt, 1995). The most common form is the sigmoid function, defined by equation 2.

$$f(\text{Net}) = \frac{1}{1+e^{-\text{Net}}} \qquad (2)$$

During the training phase, the backpropagation network takes the steepest descent from the current position to one of lower error (Fung, Iyer, Brown & Wong, 2005).

It is observed that a number of benefits of applying ANN in the medical domain have already been identified (Pattichis & Pattichis, 2001; Lei & Cheng, 2010; Grossi & Buscema, 2010). Teng and Wah (1996) presented two learning mechanisms for artificial neural networks (ANNs) that are applied to solve binary classification problems like two-spiral problem, a two-region classification problem, and the Pima Indian Diabetes Diagnosis problem. The application of neural network for pattern classification into multiple categories is shown in research by Xu and Chaudhari (2003). Janghel, Shukla, Tiwari and Tiwari (2009) developed a Clinical Decision support system (CDSS) using the pathological attributes to predict the fatal delivery to be done normal or by surgical procedure by neural network. It is a kind of binary classification problem which is solved by ANN. Apart from medical science it is also applied in many other fields. In the paper by Benjamin, Altman, O'Gorman, Rodeman and Peaz (1997), use of artificial neural networks has been demonstrated for engineering analysis of complex physical systems, in paper by Simões, Furukawa, Mafra and Adamowski (2000) a neural network was used to classify the acoustic signals into two classes of binary transmission. Bhatikar and Mahajan (2002) also demonstrated an application of artificial neural networks for fault diagnosis of manufacturing equipment where ANN can learn to associate an event with its process signature, and thus detect and classify events reliably. The paper demonstrated that the threshold rule for setting the threshold of a binary output neuron performing a classification task enhances the diagnostic performance. It is also observed that relevant feature selection and appropriate pattern representation can produce better result in classification problem as Soda, Pechenizkiy, Tortorella and Tsymbal (2010) reported that in many domains it has been recognised that the construction of the right features, feature extraction, finding appropriate ways of pattern representation and dimensionality reduction is often more important than the selection of the right classification technique.

In this paper the objective is to design a novel neural network classifier that is used in the decision support system for swine flu prediction. Initially feature selection is done for appropriate pattern representation, which is important in pattern classification problem. Several published articles are available in context of swine flu prediction. In the paper by Thakkar, Hasan and Desai (2010), a healthcare decision support system for swine flu prediction has been proposed using naïve bayes classifier. In the paper by Chakraborty, Srinivas, Sood, Nabhi and Ghosh (2011), an effort has been made to propose a model for diagnosis of swine flu using case base reasoning. Bayes classifier has a severe drawback of prior probability of happenings without knowing the knowledge of current pattern. So, it is not a good generalizer of current pattern. It is observed that feature selection is not done but it needs to be carried out to remove the redundant attributes not needed for classification problem as it brings about many benefits like increasing predictive accuracy and reducing complexity of learned results (Chakraborty *et al.*, 2011). Keeping in view of all these issues, a novel neural network classifier is proposed which is a good generalizer of stored patterns as well as current patterns.

Research Methodology

Neural networks are endowed with some unique properties, like the ability to learn from and adapt to their environment and the ability to approximate very complicated mappings. Work on artificial neural networks has been initially motivated right from its inception by the recognition that the brain computes in an entirely different way as the conventional digital computer. An artificial neural network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true for ANNs as well.

The learning process of a neural network consists of training phase and testing phase. In the training phase, the training data is fed into the input layer. It is propagated to the hidden layer and then to the output layer. This process is called the forward pass. In this stage, each node in the input layer, hidden layer and output layer calculates and adjusts the appropriate weight between nodes and generates output value of the resulting sum. The actual output values will be compared with the target output values. The error between these outputs will be calculated and propagated back to hidden layer in order to update the weight of each node again. This is called backward pass or learning. The network will iterate over many cycles until the error is minimized to some acceptable value. After the training phase is over, the trained network is ready to be used for testing with new input data. During the testing phase, there is no any learning or modification of the weight matrices. The test input is fed into the input layer, and the feed forward network will generate results based on its knowledge from trained network. So, if we have two kinds of patterns, the trained network finds two different thresholds for two kinds. If the average of two thresholds is found, it guarantees that one kind will always be below the average threshold value and another one will always be above of that. This working principle is considered in our methodology using back propagation neural network.

