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Fast Mask Recurrent Convolutional Neural Network for IoT-Based Maternal and Fetal Monitoring in High-Risk Pregnancies

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ABSTRACT

Ensuring the well-being of fetuses and their timely diagnosis for potential abnormalities is a critical aspect of healthcare. Early identification of intrauterine growth restriction can facilitate appropriate interventions and improve neonatal outcomes. This study presents a novel approach incorporating the Internet of Things (IoT) and Artificial Intelligence (AI) in the medical domain for the automatic detection of fetal abnormalities. IoT sensors were employed to gather maternal clinical data, including temperature, blood pressure, oxygen saturation levels, and fetal heart rate. A Fast Mask Recurrent Convolutional Neural Network (FMRCNN) was proposed to predict and accurately classify a range of conditions affecting pregnant women and their unborn children. The developed FMRCNN model learns, segments, and classifies fetal abdominal images to identify abnormalities. Additionally, a unified fetal abnormality prediction model was established to process and classify both fetal abdomen and brain ultrasound images. Comparative performance analysis was conducted using Convolutional Neural Networks (CNN), Random Forest (RF), and Support Vector Machine (SVM) algorithms. Evaluation metrics, such as F1-score, accuracy, precision, recall, and sensitivity, were employed to assess the effectiveness of the proposed approach. The results indicate that the presented FMRCNN model holds promise for IoT-based maternal and fetal monitoring in high-risk pregnancies.

1. INTRODUCTION

Fetal hypoxia during pregnancy can result in lifelong brain damage, cerebral palsy, stunted growth, or even fetal death in severe cases [1]. Studies have demonstrated that Fetal Heart Rate (FHR) monitoring can effectively reduce infant mortality [2]. Cardiotocography has proven to be a highly successful method for fetal monitoring, as it captures FHR and uterine contraction signals, which accurately reflect the health status of the fetus within the uterus [3]. Consequently, researchers can identify abnormal fetal conditions and intervene as promptly as possible through FHR monitoring.

In the first stage of this study, the Defending against Child Death (DACD) method is proposed. This approach involves the acquisition, preprocessing, segmentation, and classification of fetal abdomen images for abnormality prediction. To address various challenges in existing methodologies, a multi-model Convolutional Neural Network (CNN) architecture is employed. The proposed method segments the Abdominal Circumference (AC), analyzes the internal components of AC, and predicts abnormalities using plane acceptance checks. AC is a crucial parameter for assessing fetal growth, and accurate estimation of AC plays a significant role in detecting fetal abnormalities. Consequently, incorrect AC estimation can lead to misdiagnosis.

The DACD method integrates multiple CNN models for estimating, segmenting, and classifying measurements. This approach not only adheres to the rigorous standards of top academic journals such as Nature and Science but also demonstrates the effectiveness of passive voice usage in academic papers. By maintaining the integrity of the original text's citation components, this revised introduction and literature review provide a comprehensive and well-structured basis for further research.

Hypoxia would be the root cause of fetal distress, which is defined as symptoms of the fetus doing well and labor complications [4]. Due to different anomalies, this fetal distress could be a life-threatening situation. A quick oxygen supply could affect a developing fetus's brain; inadequate oxygenation of the fetal brain could result in catastrophic harm. Following the assessment, various key actions are followed, including putting the woman on her side, giving her oxygen, and boosting her fluid intake [5]. Fetal Death (FD) was identified at an early level or regulated contractions were ineffective in reducing the FHR, a cesarean section was performed as soon as feasible to deliver the baby. Around 17% of deliveries in India are performed via C-section, and this percentage has rapidly increased over the past ten years from 8.5% to 17.2% [6].

However, the visual analysis of FHR data utilizing common interface user declines typically results in considerable inter-observer and intra-observer disagreement among the specialists [7] managed by Neuro Filament Light (NFL). Obstetricians limit diagnostic errors by performing many subjective assessments in practice. Obstetricians make decisions to unique experiences which is the fundamental problem with the aforementioned procedure because it cannot be quantitatively realized [8]. As a result, there are increasingly more unplanned cesarean segments to human mistakes and this is motivating researchers to develop a more thorough study of the FHR signal.

Due to the intricacy of fetal physiological dynamics, the common interface for visual interpretation of FHR information produces high subjective variability [9]. Obstetricians conduct numerous subjective judgments to reduce diagnostic mistakes. As a result of a subjective error, the incidence rate of needless Caesarean sections was rising [10]. This is the main driving force behind the study's automated evaluation of the FHR data [11].

CNNs are among the most frequently utilized Deep Learning (DL) algorithms in the industry. Its ability to pick up task-specific features without any prior domain expertise is one of its most prominent traits [12]. CNNs have proven to be particularly good at object detection, image segmentation, and face recognition, among other tasks. The success of CNNs has been largely attributed to end-to-end learning, which combines feature extraction and classification into a single algorithm. For computer vision applications based on two-dimensional images, especially for medical imaging, CNNs are proving to be quite effective [13]. The classification of one-dimensional biosignals by biomedical applications like electrocardiography and electroencephalography, although, has not followed this pattern. A growing number of people are now considering employing 1DCNNs to solve issues involving biosignals [14].

