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ORIGINAL RESEARCH ARTICLE

Secure IoT based smart system for monitoring health care for ambulatory and fetal

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ABSTRACT

The Internet of Things (IoT) along with Artificial Intelligence (AI) has now developed the most prevalent instruments in applications in the health care industry for widespread and intelligent automatic diagnostic systems. The maternal clinical information for ubiquitous and intelligent autonomous diagnostic systems, IoT with AI has now taken the lead as the predominant instrument in the healthcare industry. With respect to the incorporation of IoT sensors along with deep learning techniques, this article suggests the establishment of smart networks to monitor maternal and fetal signs in dangerous pregnancies. IoT sensors are utilized to gather clinical information about the mother, including her temperature, blood pressure levels, and saturation in oxygen level, heart rate, and heartbeat of the unborn child. This information is then stored in the cloud for tracking and forecasting. Additionally, a brand-new optimal Gated Recurrent Unit (GRU) is suggested for improved categorization and a forecast of the several emergencies affecting both pregnant women and unborn children. Additionally, to assist the data's security and the design of IoT systems is based on a number of sensors that are interfaced with MICOT boards (Node MCU+MCP3008) and a cloud system. For the evaluation, about 500 pieces of data were gathered and utilized. With cloud-centric learning techniques like K-Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machines (SVM), Convolution Neural Networks (CNN), and Extreme Learning Machines (ELM) thorough experimentation is conducted, and various parameters including accuracy, precision, recall, and sensitivity, along with F1-score are estimated. The evaluation found that the recommended classifier outperformed the competing learning strategies. The recommended framework is a practical and useful method for maternal and foetal surveillance that is powered by IoT and AI.

Keywords: IoT; AI; GRU; IoT sensors; MICOT boards

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1. Introduction

Maternity care strives to protect health of the expectant mother and her unborn child and well-being. During pregnancy, as well as in the future, maternal health has affected the infant. Additionally, health issues in pregnancy, which include hypertension or pregnancy-related diabetes, may lead to health issues in her later years after giving birth[1]. Therefore, prenatal care is crucial for both boosting for a long-time population health and minimizing individuals' acute pregnancy issues. In 2015, forty-five percent of all infant and young child deaths occurred during the neonatal period[2]. The primary reasons for death in this category include preterm delivery issues (35%), an intrapartum incidents (25%), and infection (including sepsis/meningitis in 15%)[3]. In accordance to UNICEF 2018 report, Pakistani have a particularly high rate of newborn mortality in the entire world, per 1000 live births, at 46. Prenatal examinations are essential for spotting anomalies and averting further problems, wounds, or perhaps death[4]. AI employs several human body data points and mathematical algorithms to make diagnoses[5].

The use of these models has increased the precision of cardiovascular disease prediction[6] recurrence of cancer and mortality prediction, and to improve the diagnostic accuracy of radiological examinations[7,8], including computerized tomography monitors with magnetic resonance imaging[9]. Automation of CTG interpretation has been developed by medical and engineering specialists, which reduces inconsistent outcome classification. The most important objective measurements to keep track of during pregnancy have typically been blood pressure, glucose levels, and test results for urine, in addition to the uterus developing and the mother gaining weight[10]. In order to keep up good health, maternity care experts must also offer counselling on additional lifestyle along with managing oneself issues, especially physical activity and sleep. They aren't currently being systematically watched, though. Pregnant women's health must be continually assessed as to identify potential problems initially and boost health measures[11].

Furthermore, ongoing monitoring of several health-related indicators permits the collection of exact quantitative data that might aid in understanding pregnancy. Advances in communication and information technology (ICT) have changed the way healthcare is provided. The Internet of Things (IoT) is a modern ICT paradigm that combines various sensing, communications, and computing infrastructures to build an advanced network of objects that can be accessed from anywhere and at any time[12].