Back Propagation (BP) neural network model consists of input layer nodes (independent variables), the output layer node (dependent variable) and the hidden layer nodes. Back propagation is the training or learning algorithm rather than the network itself. Here, batch mode training is used in backpropagation training algorithm. The BP algorithm used in this approach is summarised as follows

(1) Initialize all weights to small random values, typically $\in [0,1]$ when rand function is used in Matlab.

(2) Repeat until termination criterion is satisfied:

(1.1) A training example set is presented and propagated through the network (forward pass)

(1.2) Calculate the actual output (o)

(1.3) Weights are adapted starting from the output layer and working backwards (backward pass)

If node p is the p^{th} node in a layer and node q is the q^{th} node in the next layer in the forward direction, the updated weight between a node p and a node q at time t + 1 is,

$$w_{pq}(t+1) = w_{pq}(t) + \Delta w_{pq}$$

where weight change, $\Delta w_{pq} = \eta.\delta_q.o_p$; η is the learning rate, δ_q is the error signal in the node q and o_p is the output of the node p.

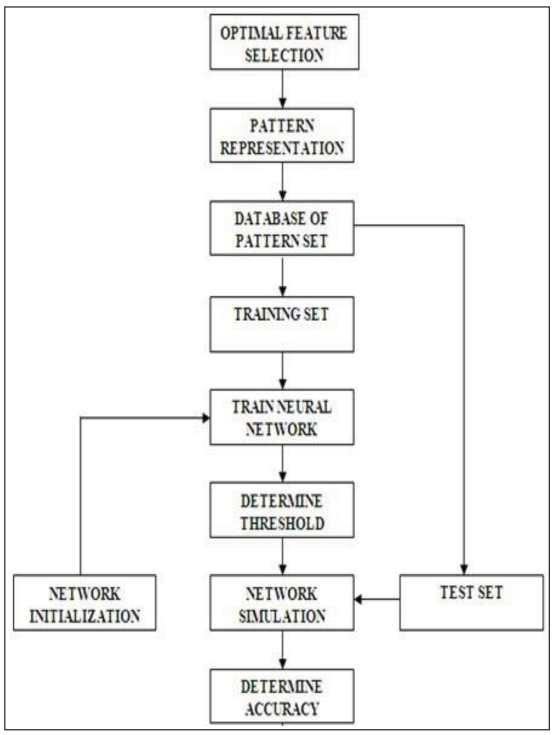
If neuron i is the i^{th} node in the output layer, the error signal in the output node i is,

$$\delta_i = (d_i - o_i).o_i.(1 - o_i)$$

where d_i and o_i are the desired and actual output of i^{th} node in the output layer, respectively
If neuron j is the j^{th} node in the hidden layer, the error signal in the hidden layer node j is,

$$\delta_j = o_j.(1-o_j).\sum(w_{ji}.\delta_i)$$

Figure 1: Design Schema of Neural Network Classifier



where o_j is the output of j^{th} node in the hidden layer, w_{ji} is the weight between j^{th} node and i^{th} node in the next layer, δ_i is the error signal in the i^{th} node and the summation is over all the nodes in the layer next to the hidden layer.

In the experiment, the stopping criterion is when the maximum number of epoch is reached. It typically takes hundreds or thousands of epochs for an NN to converge. The design schema of the proposed neural network classifier for pattern classification constructed is shown in Figure 1.

