An Outlier Based Bi-Level Neural Network Classification System for Improved Classification of Cardiotocogram Data

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Abstract: Cardiotocography (CTG), consisting of fetal heart rate (FHR) and tocographic (TOCO) measurements, is used to evaluate fetal well-being. It is one of the most common diagnostic techniques to evaluate maternal and fetal well-being during pregnancy and before delivery. By observing the Cardiotocography trace patterns doctors can understand the state of the fetus. Even few decades after the introduction of cardiotocography into clinical practice, the predictive capacity of the existing methods remains inaccurate. In a previous work (Sundar.C and et al, 2012), we showed that a model based CTG data classification system using a supervised artificial neural network (ANN) can classify the CTG data better than most of the other methods. But, the performance of the normal neural network based classifier was limited because of the presence of potential outliers in the training data. The presence of outliers in training data affects the neural network training as well as testing. In this work, we present improved classification models which will consider outliers in the data and eliminate them from training phase of the classification process. We used Precision, Recall, F-Score and Rand Index as the metric to evaluate the performance. The proposed idea considerably improved the performance in classifying Normal, Suspicious and Pathologic CTG patterns. It was found that, the improved classifier was capable of identifying Normal, Suspicious and Pathologic condition with very good accuracy than normal methods.

[Sundar C, Chitradevi M, Geetharamani G. **An Outlier Based Bi-Level Neural Network Classification System for Improved Classification of Cardiotocogram Data.** *Life Sci J* 2013; 10(1):244-251] (ISSN: 1097-8135). http://www.lifesciencesite.com. 37

Keywords: Outlier Detection; CTG; BPN; Dimensionality Reduction; RBF

1. Introduction

One of the major challenges in medical domain is the extraction of comprehensible knowledge from medical diagnosis data such as CTG data. In this information era, the use of machine learning tools in medical diagnosis is increasing gradually. This is mainly because the effectiveness of classification and recognition systems has improved in a great deal to help medical experts in diagnosing diseases.

Cardiotocography (CTG)

Cardiotocography (CTG) is a technical means of recording the fetal heart rate (FHR) and the uterine contractions (UC) during pregnancy, typically in the third trimester to evaluate maternal and fetal well-being (Diogo Ayres-de-Camposa and et al, 2005). FHR patterns are observed manually by obstetricians during the process of CTG analysis (Stirrat, Mills and Draycott, 2003). In the recent past fetal heart rate baseline and its frequency analysis has been taken in to research on many aspects (Sundar.C and et al, 2012).

Fetal heart rate (FHR) monitoring is mainly used to find out the amount of oxygen a fetus is acquiring during the time of labor (Saba et al., 2012). Even then death and long term disablement occurs due to hypoxia during delivery. More than 50% of these deaths were caused by not recognizing the abnormal FHR pattern, even after recognizing not communicating the same without knowing the seriousness and the delay in taking appropriate action. Computation and other datamining (C.Domeniconi and et al, 2007) (J. Han and M.Kamber, 2000) techniques can be used to analyze and classify the CTG data to avoid human mistakes and to assist doctors to take a decision.

In a recent work (Shomona and at el, 2012) they evaluated the performance of the ten classification algorithms with CTG -Morphology Pattern dataset. The algorithms C-RT, CS-CRT, NBC, PLS-DA and RBF show improved accuracy after outlier detection. However the algorithms C4.5, CS_MC4, ID3, PLS-LDA and Random Tree show decrease in performance after outlier removal.

2. Material and Methods

Cardiotocography (CTG), consisting of fetal heart rate (FHR) and tocographic (TOCO) measurements, is used to evaluate fetal well-being during the delivery. Since 1970 many researchers have employed different methods to help the doctors to interpret the CTG trace pattern from the field of signal processing and computer programming (Shahad Nidhal et al, 2010), (Chen CY et al, 2009). They have supported doctors with interpretations in order to reach a satisfactory level of reliability so as to act as a decision support system in obstetrics (Onisko and Druzdzel, 2011). Up to now, predictive capacity of the method remains controversial. The scope of this work is to improve the performance of a neural network based classification system for CTG data classification. In(Shomona and at el, 2012), Among the evaluated algorithms, the algorithms C4.5, CS_MC4, ID3, PLS-LDA produced improved accuracy but, the accuracy was reduces after removing the outlier. In other words, the algorithms which give high accuracy were very much affected by the outliers. This confirms that all the outliers in the data are actually not noise. Even the rarest of occurrences of a peculiar record in a dataset may provide novel insights into new patterns corresponding to a disease identification and diagnosis (Shomona and at el, 2012, Saba et al., 2011a; Saba et al., 2012).