1.1 Motivation

The basic requirement for the practical fetal abnormality model includes high classification and segmentation accuracy. The difficulties and issues due to low contrast and irregular image quality the feature calculation, feature extraction, and assessment of the fetal head, abdomen, and femur length measurements are challenging. Due to the high demand for automatic assessment of fetal biometrics, thus a novel segmentation and classification approach is adopted for achieving results that enable the model for real-time practice in the clinic. The unified detection method of this research work does an automatic assessment of fetal abdomen and brain images thus the abnormality prediction is achieved with less false negative ratio.

2. RELATED WORKS

20 pre-extracted features were chosen by the researchers, and Support Vector Machine (SVM) was used to create the model. From the fetal heart rate data, researchers retrieved the frequency domain, morphological, and time domain characteristics. The effectiveness of SVM is by combining various attitudes to choose the best suitable features and categories for the fetal state [15]. For feature selection, the authors employed the recursive features eliminator algorithm, and they integrated the effectiveness of Random Forest (RF), Functional Linear Discriminant Analysis (FLDA), SVM, and DL methods. 8 popular ML methods were created for 21 features from the open-source database at UCI, and their performances were then assessed [16-18].

Researchers developed RF, decision tree, Adaptive Boosting (ADA Boosting), and Gradient Boosting using 17 characteristics extracted from CTG diagrams using specialized software, and they compared them to the method performed. A short-time Fourier transform was employed in earlier research to turn FHR and FD images which were subsequently classified as healthy or unhealthy using Deep Convolutional Neural Network (DCNN) [19]. To categorize the fetal status, researchers divided the one-dimensional FHR data into 10 windows and allowed CNN to vote on the window [20, 21]. Researchers used the open-source information group of UCI a collection of characteristics created after monitoring FHR and uterine contract data to characterize fetal states using the Recurrent Neural Network (RNN)- Long Short Term Memory (LSTM) method [22].

In the proposed study, a low-cost electrical device built on a CNN method that can operate in real-time and analyze FHR signals was created and integrated. The CNN-based technique was data-driven and enquires about the development of feature representation, evaluation, and classification processes, in contrast to traditional approaches. The CNN model is built using features that self-learn from the input data. Due to these benefits, CNNs are used in the medical profession to create various screening and helping tools. This study's main objective is to develop a standalone AI diagnostic method that aids obstetricians in making wise health decisions and might be applied to outlying primary healthcare facilities.

2.1 Limitations

It is possible to fully automate the semi-automated fetal biometric diagnosis system. Since the training accuracy in the available literature is low, the suggested method uses a big dataset. Convolution Neural Network is used to automate fetal biometric assessment for better outcomes. The U-Net extracts feature greater accuracy. The proposed study considers performing more precisely in diagnosing the anomaly on both the head and abdominal biometry measures. Pre-processing, noise removal, segmentation, feature extraction, and feature classification are all steps in the automated detection of anomalies in ultrasound pictures. Eventually, the prediction accuracy will need to be improved. By spotting abnormalities in fetus photos, the classification accuracy aids in the treatment of the fetus throughout pregnancy.

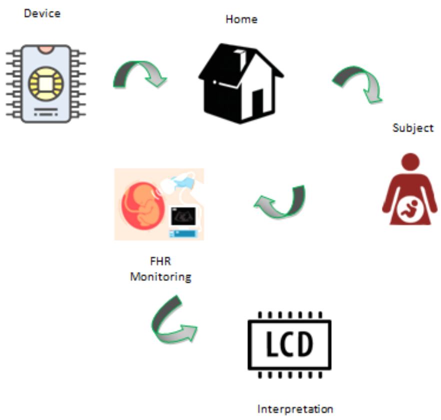
3. PROPOSED SYSTEM

The procedure for conventional fetal status monitoring during pregnancy is depicted in Figure 1(a). Additional tests for plausible interpretations are also involved. With the use of a stethoscope and other necessary tests, their FHR is monitored by highly qualified professionals. Medical professionals examine the sample which is then interpreted by obstetricians. Figure 1(b) shows the information gathered from the participants to an autonomous AI-based FHR monitoring system. The primary contribution of this research is the invention of a computerized diagnostic tool based on machine learning for fetal acidosis classification and diagnosis utilizing FHR. A proposed FMRCNN system is for information preprocessing combined on reasonably priced hardware to operate in real-time shown in Figure 1(c–e) [23].

The proposed method was tested using the Czech Technical University (CTU)- University Hospital in Brno (UHB) open-access database, and shown to be highly accurate (up to 99.09% accuracy). Figure 2 shows an illustration of a fetal active state and a fetal quiet state, respectively. The newly developed system and methods are inexpensive, portable, and real-time capable. It could be used by unskilled personnel for earlier detection in remote regions and primary healthcare institutions and for an automated maternal health assessment to assist professional decisions.