Feature Selection

Patterns are fixed-length feature vectors or instances. An instance is typically described as an assignment of values $A = (A_1, A_2, A_3, \ldots, A_N)$ to a set of features $F = (F_1, \ldots, F_N)$ and one of p possible classes $c_1, \ldots, c_p$ to the class label C. The aim is to induce a pattern classifier that accurately predicts the labels of new instances. The learning of the classifier is inherently determined by the feature-values. In practice, with a limited amount of training data, excessive features will not only significantly slow down the learning process, but also cause the classifier to over-fit the training data as irrelevant or redundant features may confuse the learning algorithm. Feature selection aims to choose a subset of original features according to a selection criterion (higher accuracy). It needs to be carried out to remove the redundant attributes not needed for classification problem. Feature selection has been active and fruitful in research and development for decades and brings about many benefits like increasing predictive accuracy and reducing complexity of learned results.

Since the attributes of the patterns are non-numeric, hamming distance is applied in k-NN for feature selection. In selecting relevant features, it will be an exhaustive technique and sometimes impractical to try out all the possible 2^N subsets of the N attributes for determining the subset that provides best classification. So, a conventional feature selection algorithm is applied to find important features, which is applied in Swine Flu patterns and the algorithm is given as follows.

Feature Selection Procedure

[N is the number of attributes in the problem description of the pattern and A_i is used to denote the i^{th} attribute of the pattern]

1. The k-NN classifier is employed.
2. The criterion is fixed to be used to assess the classifier's performance, based on its recognition (correct classification) and error (misclassification) rates. The criterion of choosing an attribute is considered by higher recognition rate.
3. Five-folded cross validation procedure is repeatedly invoked to run the classifier on the training set using only one attribute at a time. Thus, the classifier uses only attribute A_1 first, then A_2, and so on till A_N. For each attribute, we record the recognition and error rates. Based on the criterion established in step 2, we select attribute A_i, for $1 \leq i \leq N$, with which the classifier gives the best performance.
4. The cross validation is carried out with the classifier using two attributes at a time: $A_iA_1, A_iA_2, \ldots, A_iA_{i-1}, A_iA_{i+1}, \ldots, A_iA_N$. The pair is selected with which the classifier gives the best performance. Suppose the best pair is A_iA_j, for $1 \leq i \leq N$, and $1 \leq j \leq N$.
5. The cross validation is carried out with the classifier using three attributes at a time: $A_iA_jA_1$, $A_iA_jA_2$, and so on.
6. Thus at every step one attribute is added to the list of selected attributes. This process is carried out till the performance of the classifier is satisfactory (increased). The attributes are selected for which this happens and discard the remaining attributes.

This approach conducts a search for a good feature subset by using k-NN as an evaluation function. In this approach

Table 1: Features of a Pattern before Feature Selection

Sl. No.	Symptoms/Attributes
1	Age
2	Temperature
3	Cough
4	Runny nose or stuffy nose
5	Sore throat
6	Fast breathing or trouble breathing
7	Fatigue or tiredness
8	Body aches
9	Headache
10	Chills
11	Diarrhea
12	Nausea
13	Severe or persistent vomiting
14	Bluish or gray skin colour

the features of Table 1 are input of the algorithm and the features of Table 2 are output of the feature selection algorithm. The list of the attributes for correct prediction in decreasing order is given in Table 2.

Table 2: Features of a Pattern after Feature Selection

Sl. No.	Symptoms/Attributes
1	Fast breathing or trouble breathing
2	Sore throat
3	Temperature
4	Runny nose or stuffy nose
5	Cough
6	Fatigue or tiredness
7	Body aches
8	Headache
9	Chills
10	Nausea

Pattern Representation

Pattern recognition is the scientific discipline whose goal is to classify patterns into categories or classes. To this purpose, it requires creation of pattern by observing the environment or instances or objects, learning of pattern recognition from example and making decisions based on the category of the patterns. So pattern representation is one of the important steps in pattern recognition. A pattern here represents the symptoms of Swine Flu disease and a corresponding class which indicates swine flu in terms of yes or no. The representation of a pattern is given in Table 3. Proper pattern representation is very important because the patterns need to be presented in such a way that becomes suitable to be applied in ANN model. The symptoms/attributes are categorised and ranged by consulting medical practitioners. Categorical attributes with index values are shown in Table 4 as per their ranges.

