ORIGINAL ARTICLE

Fetal ECG Arrhythmia Detection Based on DensNet Transfer Learning

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Abstract

Purpose: The mortality rate of fetuses due to heart defects is a major concern for clinicians. The fetus's heart is monitored non-invasively using the abdominal Electrocardiogram (ECG) of the mother. Most of the methods in literature diagnose fetal arrhythmia based on fetal heart rate. However, there are various challenges in fetal heart rate monitoring and arrhythmia detection. Therefore, very few methods are explored for fetal arrhythmia classification and have not achieved promising results.

Materials and Methods: In this article, a fetal arrhythmia classification method is investigated. The method has exploited the transfer learning principle where DenseNet architecture is utilized to learn fetal ECG patterns. Fetal ECG (fECG) signal extracted from the mothers abdominal has been processed for denoising and heartbeats are segmented using signal processing techniques. The extracted heartbeats have transformed into 2D fECG images to re-train the pre-trained DenseNet architecture.

Results: The proposed method has been evaluated on the publicly available Non-Invasive Fetal Arrhythmia Database (NIFADB) of Physionet and achieved 98.56% classification accuracy, thus outperforming other existing methods.

Conclusion: The arrhythmia in a fetus can be detected using a non-invasive fetal ECG. Due to the faster convergence of the learning algorithm, the proposed method offers better fetal diagnosis in real-time.

Keywords: Fetal Electrocardiogram; Arrhythmia; Transfer Learning; DenseNet.

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1. Introduction

As of 2015, more than 96 million individuals were affected by congenital disabilities [1]. They impacted around 3% of infants in the United States and were responsible for over 628,000 deaths in 2015 [2]. Congenital disabilities are often referred to as congenital anomalies. Congenital anomalies are functional or structural abnormalities that arise during the prenatal period and can be discovered at birth or later in childhood, such as hearing impairments, vision defects, or heart defects. Heart defects are one of the major defects in fetuses or infants. According to the American Heart Association report, 21.8% of infants who died of a congenital disability had a heart defect [3].

Heart defect also called Cardio Vascular Disease (CVD) is the name for the group of heart disorders. Heart disease has different types of abnormalities in the fetus's heart during the mother's pregnancy [4]. In the current scenario, fetuses have common diseases during heart formation at an initial stage. Still, the baby appears healthy for a long time, and it may be severe by having some defects during labor in the heart of the fetus [5]. Therefore, it is essential to detect the malfunctioning of the fetus for the clinical cure at an early stage. The fetus's heart function can be monitored using Phonocardiogram (PCG), Electrocardiogram (ECG), Cardiography (CTG), or Fetal Magnetocardiography (FMCG) [6, 7, 8, 9]. Each of them has certain advantages and limitations over the other. CTG, for example, does not give any information regarding beat-to-beat variability and is not ideal for long-term continuous monitoring of the foetal heart [10]. PCG acquisition, on the other hand, is quite sensitive to noises. FMCG makes it simple to do fHR morphological analysis, but it is expensive and requires skilled personnel [11].

The use of non-invasive fetal ECG (fECG) is the most preferred method as it places two electrodes at the mother's abdomen to accurately monitor the mother and fetus's electrical activity. It has a number of advantages, including motion estimation, long-term continuous monitoring, lower cost, monitors both atrial and ventricular activity, and can be taken throughout the pregnancy [12]. However, its clinical usability for arrhythmia detection in fetuses has rarely been studied [13].

An abnormality in the heart rate of prenatal is referred to as fetal arrhythmia. The normal prenatal heart beats 120–160 times per minute (bpm) [14]. The prenatal heart rate beyond this range either below 120 bpm (bradycardia) or above 160 bpm (tachycardia) is considered arrhythmia. While most arrhythmias are not life-threatening, some can cause poor cardiac output, fetal hydrops, and death [15]. Therefore, several arrhythmia detection techniques have been developed in the past. Most of the methods in the literature related to fetal ECG monitoring either extract fetal ECG from abdominal ECG or detects fetal heart rate [16-21]. Few methods are found in the literature for detecting and classifying arrhythmia using fECG [16, 17, 20, 22, 23]. The major task in arrhythmia detection using fECG is its extraction from multichannel maternal recordings. Independent Component Analysis (ICA) is used for fetal ECG signal extraction [16-18].