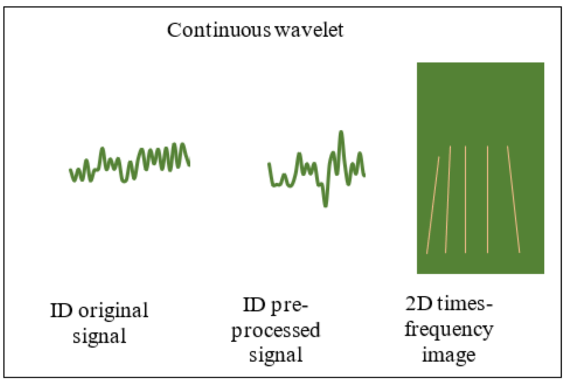
The construction of FMRCNN, which takes time-series signals as inputs, is shown in Figure 3. Non-invasive Cardiotocography signals were used to investigate 105 healthy babies with Gestational Ages (GA) ranging from 20 to 40 weeks for 3 to 10 minutes while they were lying on their backs. Twelve electrodes were positioned on the mother's belly, and signals were captured. Using maternal ECG cancellation and blind source separation with a reference, the fetal ECG was separated from the composite abdominal signal [24]. To extract features and create the input's overall feature map, Convolutional and pooling levels are applied one at a time. The fully connected layer then classifies the outcomes.

(a) Conventional-based fetal monitoring system



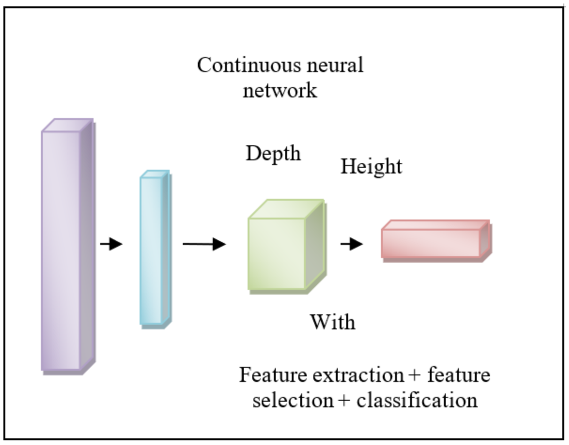
(b) AI-based FHR monitor

Step 1:



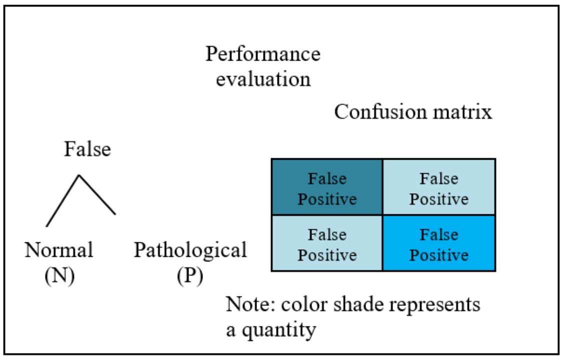
(c)

Step 2:



(d)

Step 3:



(e)

Figure 1. Smart fetal academic assessment

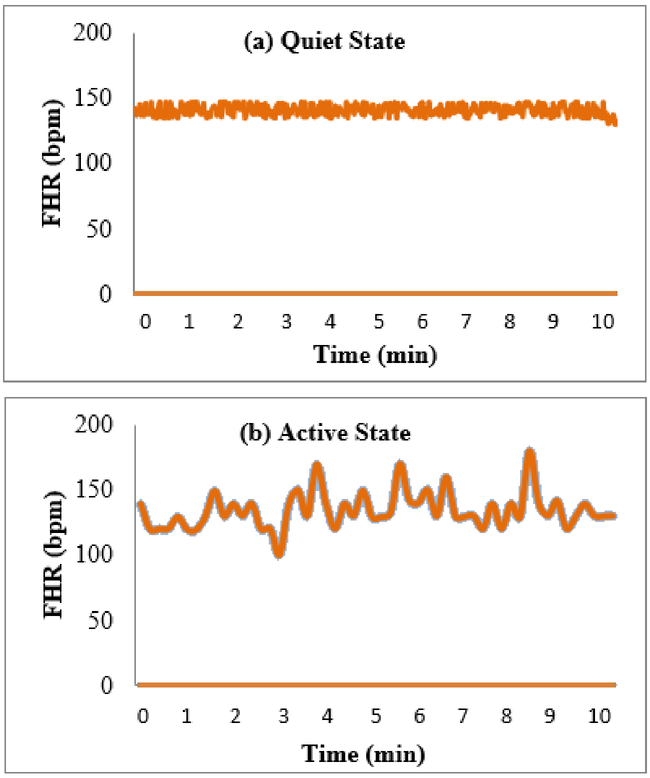


Figure 2. Instances of the quiet and active states of the fetus as determined by the FHR signal

