Optimized Residual Convolutional Learning Neural Network for Intrapartum Maternal-Embryo Risk Assessment

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Abstract

An effective fetal electrocardiogram (FECG) and ultrasound sonography (USG) signals with continues watching is a testing tool utilized by obstetricians to assess the maternal and embryo stage classification method are proposed utilizing a deep 2D convolutional neural network (CNN) which nowadays observe excellent presentation in the field of design identification. Because of the convolution and irregularity, a visible explanation of both Fetal Heart Rate or FHR and Uterine Contractions or UC signals utilizing usual instructions commonly obtained in remarkable individual inter-observer and intra-observer changeability. As a result, automated system depends on modern artificial intelligence (AI) innovation has nowadays been evolved to assist obstetricians in manufacturing targeted medical conclusions. The major object of this research was to make sure a novel, steady, strong, and effective model for maternal and embryo risk detection. Moreover, multiple CNNs is optimized through Genetic Algorithm (GA), overcomes the majority decision drawback in the traditional voting method. Improvement of the suggested classifier incorporate different deep studying methods such as transfer learning, GA initialization, multiple convolutional layers, hybrid optimization SGD with Adam and dropout with softmax were used in the experiments. And then, we differentiated our CNN classifier with four familiar CNN optimized models; such as SGD, Rmsprop, Adam and Adagrad. Depends on the experiment freely available database (CTU-UHB), we got good categorization presentation, after complete investigation, utilizing the proposed Optimized Residual Convolutional Learning Neural Network method with average cross-validation (10 fold) of the Acc, TPR, TNR, PPV, NPV, HM, Kappa, AUC, PRAUC, Log Loss, DR, Prevalence, DP and BA respectively. Once the proposed Optimized Residual Convolutional Learning Neural Network model with 10 layers is achieved 96.24 % accuracy in average with successfully trained with the 8 different risk factors, the corresponding automated system can be used as a potent device to detect maternal and embryo risk state objectively and accurately.

Keywords: *Fetal Heart Rate or FHR, signal, transfer learning, ResNet50, Genetic Algorithm, Uterine Contractions or UC Convolutional Neural Network, optimization.*

1. INTRODUCTION

During delivery, maternal-embryo respiratory transfer is transiently agreed using contraction of muscle in the uterine portion directed to limited addition of oxygen that is beneficial for the growth of fetus. The cardiac output of fetus is replayed by regulating its, redistribution of blood to focus on the heart and brain, and redesign its metabolic activity. Fetal brain injury or even death is failure of oxygen addition. Such incidents are commonly combined with replace in the FHR and UC. Because of this, fetal heart rate is detected at the time of delivery for detection of abnormalities FHR and UC, which may cause the decrease unfavorable results connected to hypoxia [29]. Women living in high economical countries will have keep up detecting abnormal condition with the help of FECG and USG; this continuously shows the FHR and UC beside contractions of muscle in the uterine. Visual examination of FECG and USG are done, for identifying the newborn got advantages from emergency delivery or cesarean. The FECG and USG that releases some signal complexes that functions as alter the periodic sleep state of fetus, contraction of muscle in uterine with response to stresses, maternal position response, pregnancy problems etc .For measuring fetus and estimating gestational age, ultrasound is the one of the method used. Most of our present experiment is based on 1980s and 1990s studies [14]. Present clinical experiments are challenged because of the emerging of novel data in fields, such as reproductive biology, perinatal epidemiology, and medical imaging. For example, “Certain” menstrual dating is less certain than previously imagined.

Forecasting suffering of fetus can be analyzed with electronic devices which are more liable than stethoscopic auscultation. Therefore, the suffering issues regularly face at the time of the labor because of oxygen short of the fetus. Examining the abdominal wall of the pregnant women, which gives the information about the fetus like, electrical potential of the heart beating rate and it's sound. [13] With the fetoscope and stethoscope, hearer can audibly hear and add up the FHR. The FHR and UC recording utilizing Cardiotocography, it is used as a analyzing method to detect practicable points for distress of fetus at the time of labor. In modern obstetrics, FHR and UC difference examination is utilized to detect the risky factors, recognize possible abnormal activities and it will helps in accomplishing delivery easily. The apparatus which at the same time take down the immediate FHR and activity of uterine is known as Fetal Electrocardiography (FECG) and Ultrasound Sonography (USG) machine [28]. Fetal electrocardiogram is determined by the help of two measuring electrode. Non-invasively utilizing electrode in maternal abdomen skin and electrode in fetal scalp is an interfering proposal of FECG detecting. FECG is one of the methods in which for evaluating the electricity from the heart of fetus. FHR (110–160 bpm) is much more than the maternal heart rate (UC) (70 to 80 bpm). The amplitude of FHR signal is very fragile and its regulation is based on different sounds and interferences. Different sounds are power line interference, random electronic noise, maternal interference and baseline wander among which maternal FECG is the most prominent intervention. For various aspects of antenatal care, correct determination of gestational age is required. Previously, a few days of inaccuracy was acceptable; but newly forming information suggests that the inaccuracy can affect the performance of screening of maternal serum, post-dates pregnancy assessment, and the subsequent labor induction.

For clinical purpose ultra sound derived dates are one of the better methods of evaluating gestational age depended on the available study. Due to biological various activities in reproduction, size of fetus, and growth might have to evaluate correct day of conception, otherwise. Clinical practices may have value in evaluating gestational age, and on rare situations may replace US dating; so, for getting most clinical advantages, the use of US dating must be dominant. Best accurate and consistent diagnosis given by deep neural network classification and prediction models, for assessment of fetus according to issues at the time of pregnancy depends on multiclass morphologic patterns and it will reduce or prevent the fetus and maternal mortality rate in developing countries.

2. LITERATURE REVIEW

The devices discovered by human can be used for the cardiotocography assessment of fetus according to multiclass pattern identification, including 10 target classes with imbalanced samples, using deep learning classification models. Early identification of Problems during pregnancy can analyzed by identifying the presence or absence of multiclass pattern of morphology with the help of newly manufactured model [11]. In the deep neural network the Convolutional neural networks is used for the biomedical signal processing and other research areas. As reported our best wisdom, the above types of networks would not utilized the information of cardiotocography for asphyxia or fetal acidosis identification. Convolutional neural networks exhibit hopefull outcomes for categorizing pictures differentiate into regular multilayer perceptron, as the latter does not use geographical design information into a report and make it remarkable from the dimensionality curse. But, convolutional neural networks hope a type of picture on the input, but the signals show only in 1D structure. This problem can be solved by different transformations. They [18] used the continuous wavelet transform or CWT into both UC and FHR signals having various levels of time or frequency parameter and in two distinct resolutions. The 2D structured output are fed to convolutional neural network or Tensorflow framework [1] and we are utilizing the cross entropy function as a criteria to be minimized at the time of the learning procedure. On the screening details set (with pH threshold at 7.15) we got the efficiency of 94.1% which is a hopeful outcome that requires to be additionally examined.

In addition with the dropout method at the time of training procedure, regularization was applicable to combat overfitting for the deepest neural networks. It concluded that, the developed deep neural network architecture allowed us to not only show a strong, alternative form of largely exponential ensemble learning but also reduce overfitting issues for the deep neural network classification and prediction models. The examination outcomes exhibit that the developed deep neural network model achieved an accuracy of 88.02%, a recall of 84.30%, a precision of 85.01%, and an F-score of 0.8508 in average. Best accurate and consistent diagnosis can be given by the developed model for assessing fetus at the time pregnancy issues [11]. For the feature acquisition of FHR signal, manual reading of morphological information from the curve of FHR in common feature based categorization methods, which is expensive and time-wasting and has a particular degree of calibration bias. They proposed [9] the categorization method of the FHR signal can prevent manual feature acquisition and reduce human factor caused errors. From the FHR data algorithm will learn directly and truly realize the real-time diagnosis of FHR data. The convolution neural network classification method named “MKNet” and recurrent neural network named “MKRNN” are designed.