Devika *et al.* used ICA blind source separation algorithm to de-noise the raw input data [16]. Further, fifth-order polynomial fitting and peak detection algorithm are employed on filtered ECG data. They used the Naive Bayes classifier for the detection of myocardial infarction based on the ST segment of ECG signal and achieved 96.77% accuracy. Apsana *et al.* have used a similar algorithm for fetal arrhythmia detection [17]. After the ICA's signal extraction, they used state machine logic for peak detection. They extracted seven temporal-amplitude domain features that are applied to a trained Naive Bayes classifier and achieved 93.71% accuracy for arrhythmia detection.

Patel *et al.* have applied a compressive sensing algorithm on abdominal ECG and employed ICA on compressed ECG signal [18]. For the separation of fetal and maternal beats, smoothed l0 algorithm was used to reconstruct the independent components. They reported the F1 scores of 94.64% and 95.82% for Physionet challenge dataset A and Silesia dataset, respectively. A continuous wavelet transform-based technique along with a histogram and heuristic algorithm was developed by Karvounis *et al.* [19]. Firstly, they detected the maternal QRS complexes using time-frequency analysis and medical knowledge and eliminated them. Secondly, complex wavelets and matching theory were used to locate the foetal R-peaks. Finally, histogram and heuristic algorithms are used in the third stage to find the foetal R-peaks overlaid with the previously excluded maternal QRS complexes. They achieved 97.47% accuracy for fetal heart rate detection.

Veenadevi *et al.* used adaptive filtering algorithms such as the Kalman filter and Least Mean Square to extract fECG from abdominal ECG [20]. They used a differentiation technique for R-peak detection and measuring the fetal heart rate. Further, the measured heart rate identifies two classes of arrhythmia i.e., bradycardia and tachycardia. A deep-learning-based fetal ECG detection from abdominal ECG is proposed by Lo *et al.* [21]. The short-time Fourier transform is applied to normalized and segmented ECG waveforms. The performance of fetal ECG detection is evaluated using two classifiers i.e., k-Nearest Neighbour (k-NN) and CNN. CNN achieved the best detection accuracy of 92.65% while the k-NN reports 83.33% accuracy. In order to detect arrhythmia affected fetuses, Pavel *et al.*, extracted eight significant features, including Tea-ger energy operator [22]. They utilized Gaussian kernel-based Support Vector Machine (SVM) and achieved 83.33% accuracy for arrhythmia detection. Recently, an algorithm for fetal arrhythmia detection and classification is proposed by Ganguly *et al.* [23]. The time domain features of ECG are extracted using 1D convolution with a wavelet kernel and fed to a trained ANN. They have used NIFEADB database and reported the overall accuracy of 96%.

Despite these studies on fetal arrhythmia detection, several existing challenges still motivated us to perform a rigorous analysis of fetal ECG to detect the arrhythmia accurately. These includes:

1. Although non-invasive abdomen recorded fECG provides valuable clinical information on the fetus's health status, effective detection, and extraction of fECG is challenging because the signal is frequently polluted with a high amount of noise and the timing and frequency of fECG and other noise signals overlap. A simple high-pass filtering of abdominal signals for fECG separation is thus not achievable.

2. Due to a lack of advanced signal processing techniques for measuring fECG morphological properties, most foetal monitoring approaches rely on foetal heart rate and do not incorporate fECG waveform characteristics. As a result, significant information concerning the foetal health may be omitted.

