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Precision Fetal ECG Signal Enhancement using Convolutional Neural Networks: Empowering Early Detection of Cardiac Abnormalities in the Prenatal Stage

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ABSTRACT

An electrocardiogram (ECG) is a simple test that is used to check the heart's rhythm and electrical activity. Similarly, FECG signals are taken from the fetus either invasively or non-invasively. Here, non-invasive FECG is used to acquire the fetal wave-forms. ECG is common and taken from both men and women, but ECG is taken from only pregnant women. FECG signals from both the mother and the fetus might be impacted by background noises and other sources. Noise may be external or internal. Signals with noise produce misinterpretation of waveform analysis and result in wrong diagnosis by physicians. The Kalman Filter (KF), and Pan & Tompkins (P&T), a machine learning technique, is employed to eradicate these disturbances from FECG ef effectively. FECG Synthetic database is used as an input test signal. QRS wave is extracted from FECG, external noises are added for testing, removal of noises using Kalman filter and finally, original denoised ECG waveforms are obtained. The Noise can be successfully eliminated by utilizing the benefits of this strategy. The effectiveness of the suggested method is evaluated using signal-to-noise ratio (SNR) as a performance metric.

Keywords - Fetal ECG, CNN (Convolutional Neural Network), Fetal Monitoring, fetal heart rate, cardiotocography

INTRODUCTION

One kind of birth defect that may harm the heart's structure and function is congenital cardiac abnormalities. According to estimates from the World Health Organization (WHO), 1.5 million people worldwide passed away from these illnesses in 2020 [1].These figures are based on the organization's most recent data from 2021.Improving the detection and handling of new-born cardiac defects is very important, as the majority of these deaths included infants whose passed away in the first month of life. It is imperative that we make time to further our knowledge, diagnosis, and treatment of this disorder because ignoring it could have fatal consequences for our health [2].Early detection and accurate diagnosis of fetal distress during pregnancy are essential to lower the risk of unfavourable consequences. On-invasive diagnostic techniques are used to examine the fetus's cardiovascular system in order to protect the health of the mother and unborn child [3]. Fetal cardiac diagnostic systems, which record the fetal ECG signal, a useful combination of fetal and maternal ECG signals, are one tool for fetal Monitoring [4]. However, because the signal may be weakand prone to interference, choosing a trustworthy fetal ECG signal can be difficult.

LITERATURE SURVEY

Support Vector Machines (SVMs) stand as a cornerstone in statistical learning techniques, wielding significant influence across various domains within statistics and computer science. It delves into the efficacy of SVMs in the realm of statistical process monitoring, offering a comprehensive review of pertinent literature employing SVM models. Particularly, it investigates the D-SVM chart, initially introduced by Fetal and endeavours to evaluate its performance leveraging real-world datasets sourced from the UCI machine learning repository. While the D-SVM chart presents promise, its optimization parameters warrant refinement, and there exists a need for a method to better translate decision values into probabilities of being out of control [3].It explores the role of feature subset selection in enhancing prediction performance in datasets with numerous variables, leveraging Random Forest's robustness in handling large variable sets, missing data, classification, and regression tasks. It assesses Random Forest's effectiveness from a variety of angles through a comparative analysis, illuminating both its advantages and disadvantages in challenging data analysis situations [8].

Analysis of the fetal electrocardiogram (FECG) is crucial for spotting cardiac anomalies in fetuses; however, FECG extraction from noisy composite abdominal signals, such as the mother's ECG and electrical interference, remains a significant research challenge. The Heuristic RNN-based Kalman Filter for Fetal Electrocardiogram Extraction is a novel approach to fetal electrocardiogram extraction that is proposed in this study. It utilizes redundant noise and signal patterns present in the remaining mECG and FECG signals. The method consists of two functional blocks: an RNN-based Heuristic Recurrent Neural Network (RNN) with heritage Long Short-Term Memory (LSTM) is used in the second block to build a knowledge base using an RNN-based Kalman filter for signal extraction. By enhancing the accuracy and efficiency of FECG extraction, this technique has the potential to enhance fetal heart diagnostics [10].