Prediction of fetal distress can be done by identifying EFM traces from over labors of 35000 by investigation of long short term memory (LSTM) and convolutional neural networks (CNN). From this study, for cross-validation and training 85% were used and the remaining part used for testing. Comparing the obtained result with clinical practice (reason for operative delivery recorded as fetal compromise) and an earlier prototype system for computerized analysis of EFM (OxSys 1.5), developed on the same data. Fetal distress can be predicted by demonstrating the CNN out performs LSTM, clinical approaches and OxSys 1.5 with 42% sensitivity at low false positive rate or comparable rate and for others 30%, 40%, and 36% requires. The stability and sensitivity of the performance of CNN on the testing set improves with increasing the size of the training set. The extraction based techniques performance were enhanced by CNN, when testing in a small open-access external database.

A novel propose for CTG analysis techniques that a) with uniform class distribution CGT time series signals splits into n-size window and b) with the usage of convolutional net work in one dimension automatically features extracting from time -series window [22] 1D CNN and multilayer perceptron or MLP ensemble. The proposed object naturally distributes classes and avoids the requirement for handcrafted characters from CTG traces. The one dimensional CNN-Multilayer perceptron models trained with various windowing strategies are analyzed to identify how they can differentiate natural birth outcomes with outcomes of pathological birth. In this technique obtained best outcomes utilizing a window size of 200 with (Sens=0.7981, Spec=0.7881, F1=0.7830, Kappa=0.5849, AUC=0.8599, and Logloss=0.4791). With the help of Support Vector Machine or SVM, a Random Forest or RF and a Fishers Linear Discriminant Analysis or FLDA classifier, the outcomes are compared, which all failed to improve on the windowing one dimensional convolutional neural network strategy approached in this research. As the multiclass cardiotographic dataset of the foetus shows a high degree of imbalance a weighted deep neural network is applied [23]. To overcome the accuracy paradox due to the multiclass imbalance, relevant metrics such as the sensitivity, specificity, F1 Score and G-mean are used to measure the performance of the classifier rather than accuracy.

Much more various proposals are recommended for forecasting fetal state classes depends on artificial intelligence in this research [19]. The diverse geology of multi-layer construction of a MLA-ANFIS, utilizing multiple characters for input, neural networks or NN, DSSAEs and deep-ANFIS are applied on a CTG information set. At the time of delivery, deep techniques registered to CTG screening will power the capability to identify fetal compromise. Outcome exhibit the approached MCNN instruct on the last 60 min of more 30000 CTGs was a good executing automated technique to identify of cord pH<7.05 attained to date. This outperformed surviving automated as well as clinical evaluation proposals was screened on internal and external information [4]. Ensemble and deep learning methods are applied for identifying oxygen starvation. Bagging Tree, AdaBoost, Voting Classifier (SVM, SGD, Decision tree, GLVQ – Classifier methods) comes under Ensemble learning method. CNN and DenseNet come under Deep learning method. The above methods were employed into CTG dataset, particularly FHR signal. pH label will act as benchmark in categorization processes[24].

The categorized characters synthesized by Fast Fourier Transform or FFT and Continuous Wavelet Transformation or CWT [17], utilized the CNN. Interpolation of Signals was applied to get out of the misplaced beat by utilizing Unscented Kalman Filter or UKF and then the recognition of abnormal patterns depends on Minimum Description Length [25]. It [10] compared various categorization methods including SVM, MLP, and CNN by the statistical characters and d-window of Short Time Fourier Transform or STFT. A character extraction by FLDA and a categorization utilizing RF were conducted [10]. The performance comparison of deep learning methods i.e. RNN and CNN. The approached technique is known as MKRNN [9] FHR signals that are processed and categorized in real-time utilizing RNN, is named as MKNet processed the pictures with Fast Fourier Transform signals using Convolutional Neural Networks. The categorization utilizing various machine learning techniques were also conducted [20].

A deep Convolutional Neural Networks framework used for detecting academia of fetus. After preprocessing of signal, the inputted 2D pictures acquire utilizing the CWT or Continuous Wavelet Transform, which gives good method to analyze as well as catch the secret properties details of the Fetal Heart Rate signals; it depends in the area of duration and occurrence. Divergent of the traditional way of computer algorithms viewpoints. Without missing detailed characters, 2D Convolutional Neural Networks model can learn beneficial characters from the input data on its own, depict the enormous qualities of deep learning or DL over ML. To calculate a evidence-of-concept proposal to differentiating caesarean section and normal vaginal labors utilizing FHR signals and machine learning. The result explain that using a highly specific leaning classifier it will make 94%of sensitivity, 99%of AUC, 100% for F-score and specificity 91% and men square error were 1%. [21]. Which express significant development more than 30% predictive positive value obtained by obstructions , midwives and warrants further identification as potential program support equipment to use the current CTG gold standard alongside. The approached technique is robust, introduced to the field of biomedical data analysis and deep leaning algorithm contribute new insight for the use when studying FHR trances that warrants further more identification.

The arrangement of remaining paper is follows; Section 3 the detail description about the dataset from the CTU-UHB database. Section 4 describing the complete procedures utilized for the FECG and USG signal classification including FHR and UC data pre-processing, feature transformation it combines with feature extraction and feature selection, classification and in addition detailed description about the proposed optimized convolutional neural network categorization.

3. DATASET DESCRIPTION FROM CTU-UHB INTRAPARTUM

A publicly accessible intrapartum database, from the Czech Technical University (CTU) in Prague and the University Hospital in Brno (UHB), constitute 634 cardiotocography (FECG and USG) recordings, [7] which are carefully selected from 9164 recordings collected between 2010 and 2012 at UHB. The FECG and USG recordings start no more than 90 minutes before actual delivery and each is at most 90 minutes long. Each FECG and USG contains a fetal heart rate (FHR) time series and a uterine contraction (UC) signal, each sampled at 4 Hz. Expertise professionals separated each signal into four pieces. Initial three parts calculate alternate of FHR designs based on the structures whereas the last piece constitute the parameters of labor results quantitatively.

The priority is to create as homogeneous a set as possible; thus only recordings fulfilling the following criteria are included is:

- Singleton pregnancy
- Gestational age >36 weeks
- No a priori known developmental defects
- Duration of stage 2 of labor ≤ 30 minutes
- FHR signal quality (i.e. percentage of the recording during which FHR data are available) > 50% in each 30 minute window
- Available analysis of biochemical parameters of umbilical arterial blood sample (i.e. pH)
- Majority of vaginal deliveries (only 46 cesarean section (CS) deliveries included)

Attribute Information:

Table.1. CTU-UHB Dataset Description

Features Extracted Using CTG ViewerLite	
Attributes	**Parameters**
Basic Features	dbID, Record type, FHR, UC, pH , BDecf (Base Deficit of extra cellular fluid level) , pCO2 ,BE , Apgar1, Apgar5, Gestational Weeks, Weight(g) , Sex, Age, Gravidity, Parity, Liquor Praecox, Pyrexia, Presentation, Induced, I.stage, NoProgress, CK/KP, II.stage, Position II. Stage, Sig2Birth.
Features Extracted Using RHRV Package	
Morphological	Baseline, ACC,DCC,UC,RR,HR
Non-Linear Analysis	Phase space reconstruction, Correlation, Maximum Lyapunov Exponent, Sample Entropy, ks-entropy, Detrended Fluctuation Analysis (dfa), Recurrence Quantification Analysis (rqa), poincareplot

	(SD1,SD2)
Time Analysis	Size, SDNN, SDANN, SDNNIDX, PNN50, SDSD, rMSSD, IRRR, MADRR, TINN, HRVi, CV, MEAN, VAR, MAX, MIN.
Frequency Analysis	Spectral Analysis: TP, ULF, VLF, LF, HF, VHF, (LF/HF), nLF, nHF, index Freq Analysis, size, shift.
	Fourier: ULF min, ULF max, VLF min, VLF max, LF min, LF max, HF min, HF max, type, wavelet, band tolerance, depth
Maternal and Embryo Risk Factors (or) Predictors	Eval_Step1: Standard FIGO Classes, Eval_Step2: Caesarean Section, Eval_Step3: Prediction of Hypoxia, Eval_Step4: Indication of Childbirth Termination, Diabetes, Hypertension, Preeclampsia, Delivery Type and Meconium.