3. Fetal arrhythmia identification and categorization is a promising but difficult area to work in because the mother's heart rate influences the fetus's heart rate.

This article presents a unique framework for classifying arrhythmias from fECG utilizing a pre-trained architecture i.e., DenseNet [24]. The novelty of the proposed method is that it employs transfer learning that is yet to be explored by any method of arrhythmia detection using fECG. With the help of transfer learning, the existing model developed for general image classification is used as the starting point specifically for the classification of fECG images. Among several pre-trained models on ImageNet dataset [25], the DenseNet model is chosen heuristically. We re-train the existing DenseNet architecture using 2D fECG images prepared from a publicly available dataset. Due to previous knowledge gathered by DenseNet, learning of fECG patterns begins at a higher level, decreasing training and testing time [26]. Thus, a novel framework for arrhythmia classification is developed utilizing transfer learning that is more resilient than existing methods currently available in the literature. In a nutshell, this work makes the following contributions (Figure 1):

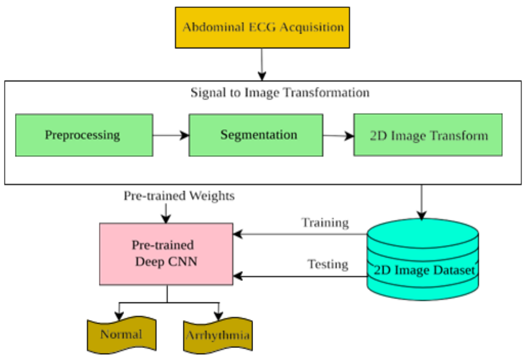

Figure 1. The proposed framework for fetal arrhythmia classification

1. Transfer learning is utilized to develop a novel framework for arrhythmia classification using fECG. It offers significantly lower training and testing time because learning of fECG patterns by pre-trained models begins at a higher level.

2.The proposed method classifies heartbeats with high sensitivity in a computationally efficient manner.

The rest of the paper is laid out as follows: Sec. 2 presents a detailed description of the proposed transfer learning model for arrhythmia classification using fECG. Sec. 3 contains the dataset details, experimental findings, and comparative analysis. Finally, the conclusion is drawn in Sec. 4.

2. Materials and Methods

The proposed architecture for classifying fetal arrhythmias via transfer learning is depicted schematically in Figure 1. It includes three major stages: abdominal

ECG acquisition, signal-to-image transformation, and transfer learning & classification. After acquiring the fECG signal, it is preprocessed for denoising and then segmented into heartbeats. Following that, the fECG signal is converted to two-dimensional images. Exploiting its previous learning, the DenseNet model learns the features of fECG images. After successful training, the proposed framework can classify fECG images as normal or arrhythmic.

2.1. Fetal ECG Basics

Despite differences in mechanical functionality, the beat-to-beat electrical activity of fetal and adult heart is quite similar. The muscle fibers of the myocardium coordinate its contraction (depolarization or systole) and relaxation (repolarization or diastole) [27]. A complete cycle of myocardium contraction and relaxation results in the so-called PQRST-complex, as represented in Figure 2. The spread of electrical impulses through the atria forms P-wave. The depolarization of ventricles results in the formation of QRS-complex. Although repolarization happens at the atria at the same time, it is obscured by the depolarization of the ventricles. While the repolarization of the ventricles forms the T-wave. The morphological patterns of ECG are quite similar for adults and fetuses. However, significant variations have been observed in relative amplitudes of the fetal complexes. For example, the T-waves change significantly, and that are found to be weak for fetuses and newborns [28].

