Classification of Fetal State using Machine Learning Models

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Abstract. In gynecology, the problem of fetus during pregnancy in pregnant women have more interests. In the literature, several means are used to follow the pregnancy such as cardiotocography to measure heart rate, accelerations, fetal movements, and uterine contractions. In this proposed study, we use some algorithms to classify some diseases, and confusion matrix to specify the normal, and suspicious pathology using Random Forest, Support Vector Machine, and Artificial Neural Network. To validate this experimentation, the dataset of UCI has suggested to classify the fetus into three classes: normal, suspicious, and pathological the best performing model for detecting the fetal state is the ANN model which gave better accuracy values for 99.19% for training accuracy and 99.09% for test accuracy.

1 INTRODUCTION

The issue of the foetus for pregnant women is the big interests. The proposed work aims to provide a prediction tool for the early diagnosis to measure heart rate, accelerations, foetal movements, and uterine contractions to measure heart rate using a machine learning algorithm on the Cardiotocography Data Set [1-7]. The most challenge of the datasets in the Cardiotocography area is the lack of medical data from pregnant women. The proposed work performed statistical significance testing on the impact of applied a multi-class neural network and multiclass random forest on a Cardiotocography Data Set [8-12]. The some algorithm of Machine learning can help in complicated decision supports system solutions [13-22]. The paper presented an efficient solution to use data to diagnose diseases by detecting the foetus issue for pregnant women. In this paper two machine learning techniques were proposed for the detection of foetus for pregnant women. The multi-class neural network proved a better accuracy with 99.19% to predict foetus for pregnant women more than the multi-class random forest which achieved 97.18%. Conclusion: Applying machine learning algorithms on health care data can help healthcare providers and individuals to pay attention to the health risks and health status changes to improve the quality of life. The proposed system was applied to a Cardiotocography Data Set. The experimental results of the proposed work proved that using the multi-class neural network method can increase the possibility of diagnostic accuracy.

2 PROPOSED METHOD

2.1 Dataset employed

In this proposed study, we use the data from the UCI that the computation of uterine contraction, and fetal heart characteristics on 2126 CTG saving, and classified by some professional obstetricians. The label of classification has represented to each of the data. In this database there are 1655 were classified as normal fetal, 295 were classified as suspicious and the remaining 176 were classified as pathological.

Table 1. Complete Dataset details

Type	Number of fetuses
Normal	1655
Suspicious	295
Pathological	176
Total	2126

The **table 1** presents the details, and number of fetuses for normal, suspicious end pathological.

2.2 Balancing the database

As shown in the following figure **Fig. 1**., the database is unbalanced, because the number of each class is quite different.

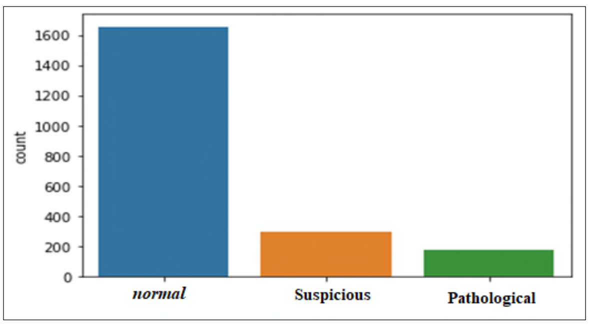

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Fig. 1. Distribution of fetus types.

To balance the database, there are two possibilities:

- ***Up-sampling:*** resample the values to make their count equal to the class label with the higher count (here, 1655).
- ***Down-sampling:*** pick n samples from each class label where n = number of samples in class with least count (here, 176)

In this study, we chose to expand the database. We obtained 1655 records for each class (fetal status), for a total of 4965 records after augmentation.

Table 2. Dataset details after **augmentation**

Type	**Number of fetus**
Normal	1655
Suspicious	1655
Pathological	1655
Total	4965

Then we divided the database into two parts, a training part (Training Dataset) and another part for testing (Test Dataset). We used 80% of the database for training and 20% for testing. i.e., 3972 fetuses for training set and 993 fetuses for test set.

2.3 Artificial Neural Network (ANN)

In this study, we took an ANN that consists of an input layer (with 128 neurons), a hidden layer (with 64 neurons) and an output layer (with 3 neurons) in **Fig.2**.