Even the best performing tree based algorithm like C4.5 will get effect by an abnormal change in individual attribute of the input data. In other words, a tree based algorithms will work good if the data is a categorical data but it cannot approximate a continuous variable better manner. So, according to our understudying, we cannot improve the accuracy just by removing all the outliners in the data. Because all the outliers in the data need not necessarily be a noise (Saba et al., 2010). Those outliers like abnormal data also should be considered during classification of the data.

In this work, we are detecting outliers or abnormal records in the training data during the first stage of training and testing of the back propagation neural network (BPN). After detecting outliers, those outliers will be removed from the training data, and again the same network will be trained with the outlier removed data to improve the training performance of the neural network and all the outliers will be included in the classification process. So, in this work, we are going to address some of the machine learning based hybrid datamining techniques for the better classification of CTG data.

Standard Neural Network Based Classification

Here in this classification (Rehman and Saba, 2012a), we use supervised learning by using a set of training data which is accompanied by class labels (Klimesova A and Ocelikova E, 2010, Rehman and Saba, 2012b). When a new data arrive, then classification of that data will be done based on the training set by generating descriptions of the classes. In addition to training set we also have a test data set that is used to determine the effectiveness of a classification. In general, commonly used and popular neural networks can be trained to recognize the data directly, whereas in simple networks there is a chance of the system being complex and training may be difficult. The time taken and the accuracy of classification depend on the dimension of the input given and also on the dimension in the training data. For input data with high dimension, the process will take a longer time (Saba and Rehman, 2012).

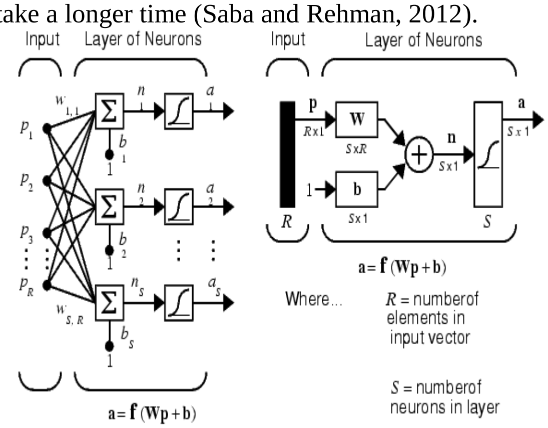

Figure 1. Feed forward Network

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons (Rehman and Saba, 2012). Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range -1 to +1. On the other hand, if you want to constrain the outputs of a network (such as between 0 and 1), then the output layer should use a sigmoid transfer function (Rehman et al., 2011a).

The following diagram shows the standard way of classifying the CTG data using a neural network.

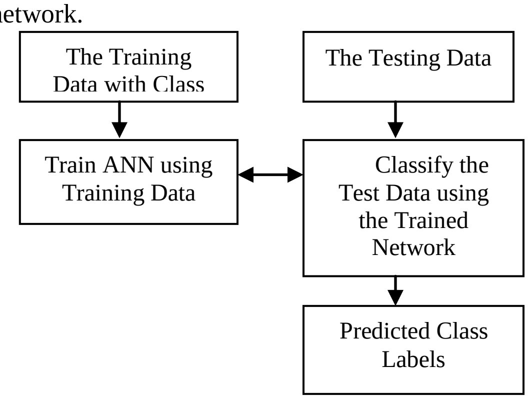

Figure 2. The Standard BPN based CTG Data Classifier

The Proposed Outlier based Bi-level BPN Approach (BL-BPN)

Outliers

In statistics, an outlier (Xiaojun Chen and et al, 2012) is an observation that is numerically distant from the rest of the data. Outliers can occur by chance in any distribution, but they are often indicative either of measurement error or that the population has a heavy-tailed distribution (Barnett. V and Lewis.T, 1994). In the former case one wishes to discard them or use statistics that are robust to outliers, while in the latter case they indicate that the distribution has high kurtosis and that one should be very cautious in using tools or intuitions that assume a normal distribution (Barnett. V and Lewis.T, 1994).