2.2. Fetal ECG Signal Processing

The abdominal-acquired fECG signal is frequently contaminated with noises such as contact, muscle and electrode motion, power line interference, and baseline drift. The distinctive features of heartbeats may be significantly affected by these unwanted noises. Therefore, for effective data representation, conditioning of the fECG signal is necessary that consequently improves the classification performance. The noise contaminated with fECG signal is usually distributed over different frequency bands. So, the signal conditioning is done with the filters of different frequency bands. A combination of low-pass and high-pass filters is designed to restrict the signal frequency in the range of 5–15 Hz. The order of low-pass filter is two that allow passing of signal up to 15 Hz [29]. For example, the raw input signal $a_{n\tau}$ generates a filtered output signal, $f_{n\tau}$. It can be represented by n data samples at the discrete instance of time τ, as follows (Equation 1) [29],

$$f_{n\tau} = 2f_{(n-1)\tau} - f_{(n-2)\tau} + a_{n\tau} - 2a_{(n-6)\tau} + a_{(n-12)\tau} \quad (1)$$

Then to reduce the edge effect, a high-pass filter with 5 Hz cutoff frequency and the following difference equation is applied to the signal (Equation 2) [29].

$$f_{n\tau} = 32a_{(n-16)\tau} - (a_{(n-1)\tau} + a_{n\tau} - a_{(n-32)\tau}) \quad (2)$$

2.3. Heartbeat Segmentation

After ECG signal processing for noise removal, the heartbeats are identified using Pan & Tompkins's QRS detection method [29]. To find the slope of QRS complex the signal is differentiated using a five-point derivative. Equation 3 and Equation 4 illustrate its transfer function and difference equation, respectively [29].

$$H(Z) = (\frac{1}{8}\tau)(-Z - 2 - 2Z - 1 + 2Z1 + Z2) \quad (3)$$

$$f_{n\tau} = (\frac{1}{8}\tau)[-a_{(n\tau-2\tau)} - 2a_{(n\tau-\tau)} + 2a_{(n\tau+\tau)} + a_{(n\tau+2\tau)}] \quad (4)$$

Once the derivative operation completes the signal is squared point-by-point. Further, a moving window integrator is calculated as follows [29] (Equation 5):

$$f_{n\tau} = (\frac{1}{N})[a_{(n\tau-(N-1)\tau)} + a_{(n\tau-(N-2)\tau)} + \dots + a_{n\tau}] \quad (5)$$

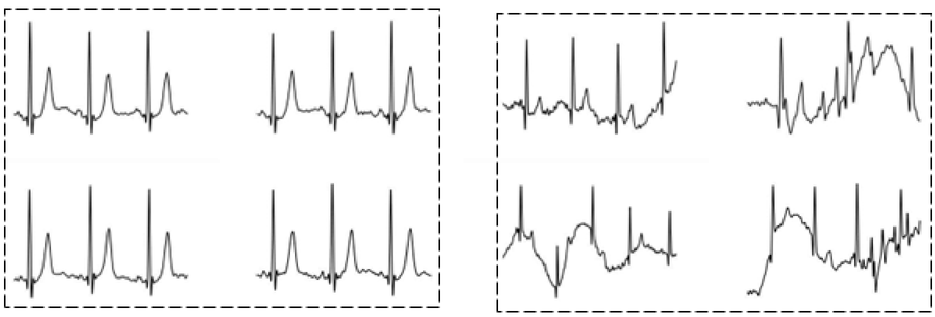

Figure 2. Representative 2D fECG images having a) normal heartbeats and b) heartbeats with arrhythmia

Where N is the number of samples within the window. Finally, from each heartbeat QRS complexes are recognized using an adaptive thresholding technique. Once the R-peaks are identified, we set a window of 700 ms around R-peak ranging from 200 ms to the left of R-peak and 500 ms to the right of R-peak. As a result, the heartbeats are segmented and normalized with z-score normalization [30]. The benefit of performing this normalization is that it transforms the outlier in the dataset so that it will no longer have as big of an influence as it might have on the model fit.

Following the extraction of the heartbeats, the amplitude values of ECG signals within the windows are plotted on Y-axis with respect to time on X-axis, thus forming one-channel 2D fECG images. The pre-trained models evaluated in this study require three-channel 2D images. So, we created two more copies of each image and superimposed them on each other and obtained three-channel 2D fECG images that are further reshaped to size 200 × 200. The procedure for signal-to-image transformation is shown in Figure 3.