In addition, depends on the age group of women, gestation period week, type of labor and gravidity, quality of signal, and delivery results assessment the writers pick out a sum of 634 CTG intrapartum recording from a recordings subset with 9164 recordings involved in this data collection. Main values and individual scattering of this data collection is shown in Table 1. Furthermore, for the 1st and 5th minute's individual calculation basis, Apgar's scores were contributed. Interchangeably, after labor, extra biochemical markers were provided for categorization of an objective; that are the pH at umbilical artery.

634 raw embryo electro cardiogram and ultra sound sonography records included in CTU-UHB database. The almost all record in the database separated into 4 parts and analyzed by 9 specialists having experience. The 1st stage of the transfer is represented the first two parts of the record and second stage that represented the third part of the record. The each stage of analysis is represented with l,ll,and ,lll .The first 4 stages of the record can be named as N(normal),S (suspicious), P(pathological) and U (uninterpretable)[15]. And also the final portion of the record is named as no hypoxia, mild hypoxia, severe hypoxia, and uninterpretable depending on the parameters gotten after the delivery, such as pH, Apgar score, and birth weight.

4. METHODS

In this research, depends on an advanced DL algorithm, we introduce a new automated recognition system objected at forecasting maternal and embryo state. The diagrammatical representation of the approach is depicted in Fig 1. As stated in the signal processing flow, a short explanation of our proposal is given, such as; it can be separated into four. Initially, an approximate FHR (pure) and UC signal is acquired with a preprocessing algorithm. Secondly, the ultimate signal dataset is enlarged by converting the optional parameters using feature extraction method and features selection. A planned CNN copy is allowed to learn the intrinsic patterns automatically it depending on the enriched preprocessed data representation, it considers that dataset act as i/p and permit parallel feature learning by ourself, for different features. The discovered characters studied using internal parameters of the Convolutional Neural Network are utilized to enhance maternal and embryo state estimation. A CTU-UHB database, with access opened and is utilized for detection of the execution and pH which are selected as aim criteria to divide maternal and embryo state into a usual, suspicious or pathological class. Ultimately, utilizing 10-fold cross-validation, the categorization execution of the proposed system is calculated (see Performance Evaluation). Overall procedures are shown in Fig.1

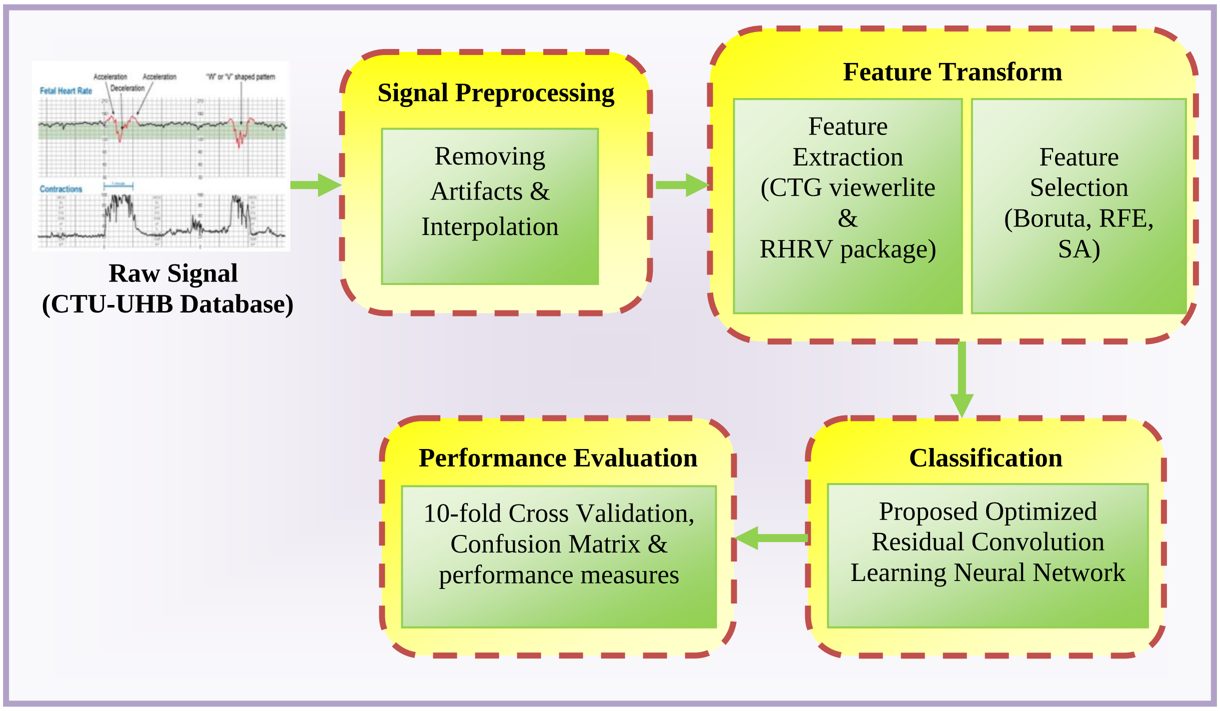

Fig. 1 Overall procedures processed in FECG and USG classification

Preprocessing, feature transform (feature extraction and selection), and classification, were three stages of the proposal, fig.1 which can be shortly explained as follows:

Pre-processing

Preprocessing step is an essential in almost uses of processing of biomedical signal and it will influence isolated characters and the ultimate categorization execution. In medical, the FHR and UC signal have two acquisition methods: Doppler ultrasound or US implementation of probe on the pregnant women abdomen and signal recorded externally and the fetal electrocardiogram or FECG an electrode associated with the fetal scalp so signal recorded internally.

For signal quality improving and also for prevent artifacts by movements of maternal and fetus, equipments, delivery-depended stresses [26]. A schema of primary preprocessing layout is operated in this research. Initially, from CTU-UHB database the raw CTG having both FHR and UC signals are acquired, the values of feature extraction and categorization performance are influenced using the procedure. Artifacts rejection and interpolation are the two steps in preprocessing. Unexpected changes in FHR and UC were removed and replaced by those above steps. The reasons behind the changes are rearrangement of the transducer, changes of maternal/embryo or both and stress at the time of delivery [28]. In an entire data, some amount is eliminated as artifacts or missing values. Artifact rejection project is occupied to interpolate the values and to fill up the losing beats [18].

Feature Transform

Data transformation in the machine learning field is essential for depiction of signal. The essential parts of the computerized FHR and UC screening are basic structural characters such as baseline the number of acceleration and deceleration design and difference in the short-term and long-term. Addition to that, automated analysis is assisted by the isolation of non-linear and numerical characters developed from in the field of duration and occurrence. Under preprocessing, mental picturisation of all the changes differentiated before and after. Features of FHR and UC signal include some worthy support, that is Nowadays software Apgar score, maternal age, sex, pH of umbilical artery, BE, and BDecf, in addition to that some features are extracted using the CTG ViewerLite. Diversely, since not all bring out characters are worthy for characterization, feature option algorithms have been used to pick an optimal property set to enhance the executions, consisting a boruta, recursive feature elimination and simulated annealing.