In a neural network based classification system, the presence of outliers in training data will have significant impact on classification performance because, the network will not get optimum training due to the presence of outliers in training data. In this proposed classification model the outliers from the training CTG data is removed after training the network with the training data. After that, the network is again trained with the outlier removed data to get better classification performance.

Outlier Separation Using Log-Sigmoid Transfer Function

Transfer functions of the neural network calculate a layer's output from its net input. During the unsupervised competitive learning process of the neural network, the nodes compete for the right to respond to a subset of the input data. We used Log-Sigmoid Transfer function in the layers of the neural network. The Log-Sigmoid Transfer function will try to produce output between 0 and 1(Rehman and Saba. 2011b).

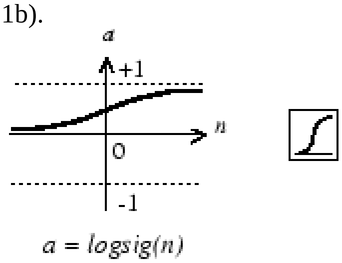

Figure 3. Log-Sigmoid Transfer Function

So, we can predict outliers in the training data based on the Log-Sigmoid Transfer function output in the output layer. The value of near 1 value will signify that the input is classifiable. The near zero values signifies that the input belongs to a potential outlier. In our implementation, we consider an input as outlier if it produces the Log-Sigmoid Transfer Function outputs of value less than 0.5 at the output layer. The following algorithm explains the proposed classification model.

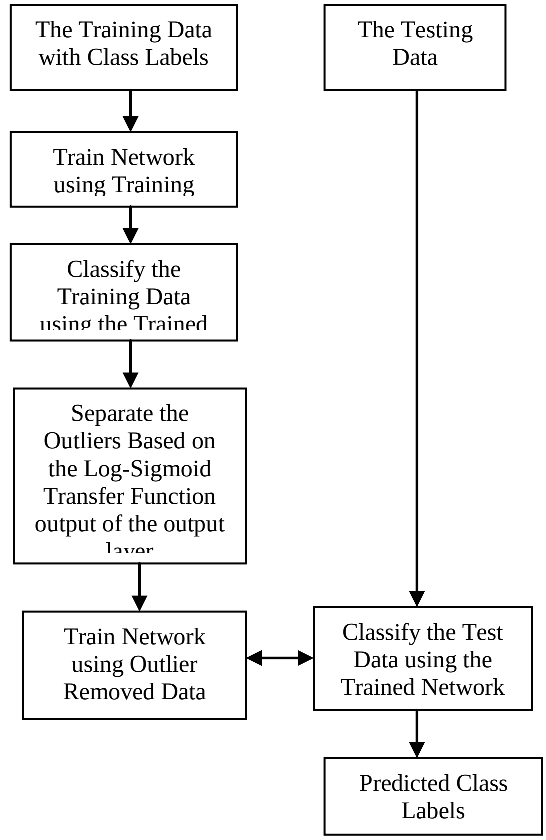

Figure 4. The Outlier Removed Training and Classification Model

The above block diagram shows the proposed BL-NN system. We can consider this model as virtual cascade of two Neural Networks in serial (but we use only one network to simulate this virtual cascade). The first level network is removing outliers and the second level network is trained to classify the normal CTG data in a better manner.