Existing Method

Adaptive filters are crucial to contemporary digital signal processing (DSP) products in applications including noise cancellation, biomedical signal augmentation, and telephone echo cancellation, among others. Adaptive filtering techniques are used to separate the fetal ECG signal from the mixture of signals that include the maternal and fetal ECG signals along with other potential noise artifacts. By modifying the adaptive filter coefficients in real-time according to the properties of the input signals, the intended fetal ECG signal can be distinguished from the interfering signals. In order to separate the fetal ECG signal from a mixture of signals and remove the maternal heartbeat, the graphic depicts the structure of adaptive filtering. The input signals, the adaptive filter, and the filtered output are all displayed by t[7].The fetal ECG signal can be distinguished from other signals using this graphic, which also helps to explain how adaptive filtering operates[9].In noisy or interference-filled environments, or when dealing with specific signal types, adaptive filters may exhibit a slow convergence rate. The filter's inability to swiftly and efficiently adjust to changing conditions may be impacted by this sluggish convergence. Adaptive filters occasionally experience instability, which can result in strange behavior. These filters can show oscillations or divergent behavior if they are not properly designed or applied, which could produce inaccurate or untrustworthy results.

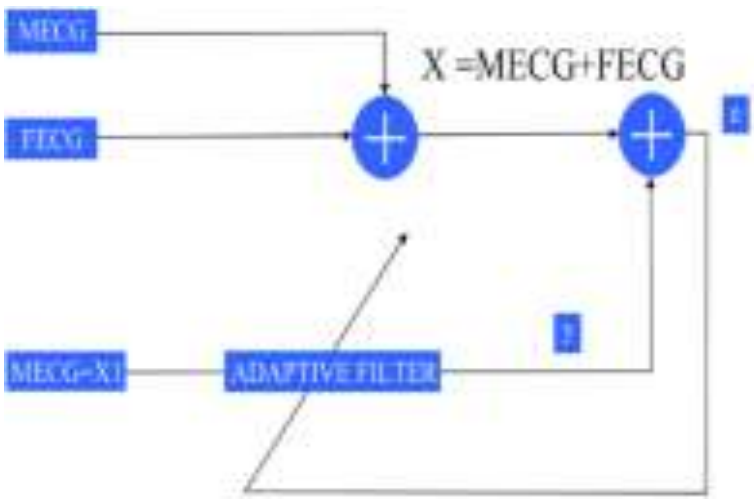

Figure 1. Adaptive Filter Implementation

Proposed Method

A number of essential phases make up the suggested algorithm for fetal ECG extraction, which is intended to precisely separate and analyze fetal heart signals from the mother ECG recordings depicted in figure 2.First, the algorithm starts by obtaining ECG signals from the mother's chest and abdomen. After filtering out high-frequency noise, these signals are amplified to improve the signal-to-noise ratio and provide more readable data for analysis. The filtered and amplified signals are then subjected to R-peak identification, which is a crucial step in identifying the ECG waveform's most noticeable characteristics. This step involves employing a peak detection algorithm to precisely pinpoint the R-peaks. Subsequently, the algorithm focuses on detecting fetal ECG signals by leveraging morphological discrepancies between maternal and fetal ECGs.

Because fetal signals are generally weaker and have lower frequencies than those of the mother, low-pass and high-pass filtering are combined. Fetal ECG signals are effectively isolated by the high-pass filter, which targets low-frequency noise, and the low-pass filter, which targets high-frequency maternal noise. To further refine the fetal ECG signal and calculate the fetal heart rate, a Convolutional Neural Network (CNN) algorithm is implemented. In order to further reduce high-frequency noise, this CNN uses particulate filter coefficients. It also establishes a threshold value in order to identify R-peaks in the FECG signal whose values exceed it. Lastly, counting the number of R-peaks found is used to calculate the fetal heartbeat based on the R-R interval. This all-encompassing method guarantees precise fetal ECG signal extraction and analysis, offering insightful information about the health and development of the fetus.