Classification

Differentiation of pathological embryo from a normal embryo followed by two or multiclass classification tasks through the computerized systems occupied ML algorithms, after signal preprocessing and property conversion. Evidently, although the previous research treating with the method showing good categorization performance in estimating the maternal and embryo state with an exactness of 90– 95% with the help of automated FHR and UC analysis, the traditional way of machine learning technique wants to extract data's and choose finest property. So, this proposal needs a huge work and complete data's of living organisms about the embryo that may be lost at the time of the whole process. Recently, Deep learning (DL) has become a mostly utilizing device for signal dispensation. Specifically, CNNs, which demand many layers, have been identified to be quite well organized for almost signal categorization issues. For the prognosis of maternal and embryo compromise CNN plays in investigating continuous FECG and USG traces from over 634 labors. Persistent categorization process is performed to discover the maternal and embryo state utilizing CNN algorithm, have the capacity to self-analyze needed properties from the input of heart rate of fetus and UC signals, which is stimulated by previous study.

Convolution, max-pooling, and classification were the combination three types of layers consisting in CNN architecture. In low and middle-level of the network, there are two types of layers: both convolutional layers(even numbered layers) and max-pooling layers(odd numbered layers). Feature mapping is the 2D plane, in which the grouping of output nodes of the convolution and max pooling layer. Each plane of a layer is normally obtained from a mixture of multiple planes of previous layers. In previous layer, a short region of each associated planes are coupled to the nodes of a plane. Using convolution operations on the input nodes, the convolution layer extracts of each node, the properties from that input pictures. Higher-level properties are obtained from properties generated from lower layers. Specific convolutional and max-pooling operations, the proportions of property are decreased based on the size of the kernel as the property generate to the highest layer. For securing categorization accuracy, the feature maps count will usually expand for presenting good characters of the input pictures. Categorization layer is the result of the final layer of the CNN is utilized as the input to a completely associated network. If feed-forward neural networks have good performance, can be utilized as the classification layer. Regarding to the dimension of the weight matrix of the last neural network, the extracted properties are hold as inputs in the categorization level. So, with regard to network or learning parameters the completely coupled levels are costly. Nowadays, there are different novel techniques, consisting average pooling and global average pooling, utilized as an alternative of completely-associated networks. The score class is evaluated in the top categorization layer utilizing a soft-max layer. Classifier provides output for the specific classes based on the highest score.

4.1 Proposed Optimized Residual Convolutional Learning Neural Network Classifier

An association of both property extractor and classifier is CNN, and the 10-layer deep CNN 2D construction for the study including input layer, transfer learning, genetic algorithm, the pooling layers of convolution-activation-normalization, the completely-coupled-missed layers, the hybrid optimization as SGD with Adam and the final classification layer with softmax activation function. The connection of one individual layer with another layer were accepted via various computational neural nodes from input to output, and thus the input data is conveyed layer by layer. The feature data of the original information will decodes, interprets, converges, and maps by uninterrupted convolution pooling plan to the invisible character space [8]. Next, a completely associated layer performs the categorization task as stated in extracted characters. The output structure provides the large size information of the o/p character diagram of individual layer and values depicts the overall count of weights along with biases [16]. It will initiate by forming the main network branch. Thus the branch includes five sections.

- As first section include the dataset as an input layer and first convolution have ResNet50 (transfer learning) and establishment.
- Three stages of convolutional layers having unusual dimensions of character. Individual stage possesses *N* convolutional units. The net Width measurement is the network width, referred as the counts of filters in the traditional layers in initial stage of the network. The first convolutional units in the second and third stages down-sample the spatial dimensions by a factor of two.
- The last section having global average pooling, completely connected, softmax, and categorization layers. Complete explanations of the layers utilized in the CNN model are shown below.

Pseudo code for the Proposed Optimized Residual Convolutional Learning Neural Network:

```
Initialization:
        filters: the number of filters in the CONV layers
        dataset: input dataset
        input shape: dataset shape classes: number of classes, integer
        epochs: no of epochs
        batch size: number of training examples utilized in one iteration
        F: no of filters

Begin:
        training_dataset, test_dataset←load dataset
        training_dataset←normalize training dataset
        testing_dataset←convert test dataset using one hot encoding
        model←call ResNet50 function with input_shape←8x8x3 and classes ←10
        model←compile model using 'SGD+Adam' optimizer and 'categorical_crossentropy' loss
        value.
        fit ←model with training_dataset, testing_dataset, epochs and batch size as parameters.

Function GA (input shape, classes)
        Initialization of population
        Sort population by fitness
        If
           Fitness reached
        Else if
           Max iteration reached
                Select population
                Crossover
                Mutation
        End
```

```
Function ResNet50 (input shape, classes)
        Stage 1:
        dataset←zero_padding(padding_shape)
        dataset←   2D_Convolution (F,filters)
        dataset←Relu_Activation(dataset)
        dataset←max_pooling(window_shape)

        Stage 2:
        filter←8x8x32
        stage←2
        dataset←   call convolutional_block function with dataset, filter, stage and block
        dataset←   call convolutional_block function with dataset, filter, stage and block
        dataset←   call convolutional_block function with dataset, filter, stage and block

        Stage 3:
        filter←16x16x64
        dataset←   call convolutional_block function with dataset, filter, stage and block
        dataset←   call identity_block function with dataset, filter, stage and block
        dataset←   call identity _block function with dataset, filter, stage and block
        dataset←   call identity _block function with dataset, filter, stage and block

        Stage 4:
        filter←32x32x128
        dataset←call convolutional_block function with dataset, filters, stage and block
        dataset←call identity_block function with dataset, filters, stage and block
        dataset←call identity _block function with dataset, filters, stage and block
        dataset←call identity _block function with dataset, filter, stage and block
        dataset←call identity _block function with dataset, filter, stage and block
        dataset←call identity _block function with dataset, filters, stage and block

        Stage 5:
        filter←64x64x256
        dataset←call convolutional_block function with dataset, filters, stage←5 and block
        dataset←call identity_block function with dataset, filters, stage←5 and block
        dataset←call identity _block function with dataset, filters, stage←5 and block
        dataset←average_pooling(pool_size, padding_shape)
        dataset←convert output into categorical values using softmax activation function
        model←compile

Function identity_block(dataset, filters)
        prev_dataset←dataset
        dataset←2D_Convolution(filters)
        dataset←BatchNormalization(dataset)
        dataset←Relu_Activation(dataset)
        dataset←Add(prev_dataset, dataset)
        dataset←Relu_Activation(dataset)
        return dataset

Function convolutional_block(dataset, filters)
        prev_dataset←dataset
        dataset←2D_Convolution(filters)
        dataset←BatchNormalization(dataset)
        dataset←Relu_Activation(dataset)
        prev_dataset←2D_Convolution(filters)
        prev_dataset←BatchNormalization(prev_dataset)
        dataset←Add(prev_dataset, dataset)
        dataset←Relu_Activation(dataset)

End
```

The 2D Average Pooling uses a window of shape (2,2) and its name is "avg pool".
Create model
Run the following code to build the model's graph ResNet50.
To configure the learning process by compiling the model with proposed SGD+Adam as SAdam.
Output Layer has the combination of flatten and Fully Connected (Dense) layer using a softmax activation.