Bi-level BPN Classification Algorithm

Inputs:

Training Data: DL= {d1, d2…,dn}
Training Targets: CL= {c1, c2…, cn}
n = Total Number of Training records
Testing Data: DT= {t1, t2…, tm}
m = Total Number of Testing Data

Outputs:

Predicted Class labels of Test Data
CT = {l1, l2… lm}

Procedure BL-BPN {

1. Read training data DL and targets CL and test data DT
2. Create Network N1 to learn DL and map it to the original output class CL
3. Classify DL using the trained network N1.

4. Separate the Outliers OL from DL Based on the Log-Sigmoid output of the output layer of N1
5. Train Network N1 only using data without Outliers OL
6. Classify the DT using the trained network N1 and find the Predicted Class labels.

}

Advantages

Since the outliers are removed from the training, the trained network will get optimum training for the normal data and so the classification will get improved in the case of normal data in the test data set (Rehman et al., 2011).

Still the system will not classify the potential outliers in the testing dataset in a accurate manner since the network is not trained to handle abnormalities in the input data.

The Metrics Used for the Evaluation

Precision, recall and F-Score are computed for every (class, cluster) pair. But Rand index is a metric which will consider all the classes and the clusters as the whole (Rehman and Saba, 2011c).

Rand Index

The Rand index or Rand measure is a commonly used technique for measure of such similarity between two data clusters.

Given a set of n objects S = {O1, …, On} and two data clusters of S which we want to compare: X = {x1, ..., xR} and Y = {y1, ..., yS} where the different partitions of X and Y are disjoint and their union is equal to S; we can compute the following values (Rehman and Saba, 2011b):

- a is the number of elements in S that are in the same partition in X and in the same partition in Y,
- b is the number of elements in S that are not in the same partition in X and not in the same partition in Y,
- c is the number of elements in S that are in the same partition in X and not in the same partition in Y,
- d is the number of elements in S that are not in the same partition in X but are in the same partition in Y.

Intuitively, one can think of a + b as the number of agreements between X and Y and c + d the number of disagreements between X and Y. The Rand index, R, then becomes (Rehman and Saba, 2011a).

$$RI = \frac{a+d}{a+b+c+d}$$

The Rand index has a value between 0 and 1 with 0 indicating that the two set of data clusters do not agree on any pair of points and 1 indicating that the two data clusters are exactly similar.

Precision

Precision is calculated as the fraction of correct objects among those that the algorithm believes belonging to the relevant class. The Precision is calculated as (Sundar.C and et al, 2012):

$P(Lr, Si) = n_{ri}/n_i$

for

class Lr of size n_r

cluster Si of size n_i

n_{ri} data points in Si from class Lr

Recall

Recall is the fraction of actual objects that were correctly identified. The recall is calculated as (Sundar.C and et al, 2012) :

$R(Lr, Si) = n_{ri} / n_r$

F-Score

F-Score or F-Measure is the harmonic mean of Precision and Recall and will tries to give a good combination of the two. It is calculated with the equation (Sundar.C and et al, 2012):

$$F(L_r, S_i) = \frac{2 * R(L_r, S_i) * P(L_r, S_i)}{R(L_r, S_i) + P(L_r, S_i)}$$

In a classification task, a precision score of 1.0 for a class C means that every item labeled as belonging to class C does indeed belong to class C (but says nothing about the number of items from class C that were not labeled correctly) whereas a recall of 1.0 means that every item from class C was labeled as belonging to class C (but says nothing about how many other items were incorrectly also labeled as belonging to class C). Often, there is an inverse relationship between precision and recall, where it is possible to increase one at the cost of reducing the other. Usually, precision and recall scores are not discussed in isolation. Instead, either value for one measure are compared for a fixed level at the other measure (e.g. precision at a recall level of 0.75) or both are combined into a single measure, such as their harmonic mean the F-measure, which is the weighted harmonic mean of precision and recall (Sundar.C and et al, 2012).

Validating the Performance of the Classification

Classifier performance depends on the characteristics of the data to be classified. Performance of the selected algorithms is measured for Rand Index, Precision, Recall and F-Measure. Various empirical tests can be performed to compare the classifier like holdout, random sub-sampling, k-fold cross validation and bootstrap method. Here we did Holdout Cross validation for evaluating the proposed classification models.