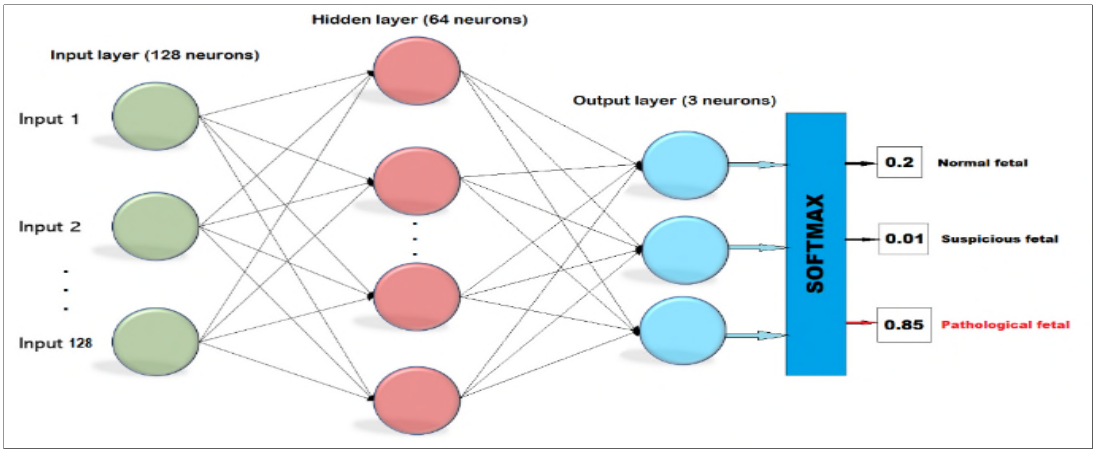

Fig. 2. Proposed ANN model.

3 EXPERIMENTAL RESULTS AND DISCUSSION

The **Fig. 3** Represents the confusion matrix for Normal, Suspicious and Pathological classification using ANN model., the performance of the ANN model for the test dataset is evaluated after the completion of the training phase and was compared using four performance measures such as precision, sensitivity or recall, specificity, precision (PPV), area under the curve (AUC), F1 score. The **Fig. 4** also presents the confusion matrix for Normal, Suspicious and Pathological classification using Random Forest model and SVM model. To measure the performance of the model the **Fig.5** represents the Train and validation accuracy curve.

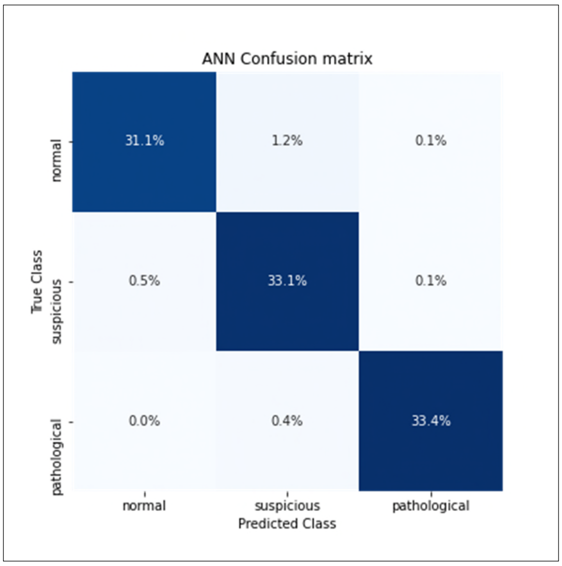

Fig. 3. Confusion matrix for Normal, Suspicious and Pathological classification using ANN model.

