PREDICTION OF FETAL HEART RATE BASED ON CARDIOTOCOGRAPHIC DATA USING DENSE MODEL

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Abstract

Health issues during pregnancy have become a serious predicament. The mortality of the fetus can infrequently arise from these issues, which are more prevalent in underdeveloped and emerging nations. Cardiotocography, also known as CTG, is a non-invasive technique frequently utilized by obstetricians to evaluate the physical health of a fetus at any point during pregnancy. CTG provides a visual graphical representation of normal or pathological uterine contractions and fetal heart rate, which avails in identifying newborn's overall health conditions including any birth defects or abnormalities. To proceed with treatment, a precise examination of the cardiotocograms is required. The evaluation of the fetal state that utilizes the machine learning and deep learning method and incorporates the cardiotocogram data has consequently received substantial attention. Due to its expeditious development, deep learning (DL) is widely utilized in disciplines such as medicine and healthcare to address several ailments. This study examines the results and analysis of a deep-learning classification model for fetal health. Utilizing an open access cardiotocography dataset, the approach was built. Although the dataset is relatively small, it has several eminent values. This data was analyzed and incorporated into numerous Machine Learning models. It is discovered that the proposed dense model employed in this study yields an accuracy of 89% which outperforms previously state-of-the-art techniques in classifying CTG and computational momentum for informed decision-making and quality care.

Keywords: Cardiotocography, Fetal Heart Rate, Fetal Health, Dense Model

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1. Introduction

Monitoring the growth of the fetus throughout pregnancy is one of the most arduous and complex tasks in the medical industry. In 2013, 293,336 women died globally from complications related to pregnancy, including as high blood pressure, abortion complexity, maternal bleeding, labor obstruction, and maternal infection. World Health Organization (WHO) report claims that approximately 810 pregnant women die each day despite the use of preventative measures [1]. The Maternal Mortality Ratio (MMR) is significantly lower in wealthy nations than in developing nations. Pre-eclampsia, insufficient monitoring of the state of the fetus and the mother, and gestational diabetes are common causes of increased maternal mortality. This uneven and unbalanced dispersal of death reflects global unjustness in access to treatment and medical care. There are significant disparities in mortality not only across nations but also within nations. Despite comparison of low-income and high-income women, as well as urban and rural women, mortality rates vary [2]. As a result, delivery and pregnancy complications considered as the leading causes of death in developing nations. While the majority of these issues arise during pregnancy, some begin beforehand and are exacerbated by pregnancy. The vast majority of these maternal deaths, however, could have been prevented or treated had there been adequate access to resources. Complications of pregnancy consist of gestational diabetes, hypertension, infection, pregnancy loss, preeclampsia, preterm labor, miscarriage, and stillbirth. The mortality rate can be minimized and prevented by the provision of adequate medical treatment [3]. Fetal monitoring is a routine practice performed throughout the third trimester. Fetal monitoring is the examination of the unborn child's health. The growth of the fetus is entirely dependent on the health of the mother. To avoid such issues, cardiotocography is used to continuously monitor fetal health and growth rate. The objective of the cardiotocography is to monitor the fetus' heartbeat while simultaneously measuring the mother's uterine contractions. This procedure would be conducted during the third trimester, when the fetus' heart rate and development are well coordinated. In order to detect fetal status early and decrease fetal mortality, medical professionals are required to use this procedure, which is deemed cost-effective and uncomplicated. The outcome of CTG will reveal the mother's uterine contractions, as well as the fetus' heart rate, incidence of acceleration, series of deceleration, and a number of other complex measurements. During the contractions of uterine, the fetal heart rate and its responsiveness, variability, and likely decelerations are crucial indicators of fetal health [4]. The fetal heart rate can be measured by placing an ultrasonic sensor on the mother's abdomen. On the basis of the fetal heart rate, fetal movement activity, and uterine contractions, the CTG is used to identify and detect potentially hazardous birth defects. Obstetricians frequently utilize the CTG to monitor and evaluation of fetal status during the prenatal, postnatal, and delivery periods of pregnancy. Significant advances in health care technology have enabled the use of strong and efficient artificial intelligence and machine learning approaches to provide the prediction in an automated way for a variety of medical purposes on the basis of findings from prior detection [5]. Demonstration and implemention of the suitability of machine learning tools can aid health practitioners in making more informed diagnoses and medical decisions, thereby lowering fetal and maternal mortality rates and complications during childbirth and pregnancy, thereby assisting both developed and developing populations. Despite the difficulty of detecting the fetal heart rate, machine learning-based computer-aided detection (CAD) techniques have been developed for the purpose of automated fetal status classifications at the time of pregnancy [6]. Due to this reason, the primary motive for this study is to construct a dense deep learning model to detect fetal health-related concerns quickly.