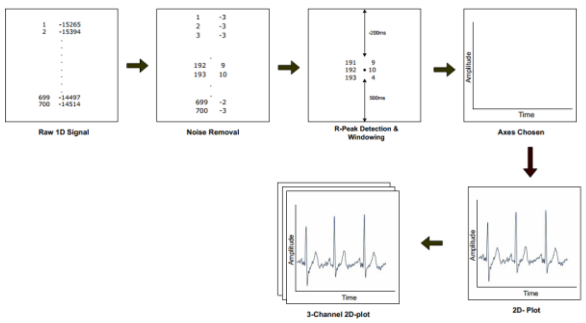

Figure 3. Signal-to-image transformation

2.4. Transfer Learning Architecture

Transfer learning refers to applying a learned model in a different context. It enables the training of deep neural networks with data of a smaller size [31]. The rationale behind using transfer learning is that it provides faster convergence of optimization algorithms. With transfer learning, a machine utilizes previous task expertise to increase generalization about another [26]. For example, the patterns of the fECG are learned in this study using the learning of the DenseNet architecture on the Imagenet dataset. Formally, suppose we have an architecture pre-trained on a dataset κ1 and its learning curve is represented by ϕ1. Transfer learning enables the improvement of a new model's learning curve (ϕ2) using a fresh dataset (κ2). It transfers the pre-trained model's learned behaviour to a prediction function, φ, which improves the learning curve ϕ2 on the dataset κ2.

The ImageNet dataset comprises millions of images of diverse categories [25]. Several image classification tasks were performed utilizing the ImageNet dataset with the help of different deep neural networks. The learning of these architectures is utilized to develop transfer learning models in different areas such as computer vision, pattern analysis, object classification and image analysis. The vanishing gradient problem is a common issue that affects deep neural networks. This problem occurs when the back-propagated gradient gets indefinitely smaller due to repeated multiplication. The DenseNet architecture avoids the vanishing gradient problem by repetition of the dense block. This work of arrhythmia classification from fECG images uses DenseNet architecture [24]. The upper layers are fine-tuned to utilize the DenseNet architecture on the prepared fECG dataset.

The architecture of DenseNet is shown in Figure 4. It comprises several densely connected blocks to avoid feature loss at output layer through larger network depth. It also requires few parameters. Formally, let us pass an fECG image ξ0 through a convolutional network of n layers. Each layer of the network performs a non-linear transformation Φn(.) that includes Batch Normalization (BN), rectified linear units (ReLU), pooling, and convolution. At nth layer of DenseNet, the output ξn is calculated as follows (Equation 6),

$$\xi n = \Phi n([\xi 0, \xi 1, \ldots, \xi n-1]) \tag{6}$$

Where [ξ0, ξ1, ..., ξn−1] is the concatenated feature-maps of the layers (0, 1, ..., n − 1).

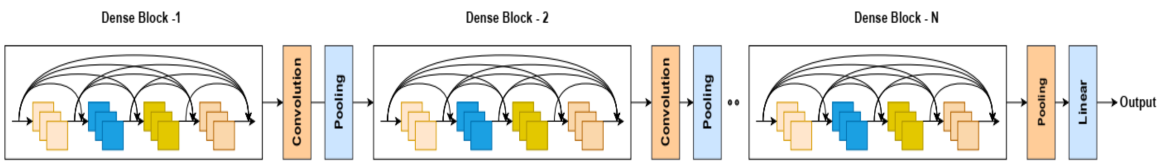

Figure 4. Dense block of DenseNet architecture

A 1×1 convolution is introduced to limit the number of input feature-maps in order to eliminate redundant features owing to recursive concatenation. This step lowers by a factor of four the number of feature maps generated by succeeding 3×3 convolutional layers. Several architectures implement this design option to optimize computational cost, and we realize it is particularly useful for DenseNet. Further, to change the feature-map size the pooling layers are generally used in convolutional networks. Here, the network is divided into multiple densely connected blocks and there is a transition layer between two dense blocks. This network has a transition layer between two dense blocks, separated into many densely connected blocks. The transfer layer is responsible for convolution and pooling. The architecture's transition layer is made up of a batch normalization layer, a 1 × 1 convolutional layer, and a 2 × 2 average pooling layer, among other components.