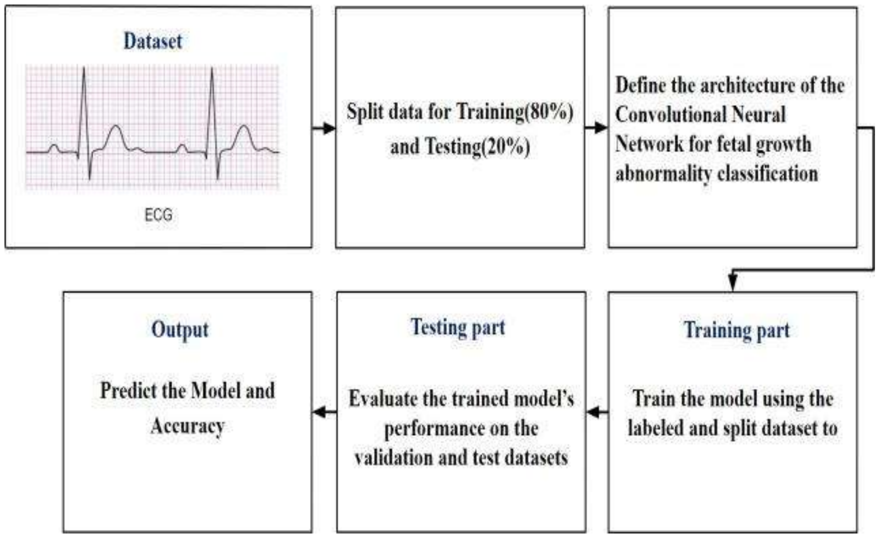

Figure 2. Block Layout for the Supposed 1D-CNN Model

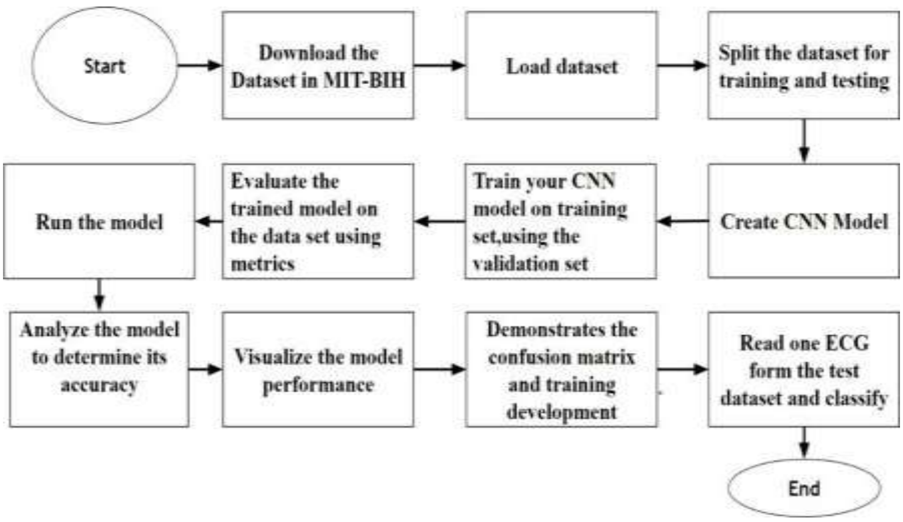

Figure 3: Flowchart representation of the proposed model

MODULES

Data Collection and processing:
Download the MIT-BIH Arrhythmia Database from Physio Net shown in Table 1.Pre-process the ECG signals by applying filtering and normalization techniques. Segment the signals to extract individual beats using peak detection. Label each beat according to its type using the provided annotations. Classify beats as normal, premature ventricular contractions (PVCs), atrial fibrillation (AF), etc., based on the annotations. It is dedicated to acquiring and preparing electrocardiogram (ECG) signal data pertinent to fetal growth for CNN model training.

It encompasses several sub modules aimed at ensuring the quality and readiness of the data for analysis. The first sub module, Data Acquisition, is tasked with sourcing ECG signal datasets specifically associated with fetal growth abnormalities. This involves accessing relevant databases, collaborating with medical institutions, or employing other means to gather comprehensive datasets. Following data acquisition, the Data Cleaning sub module comes into play. Here, efforts are focused on addressing issues such as missing values, noise, or artifacts present within the ECG data.