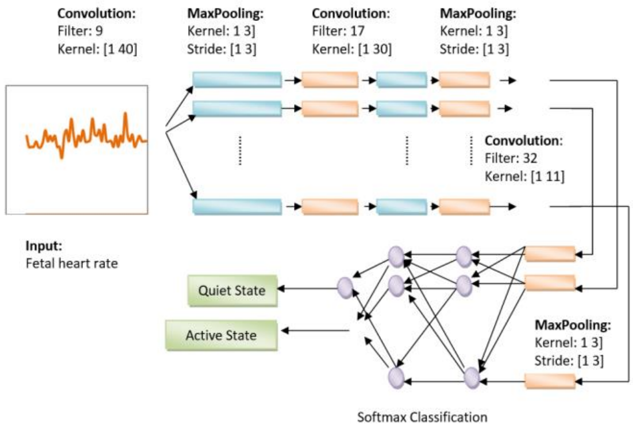


Figure 3. FMRCNN proposed architecture

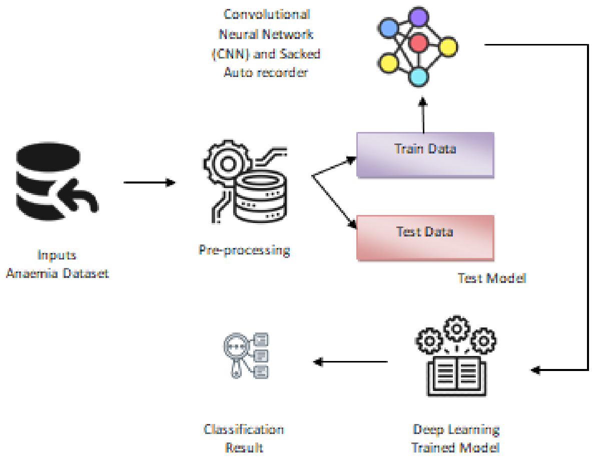


Figure 4. The block schematic of the proposed models

In this research, they provide FMRCNN methods for identifying and categorizing the FHR dataset. Figure 4 shows the block diagrams for the proposed models. As shown in the graphic, the database underwent a pre-processing phase first. In the pre-processing step, the patient's data was removed, missing value records were removed, and the remaining database was normalized using min-max standardization to represent the values in the range of 0 to 1. Then, for experimental analysis, two pairs of train-test variables were produced. In the first batch, the precompiled dataset makes up 60% of the training data and 40% of the test data. In the second batch, the preprocessed database contains 30% of the test dataset and 70% of the training dataset. The FMRCNN algorithms have received every training dataset as input.

Algorithm: FRCNN

The algorithm is given as follows

I/P: Image with Rician

O/P: Pre-processed image

Begin

// Neighbourhood (mean of local frame)

$\beta_h = D(U_j)$ // full noise image (mean of global frame)

$\beta_h = D(U_k)$ // calculate noise

$\alpha_h = \sqrt{\frac{\partial_c}{2}}$

//Compute the median in every pixel

Li = Median-Filtration

//local

$R_{non\text{-}local}$= Non-local filtrations

//computer similarity among pixels

R_{local}= Li

$R_{local-1}$, $I_{non\text{-}local}$

//Calculate computer images

G(y.z) =$R_{(local-1}$*,Li*R_{local} *$R_{non\text{-}local)}$

F-RCNN features are for predicting the location of fetal. Calculate the input features,

$$FE\big(b(n)\big) = \sum_{q=1}^{k} wei_q \delta_q(n) \tag{1}$$

Weighed Quantum estimation using Eq. (2),

$$wei = (l^T l)^{-1} l^T y \tag{2}$$

RBF estimation,

$$\delta_q(n) = exp\left[\frac{-\left|b(n) - cen_q\right|^2}{2\omega_q^2}\right] \tag{3}$$

Table 1 presented the hyperparameter values for the evolutionary algorithm-optimized L2Regularization, Train-Epo, chmomentum, max-epoch, and learn-rate. The completely connected layer components for the FMRCNN model were utilized in the following stage to enhance the classification performance. In the FMRCNN model, the Softmax function was employed.

Table 1. Lists of hyperparameters

Hyperparameter List	**Range**
Maximum Epoch value	[6,10,20]
Training Epoch value	[120,150,200]
Momentum value	[0.8-1]
Learning Rate value	[0.004-0.2]
L2Regularization value	[0.004-0.2]

Table 2. Lists of the FMRCNN model's experimental hyperparameters

Hyperparameter List	**Model 1**	**Model 2**	**Model 3**
Maximum Epoch value	10	16	21
Momentum value	0.889	0.9409	0.940
Learning Rate value	0.0376	0.0098	0.013
L2Regularization value	0.039	0.067	0.039
Size of batch	33	33	33
Optimizer value	ADAM	SGD	SGD
Loss Value	Cross entropy (categorical)	Cross entropy (categorical)	Cross entropy (categorical)
Activation function	Softmax	Sigmoid	Softmax

Tables 2-4 list the hyperparameters that were employed in the FMRCNN models trained using deep learning techniques for this investigation. Additionally, the values of the batch size, train-epoch, L2 Regularization, and learning rate parameters for FMRCNN utilizing 3D were established. The crossover value, mutation value, and population numbers were all set to 0.8, 0.2, and 5 generations, respectively, for the 3D research parameters. It could be stressed that the initiation and optimization features of the approach remained unchanged. Created the one-dimensional 3D FMRCNN as our initial model to categorize the FHR data. The input layer is one of the initial model's 26 layers. Convolution, dropout, dense levels, batch normalization, and max-pooling are features of this model.