3. Experimental Setup and Results

In this part, we provide details about the dataset, experimental setup, and metrics used for performance evaluation. Moreover, the section demonstrates the experimental results and a comparative analysis with existing methods for fetal arrhythmia classification is also presented.

3.1. Database

The performance of the proposed fetal arrhythmia classification method is evaluated on Non-Invasive Fetal ECG Arrhythmia Database (NIFEADB) [32]. The database consists of twelve fetal arrhythmia and fourteen normal rhythm recordings. The median gestational age for arrhythmia recording is 36 weeks, ranging from 22 to 41 weeks, and for normal recording it is of 21 weeks, ranging from 20 to 36 weeks. The sampling frequency is 1 kHz except for the four arrhythmia recordings (ARR06–ARR09) that are sampled at 500 Hz. Four to five abdominal channels and a maternal chest channel are recorded for each session. The duration of each recording varies from 7 to 32 minutes and the average length of recordings (in min:sec) are 13:03 and 10:06 for abnormal and normal subjects, respectively. Around 250-300 heartbeats are extracted from each recording. For this experiment, 3500 heartbeat images are taken from each normal and arrhythmia classes. Thus, a dataset is created with a total sample size of 7000 images that are further divided in the 80:20 ratio across training and testing datasets.

3.2. Performance Evaluation Metrics

The proposed method for classifying fetal arrhythmias is evaluated using different performance metrics based on True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). The correct classification of a sample is TP and the system's rejection of unknown samples is termed TN. The FP and FN are called Type-I and Type-II errors, respectively. When the system accepts the unknown sample as a legitimate class, it is Type-I error; whereas, Type-II error occurs when a legitimate sample is classified as an incorrect class. These metrics form the basis for the calculation of the following error metrics:

• False Positive Rate (FPR): The FPR measures the proportion of falsely reported positive cases in the data (Equation 7):

$$FPR = \frac{FP}{FP + TN} \tag{7}$$

• False Negative Rate (FNR): The FNR is the measure of the proportion of falsely reported negative cases in the data (Equation 8):

$$FNR = \frac{FN}{TP + FN} \tag{8}$$

• Accuracy: The ratio of correct classifications to the total samples (Equation 9).

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{9}$$

• Precision: Precision measures the fraction of correctly classified positive predictions (Equation 10).

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

• Recall: Recall measures positive class predictions from the dataset's positive instances (Equation 11).

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

• F1-score: It considers both false positives (FP) and false negatives (FN) and is measured as a weighted average of precision and recall (Equation 12).

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{12}$$

3.3. Results

The proposed method for fetal arrhythmia classification utilizes pre-trained DenseNet architecture chosen heuristically. All experiments are performed on AMD ryzen 5 3600 CPU, 32 GB RAM, RTX 2060 Super GPU using Anaconda 1.10.0, Jupyter Notebook 6.2.0 environment for Python. To leverage transfer learning the required pre-trained models are taken using Keras application. For mathematical calculations using tensors and incorporating GPU for these calculations, Tensorflow-GPU is used. The conversion of images to respective multidimensional arrays is performed with the help of CV2 library.