Input Layer (Layer 1)

In this paper, conversion of our signal raw data (which contain datasets) into excel data format, a group of file formats which is planned to keep and arrange large data volume. Then, the transformed excel dataset into .csv file format due to its hierarchical shape that is similar to files/folder and fast availability. Then, the produced datasets of each class out of 8 classes which outcomes in 634 instances datasets in total with 89 attributes that is independent variables. The CTG ViewerLite and RHRV are used to convert the original raw signal into a dataset with the relevant parameters exactly the input layer of the CNN. At the same time, in order to prevent overfitting, the transfer learning as pre-trained technique is applied to the CNN planning in the input layer to improve the performance of the Convolutional layer. For conversion of picture, a random crop technique was hired, which enhances the dataset of picture and upgrade the generalization capacity of the model.

Transfer Learning – ResNet50 (Layer 2)

Transfer learning is the process of taking a pre-trained deep learning network and fine-tuning it to learn a new task. You can quickly transfer learned features to a new task using a smaller amount of data. . The design of residual network includes following components: 1) A important part with convolutional, batch normalization, and ReLU layers associated in sequence. 2) Residual associations that bypass the convolutional units of the important section. The outputs of the residual connections and convolutional units are added element-wise. Residual associations enable the measurement gradients to flow more easily to the earlier layers of the network from the output layer; it helps in train deeper networks. Use CNN to perform transfer learning for classification by following these steps:

- Choose a pre-trained network.
- Import the novel data set.
- Replace the final layers with new layers adapted to the new data set.
- Set learning rates so that learning is faster in the new layers than in the transferred layers.
- Train the network using CNN.

Genetic Algorithm (Layer 3)

Genetic algorithm (GA) is a metaheuristic that is generally used to solve combinatorial optimization problems. It mimics the selection and crossover processes of group reproduction and how that contributes to development and enhancement of the group vision of continued existence. The crossover process parts of the relevant genetic sequence are combined from both the parents to form the new genetic sequence in the children [2]. The goal is to discover a population member that meets the fitness requirement. The mutation process then makes random changes to the quantity sequence and the complete process continues until a preferred fitness or maximum numbers of iterations are reached.

Convolution layer (Layer 4)

To the input data, the convolution operation is registered in this layer and to neighboring layer the extracted characters are transferred, made up of map containing multiple character of yield. Individual character map was prepared using the operation done by convolution filter for character map of last layer. Both the number of parameter present in network and the quantity of memory settlement by the deep network, because it is an arrangement of deep neural network with particular form of convolution. Extraction of pixel-level abstracted picture characters through, one or more than one convolution filter, by convolution operations, a character map in which unseen layers were related to each other is utilized, in the convolution layer [26]. In each one, there is a collection f_1 convfilters. The quantity of filters are used in single Phase is corresponding to the deepness of the quantity of the output feature maps. In every convfilter it finds a related feature at each position of the input. The output layer $O_x^{(m)}$ of layer m consists of $f_1^{(m)}$ feature maps of dimension$f_2^{(m)} \times f_3^{(m)}$. The x[th] feature map, denote as $O_x^{(m)}$

$$O_x^{(m)} = W_x^{(m)} + \sum_{y=1}^{f_1^{m-1}} P_{x,y}^{(m)} * O_x^{(m-1)} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

In which $W_x^{(m)}$ is a Weight (bias) matrix and $P_{x,y}^{(m)}$ is the filter of dimension relating the y[th] feature map in layer (m-1) with x[th] feature map in layer.

To finalize the depiction of a half feature of the input picture, registers a method of sliding window by individual convolution filter, to cross the whole character map, and collect & combine the data of each small portion. Due to two reasons, the kernel parameters utilized in each individual convolution layer are normally consistent, in a CNN: (i.) partition permits the picture matter to be unchanged by its place; and (ii.) this state of constant can decrease the parameters of optimization. The parameter mechanism partitioning is much crucial and interesting feature of algorithm of CNN.

Activation Layer (Layer 5)

To forming the feature mapping connection, via an activation function or AF the outcome of the convolution layer is mapped. AF is usually execute a map conversion of the given data and gives the capacity of nonlinear modeling of those networks, because it was employed in between the layers of a neural network [12]. When at the time of process, element evaluations of element without replacing the size of the original data. For analyzing merits with another linear functions, rectified linear unit was opted in CNN model; such as, firstly, faster convergence speed and secondly, for getting the effective activation point only one threshold is needed and they do not having final complex computations,. Sigmoid function- It is an S-shaped curve ranging from 0 to 1.

$$R_j^{(m)} = max\left(0, R_j^{(m-1)}\right) \quad \ldots\ldots\ldots\ldots\ldots (2)$$

ReLU function- it is a piecewise function that outputs a 0 if the input is less than a certain value or linear multiple if the input is greater than a certain value.

Normalization Layer (Layer 6)

At the time of training process of the neural network, the BN layer is for systematization of i/p data in individual layer, so that gradient got enlarged, keep away from the issue of gradient vanish and extremely speed up the training speed [6].

Pooling Layer (Layer 7)

Generally, in between consecutive convolution layers, the CNN model adds a pooling or sub-sampling layer periodically [6]. After all, the picture property is useful in an area may be uniformly applied to other area. Pooling layer includes semantically unique characters. Model complexity can be reduced by pooling and fasten the computation while avoiding overfitting because the operation of pooling decreases the character vectors of the output of convolution and the counts of parameters. Uniqueness with the convolution layer, the operation of pooling will execute character diagramming for every small sub-area on the input character diagram in portions of improvement. Generally using pooling methods are max pooling, average pooling and random pooling. The previous operation evaluates the maximum point of the picture region as the pooled outcome; it is utilized in convolutional neural network model.

Fully-Connected Layer (Layer 8)

Fully-connected layer is also known as conventional MLP network and is situated at the ending point of the network structure [5]. The final results of the network layer were shows that increased-layer characters of input features, and the statistical evaluation for a classifier, as well as computed chances for relative section measurement for the input features. After various circles of convolution and processing of pooling, the input picture details can be abstracted into detailed absolute characters. Both the convolution and pooling layers were taken as the compulsory proposals to compute the extraction of significant features. The fully-connected layer is utilized to perform the last categorization task, after character conversion got over.

Dropout Layer (Layer 9)

The categorization, we generally try to prevent an incident of the over fitting of the model forms that are trained increased correctness on the training records, still the common error on the test records is comparatively high. Overfitting can cause by different factors and the following particular solutions are approached in this study [27]: (a.) Regularization: It is a powerful method to clear a negative issue to avoid over fitting by initiating extra data. L2 regularization is employed to put a regularize function of cost for this experiment. (b.) Dropout method: The fully-connected layer is settled by drop out layer. Different neural units were dropped with certain probability form the network at the time of training method, temporarily.

Classification Layer (Layer 10)

Ultimately, categorization layer was utilized for division of output classes utilizing function softmax. In this research, Table 2 represents the detailed values of individual layer of the proposed Convolutional Neural Network model, and they do not effect on categorization execution, when alert observation got completed.

Table.2. Detailed parameters used for the proposed Optimized Residual Convolutional Learning Neural Network model.