The paperwork is organized as follows: Section 2 discusses ML and DL algorithms and their effectiveness in fetal development. Section 3 discusses the prediction of fetal health and exploratory CTG data analysis. Section 4 displays the experimental findings of the dense model and algorithm validation using various assessment criteria such as accuracy, recall, precision, support, and F1-score. Finally, the study concludes with a consideration of possible enhancements in Section 5.

2. Related Work

Machine Learning approaches can assist medical professionals in making prompt decisions on complicated circumstances such as diagnosis, for reducing the mortality and difficulties during labor. Categorizing the phases of fetal health is a difficult endeavor, however ML and DL classification algorithms perform admirably in this regard. SVM, Random Forest, and neural networks (NN) are a few of the common classification techniques. The deep learning and machine learning classifier performs better on CTG data and gives greater accuracy when classifying the phases of fetal health.

Krupa et al. [7] demonstrated the application of statistical characteristics derived from empirical mode decomposition (EMD). The features of sub-band breakdown were separated into two categories: normal and hazardous. They achieved an 86 percent accuracy rate with regard to test data. In a different study, fetal heart rate data were evaluated in two steps, allowing for reliable risk prediction. Signals from the FHR are classified using fuzzy logic, SVM, and multilayer perceptrons. Sundar et al. [8] employed an artificial neural network to develop a new classification scheme for CTG data. Recall and F-score were applied for performance evaluation. Additionally, they suggested utilizing k-means clustering to classify CTGs. Sindhu et al. [9] introduced a unique clinical decision support system based on the CTG dataset using an Extreme Learning Machine (ELM) and Improved Adaptive Genetic Algorithm (IAGA). To avoid premature convergence, IAGA incorporates a new scaling technique termed sigma scaling, as well as mutation and adaptive crossover procedures with masking ideas to increase population variety. In addition, to evaluate its effectiveness, this search algorithm employs three separate fitness functions (one multi-objective fitness function and two single objective fitness functions).

On the CTG dataset, Nadia et al. [10] employed SVM-merged Deep Neural Networks to obtain quicker hyperplane convergence, resulting in clinically significant time performance. DNN extracts features automatically, and the generalized ability of SVMs was used for multiclass classification. Transfer learning is also used to improve classification speed by skipping the data sample training period. In terms of fetus categorization accuracy, their model exceeds the leading methods. Ersen et al. [11] conducted a comparison study on fetal status assessment utilizing three ANN models: the probabilistic neural network, the multilayer perceptron neural network, and the generalized regression neural network. The models' performance is assessed using publicly available CTG data and a tenfold cross-validation process. The performance of the models is compared in terms of overall classification accuracy. Further analysis is carried out using the cobweb representation technique and receiver operation characteristic analysis. Yue et al. [12] suggested an adaptive neuro-fuzzy inference system (FCM-ANFIS) based on fuzzy C-means clustering to automatically categorize CTG for prenatal fetal monitoring. To identify CTG characteristics, data visualization and spearman correlation analysis were used. The fuzzy area was then divided using the fuzzy Cmeans clustering algorithm, and the adjustment parameters were changed using the least squares approach and the neural network self-learning approach. The outcome suggests that fuzzy space partitioning based on FCM clustering can enhance ANFIS result, and the suggested FCM-ANFIS model surpasses state-of-the-art automatic classification of CTG models.

3. Materials and Methods

Fetal development is a positive indicator of fetal safety detection. A primary cause of fetal death is inconsistency. As a result, fetal health issues must be identified early. The project intends to construct classification models based on dense model in order to increase diagnostic efficiency. Figure 1 depicts the suggested model's system architecture.