By merging AI techniques to aid in the sketching of intelligent and highly effective diagnostic systems, with an emphasis on simultaneous monitoring of both the mother and the foetus, IoT solution ideas have advanced to a new level. In addition, several algorithms, including KNN, SVM, RF, and CNN, have been proposed for the inclusion of an IoT-dependent maternal and foetal inquiry system. The existing system requires further improvement with relation to costs, operational challenges, and a decreased misclassification ratio. To overcome these drawbacks, this paper proposes novel Intelligent (Internet of Optimized Deep Neural Networks) which offers the integrated system having the ability to get various medical data via IoT sensors and nodes and then implements an Optimized Convolutional Neural Network, the use of a prediction algorithm to automatically identify the status of fetal and maternal health conditions. The main contribution of the proposed IONETS are as follows as:

1) To design the intelligent system for ambulatory vital sign monitoring and prediction systems for maternal and fetels.
2) A cloud-based deep learning classifier that is tailored for analysis of numerous parameters and classification/prediction of fetal and maternal health status.
3) To deploy the chaotic security algorithm to defend the stored cloud data against the cloud attacks.
4) Evaluation of different performance standards for the suggested algorithm and comparison with the distinct state-of-art algorithms. Results demonstrate the suggested framework outperforms the alternative models and proves to be vital role in the prediction of maternal and fetel conditions.

The organization of the paper is as pursues: Associated works by multiple authors are enclosed in Section 2 The suggested framework is described in Section 3 together with an IoT data gathering device and an improved deep learning model. In Section 4, dataset descriptions, experimentations, results along with its contrastive analysis is presented. The study is completed by discussing future improvements in Section 5.

2. Related works

Using supervised learning models, Zhao et al.[13] investigated the classification of baby's heart rate. The heart rate signals of the developing embryo are monitored and classified using ANN, SVM, RF, and ELM labelled frameworks that were based on maternal characteristics that are routinely observed. The "Sis Porto" open access database, which has been employed for purposes of testing and training, contains a number of features. The author came to the conclusion that, when tested with recordings from a synthetic dataset, ANN performed well for identifying fetal heart rates.

Sarhaddi et al.[14] suggested an automated method of detecting prenatal hypoxia by examining the FHR during childbirth. The three stages of the proposed model include segmenting the fetal signals into time series frame with normalized compressing distance measures for classification. Continuous monitoring of the fetal heart rate during labor allows doctors to detect fetal hypoxia by comparing it to the normal heart rate. As fetal movement detectors, two different machine learning techniques KNN and SVM were designed and achieved 88 percent accuracy using data from 1000 subjects. This proposed model’s flaw is that it cannot handle large databases and causes significant estimation delays.

To avoid fetal hypoxia, Ahmed et al.[15] introduced an unsupervised learning technique for FHR and EFM inputs. The recurrence plot, which is believed to be a good representation of the non-linear features, was used to turn the 1-dimensional pre-processed FHR signal into a 2-dimensional image. The final photo collection, which was fed onto the CNN, was enhanced by altering a number of the RP’s parameters. This model’s disadvantage is that it has a high computational burden and requires more training time than other cutting-edge classifiers.

In this study, Baccouche et al.[16], developed an IoT based framework for monitoring maternal health during pregnancy and postpartum. Numerous data gatherers built into the device keep track of the mom’s health, including her activity phases, sleep schedule, and stress concerns. According to the author’s research, the installed system can be used effectively for nine months. The digital watch can collect accurate photo plethysmography data and has been developed to have a sufficient energy economics for long-term monitoring.

Another clever method was created by Matonia et al.[17] for monitoring maternal health and diagnosing low fetal heart rate in pregnant women. Real-time datasets are used to create and evaluate all supervised learning models. In order to prevent the children from suffering from hypoxia, the objective of this investigation is to create a revolutionary real-time database of the state of the mother during her labor. The dataset comprises unique characteristics such as subject’s age, regular heart rate, fetal heartbeat, sampling time, etc. Each identical record has been uploaded to the cloud utilizing an IoT environment. Alternative unsupervised learning methods can be used to validate the proposed database’s limitations.