The testing accuracies, precision, recall, and F1-score of different tested architectures, including DenseNet are given in Table 1. The testing accuracies of MobileNet–V2 and ResNet–152 are not satisfactory on the prepared database of fetal ECG images and are reported as 69.14% and 86.41%, respectively. Although Inception–V3 and InceptionResNet–V2 achieve better accuracies, the DenseNet outperforms these architectures and obtains the highest accuracy of 98.56%. The values for other performance metrics such as precision, recall, and F1-score also confirm the efficacy of DenseNet model. Therefore, we use DenseNet architecture for fetal arrhythmia classification.

Table 1. Values of different performance metrics for transfer learning architecture on different pre-trained models

Pre-trained architectures	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Inception–V3	95.07	95.12	95.09	95.22
ReseNet–152	86.37	86.38	86.38	86.41
InceptionResNet–V2	95.98	95.98	95.98	96.17
MobileNet–V2	68.97	68.96	69.96	69.14
Xception	91.2	91.19	91.19	91.34
DenseNet	98.28	98.27	98.28	98.56

The training and testing accuracy of DenseNet architecture concerning the number of epochs is shown in Figure 5. From the very first epoch, the training and testing accuracies of DenseNet are reported as 67.47% and 57.89%, respectively. It shows that the utilization of the transfer learning principle can start training the model from a higher level, thus reducing computation costs. It is apparent from the figure that the model achieves

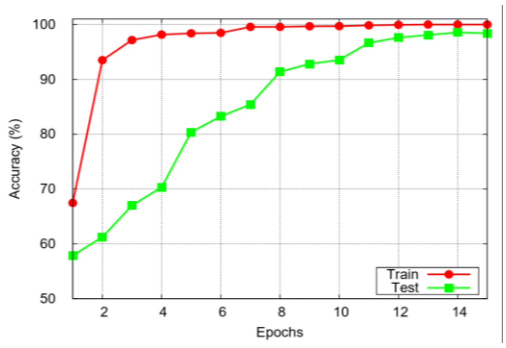

Figure 5. Training and testing accuracies achieved by transfer learning architecture

the highest accuracy of 98.56% at epoch 14. Thus, the proposed fetal arrhythmia classification system is computationally efficient due to the exploitation of transfer learning through DenseNet.

In order to effectively depict the classification accuracy of the system, a Receiver Operating Characteristic (ROC) curve is drawn. It plots the False Positive Rate (FPR) on the x-axis and True Positive Rate (TPR) on the y-axis. The ROC curve for the proposed fetal arrhythmia classification system is shown in Figure 6. The proposed method reports TPR of 91.7% at 0% FPR while at a marginal FPR of 0.1% it becomes 99.8%. The experimental results of precision, recall, and f1-score for normal and arrhythmia classes are also shown in Table 2. It shows that the proposed method achieves higher values for these metrics. Further, there are fewer variations among these metrics values that prove the proposed method's robustness.

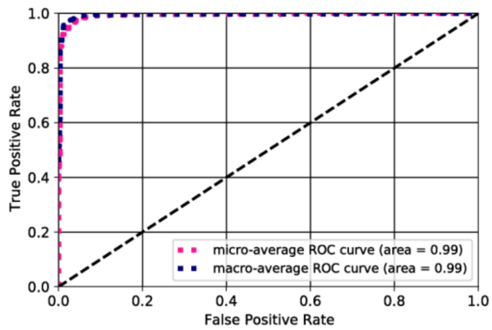

Figure 6. ROC curve achieved by proposed transfer learning architecture

Table 2. Values of different performance metrics obtained for normal and arrhythmia classes

	Precision	Recall	F1-score
Normal	0.9818	0.9853	0.9835
Arrhythmia	0.9839	0.98	0.982

A confusion matrix is also drawn to visualize the proposed method's performance for fetal arrhythmia classification. It represents a description of the outcomes of the identification. The confusion matrix effectively shows the accuracy of predictions for each class. The confusion matrix obtained using the proposed method is shown in Figure 7.