Through various techniques, including Interpolation, filtering, or artifact removal algorithms, the integrity and reliability of the data are enhanced. Signal Pre-processing constitutes another vital aspect of this module. It involves normalizing the data to ensure consistency across different moles, filtering out unwanted frequencies to extract the essential cardiac information, and segmenting the signals into manageable units for subsequent analysis

Table 1: Total number of dataset for each class

Dataset	Division	Class	No.of Data
MIT-BIH Dataset	Train	Normal	72471
		Unknown Beats	2223
		Ventricular Beats	5788
		Supraventricular Beats	641
		Fusion Beats	6431
	Test	Normal	72471
		Unknown Beats	2223
		Ventricular Beats	5788
		Supraventricular Beats	641
		Fusion Beats	6431
		Total Images	87554

Data Representation

Each category represents a distinct type of beat that can be observed in the dataset shown in figure 4. For example, 'normal beat' indicates the normal rhythm of the heart, 'Ventricular ectopic beats' refer to abnormal heartbeats originating from the ventricles, 'Supraventricular ectopic beats' indicate abnormal heartbeats originating above the ventricles, and 'Fusion Beats' represent a combination of normal and abnormal heartbeats. By labelling each segment with these specific beat type categories, the pie chart provides a clear visual representation of the distribution of different types of beats within the dataset, allowing for easy identification and interpretation of their relative frequencies.

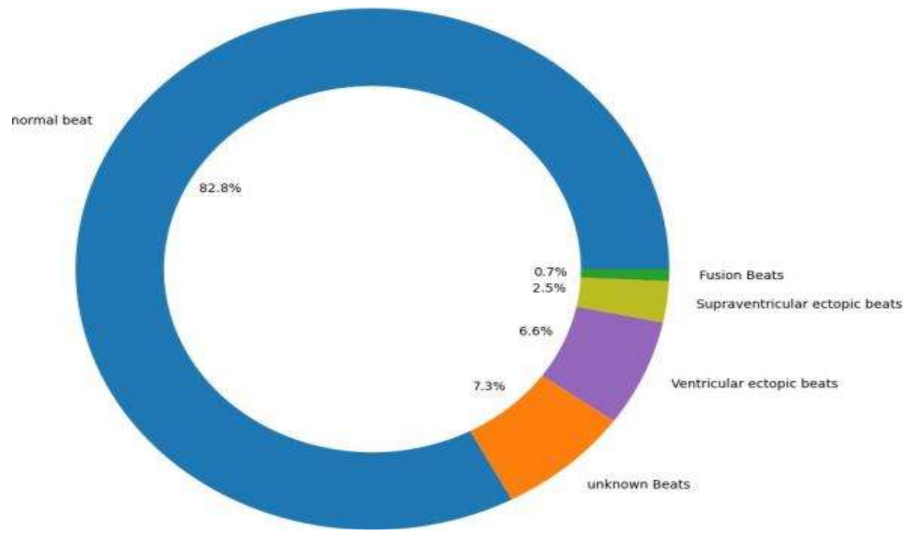

Figure 4. Data visualization for various classes

Data Labelling and Splitting

Involves assigning labels to pre-processed data to signify normal or abnormal fetal growth and partitioning the dataset into training, validation, and testing sets. The Annotation sub module entails the manual or algorithmic labelling of ECG signals with corresponding fetal growth classifications. Through this process, each data point is categorized as either representing normal or abnormal fetal growth conditions. Following annotation, the dataset is then divided into distinct subsets for training, validation, and testing purposes, ensuring a balanced distribution of data across the sets. This systematic approach facilitates the training and evaluation of models to accurately classify fetal growth abnormalities based on ECG signals.

CNN Model Architecture

This module entails crafting the architecture of a Convolutional Neural Network (CNN) for classifying fetal growth abnormalities and their parameters are shown in table 2. It incorporates several sub modules: Convolutional Layers, which are designed to extract hierarchical features from input data; Pooling Layers, introduced to decrease spatial dimensions and enhance computational efficiency; Fully Connected Layers, responsible for classification based on extracted features; Activation Functions, such as ReLU, to introduce non-linearity and enhance model capacity; Dropout layers, included for regularization purposes to mitigate over fitting by randomly dropping connections during training. Together, these components form a comprehensive CNN architecture tailored for accurate classification of fetal growth abnormalities based on learnedECG signal features.