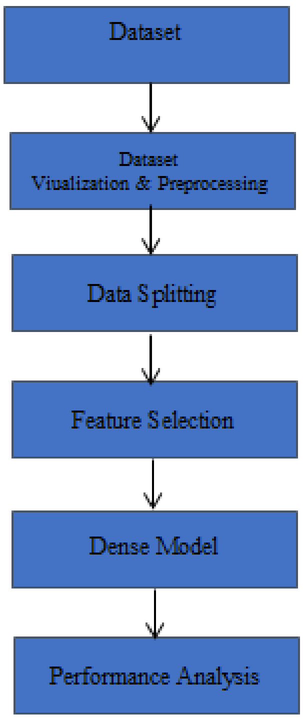

Figure 1. System Architecture Diagram

3.1. Dataset Description

The descriptions and features of the cardiotocography (CTG) dataset associated to pregnancy issues are introduced in this section. The UCI ML repository database was used to obtain the cardiotocography dataset that was used in this work. This dataset contains information on the uterine contraction parameters and Fetal Heart Rate (FHR) assessed during pregnancy using cardiotocograms. The information was given by the Medicine Faculty at the University of Porto in Portugal and the Biomedical Engineering Institute in Porto, Portugal. This dataset consists of 2126 records that indicate traits gleaned through cardiotocogram tests and divided into three groups by expert obstetricians: normal, suspicious, and pathologic [13]. The labeled distribution of dataset is shown in Table 1. Positive and negative correlation among attributes is shown in Figure 2.

Table 1. Dataset Category Distribution

Fetal Condition	**Class**	**Numeric Category**	**FHR records**
Normal	N	1	1655
Suspect	S	2	295
Pathologic	P	3	176
Total			**2126**

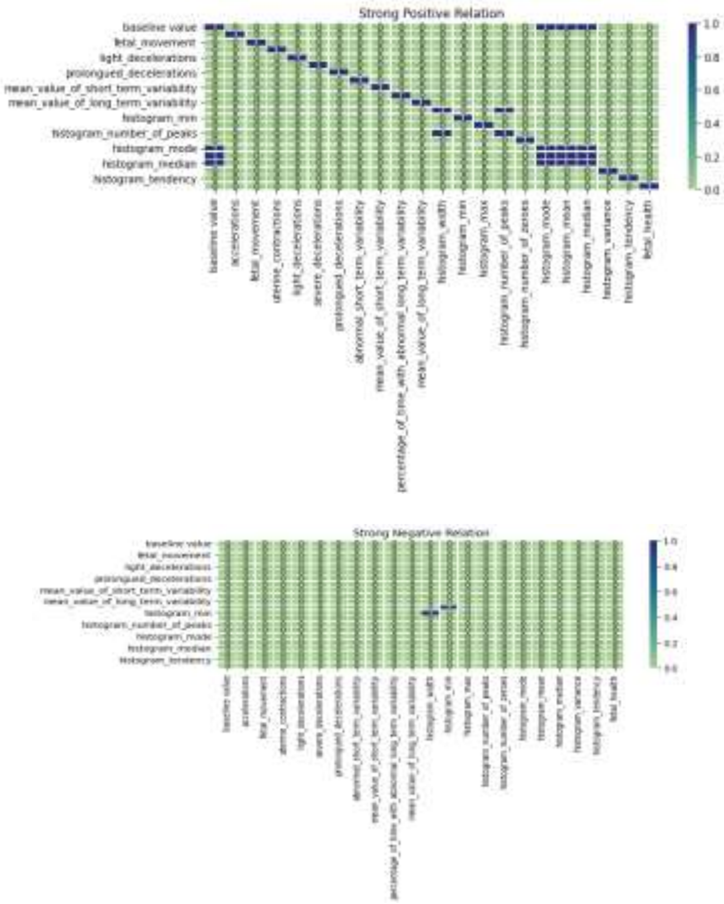

Figure 2. A Depiction of Correlation Among Different Attributes of the CTG Dataset (a) Strong Positive Relation, (b) Strong Negative Relation

3.2. Feature Selection

In order to create a smaller, filtered data set without compromising the effectiveness of machine learning techniques, important features are chosen as a form of data preprocessing. Feature selection strategies can be supervised, unsupervised, or semi-supervised depending on whether a group is present or not. All aspects are rated and ranked using specific statistical parameters in this procedure. Features with high ranking values are chosen, and features with low grades are excluded [14]. The feature selection process in a dense model is self-contained. Many features are below the mean importance**,** Dense Models can drop it on their own [15].