Neural Network Analysis

The training of the neural network processes a random set of weights which are gradually updated to fit the parameters of classifier in the network model. The steps involved in training the network by backpropagation algorithm are: feed-forward of the input training pattern, the calculation and backpropagation of the associated error, and the adjustment of the weight.

Feed-forward neural network is one of the most commonly used function approximation techniques. Feed-forward neural networks consist of a graph of nodes, called neurons, connected by weighted links. These nodes and links form a directed acyclic graph, hence the name “feed-forward”. A 3-layer feed-forward neural network can approximate any nonlinear continuous function to an acceptable accuracy. Single-hidden-layer neural networks are superior to networks with more than one hidden layer with the same level of complexity mainly due to the fact that the later are more prone to fall into poor local minima (Villiers & Barnard, 1993). Moreover, over-fitting can occur by having too many hidden nodes and thus it loses the ability to generalise (or predict) input data that has never been seen. In view of that a 3-layer feed-forward neural network is taken in this approach.

The performance of neural network depends on the number of nodes in the hidden layer. So variations of neural network structure with different number of nodes in the hidden layer are taken into account and the accuracy estimation of performance is calculated for all the structures where the number of nodes in the hidden layer is in between 11 and 19. The results obtained from these network structures are shown in Table 5.

From the experiment it is observed that the accuracy is comparatively higher for the network structure where the number of nodes in hidden layers is 14. Therefore, in this experiment, a BP neural network classifier is constructed with the simple basic network configuration of 10-14-1 structure, i.e., 10 input nodes, 1 output node, 1 hidden layer of 14 nodes.

The topology of the network is showed in Figure 2. The 10 inputs X_1 to X_{10} in the input layer receive 10 attribute

Table 3: Description of a Pattern

F1	*F2*	*F3*	*F4*	*F5*	*F6*
Fast breathing	Sore throat	Temperature	Runny nose	Cough	Fatigue
F7	F8	F9	F10	Swine flu	
Body aches	Headache	Chills	Nausea	Yes/No	

Table 4: Indexing of Attributes Based on Their Ranges

Feature	Ranges and Their Index Values			
F1	None	Mild	Moderate	severe
	0	1	2	3
F2	None	Mild	Moderate	severe
	0	1	2	3
F3	<=98.4	98.5-100.4	100.5-102.4	>102.4
	0	1	2	3
F4	None	Mild	Moderate	severe
	0	1	2	3
F5	None	Mild	Moderate	severe
	0	1	2	3
F6	None	Mild	Moderate	severe
	0	1	2	3
F7	None	Mild	Moderate	severe
	0	1	2	3
F8	None	Mild	Moderate	severe
	0	1	2	3
F9	None	Mild	Moderate	severe
	0	1	2	3
F10	None	Mild	Moderate	severe
	0	1	2	3

Table 5: Results Obtained from Different Network Structures

No. of Nodes in Hidden Layer	Accuracy %
11	92
12	92
13	92
14	94
15	90
16	92
17	92
18	88
19	90

values per pattern. Z_1 gives the actual output of the network and Y_1 to Y_{14} are the hidden units in the hidden layer. The architecture and parameters of the neural network structure are given in Table.6.

After initialisation of the neural network, back propagation training and simulation of the neural network are carried out using training and test sets, respectively, from 250 data patterns of Swine Flu. The proposed binary pattern classification algorithm using ANN used in classification of Swine Flu patterns is given as follows

Figure 2: Topology of a BP Neural Network

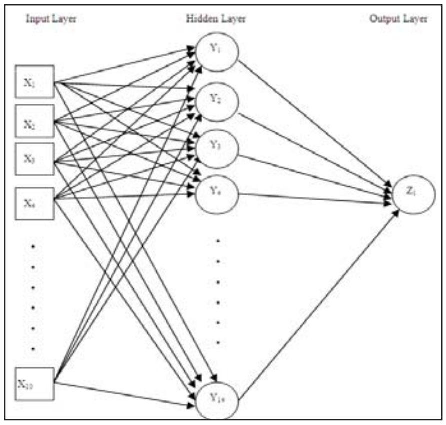


Table 6: Architecture and Parameters of the Neural Network Model

Number of input nodes	10
Number of output nodes	one
Number of hidden layers	one
Number of nodes in hidden layer	14
Paradigm	Multilayer Feed-forward Net (Back-propagation)
Weight updating rule	delta weight
Activation function	sigmoid function