Table 2: Parameter Metrics for the CNN Model

Parameters	CNN Model
Learning Rate	0.001
Mini Batch size	32
Optimizer	ADAM
Loss	Categorical Cross Entropy
Epochs	5
Iteration per Epoch	3125 of 3125
Hardware Resource	Single CPU
Elapsed Time	2 min 2 sec

Normal beats in fetal electrocardiogram represent the regular, expected electrical impulses generated by the fetal heart. Healthy fetal heart function, normal cardiac development Unknown beats in FECG refer to beats that cannot be precisely classified into specific categories due tovarious reasons such as noise, artifacts, or irregularities not covered by standard classifications. Technical issues in recording, movement artifacts, or abnormalities not well understood in fetal cardiac electrophysiology. Ventricular beats in FECG originate from the ventricles of the fetal heart, which may indicate abnormal heart rhythms is shown in figure 5.Ventricular ectopic beats can occur due to various factors including fetal distress, maternal factors such as drug use, fetal structural abnormalities affecting cardiac conduction, or genetic conditions affecting the fetal heart. Supraventricular beats in FECG originate above the ventricles, typically in the atria of the fetal heart. These beats may include premature atrial contractions (PACs) or other supraventricular arrhythmias. Supraventricular ectopic beats can occur due to factors such as fetal distress, maternal factors such as drug use or maternal conditions affecting fetal circulation, or structural abnormalities in the fetal heart. Fusion beats in FECG occur when both normal and ectopic impulses coincide, resulting in a complex waveform that combines features of both.

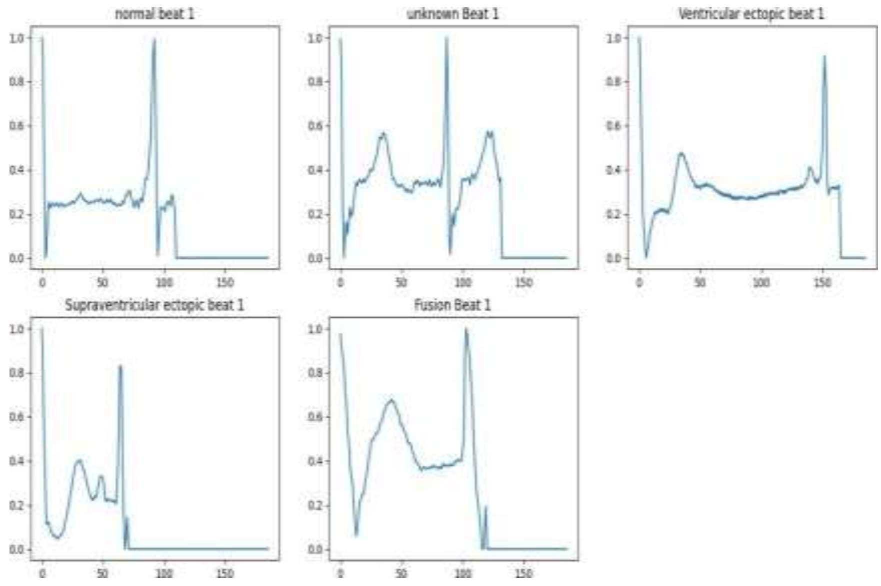

Figure 5. FECG wave shape across different classes

Model Training

It trains the CNN model using the labelled and split dataset, focusing on learning patterns associated with fetal growth abnormalities. It involves defining an appropriate loss function and optimizer, then iterating through the datasetin a training loop to update the model weights accordingly