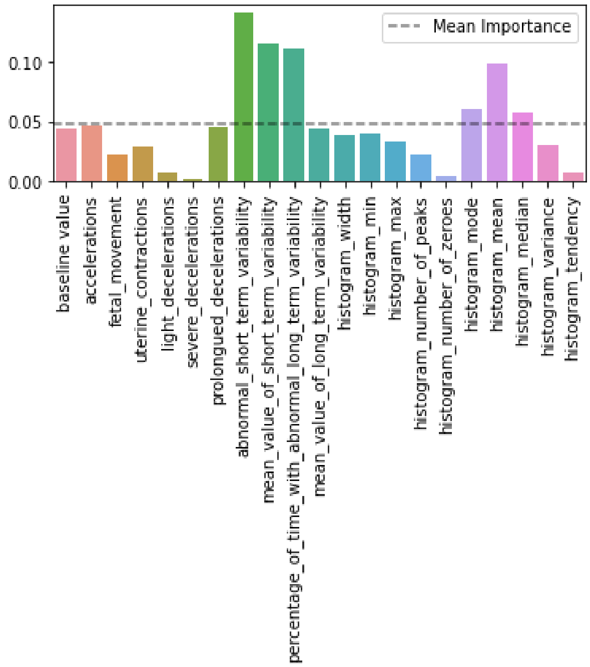

Figure 2.1 Features with relevant mean importance

3.3. Dense Model

The process of segregating training and testing datasets into normal, suspect, and pathologic is carried out using Densenet model.

Densenet, as the term implies, is a dense network pack designed to overcome the vanishing gradient problem that commonly occurs in deep networks. Every layer of the densenet is joined to every other layer in this case [16]. Aside from the fact that it needs fewer variables, the key benefit is that it enables feature reuse. This occurs because of the way the layers are interwoven. Unlike feed forward CNNs, which combines the feature maps from all prior layers, Densenet concatenates the feature maps, allowing it to remove repeated and superfluous features gathered from prior layers [17].

The concatenation process is ineffective when the feature maps size is constantly adjusted owing to dimensionality reduction. The answer is to build numerous dense network that manage the feature map size constant but vary the number of filters between them. Transition layers are placed between thick blocks to condense the networks into half the value of currently active channels. Batch normalisation, RELU, and convolution processes are applied sequentially to each dense layer. Less weights are given to the output of the transition layers in the second and third dense blocks in order to eliminate many redundant features. As a result, when compared to its rival architectures, densenet provides shorter training times and generally the best results. Additionally, features can be transmitted repeatedly through the network with fewer parameters [18]. The algorithm of proposed work is given below:

proposed work algorithm
Input: CTG Dataset Features, Dense Model Parameters **Output**: Performance analysis; Recall,Precision,F-1Measure for three multiple classes, Normal, Suspect, and Pathologic.
1. Load data and check for null values, and make all the values in numerical form.
2. Data Visualization: checking correlation among features
3. Data Splitting: Stratified Splitting to maintain the Class Distribution.
4. Define dense model parameters Model Compilation ← Loss sparse_categorical_crossentropy Adam.optimizer

5. Model.evaluate()
6. Calculate and compare results (precision, recall, accuracy, f1 measure)
7. End

4. Results and Discussion

The fetal CTG data are given as input to dense model for an increased learning sense. The classification accuracy is calculated and confusion matrix is produced. Also, precision, recall, F1 score, and support values are generated.