Holdout Cross validation (It is equal to k-Fold Validation with k=2)

The holdout method is the simplest kind of cross validation. This 2-fold cross validation is the simplest variation of k-fold cross-validation. For each fold, we randomly assign data points to two sets d0 and d1; so that both sets are equal size (this is usually implemented by shuffling the data array and then splitting it in two). We then train on d0 and test on d1, followed by training on d1 and testing on d0. The advantage of this method is that it is usually preferable to the residual method and takes no longer to compute. However, its evaluation can have a high variance. The evaluation may depend heavily on which data points end up in the training set and which end up in the test set, and thus the evaluation may be significantly different depending on how the division is made.

This has the advantage that our training and test sets are both large, and each data point is used for both training and validation on each fold.

We used Holdout Cross validation (or k-Fold Validation with k=2) because, the dataset contains sufficient amount of samples which can be separated and used for training and testing (50%, 50%).

Further, instead of doing holdout cross validation for one time, the data set is randomly permuted and the training and testing records were randomly taken for 10 times and the average result of 10 such holdout cross validations were only considered.

3. Implementation and Evaluation

For implementing and evaluating the proposed improved neural network based classification system, and normal BPM and SVM based classifier, we used Matlab 7. The RBF method is implemented and evaluated using Weka data mining tool (Rehman and Saba, 2011a)

Data Set Information

For evaluating the algorithms under consideration, we used cardiotocograms data from UCI Machine Learning Repository.

This data set contains 2126 fetal cardiotocograms belonging to different classes. The data contains 21 attributes and two class labels. The CTGs were classified by three expert obstetricians and a consensus classification label assigned to each of them. Classification was both with respect to a morphologic pattern (A, B, C. ...) and to a fetal state (N, S, and P). Therefore the dataset can be used either for 10-class or 3-class experiments. Here we use this data set for these evaluations.

Attribute Information

1. LB - FHR baseline (beats per minute)
2. AC - # of accelerations per second
3. FM - # of fetal movements per second
4. UC - # of uterine contractions per second
5. DL - # of light decelerations per second
6. DS - # of severe decelerations per second
7. DP - # of prolongued decelerations per second
8. ASTV - percentage of time with abnormal short term variability
9. MSTV - mean value of short term variability
10. ALTV - percentage of time with abnormal long term variability
11. MLTV - mean value of long term variability
12. Width - width of FHR histogram
13. Min - minimum of FHR histogram
14. Max - Maximum of FHR histogram
15. Nmax - # of histogram peaks
16. Nzeros - # of histogram zeros
17. Mode - histogram mode
18. Mean - histogram mean
19. Median - histogram median
20. Variance - histogram variance
21. Tendency - histogram tendency
22. CLASS - FHR pattern class code (1 to 10)
23. NSP - fetal state class code (Normal=1; Suspect=2; Pathologic=3)

Class Information

We used the data for a three class classification problem. The descriptions for the three classes are

Normal: A CTG where all three features fall into the reassuring category

Suspicious: A CTG whose features fall into one of the non-reassuring categories and the reassuring category and the remainder of features are reassuring

Pathological: A CTG whose features fall into two or more of the Non-reassuring the reassuring category or two or more abnormal categories.

The Visualization of Data Space

The image (Figure 5) shows the projection of this 21 attribute (dimension) data in to a virtual three dimensional data space. We used three principal components of the data for this projection. In this plot, the normal CTG data points are shown in black dots, the suspicious data points are shown as blue dots and the Pathologic data points are shown as red 'x' mark. This figure roughly shows the distribution of the data in the virtual space.

4. Results

The following table shows the performance of RBF Networks.