Parameter	Description	Default
Pre-trained	Transfer Learning	ResNet50
GA	Genetic Algorithm for hyper parameter tuning	Selection, mutation, crossover
Filters	The number of filters in the convolution operation	8, 16, 32,64
kernel_size	The size of the convolution kernel	(3, 3), (5, 5)
Strides	Convolution step size	(4,4)
Activation	Activation function	relu, adam
pool_size	Pool size	(2,2)
Padding	Whether zero padding	Same, valid
drop_out	The proportion of nonworking neurons	0.25
Optimizer	Optimization function	Hybrid SGD+Adam (SADAM)
Epochs	The number of complete training samples of the data set	10, 20, 50, 100
batch_size	The number of training samples per iteration	32, 64, 128,256
Output_Layer	Classification (Dense Layer)	Softmax

The paper shows that, we adopted CNN as the FECG and USG signal classifier. With the appearance of the CNN model, correlation of spatially adjacent values can be extracted by applying, both nonlinear filter and multiple filters, it is able to extract different normal characters of the dataset. 2D convolutional and pooling layers are specific for filtering the spatial locality of the FECG datasets that is why we applied 2D CNN by converting the FECG signal into FECG dataset form. Outcome shows that, higher FECG and USG signal categorization accuracy can be obtained. The physician diagnoses a maternal and embryo state in FECG and USG signal of the patient during visualization handling and through eyes. So for that reason, applying the 2D CNN model to the FECG and USG signal is similar to the physician's diagnosis process. The basic structure of ResNet50 is combining with the Optimized Convolutional Neural Network model to show optimal performance for FECG and USG signal classification accurately. Performance comparison of the proposed Optimized Residual Convolutional Learning Neural Network model was performed with SGD, Rmsprop, Adam and Adagrad. Hence there is a requirement to have a deep depth layer and an raise in free parameters to avoid the over-fitting and for improving the performance it should be degraded.

5. Performance Factors

The classification valuation considered the following factors: Accuracy, TPR, TNR, PPV, NPV, HM, Kappa, AUC, PrAUC, Log loss, Detection Rate, Prevalence, Detection Prevalence and Balanced Accuracy values. AUC is a region under the Receiver Operating Characteristic or ROC curve. For computing pairs of True Positive Rate or TPR and False Positive Rate or FPR by evaluating AUC with the help of Riemann sum with a set of thresholds. PPV is defined as the actual positive test result divided by all positive result. Except for the AUC, other four factors are distinct with dimensions in following:

$$\text{Accuracy} = \frac{TP+TN}{(TP+FP+FN+TN)} \quad \text{--------------------} (3)$$

$$\text{True Positive Rate (TPR)} = \frac{TP}{(TP+FN)} \quad \text{--------------------} (4)$$

$$\text{True Negative Rate (TNR)} = \frac{TN}{(FP+TN)} \quad \text{--------------------} (5)$$

$$\text{Positive Predictive Value (PPV)} = \frac{TP}{(TP+FP)} \quad \text{--------------------} (6)$$

$$\text{Negative Predictive Value (NPV)} = \frac{TN}{(TN+FN)} \quad \text{--------------------} (7)$$

$$\text{F1} = 2 * \frac{(PPV * TPR)}{(PPV+TPR)} \quad \text{--------------------} (8)$$

$$\text{Detection Rate} = \frac{TP}{(TP+FP+FN+TN)} \quad \text{--------------------} (9)$$

$$\text{Prevalence} = \frac{TP+FN}{(TP+FP+FN+TN)} \quad \text{--------------------} (10)$$

$$\text{Detection Prevalence} = \frac{TP+FP}{(TP+FP+FN+TN)} \quad \text{--------------------} (11)$$

$$\text{Balanced Accuracy} = \frac{(TPR+TNR)}{2} \quad \text{--------------------} (12)$$

Where

- The True Positive or TP is the proportion of positive cases identified correctly
- The False Positive or FP is the proportion of negatives cases classified incorrectly as positive
- The True Negative or TN is defined as the proportion of negatives cases that are identified correctly.
- The False Negative or FN is the proportion of positives cases classified incorrectly as negative.

6. EXPERIMENTAL RESULT AND DISCUSSION

6.1 Experiment One: Optimization of the CNN Parameters

There are several parameters used for tuning the Convolution Neural Network algorithm that can affect the execution of the classification to different degrees. The first learning rate was set to 1X 10−3 in this experiment, which regulates the reasonably stable learning speed. To solve over-fitting with a factor of 1 X10−4, L2 regularization was applied.

The Convolutional Neural Network model's training and validation process is done. It can be clearly seen that the Acc raise and the loss falls for both training and validation as the iteration or epoch evolves. To get every layer in neural network's weight and bias parameters. Researchers have recently presented various powerful BP algorithms, including SGD, RMSP, ADAM, and Adagrad, for CNN training.

Table.3 Comparison of the accuracy with four optimization algorithm with proposed SADAM Optimization Method

Optimization Methods	D1	D2	D3	D4	D5	D6	D7	D8
SGD	93.65	92.26	91.36	91.63	91.63	92.68	92.23	91.99
RMSP	90.03	91.52	90.56	91.58	91.03	90.36	91.45	90.54
Adam	94.25	93.23	93.36	90.25	93.20	94.60	91.98	92.02
Adagrad	91.03	92.52	92.56	92.58	90.03	91.98	90.58	89.36
Proposed SADAM	**95.85**	**94.69**	**94.82**	**93.74**	**94.36**	**95.56**	**93.99**	**94.89**

Note - D1: FIGO Class, D2: Caesarean, D3: Hypoxia, D4: Indication of childbirth, D5: Diabetes, D6: Preeclampsia, D7: Hypertension, D8: Meconium