For the purpose of diagnosing heart disorders, Hoodbhoy et al.[18] presented a collection of models for unsupervised learning dubbed BiLSTM and Bi-Gated Recurrent Unit (BiGRU) models. The suggested NN is modelled as a binary classification system to determine whether heart attack risk is normal or abnormal. Burgos-Artizzu et al.[19] created the techniques for feature extraction of principal component analysis (PCA) and independent component analysis (ICA) so as to extract the important features from a large heart rate database of pregnant women. With fetal electrocardiography signals, the main goal is to determine the fetal locations and level of labour.

According to the study’s proposal by Du et al.[20] high-risk fetuses will be identified with high accuracy using machine learning algorithm approaches using CTG data. The University of California Irvine Machine Learning Repository provided CTG data for 2126 pregnant women. Using CTG data, ten distinct machine learning classification algorithms were trained. To predict normal, suspicious, and abnormal fetal states, sensitivity, precision, F1-score for each class, and overall model accuracy were achieved.

In a real-life maternal-fetal clinical situation, Priyanka et al.[21] offered the development of currently available Deep Learning classification techniques. A vast data collection of routinely collected maternal fetal screenings ultrasound images from two different hospitals was gathered by a number of operators and ultrasound machines. These photos will be made available to the public. Each image was manually annotated by a knowledgeable maternal foetal physician. Six groups were created using the four most frequently utilized fetal anatomical planes (the abdominal region, the brain, the femur and thoracic), the mother's cervix (which is frequently used for prematurity screening), and any other type of less common imaging.

3. Proposed methodology

3.1. Preliminary views of the state-of-art learning methods

This section gives the clear view about the state-of-the-art learning methods incorporated for the proposed frameworks. The Gated Recurrent Unit's (GRU)[22] and cuttlefish algorithm's comprehensive explanation is given in preceding section.

3.1.1. Gru networks

The LSTM version GRU is thought to be the most fascinating. The goal of this concept, which was put forth to integrate the forget gates with input vectors into a vector. Both long term sequences along with long memories are supported by this network. When contrasted to the LSTM, the complexity is drastically reduced. The term "minimal gated unit" refers to a condensed version of the complete gated unit. The full gated unit can be gated in a variety of ways, with the bias and the prior concealed state being used in different configurations. Since it relates to the subject, the security system also forms a component of the originality. The operator ⊙ denotes the Hadamard product in the following.

Initially, for $t = 0$, the output vector is $h_0 = 0$.

$$h_t = (1 - z) \odot h_{t-1} + z_t \odot h_t \tag{1}$$

$$\widetilde{h_t} = \phi(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h \tag{2}$$

$$z_t = \sigma(W_h x_t + U_z h_{t-1} + b_z) \tag{3}$$

$$r_t = \sigma(W_h x_t + U_r h_{t-1} + b_r) \tag{4}$$

The following is the general GRU characteristic equation:

$$P = GRU(\sum_{t=1}^{n} [x_{t,} h_{t,} z_{t,} r_t (W(t), B(t), \eta(tannh))] \tag{5}$$

where x_t: "input at the present position"; y_t: "output state"; h_t: "output of the module at present instant"; Z_t and rt: "update and reset gates"; $W(t)$ and $B(t)$: "weights and bias weights at present position".