Table 1. Classification Performance of RBF Network

Class	Precision	Recall	F-Measure
Normal	0.952	0.897	0.924
Suspicious	0.512	0.729	0.601
Pathological	0.822	0.682	0.745

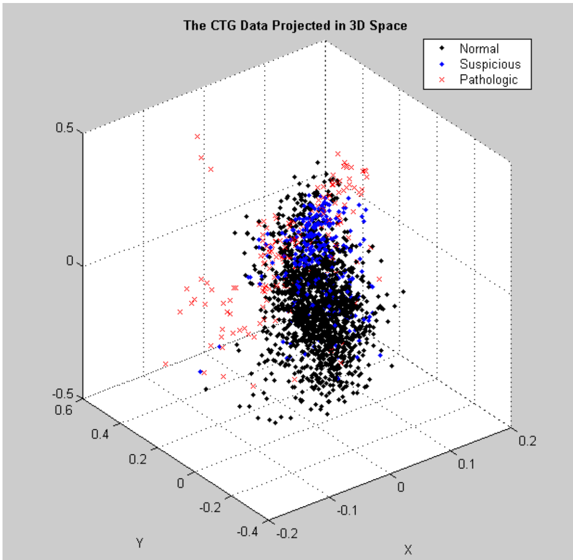

Figure 5. The 3D projection of CTG data shows Potential Outliers

The following tables show the performance of SVM algorithm.

Table 2. Classification Performance of SVM

Class	Precision	Recall	F-Measure
Normal	0.84	1.00	0.91
Suspicious	0.52	0.20	0.29
Pathological	0.98	0.30	0.46

The following tables show the performance of BPN algorithm.

Table 3. Classification Performance of BPN

Class	Precision	Recall	F-Measure
Normal	0.9238	0.9697	0.9452
Suspicious	0.6292	0.6176	0.6220
Pathological	0.7482	0.6238	0.6780

The following tables show the performance of the proposed BL-BPN algorithm.

Table 4. Classification Performance of BL-BPN

Class	Precision	Recall	F-Measure
Normal	0.9345	0.9637	0.9488
Suspicious	0.7110	0.6723	0.6905
Pathological	0.9021	0.6978	0.7584

5. Discussions

The following chart shows the Comparison of Precision under four different methods. The proposed BL-BPN based classifier provided good Precision in all the cases (Normal, Suspicious and pathological). Even though the performance of SVM in terms of Precision is good while classifying the Normal and Pathologic records, it was not good in identifying the suspicious cases. Particularly, the proposed method significantly improved the performance in the case of suspicious class.

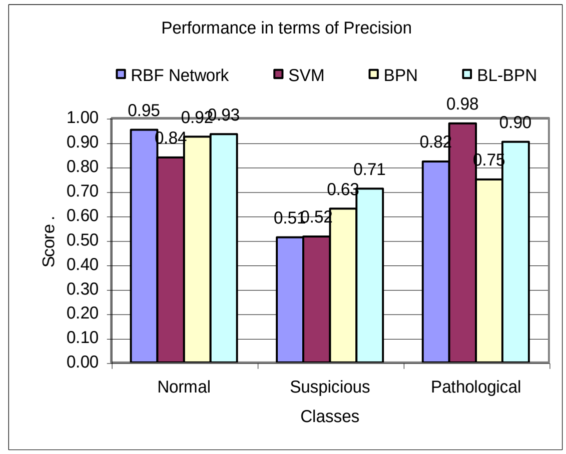

Figure 6. Performance in terms of Precision

The following chart shows the Comparison of Recall under four different methods. The ANN based classifier provided good Recall in all the cases. In terms of recall, SVM was not good in identifying the suspicious cases.

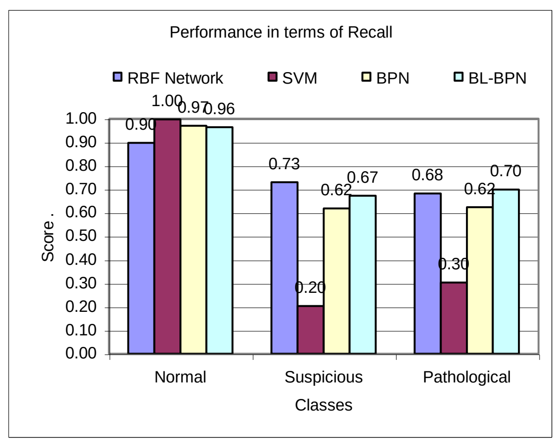

Figure 7. Performance in terms of Recall

The following chart shows the Comparison of F-Score under four different methods. The proposed BL-BPN based classifier provided good F-Score in all the cases (Normal, Suspicious and pathological). Even though the performance of SVM in terms of recall is good while classifying the Normal and Pathologic records, it was not good in identifying the suspicious records.