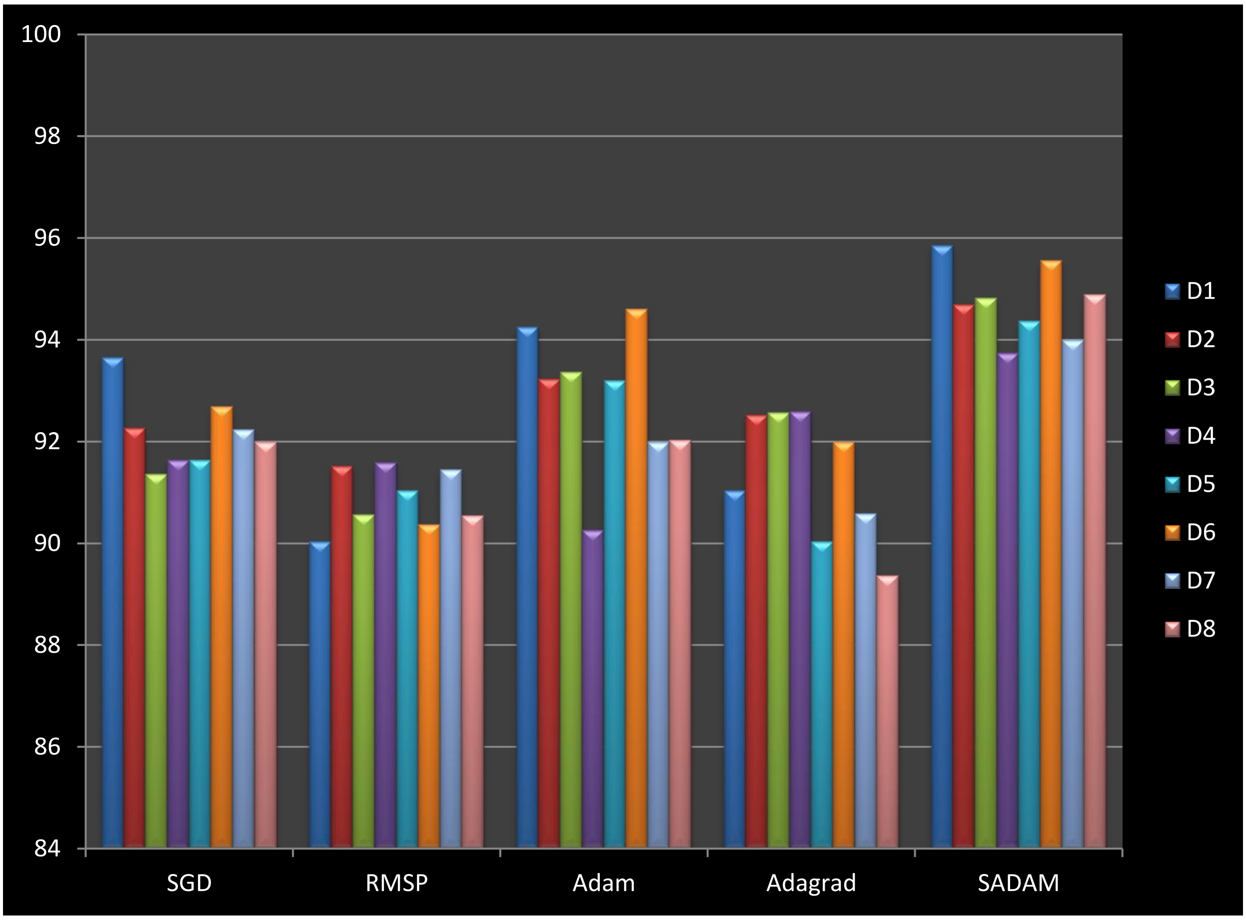

Fig. 2 Comparison of accuracy with proposed SADAM Optimization Method

Table 3 and Fig.2 represents the four algorithms jointly with different parameter settings and their outcome. The performance comparison of the best two Acc achieved by the optimization are SGD and Adam algorithm was higher when compared with others. So the best two methods is combined and got the best accuracy result. The combined method is known as SADAM new proposed method.

6.2 Experiment Two: Performance of the Proposed Optimized Residual Convolutional Learning Neural Network

Obviously, as the amount of layers increased in the initial state, the implementation of our suggested framework improved. The best execution was achieved when the number of layers reached 10 layers. We investigated the effect of different layers of the CNN model with their CNN parameters on the execution of categorization, the related optimal research method explained in Experiment 1, and Table 4 represents the research outcome using the screening collection. Architectures representing overfitting or under fitting of more than 12 layers were therefore not considered.

Table.4 Performance Measures for the Proposed Optimized Residual Convolutional Learning Neural Network

Risk Factors / Metrics	D1	D2	D3	D4	D5	D6	D7	D8	Avg
Accuracy	**96.65**	**95.26**	**96.36**	**94.63**	**96.63**	**97.56**	**95.99**	**96.89**	**96.24**
TPR	99.51	94.80	99.39	99.39	90	92.36	89	91.25	**94.46**
TNR	94.90	84.46	94.18	93.97	90.70	89.07	75.83	80.05	**87.89**
PPV	92.08	91.71	95.71	94.01	88.40	91.22	93.47	82.92	**91.19**
NPV	85.26	94.13	86.25	85.00	81.53	84.81	81.64	87.68	**85.79**
HM	82.30	74.20	71.59	85.23	83.53	84.17	81.28	88.63	**81.37**
Kappa	82.44	82.36	80.12	87.91	82.44	82.36	80.12	87.91	**83.21**
AUC	89.70	91.82	94.57	80.14	88.40	91.22	93.47	82.92	**89.03**
PR AUC	93.81	88.69	81.28	83.53	84.54	90.69	72.09	90.69	**85.66**
Log Loss	82.33	83.66	84.23	86.23	84.23	86.10	81.09	91.06	**84.87**
Detection Rate	83.46	84.33	82.23	87.02	83.25	85.20	80.93	90.57	**84.62**
Prevalence	82.04	82.69	83.25	86.63	85.23	86.23	82.85	91.47	**85.05**
Detection Prevalence	85.20	88.58	80.68	89	84.50	82.96	81.16	80	**84.01**
Balanced Accuracy	81.75	90.62	81.84	82.30	84.54	90.69	82.09	90.69	**85.56**

Note - D1: FIGO Class, D2: Caesarean, D3: Hypoxia, D4: Indication of childbirth, D5: Diabetes, D6: Preeclampsia, D7: Hypertension, D8: Meconium

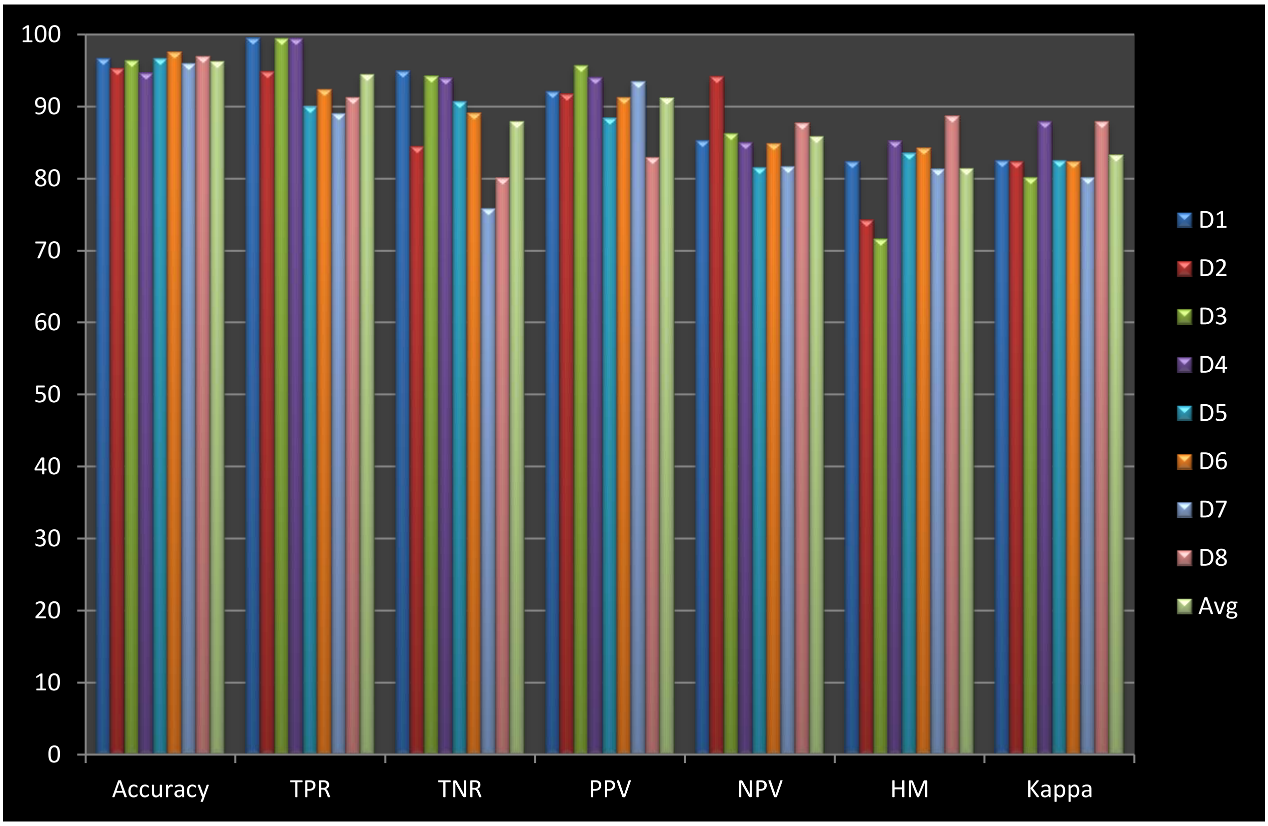

Fig.5. Performance metrics (Accuracy, TPR, TNR, PPV, NPV, HM, Kappa) for the respective Proposed Optimized Residual Convolutional Learning Neural Network.