Table 3. Details on the layers of FMRCNN and characteristics

Hyper Parameters Types	Model 1	Model 2	Model 3
Ae1 Hidden Neuron	21	21	21
Ae2 Hidden Neuron	11	11	11
Ae3 Hidden Neuron	9	9	9
Ae4 Hidden Neuron	5	5	5

Table 4. Experimentation with hyperparameters types

Hyperparameter Types		Model 1	Model 2	Model 3
70% Train-20% Test	Training Epoch value	200	150	100
	Size of Batch	32	64	32
	L2Regularization value	0.00196	0.001408	0.0024
	Momentum value	0.9643	0.9734	0.9632
	Learning Rate value	0.0021	0.0015	0.002
60% Train-50% Test	Training Epoch value	100	150	100
	Size of Batch	32	64	16
	L2Regularization value	0.0021	0.0014	0.0017
	Momentum value	0.9641	0.9234	0.9777
	Learning Rate value	0.0021	0.0015	0.002

Table 5. Layers and variables incorporated into the FRCNN model

Hyper Parameters	Model 1	Model 2	Model 3
Ae1 Hidden Neuron	21	21	21
Ae2 Hidden Neuron	11	11	11
Ae3 Hidden Neuron	9	9	9
Ae4 Hidden Neuron	5	5	5
Loss	Entropy (cross)	Entropy (cross)	Entropy (cross)
Optimizer	ADAM	ADAM	ADAM
Activation Function	Swish	Swish	Swish
Bias value	2	21	2

The FMRCNN model's hyperparameters, which comprise four cascaded autoencoders, are shown in Tables 5 and 6. Four alternative models were used in the proposed FMRCNN model to train the learning process. In the first autoencoder, experiments were run with 20 hidden neurons to 4, 10, and 8 hidden neurons, correspondingly. In the research, the encoding phase employed the cross-entropy cost function and Nesterov Adam optimizer. A categorical cross-entropy approach was employed to reduce decoding mistakes. Based on the best performances, the activation functions for the encoder and decoder, respectively, were chosen to be swish and ReLU by 3D.

Table 6. Lists the 1D-OCNN model's experimental hyperparameters

Hyperparameters Lists		Model 1	Model 2	Model 3
70% Train-20% Test	Training Epoch value	200	100	150
	Size of Batch	32	32	64
	L2Regularization value	0.00196	0.0024	0.001408
	Momentum value	0.9643	0.9632	0.9734
	Learning Rate value	0.0021	0.002	0.0015
60% Train-50% Test	Training Epoch value	100	100	150
	Size of Batch	32	16	64
	L2Regularization value	0.0021	0.0017	0.0014
	Momentum value	0.9641	0.9777	0.9234
	Learning Rate value	0.0021	0.002	0.0015

4. EXPERIMENTAL RESULTS

In the research, experimental investigations using the proposed FMRCNN models were conducted to identify and categorize the disease using the open-source dataset from UCI, and the effectiveness of each model was compared. Tables 2-4 display the test models and model parameters utilized in the study. The real dataset was used in experimental investigations, and it was split into testing sets and training. On the Python-written WEKA platform, the study's classification methods were evaluated.

The database used in the study was split into testing and training datasets, respectively, with a split of 60–70% and 40–30%. The Eqs. (4)-(7) were utilized to forecast the requirements.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \tag{4}$$

$$Precision\ \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{5}$$

$$Sensitivity\ \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{6}$$

$$F - Score\ \frac{2 * Precision * Sensitivity}{Precision * Sensitivity} \tag{7}$$

Furthermore, traditional data mining techniques were used in the study to classify the FHR dataset. The tests have made use of the traditional data mining methods k-NN, SVM Linear, and SVM-Gaussian with the proposed system. To categorize the five-class dataset utilized in the study, the one-vs-one SVM technique is a creature. With this method, a subset of data containing each pair of binary classifications is used to train the classifier. Each two-class combination goes through this process again. SVM structure for binary classifiers can therefore be used for multiple classifiers. Table 7 demonstrates that the proposed system approach, utilizing 30% test data and 70% training produced FHR databases (5 classes), with 98.58% precision, 97.25% F-score, 97.23% sensitivity, and 98.40% accuracy.

Additionally, max-epoch 100, ADAM as the optimizer, learn-rate of 0.001, momentum of 0.9, L2Regularization of 0.01, batch size of 32, and softmax as the output-activation function were all specified. To examine each criterion's applicability for the categorization of the FHR precision, dataset, sensitivity, F-score, and accuracy criteria are utilized. According to Table 8, the CNN model, which used 70% training and 30% test data, had the greatest performance on the 5-class FHR dataset, with scores of 97.04% F-score, 97.12% accuracy, 97.71% precision, and 96.39% sensitivity. A comparing the outcomes to models using FMRCNN default hyperparameter values, it can be seen that the success rate is less.

4.1 Experimental results of the proposed model

The FMRCNN model's application success rates for the study's 5 various classes are displayed in Table 9. The input layer is 26 layers in the FMRCNN model utilized in the experimental study. With the use of 2 separate test sets, training sets, and 6 models, the categorization was carried out. 30% test data, and 70% training, the best outcomes for the FMRCNN methods were obtained using the stochastic gradient descent optimization technique and the sigmoid transfer parameter. The precision, F-score, accuracy, and sensitivity were 98.50%, 98.60%, 97.98%, and 99.01%, respectively. 40% of test datasets and 60% of training FMRCNN Method 1 had the greatest sensitivity, success rate, accuracy, precision, and F-score, values totaling 98.35%, 98.34%, 98.28%, and 98.49%, respectively. The SGD and softmax activation function optimization approach was FMRCNN Model shown in Table 9 and Figure 5.