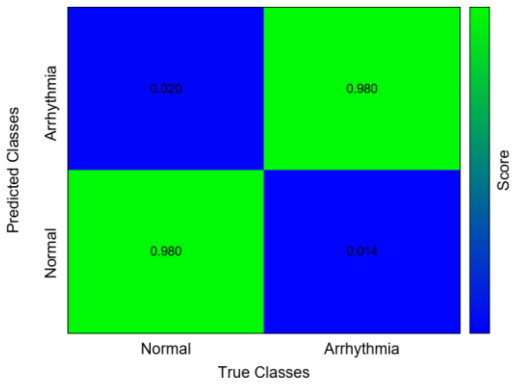

Figure 7. Confusion matrix obtained by proposed transfer learning architecture

The true and predicted class designations are displayed on the x and y-axes, respectively. Each square in the confusion matrix shows how likely it is that the predicted class and the real class are the same. The confusion matrix makes it easy to figure out the number of TP, TN, FP, and FN. The probability of correct classification for both classes is higher and reported as 0.98. The probability of predicting 'Normal' class as 'Arrhythmia' class is 0.2, whereas the probability for arrhythmia prediction for a normal class is 0.14. It shows that there is less chance of incorrect prediction by the proposed method.

3.4. Comparative Analysis

There are very few existing methods for fetal arrhythmia classification. We evaluated our proposed method on the Non-Invasive Fetal ECG Arrhythmia Database (NIFEADB) of Physionet [32]. Pavel *et al.* and Ganguly *et al.* also worked on the same database to detect fetal arrhythmia [22, 23]. Pavel *et al.* used 8 fiducial features and support vector machine classifiers for fetal arrhythmia detection and achieved an overall classification accuracy of 83.33% [22]. The abdominal signals are usually contaminated with noise elements that may affect the accurate detection of fiducial points, and thus may not be able to extract discriminating features of fetal ECG. It may be one of the reasons behind the lower accuracy achieved by their method.

Ganguly *et al.* extracted time-domain features of fetal ECG using a 1D convolution network that are fed to the artificial neural network [23]. They achieved 96% classification accuracy. It is obviously reducing the computational burden of feature engineering as required in fiducial-based methods. We used a pre-trained DenseNet architecture for arrhythmia detection using fECG that reported the best accuracy of 98.56% and outperformed other methods.

4. Discussion and Conclusion

The studies show that infant heart defects are more prominent than other birth defects. So, the accurate diagnosis of fetal arrhythmia is essential for lowering the mortality rate of infants. One convenient and non-invasive method for fetal arrhythmia diagnosis is the analysis of fetal ECG taken from mother's abdomen.

This paper has proposed an automatic diagnosis system for the detection of arrhythmia in fetuses using the principle of transfer learning. The proposed diagnosis system takes ECG signals from the abdominal of pregnant women as input. The fECG signals are qualitatively improved using signal-processing techniques and heartbeats are detected [33]. The heartbeat detection forms the basis for signal-to-image transformation. We transformed the 1D signal of the heartbeat into 2D fECG images. Thus, a 2D fECG image database is prepared from the publicly available Non-Invasive Fetal ECG Arrhythmia Database (NIFEADB).

The proposed method has used the pre-trained DenseNet architecture to exploit the transfer learning principle. DenseNet is pre-trained on a diverse category of millions of images from ImageNet database. The architecture is well-trained and achieved 98.56% accuracy in image classification. Therefore, the architecture of DenseNet is utilized and it is re-trained on the fECG images freezing the existing weights and biases. The utilization of pre-trained architecture causes the optimization algorithm to converge faster, thus reducing the training time.

The performance of the proposed method for arrhythmia classification from fECG has been evaluated on publicly available Non-Invasive Fetal ECG Arrhythmia Database of Physionet. The method has reported higher classification accuracy of 98.56% and outperformed other existing methods. Further, the proposed method has proved to be computationally efficient. Future research may include a deeper analysis of different types of arrhythmia present in fetuses.

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