Proposed Pattern Classification Algorithm

Th: Threshold

P_{low}: the lowest value of actual output (of class-1 patterns)

N_{up}: the highest value of actual output (of class-2 patterns)

D: desired output value

O: actual output value

O(s): set of actual outputs

I_X: set of features

I_Y: class label- class-1 and class-2

Input: set of attributes

Output: Class label (accuracy)

Procedure

// TRAINING PHASE//

(1) Present input patterns, which are represented by feature values and class labels in the form I_X I_Y (I_X: I_1 I_2 I_3 …. I_{10}, I_Y in case of swine flu pattern)

(2) Initialize the network:

a. Determine the architecture: how many input and output neurons; hidden neurons and layers; what output encoding

b. Initialize all weights to small random values, typically [0,1]

c. Along with the initialization of other functions, the training function of the network is initialized as 'traingd' (Gradient descent back propagation)

(3) Repeat until termination criterion is satisfied: (maximum number of epoch)

a. Present training set and propagate it through the network (forward pass)

b. Weights are adapted starting from the output layer and working backwards (backward pass)

(4) Simulate the network using the same training set to obtain O(s)

(5) Determine Th:

a. Find P_{low} for class-1 patterns (say positive Swine Flu patterns), i.e., for patterns in which D = 1

b. Find N_{up} for class-2 patterns (say negative Swine Flu patterns), i.e., for patterns in which D = 0

c. Obtain the average of these two numbers as threshold, i.e.,

$$Th = (P_{low} + N_{up})/2$$

// VALIDATING PHASE//

(6) Simulate the network for the test set

(a) If the O of a test case is greater than or equal to Th, the test case belongs to class-1 patterns (positiveness of Swine Flu for the patterns). Otherwise it belongs to class-2 patterns (negativeness of Swine Flu for the patterns): i.e.,

$$O = 1 \quad \text{if } O \geq Th$$

$$O = 0 \quad \text{otherwise}$$

// PERFORMANCE CALCULATION//

(7) Determine Accuracy by finding the number of correctly classified and misclassified patterns:

a. Actual output and desired output of each of the correctly classified patterns of the test set are the same

b. Actual output and desired output of each of the misclassified patterns of the test set are different, 0 for one and 1 for the other

Step 1 depicts that the patterns are available to be given to the network. *Step 2* depicts that an artificial neural network is created and the architecture, parameters and functions of the Neural Network are set. In *Step 3* the training set which is taken from the data set by partitioning it into two sets (training set and test set) is used to train the BP network. *Step 4* depicts that the network is simulated with the training set to determine a threshold value so that when the network is tested with the patterns in the test set, some of the patterns will be classified as swine flu positive when the corresponding output values of the network are more than or equal to the threshold and some as swine flu negative when the corresponding output values of the network are less than the threshold. In *Step 5* the threshold value is determined. *Step 6* depicts that the network is simulated with the test set to determine how many patterns from the test set are correctly classified. Finally in *Step 7* the number of correctly classified and misclassified patterns from the test set is determined to evaluate the accuracy of performance.

Results

Data Set

The application domain in our proposed framework is Swine Flu. Various records of swine flu were gathered from physicians in several hospitals and from the Internet (www.nhs.uk, http://www.cdc.gov/h1n1flu, www.flutrackers.com). With the aid of Internet and consulting local medical practitioners, the symptoms of swine flu are categorised (indexed) and ranged and accordingly cases are generated and validated by medical institutions. A total of 250 swine flu records were incorporated in this work. The experimentation of the proposed model is done by MATLAB 7.12.0.635 (R2011a) in windows environment.