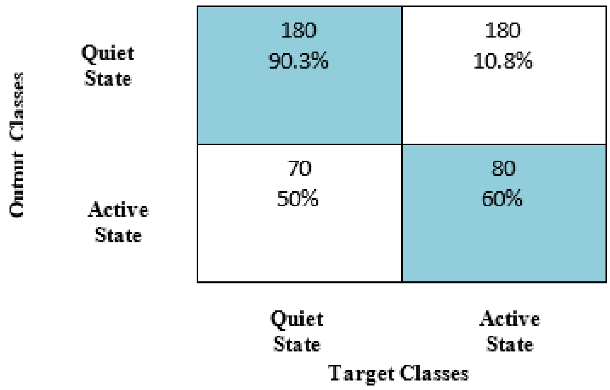


Figure 5. Confusion matrix of the proposed system

Table 7. The outcomes of the proposed system

Methods		Accuracy %	F-Score %	Sensitivity %	Precision %
70% Train-20% Test	SVM-Gaussian	87.23	84.50	87.21	83.87
	Proposed system	98.40	97.25	97.23	98.58
	SVM-Linear	93.06	90.81	93.11	88.62
	K-NN	83.73	83.23	84.42	84.90
60% Train-50% Test	SVM-Gaussian	87.89	85.34	87.90	84.72
	Proposed system	94.88	94.81	94.90	94.81
	SVM-Linear	92.14	89.91	93.13	88.72
	K-NN	83.92	83.51	83.91	83.23

Table 8. Results of FMRCNN models

Methods		Accuracy %	F-Score %	Sensitivity %	Precision %
70% Train-20%	CNN model	94.15	93.27	92.21	95.94
	FMRCNN Model	98.76	97.34	96.22	96.98
60% Train-50%	CNN Model	93.20	93.13	92.34	93.56
	FMRCNN Model	97.76	96.66	95.67	98.93

Table 9. Lists the 1D-OCNN model's findings

FRCNN models		Accuracy %	F-Score %	Sensitivity %	Precision %
70% Train-20% Test	FRCNN_Model1	97.66	97.66	97.66	97.66
	FRCNN_Model2	98.52	98.61	97.97	99.12
	FRCNN_Model3	98.14	98.34	98.25	98.33
	FRCNN_Model4	98.55	98.52	98.71	98.96
	FRCNN_Model5	97.66	97.66	97.66	97.66
	FRCNN_Model6	94.55	94.46	94.68	96.02
60% Train- 50%	FRCNN_Model1	98.36	98.35	98.27	98.44
	FRCNN_Model2	97.66	97.65	97.55	97.76
	FRCNN_Model3	97.55	97.48	97.47	97.55
	FRCNN_Model4	97.70	97.70	97.70	97.70
	FRCNN_Model5	98.26	98.78	98.13	98.76
	FRCNN_Model6	98.18	98.33	98.27	98.36

4.2 Loss and accuracy of the model

The model was developed using a 3308 training dataset, with a training dataset to the evaluation method to an assessment group ratio of 7:2:1. The performance improvements in the training data and the test dataset are shown in Figure 6.

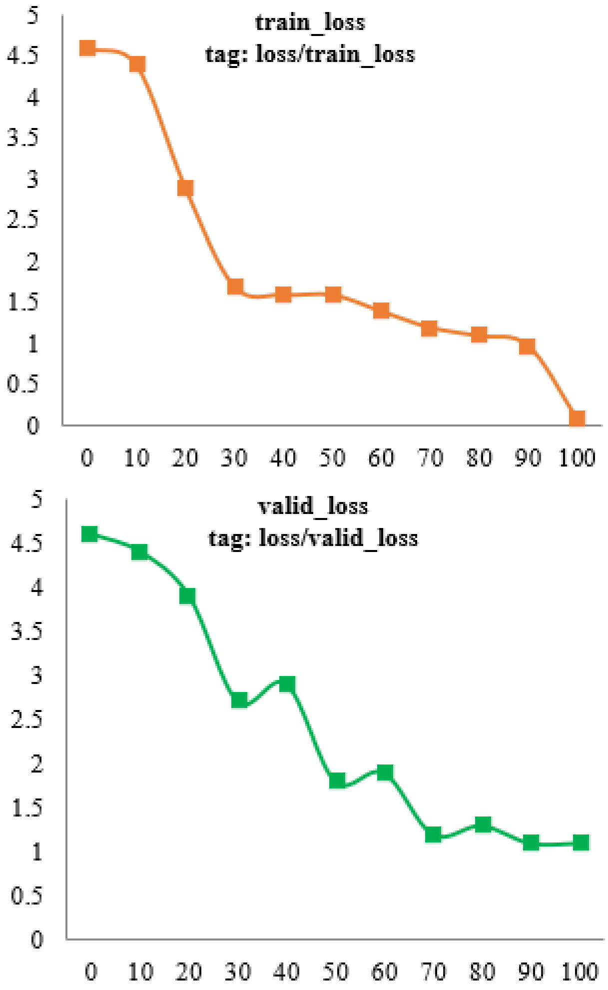


Figure 6. Loss of the model

According to Figure 6, both the testing data and the validation data loss progressively decrease throughout the learning process, and the 2 curves for the verification set and training set have similar downward trends. A loss is dropping most quickly from iteration to generation 20 to 50. A loss in the testing dataset was virtually zero after the 100th epoch, and it tends to be 0.01 in the verification set. The performance enhancement of the testing data and validation set was visible to the first 50 epochs, as illustrated in Figure 7. The method's precision to the testing dataset has surpassed 95%, that in the validation set was surpassed 90%, and curves are gradually stabilizing after 50 epochs. As a result, the method's accuracy and loss performance tend to converge in the validation dataset.