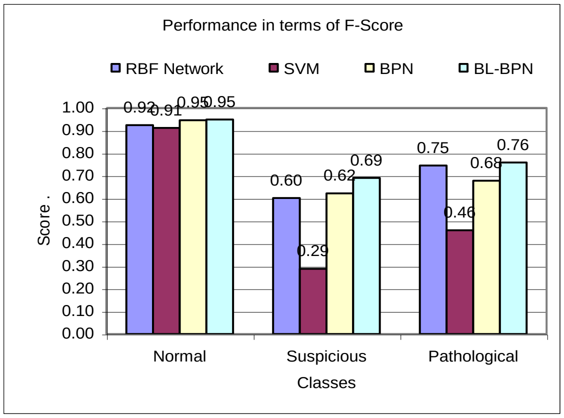

Figure 8. Performance in terms of F-Score

The following chart shows the performance of BPN algorithm. In general, the algorithm gives good performance for normal records and poor performance in all other cases.

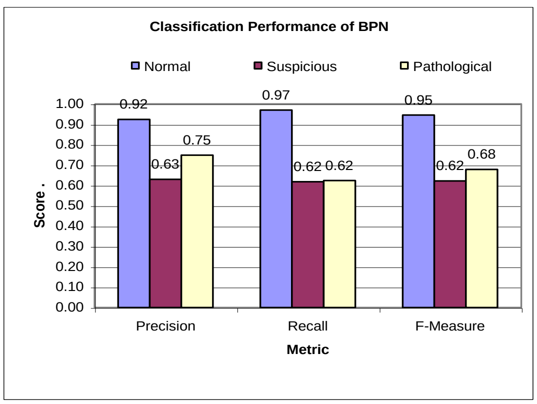

Figure 9. Performance of BPN

The following chart shows the performance of BL-BPN algorithm. In general, the algorithm gives good performance for normal and pathological records and poor performance in suspicious records.

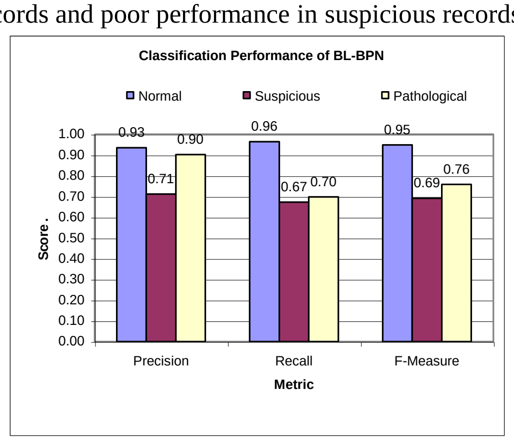

Figure 10. Performance of BL-BPN algorithm

The derived results obviously show that the proposed bi-level training improved the classification performance of system. The BL-BPN approach provided good performance in all cases than compared other methods (Saba et al., 2011b).

6. Conclusion

We have evaluated the performance of the four methods with respect to three different metrics. The performance of standard neural network based classification model, RBF, and SVM were has been compared with proposed BL-BPN Model. According to the derived results, the performance of the proposed supervised machine learning based classification approach provided significant performance than other compared methods.

It was found that, the proposed BL-BPN based classifier was capable of identifying Normal, Suspicious and Pathologic condition, from the nature of CTG data with very good accuracy. If we see the performance of BL-BPN with respect to all the metrics, then we can say that it almost provided double the performance of the other three compared methods. So, future works may address the way to improve the system to recognize the suspicious CTG patterns and treat them separately while training and testing. One may address the way to improve the system for getting proper training with different classes of CTG patterns. Future works may address hybrid models using statistical and machine learning techniques for improved classification accuracy.

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