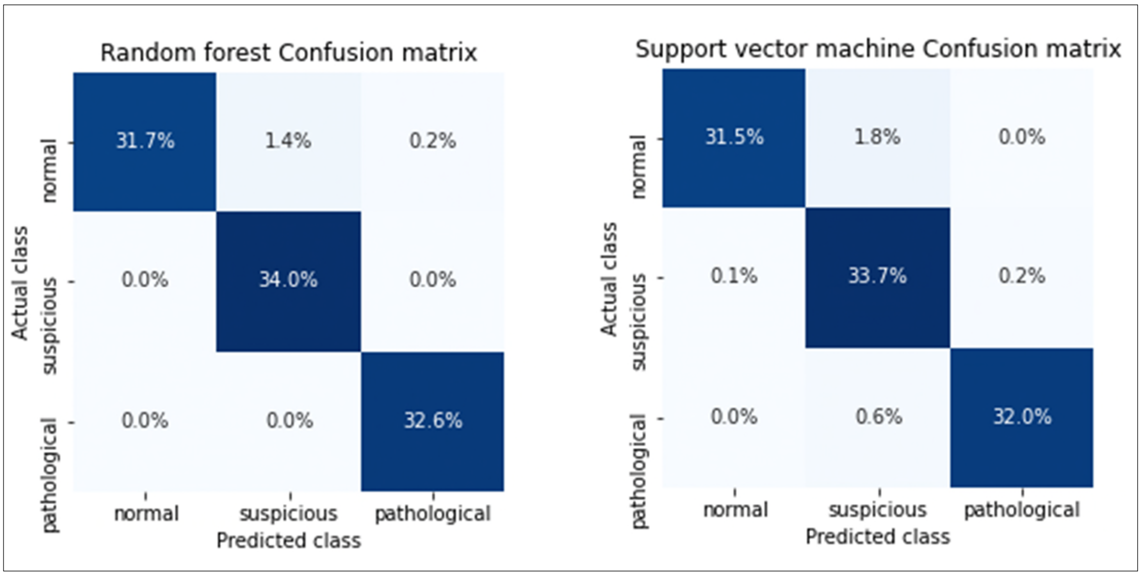

Fig. 4. Confusion matrix for Normal, Suspicious and Pathological classification using Random Forest model (a) and SVM model (b).

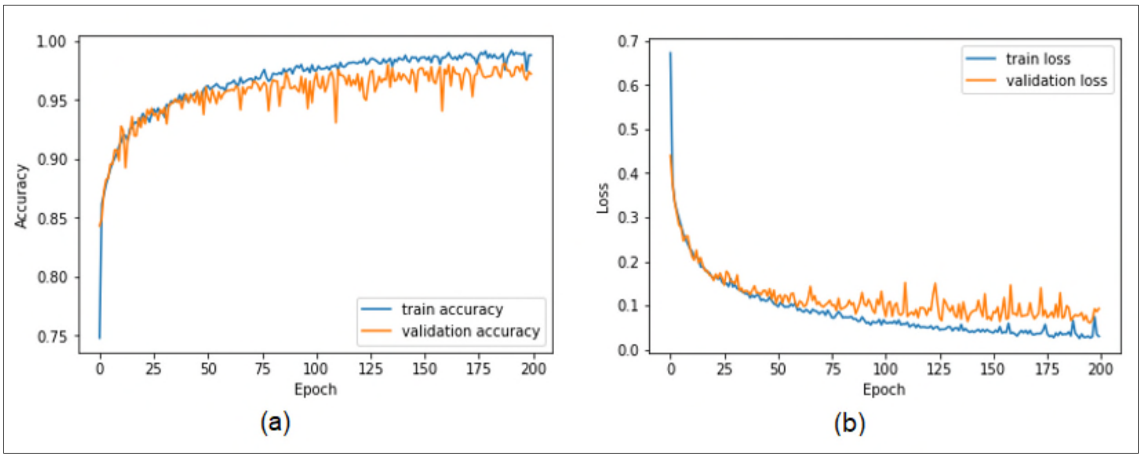

Fig. 5. Train and validation accuracy curve (a) Train and validation loss curve

Table 3. Values obtained for the different metrics.

	Random Forest	SVM	ANN
Accuracy	0.9718	0.9588	0.9909
precision	0.9719	0.9611	0.9911
Sensitivity (Recall)	0.9718	0.9587	0.9909
F1 score	0.9716	0.9587	0.9909

As shown in table 3, the best performing model for detecting the fetal state is the ANN model which gave better accuracy values (99.19% for training accuracy and 99.09% for test accuracy

4 CONCLUSION

In this paper, we used some algorithms in Machine Learning to classify some dis-eases of fetus during pregnancy in pregnant women. The confusion matrices are used to specify the normal, and suspicious pathology using Random Forest, Support Vector Machine, and Artificial Neural Network. To validate this experimentation, we used dataset of UCI to classify the foetus into three classes: normal, suspicious, and pathological.

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