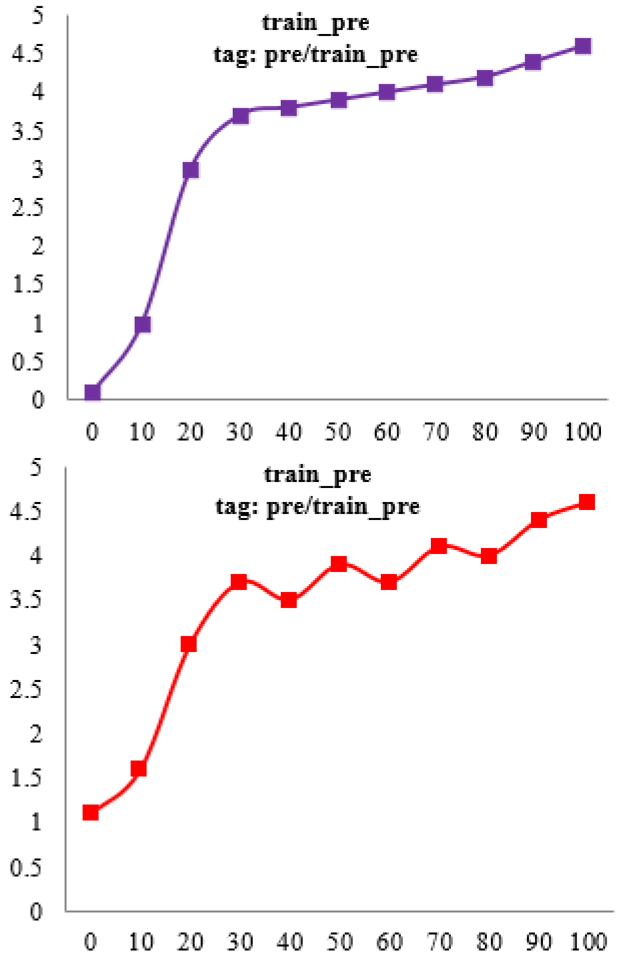


Figure 7. The model's performance

4.3 Comparison of the FMRCNN with existing systems

Figure 8(a)–(d) displays the data distributions and variations in distributions across the groups using box plot graphs related to the performance measures values. According to an examination of Table 10, MRCNN has the greatest classification accuracy on average.

Table 10. Compare FMRCNN with other systems

Methods	F-Score		Precision		Accuracy		Sensitivity	
	Average	98.78%	Average	98.96%	Average	98.71%	Average	98.69%
FMCNN	Best	98.88%	Best	99.03%	Best	98.54%	Best	98.56%
	SD	1.98%	SD	1.03%	SD	1.08%	SD	0.94%
	Average	94.67%	Average	95.19%	Average	95.18%	Average	93.67%
CNN	Best	97.08%	Best	97.23%	Best	97.04%	Best	96.53%
	SD	1.43%	SD	1.53%	SD	1.28%	SD	1.44%
	Average	88.48%	Average	88.56%	Average	78.81%	Average	86.63%
Random Forest	Best	98.38%	Best	97.83%	Best	97.88%	Best	97.36%
	SD	10.18%	SD	7.43%	SD	14.08%	SD	9.34%