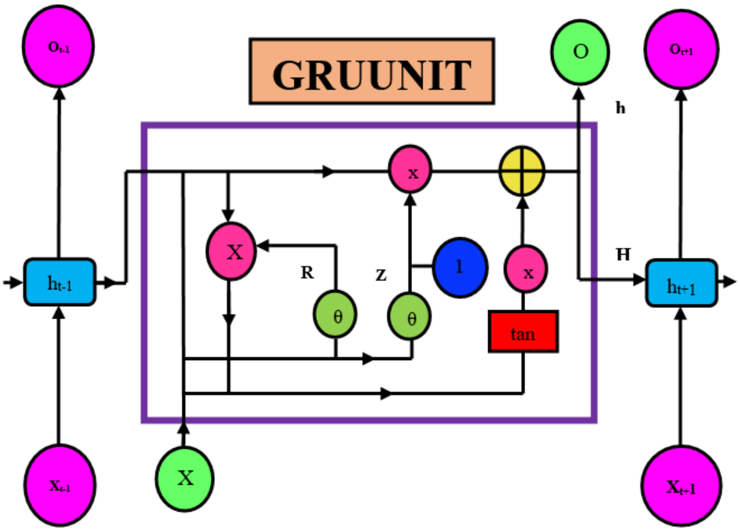


Figure 1. GRU-network architecture.

Chung developed the following equations to illustrate the traits of GRU. The GRU's architecture is illustrated in **Figure 1**. With the preprocessed ECG data, these GRU networks are utilized to determine the temporal properties. In order to prevent over-fitting issues, the GRU framework recognizes the R-R interval maxima with bigger changes and employs the Cuttlefish approach for optimizing the weights assigned to the

GRU. This study employs a modified GRU to address the complexity issue, with the gates tweaked using weights from the prior state and bias information.

3.1.2. Cuttle fish algorithm

The adaptive color properties of cuttlefishes served as the basis for the development of the revolutionary meta-heuristic optimization algorithm known as the Cuttle Fish Algorithm[23]. Three layers, including chromatophores, iridophores, and leucophores, reflect light to create the many color patterns in cuttlefish. These cells are piled one on top of the other, and cuttlefish have a wide variety of color patterns due to the direct mixing of these cells. In a nutshell, this innovative algorithm. The cuttlefish can create intricate patterns and hues thanks to this talent. This algorithm consists of two processes: the visibility of the matching pattern utilized by cuttlefish for matching its backdrop color, and the reflection mechanism, which simulates how light reflects through three different layers. The two processes' mathematical formulation is provided by

$$n(p) = R + V \tag{6}$$

where R is reflection and V is visibility. Following is a description of the equation for the interaction among all three separate types of cells in six scenarios.

For case 1 and Case 2

$$R[k] = R \times X1[i].points[k] \tag{7}$$

$$visiblity\ V[k] = V \times \{best_{points[k]} - X1[i].points[k]\} \tag{8}$$

where R and V: "random variables (−1, 1)"; X1: "subset of the result"; i and k: "ith and kth element in X1". Best refers to the best possible solutions. In these two scenarios, setting V to 1 generates the value of R.

For Case 3 and Case 4

$$R[k] = R \times best_{points[k]} \tag{9}$$

$$visiblity\ V[k] = V \times \{best_{points[k]} - X2[i].points[k]\} \tag{10}$$

where $R = 1$, and V: "random value".

For Case 5

$$R[k] = R \times best_{points[k]} \tag{11}$$

$$visiblity\ V[k] = V \times \{best_{points[k]} - Final\_best\} \tag{12}$$

where Final_best: "average of every optimal results". In this instance, R is produced, and V is initialized to 1.

For Case 6

$$newP = random \times (U - L) + L \tag{13}$$

where random = [0, 1]; U and L: "upper and lower limits".

The population is divided into four groups by the algorithm, designated as X1, X2, X3, and X4. Equations (1) and (2) in cases 1 with 2 are framed to be employed for the initial subset of cells X1 whereas Equations (4) and (5) in cases 3 with 4, Equations (6) and (7) in case 5 with Equation (8) in case 6 are formulated for X2, X3, and X4. Algorithm 1 presents the working mechanism of the cuttlefish algorithm. **Figure 2** gives the cuttles fish algorithm's working flow chart.