4.1. Evaluation Metrics

Evaluation metrics are critical for measuring performance of classification. Accuracy is the commonly used metric for performance checking. A classifier's accuracy on a specified test dataset is the proportion of those datasets classified correctly by the classifier. And, as the accuracy measure is not sufficient in the text mining analysis to make a valid judgment, we also implement some other metrics to evaluate classification performance [19]. F-measure, recall, and precision are three fundamental measures which are generally used [20]. Before delving into various measures, there are a few terms we should become acquainted with:

- TP (True Positive) shows the number of data points that were classified correctly.
- FP (False Positive) shows the number of misclassified correct data.
- FN (False Negative) shows the number of incorrect data that has been classified as positive.
- TN (True Negative) represents the number of incorrect data classified as negative.

Accuracy- Accuracy indicates how oftenly the classifier appears to make correct prediction. The accuracy ratio is calculated by dividing the number of correct predictions to the total number of predictions [21].

$$Accuracy = \frac{\text{Correct Prediction}}{\text{Total prediction}} \qquad (1)$$

Recall: Recall calculates a classifier's sensitivity. More recall means lesser false negatives. The recall ratio is the number of correctly classified occurrences divided by the total number of predicted occurrances. This can be illustrated as-

$$Recall(R) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (2)$$

Precision- The exactness of a classifier can be measured by its precision. A low level of precision will result in a greater number of false positives, whereas a high level of precision will result in fewer of these errors. The term "precision" (P) is defined as-

$$Precision(P) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad (3)$$

F-Measure- A single metric called F-measure (the weighted harmonic mean of recall and precision) is formed when precision and recall are combined. It is defined as follows-

$$F - measure = \frac{2\mathrm{PR}}{\mathrm{P} + \mathrm{R}} \qquad (4)$$

4.2. Experimental Results

In this work, the CTG dataset is randomly divided into training and testing set in the ratio of 80:20.

	precision	recall	f1-score	support
0.0	0.94	0.95	0.94	166
1.0	0.61	0.69	0.65	29
2.0	1.00	0.72	0.84	18
accuracy			0.89	213
macro avg	0.85	0.79	0.81	213
weighted avg	0.90	0.89	0.89	213

Table 2. Classification Report

Table 2. shows the evaluation results of dense model in CTG test set. For the testing data set, the overall classification accuracy is 89%. The data set contains 21 features. It is likely that not all features contribute equally to classification. Thus, features with high ranking values are chosen, and features with low grades are excluded implicitly in dense model.

Figure.3 shows the confusion matrix of the Dense Model. The vast majority of samples are accurately predicted, as can be shown in confusion matrix.

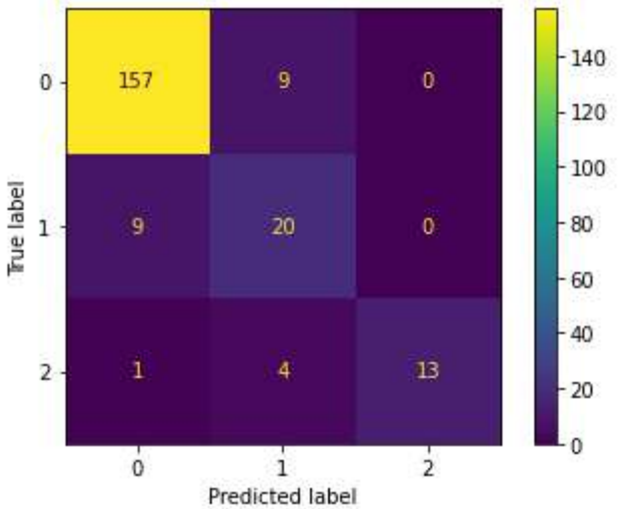

Figure 3. Confusion Matrix

5. Conclusion and Future Scope

The suggested deep learning methods are translated and fused with CTG data, yielding promising results in terms of computation speed and classification accuracy. We generated better time-performance results, which are required in clinical situations. Our approach produced an accuracy of 89% for classifying CTG data into three multiple classes. Our model produced a more local objective function when compared to cutting-edge algorithms. The implementation of our approach to anticipate impaired fetuses in clinical practice would allow informed decision-making. Because of the CTG dataset's limitations, this paper can be improved in the following ways:

(1) The dataset used in this research may be insufficiently rich, and the performance may have been improved if there had been more data.

(2) Other models can be taken for evaluation and feature extraction will be performed in the future to increase the model's performance.

Disclosure Statement

The authors report no conflict of interest.

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