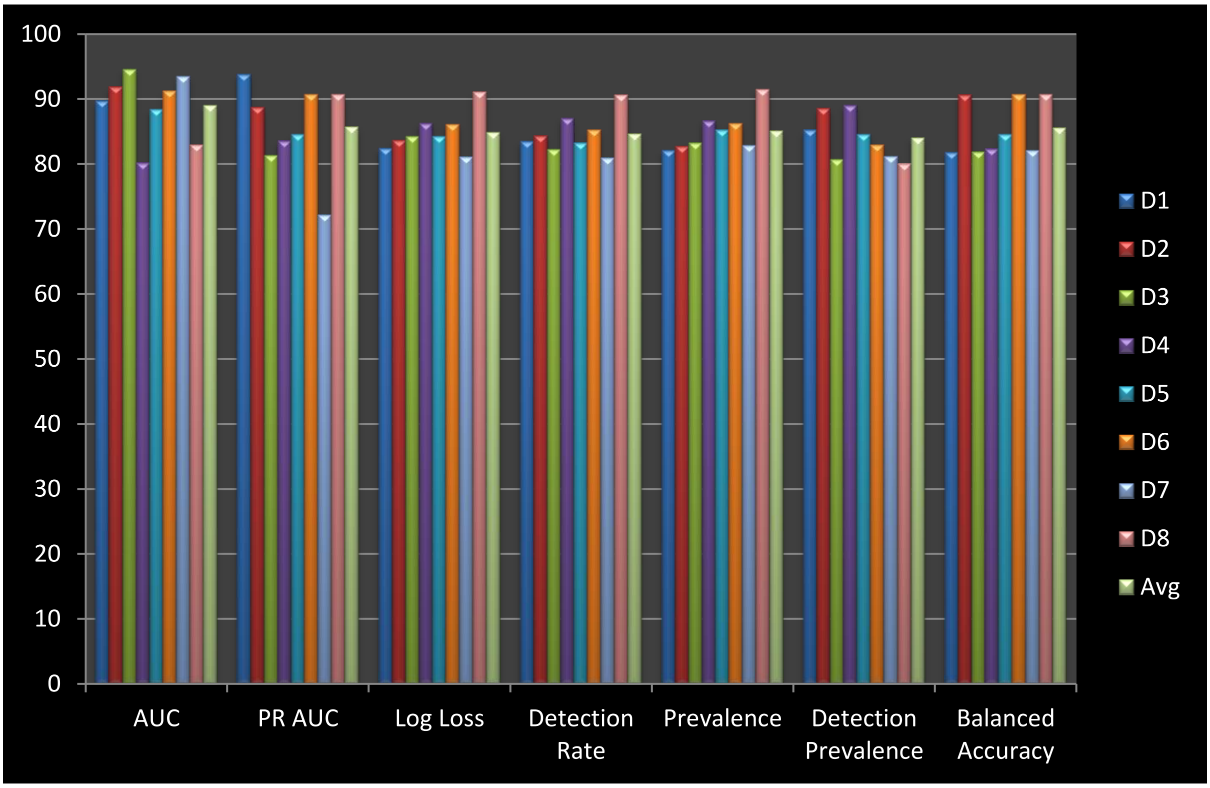

Fig.6. Performance metrics (AUC, PR AUC, Log Loss, Detection Rate, Prevalence, Detection Prevalence, Balanced Accuracy) for the respective Proposed Optimized Residual Convolutional Learning Neural Network.

In other words, the corresponding automated system could automatically recognize an unknown embryo, irrespective of the number of layers. The several performance metrics, which are Acc, TPR, TNR, PPV, NPV, HM, Kappa, AUC, PRAUC, Log Loss, DR, Prevalence, DP and BA, derived from confusion matrix were also considered. In other words, the corresponding automated system could automatically recognize an unknown embryo, irrespective of the number of layers when the proposed Convolutional Neural Network algorithm was trained successfully. The Proposed Optimized Residual Convolutional Learning Neural Network result is presented graphically is shown in Figure.5 and 6, for a better illustration.

6.3 Discussion:

First of all, the proposed method of FECG and USG signal classification using deep two-dimensional CNN with FECG and USG signals in this paper. This is critical because in noise filtering and feature extraction, some of the FECG and USG beats are overlooked. The use of the FHR and UC signal as input data from the classification of the FECG and USG also benefits in the sense of robustness. As every FHR and UC one-dimensional signal value is handled, existing FECG and USG signal discovery techniques are susceptible to the noise signal. However the proposed CNN model will automatically disregard the noise data while translating the FECG and USG signal to the two-dimensional image while extracting the related feature map in the convolutional and pooling layer. The FECG and USG signals from the different FHR and UC devices with different sampling rates and amplitudes can therefore be applied to the proposed CNN model, whereas previous literature requires a different model for the different FECG and USG devices In addition, the identification of FECG and USG signals is close to how medical experts diagnose maternal and embryo status by examining patients' FECG and USG graphs throughout the monitor, displaying a sequence of FECG and USG signals.

The following steps are included in our classification method: FECG and USG raw signal, data pre-processing, and CNN classifier. The CTU-UHB database, which is commonly used as an FHR and UC database in FECG and USG signal classification study, obtains the FECG and USG signal data treated in this article. With these FECG and USG recordings, because our CNN model needs two-dimensional signal as an input, we have converted every single FHR and UC signal beat. Finally, to identify nine different risk factors for FECG and USG beats, the CNN classifier is optimized as follows: Regular FIGO classes, Caesarean Section, Hypoxia Prediction, Childbirth Termination Indication, Diabetes, Hypertension, Preeclampsia, Delivery Type and Meconium. With contemporary deep learning techniques such as ResNet50 (transfer learning), genetic algorithm, batch normalization, dropout, and Xavier initialization, the proposed optimized CNN model. As a result, 96.24 percent average accuracy, 94.46 percent TPR, 87.89 percent average TNR, and 91.199 percent average PPV is achieved by our CNN classifier, while the 10-fold CV method is applied to the assessment to accurately validate the proposed classifier that includes both FECG and USG recordings as test data.

7. CONCLUSION

A visual examination of the heart beat of embryo with the naked eye, however a daunting mission is for obstetricians as this kind of measurement is biased and ir-reproducible. In this review, our major input is to suggest a data-driven suggestion using a proposed optimized convolution transfer learning to automatically evaluate the maternal and embryo state. The current study, deals with the data-driven suggestion that mechanically evaluate the maternal and embryo state using a proposed optimized convolutional transfer learning. After signal preprocessing, the input parameters dataset were obtained using the CTG ViewerLite and RHRV with different types of maternal and embryo signals. In addition, the combination of FHR signals with other biomedical signals (e.g. UC) can enhance the precision of the decision method to be more accurate. Best possible configuration after extensive experimentation based on tuning the parameters are (10 layers, size of the convolution kernel=3x3,5x5, number of filters=15 (8x8x32, 16x16x64, 32x32x18, 64×64×256), maximum number of epochs=10,20,50,100 size of the mini-batch=32,64,128,256 and input shape=8x8x3), identity block, convolutional block and the averaged Accuracy with 96.24% across ten folds, respectively. Overall, the findings showed the efficacy of our proposed optimized CNN, which can be applied in clinical practice and help obstetricians critically make specific medical decisions.

In addition, the findings are promising in the future and offer the foundation for prospect research linking approaches without taking out and collection of features and completely depending on the convolutional neural network for maternal and embryo state evaluation in the deep learning model. To decrease the difficulty and speed up the training phase in terms of computing, GPUs will be incorporated into the workstation. It is also a big challenge to build the method additional understandable for obstetricians and maternal. The introduction of an integrated artificial intelligence system in clinical settings would also ensure that maternal and embryo pain can be more objectively predicted rapidly and accurately.

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