Estimation of Overall Accuracy of the Proposed Model

In order to estimate the performance of the proposed classification algorithm, firstly, the dataset is split into 80% as training set and 20% as test set. In the 1st iteration, the network is trained using 20% data of dataset as the training set and then simulated using the same training set. The test samples are then predicted by the trained neural network classifier. Similar procedure is followed by considering, 40% data as training set and the same test

Table 7: Final Results Obtained from Experiments

Iteration	*Upper value for -ve case*	*Lower value for +ve case*	*Required Threshold value*	*No. of correctly classified patterns*	*Accuracy for each partition*
1st	0.317626	0.585138	0.451382	45	90%
2nd	0.361524	0.554822	0.458173	44	88%
3rd	0.780520	0.359558	0.570039	45	90%
4th	0.868178	0.315562	0.591870	47	94%

set in 2^{nd} iteration, 60% data as training data and the same test set in 3^{rd} iteration and 80% data as training set and the same test set in 4^{th} iteration.

The experiment is done in that way to observe the behaviour of the model if the number of patterns is gradually increased. As a result, the threshold values and the number of correctly classified patterns for the different iterations by considering different datasets are found out, which is shown in Table.7.

In Figure 3, green bars are showing the highest value of actual output among all of the negative swine flu test patterns and blue bars are showing the lowest value of actual output among all of the positive swine flu test patterns from the training sets of the four iterations. The red bars in the figure are showing the threshold values required for testing the neural network for the four iterations taking different training sets. In Figure 4, it shows how accuracy changes over datasets. Eventually, it is found out the number of samples out of 50, which are correctly classified and thus, through the pattern classification algorithm using ANN, obtained accuracy is 94%.

Figure 3: Determination of Threshold Values for the Four Iterations

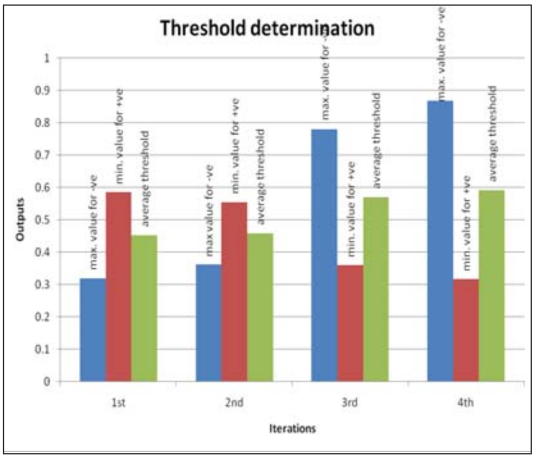
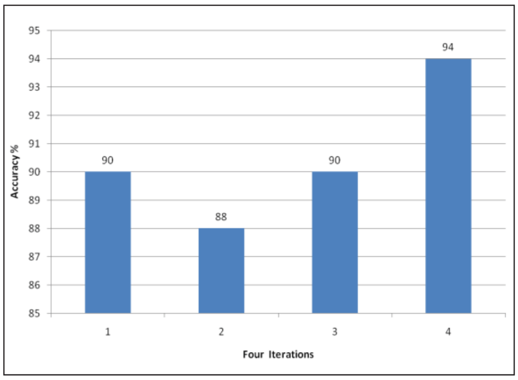


Figure 4: Percentage of Accuracy for the four Different Datasets



Network Evaluation for Novice Case

The proposed model resolves pattern classification problem for novice pattern. A new positive swine flu case is shown in Table 8. A threshold is required such that while simulating the network with the novice input, if the actual output of the network is above or equal to the threshold, it is considered as close to 1 and to fall under the positive category. And if the actual output of the network is below the threshold, it is considered as close to 0 and to fall under the negative category.

The neural network is trained using the 200 patterns and simulated with the novice input pattern. The threshold is estimated out using the 200 training patterns. For the novice pattern if the actual output value is less than the threshold, it is classified as non-swine flu pattern; otherwise, it is classified as swine flu pattern. As obtained from the experiment, the actual output of the network when tested with the new input pattern is more than the threshold and is shown in Table 9. So, the new test sample is classified by the trained BP neural network classifier as to fall into the swine flu positive class.