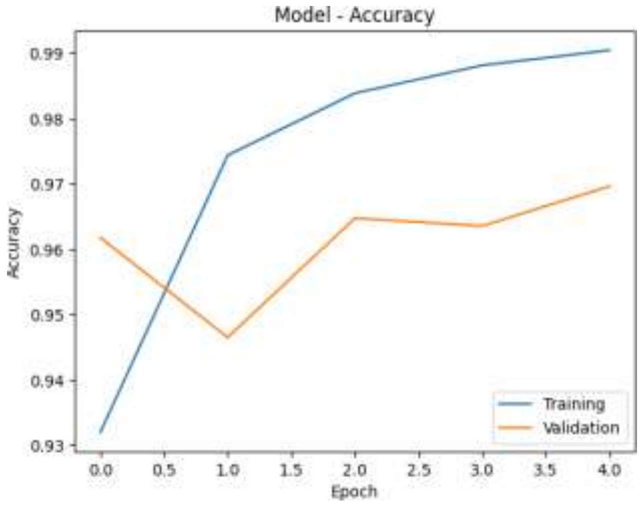

Figure 6. Accuracy of the Proposed Method

A machine learning model's training accuracy is determined during the training process using the training dataset. As seen in figure 6, it gauges how well the model predicts the labels of the training data it was trained on. During training, a machine learning model is tested for validation accuracy using a different validation dataset. It gives an estimate of the model's performance on fresh, untested examples by gauging how well the model generalizes to unknown data. During the training process, an epoch is one full run through the entire training dataset. As demonstrated in Table 3, training accuracy and validation accuracy are usually tracked over several epochs to track how the model learns and generalizes over time. It is possible to determine whether a model is over fitting, performing well on training data but not on validation data under fitting not learning enough from the training data by looking at how these accuracies vary over epochs.

Table 3: Training - Validation Accuracy for the CNN Model

Epoch	**Trainingaccuracy**	**Validation accuracy**
1	0.932	0.934
2	0.974	0.953
3	0.983	0.964
4	0.988	0.963
5	0.990	0.969

Each bin in the histogram represents a specific range of energy values, and the height of each bin indicates the frequency of fetal cardiac signals with energy levels falling within that range. Monitoring Fetal Health in the distribution of signal energies over time or across different fetal development stages may provide insights into fetal health and well-being. Anomalies or trends in energy distribution could prompt further medical evaluation and intervention. Comparing histograms of signal energies before and after signal processing operations (e.g., noise reduction, artifact removal) as shown in figure 7 can help evaluate the effectiveness of these techniques in enhancing the quality of ECG signals.

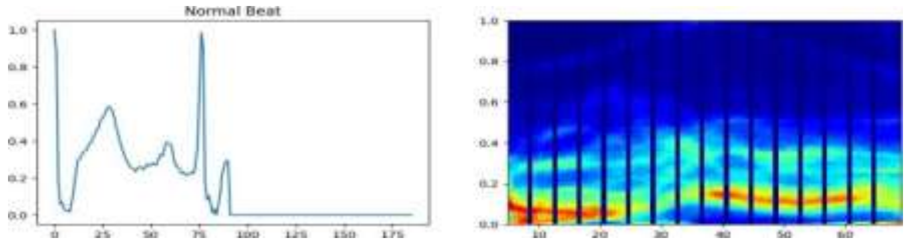

Figure 7. Model's Signal Energy of the Proposed Method

Model Evaluation

Metrics like accuracy, precision, recall, and F1 score are computed to evaluate the trained CNN model's performance on validation and test datasets. The Receiver Operating Characteristic (ROC) curve is also plotted for additional analysis.

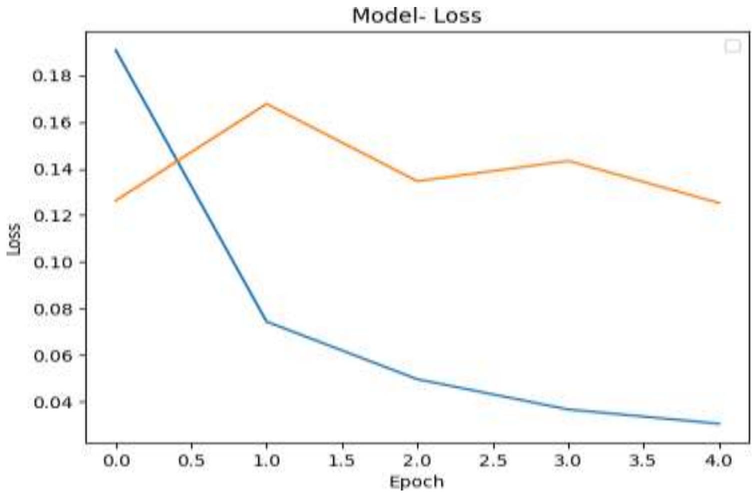

Figure 8. It depicts the model loss of the proposed model

The error or gauge of the model's performance on the training set is called the training loss. As illustrated in figure 8, it is normally computed at each training epoch or iteration.

The objective is to reduce this loss, which shows that the model is improving its ability to predict things based on the training set. Though it is calculated on a different dataset known as the validation dataset, one that the model hasn't seen during training validation loss is comparable to training loss. Validation loss is used to assess how well the model applies to fresh, untested data. The model may be over fitting to the training set if the validation loss begins to rise while the training loss is falling.