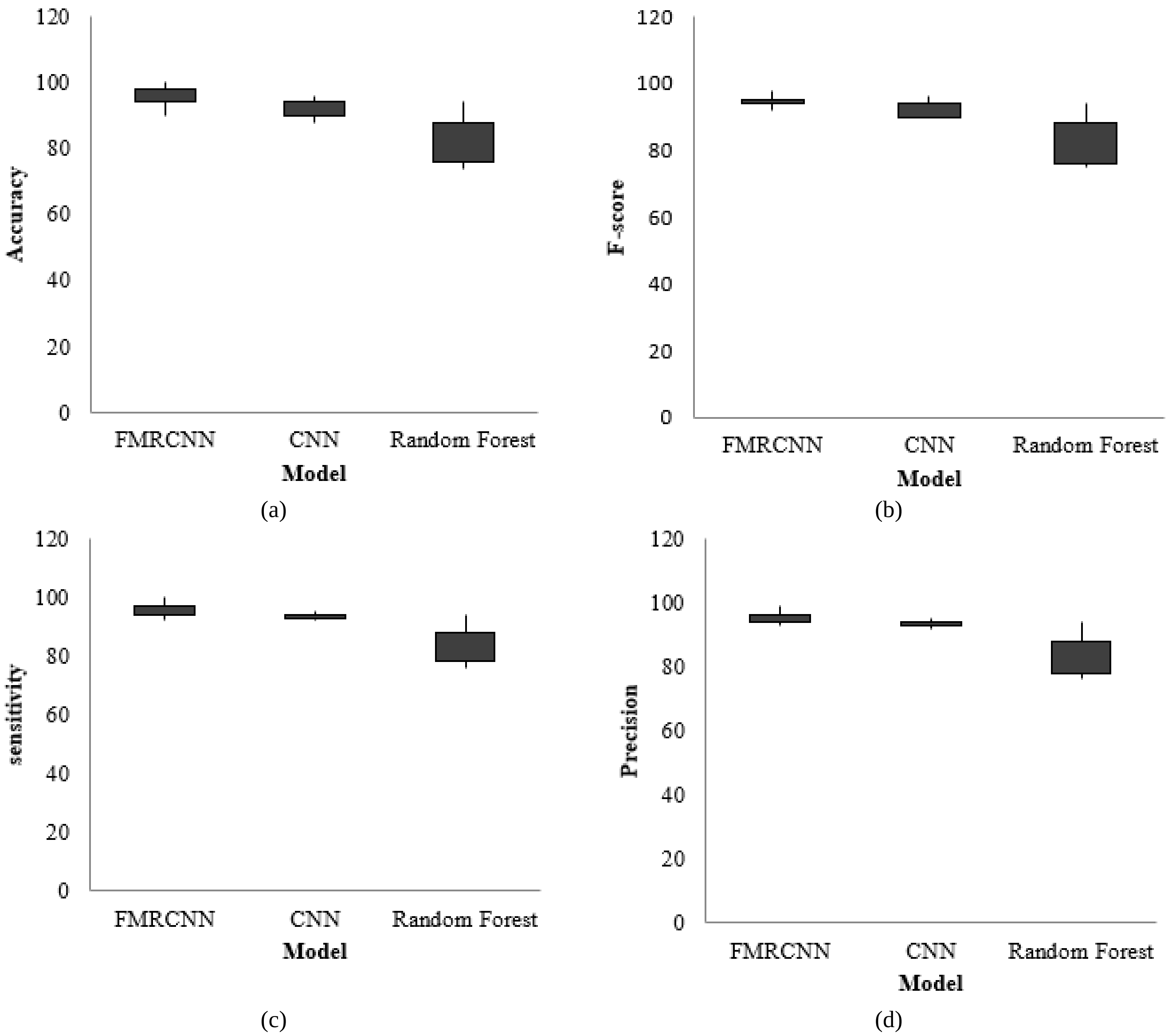


Figure 8. Boxplots approaches' performance index distributions

4.4 Proposed integration model

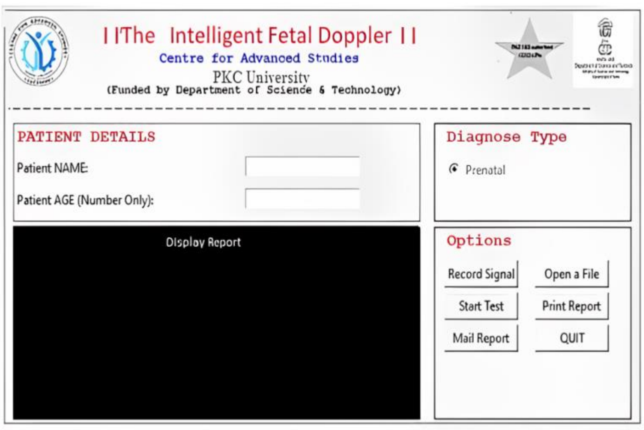


Figure 9. User-implemented interface architecture

The developed framework could be integrated into a low-cost processor to create a practical and useable device that can be used as a standalone diagnostic tool. The proposed method could be easily integrated with straightforward and reasonably priced computer devices to provide useful diagnostic tools since it could be incorporated with excellent effectiveness and minimal time complexity. Figure 9 and Table 11 provide descriptions of the particulars.

For viewing and analyzing the generated reports, an interface user program based on Python was also built. The fact that the testing methods were created effectively in this hardware configuration shows that the proposed model could be used in a real-time setting.

Figure 8 shows the user experience for the developed methodology for the automated detection of neonatal acidity. There are four user-friendly elements in this interface: diagnosis type, options, display report, and patient details. The patient's name and age must be entered in the patient details section since they will be recorded and used to create an electronic report later. The graphs are shown in the display area either immediately following the signal's recording or by opening a previously recorded signal. Additionally, it is done to display test-related information. After that, the signal is tested by pressing the "start test" button. A device was linked to a network using Wi-Fi, and the option to print and mail reports are available.

Table 11. Combination of the hardware and software

Hardware/Software	Specification
Memory	4GB LPDDR4-3200 SDRAM
WIFI	2.4 GHz and 5.0 GHz IEEE 802.11 ac wireless
USB ports	2 USB 3.0 ports; 2 USB 2.0 ports
HDMI port	2 x micro-HDMI ports
Display port	2-lane MIPI DSI display port
Graphics	OpenGL ES 3.0 graphics
SD slot	Micro-SD card slot
Power Supply	5V DC via USB-C connector
GPIO pins	5V DC via GPIO header

5. CONCLUSIONS

To evaluate fetal health, FHR, and UC signals are frequently used in clinical practice. The obstetrician's own experience, however, may have an impact on how they evaluate the fetal state of health. Therefore, it is essential to employ an objective evaluation strategy. A technique for bidirectional GRU and FRCNN is put forward in this paper. To assess whether the fetus is hypoxic, the FHR and UC signals are used to classify the fetal health state. Our approach surpasses BiGRU and BiLSTM in terms of performance and FRCNN in the front-to-back relationship of time series. It is also quite good at generalization. Overall, the results show that our method helps identify the fetus's health status and can aid obstetricians in making therapeutic choices. It serves as the basis for the application of the FRCNN and bidirectional GRU algorithms and the utilization of the UC signal to determine the fetus's state of health. In addition, include UC and FHR signals in future investigations and consider information-enhancing strategies.

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