Table 8: A Novice Pattern

ATTRIBUTES	DEGREE	INDEX
Temperature	<=98.4	1
Cough	Mild	1
Runny nose or stuffy nose	Moderate	2
Sore throat	Mild	1
Fast breathing or trouble breathing	Moderate	2
Fatigue or tiredness	Mild	1
Body ache	Mild	1
Headache	Mild	1
Chill	None	0
Nausea	Mild	1

Table 9: Results Obtained from Experiments

Sl. no.	Desired Output	Threshold	Actual Output	Classification
1.	1	0.591870	0.858747	Positive

Comparative Discussion on CBR Approach

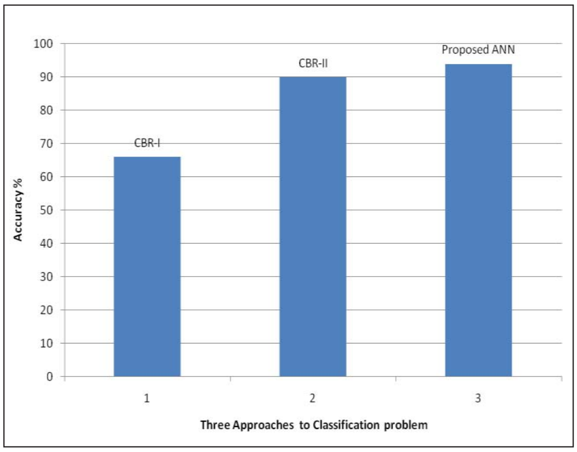
The diagnostic assessments of Swine Flu have been made in paper by Chakraborty *et al.* (2011) with Swine Flu Diagnostic Assistant (SFDA) using CBR methodology without optimal subset of features and heuristic weight assignment. Each case is represented by the symptoms: age, temperature, runny nose, cough, nausea and diarrhoea. Considering these symptoms and the weights assigned to each symptom, accuracy of the system SFDA is found out (Chakraborty *et al.,* 2011).

A second method of CBR is also considered with optimal subset of features and legitimate weight assignment and the accuracy of this approach is found out. Figure 5 shows the performance estimation of the two methods of CBR approach and proposed ANN classification method. Comparative results obtained from the experiments for the above mentioned approaches are also shown in Table 10.

Table 10: Comparative Results Obtained from Experiments

Approach	Correctly Classified Patterns	Accuracy %
Case based Reasoning I	33	66%
Case based Reasoning II	45	90%
Proposed ANN classification method	47	94%

Figure 5: Comparison of Percentage of Accuracy



Discussions

To obtain higher level of accuracy from a better neural network structure, variations of neural network structure have been experimented with different number of nodes in the hidden layer. From the experiments it is observed that comparatively the neural network configuration of 10-14-1 structure provides higher accuracy of performance.

It is noted that since CBR is based on the principle of specialized knowledge, it would never be able to predict better than what exists as the solution of the closest case in its case base. The work which is carried out based on ANN with optimal subset of features and a learned set of weights provides better accuracy over CBR. From the experimental analysis it can be observed that the accuracy of the binary classification problem becomes high when done by neural network.

Conclusion

An ANN based binary pattern classification algorithm has been proposed and implemented for swine flu pattern classification problem. Firstly, important and meaningful features of swine flu are determined using k-NN classifier and cross-validation technique. Then the structure of a pattern is represented by these important features along with a class label. Then a multilayer feed-forward neural network is trained and tested to resolve swine flu classification problem. The proposed algorithm manifests a better approach of pattern classification.

Moreover, unlike the case of CBR approach, ANN approach is based on the concept of generalised knowledge and this principle is suitable to be applied for classification of the data patterns in medical science domain. These advantages enable the model to provide superior prediction results over CBR (Chakraborty *et al.,* 2011). Thus, the ability of proposed pattern classification algorithm is demonstrated to provide high level of accuracy for Swine Flu pattern classification problem. This model may be extended to various kind of expert and intelligent decision support system to make classification and decision.

An improved version of the model can be achieved by incorporating more intelligent features while training the ANN model to improve the performance of the approach for medical classification process.

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