RESULTS VISUALIZATION

This module produces ROC curves, loss curves, and metrics visualizations to give users an understanding of how well the CNN model is performing. It includes plotting graphs depicting the variation of metrics over epochs and visualizing ROC curves to assess the model's discrimination ability. Additionally, it showcases prediction examples alongside their corresponding ground truth labels, offering a qualitative understanding of the model's classification accuracy and potential misclassifications.

All things considered, these Visualizations help interpret the strengths and weaknesses of the trained CNN model for the classification of fetal growth abnormalities.

All things considered, these visualizations help interpret the strengths and weaknesses of the trained CNN modelfor the classification of fetal growth abnormalities. The efficacy of a classification model is evaluated using the accuracy formula. The ratio of correctly predicted instances to all instances in the dataset is computed.

The calculation for accuracy is as follows: Accuracy =Number of Correct Predictions/ Total Number of Predictions.

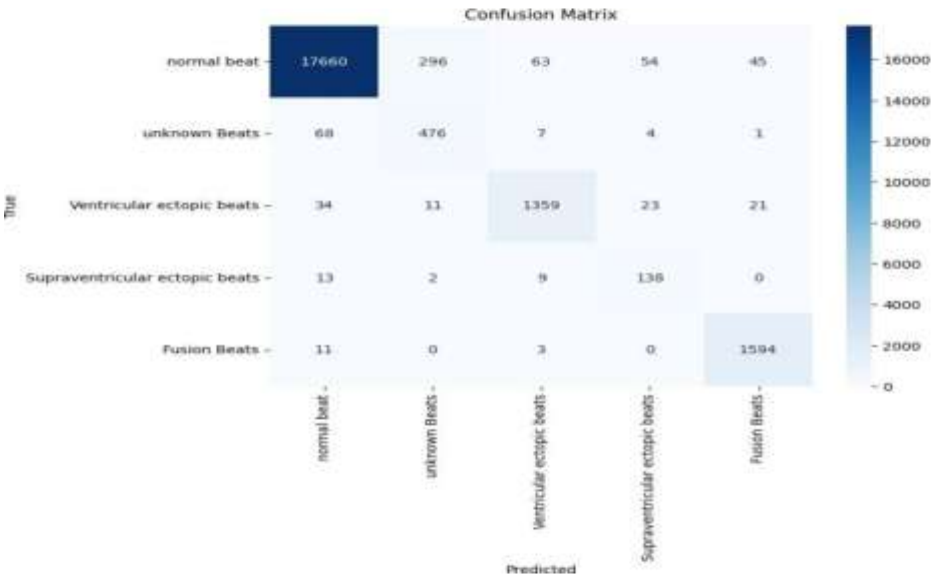

Figure 9. The confusion matrix of our model

Table 4: Comparison result of Proposed and Existingmethod in term of Accuracy

Classifier	Accuracy
Convolutional Neural Network(Proposed Method)	99%
Recurrent Neural Network	87%
Support Vector Machine	85%
Random forest	83%
Decision Tree classifier	80%

Deployment

This module facilitates the deployment of the trained CNN model for real-world applications, enabling users to classify fetal growth abnormalities directly from ECG signals. It involves integrating the model into a user-friendly interface or application, allowing seamless input of ECG data for classification. Through this deployment, healthcare professionals can efficiently utilizethe model to aid in diagnosing fetal growth abnormalities, improving patient care and outcomes.

CONCLUSION

The proposed algorithm for fetal ECG extraction presents a robust framework for accurately isolating and analysing fetal heart signals from maternal ECG recordings. By meticulously executing several crucial steps, including signal filtering, amplification, R-peak identification, and morphological analysis, the algorithm ensures precise detection of fetal ECG signals amidst maternal noise.

The incorporation of advanced techniques, such as Convolutional Neural Network (CNN) algorithms, enhances the accuracy of fetal heartbeat extraction by effectively eliminating high-frequency noise and setting appropriate thresholds for R-peak identification.

This not only improves the reliability of the extracted fetal ECG signals but also facilitates the calculation of fetal heart rate with a remarkable accuracy of 99% as shown in Table 4.The deployment of our trained model into real-world applications promises to empower healthcare professionals with a valuable tool for timely and accurate diagnosis, ultimately improving maternal and fetal health outcomes.

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