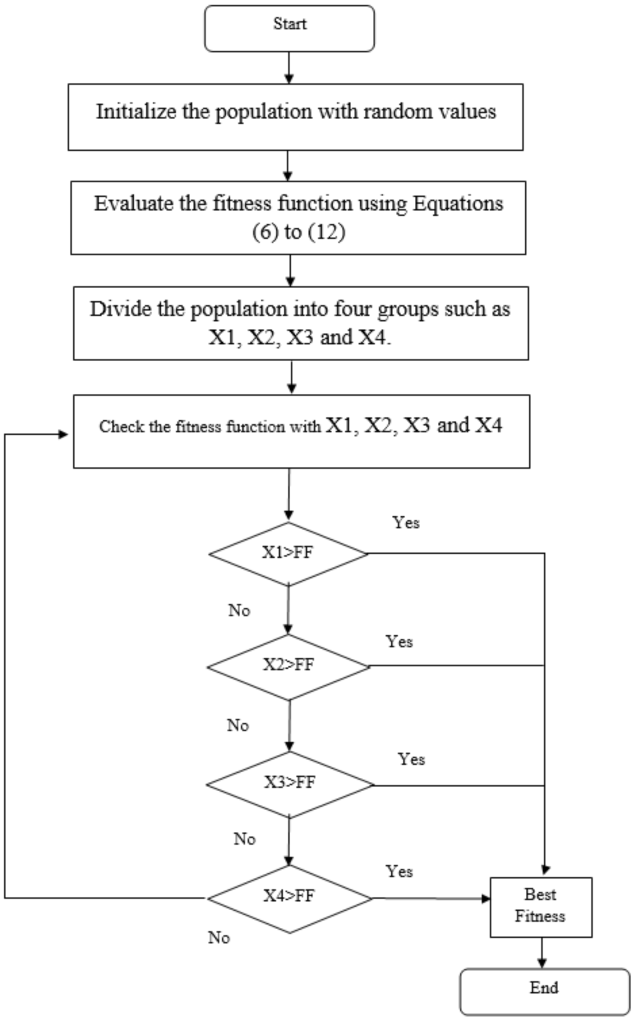


Figure 2. Cuttle fish algorithm's working mechanism.

3.2. Proposed IoT based learning mechanism

The suggested framework is shown in **Figure 3**, and the following data flow is described in more detail: IoT nodes with sensors are utilized to gather various data from mothers and babies, which is then transferred to the clouds for the purpose of prediction and an emergency alerting system. Preprocessed data from the cloud is used as inputs for optimized GRU, classify and alert users to emergency situations. The medical team is then given a medical report according to the classification and given further instructions. According to the description and presentation in **Figure 3**, the suggested solution is divided into three sections.

The IoT layer, which combines sensors, microcontrollers, and transceivers, is the initial section. The second and third layers of cloud computing[24] are made up of efficient deep learning models for data preparation, followed by security mechanisms for the data that has been stored. The suggested structure for the IoT-based Secure Smart Health Care System is shown in **Figure 3**.

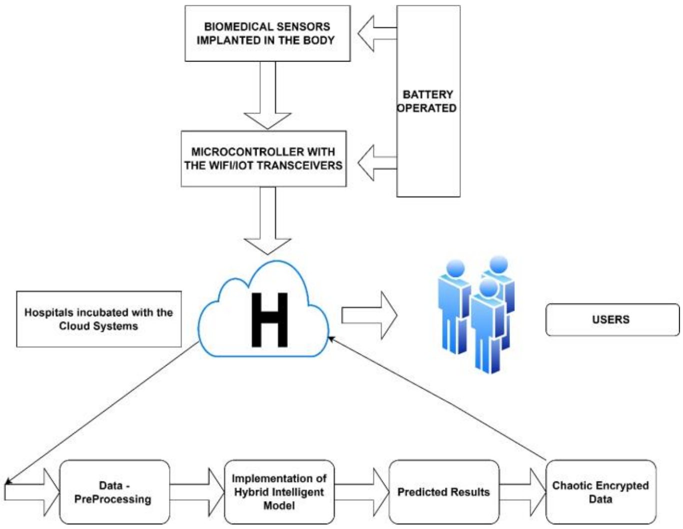


Figure 3. Proposed framework for the secured smart health care applications.

3.3. IOT—Sensors and medical systems

These layers are made up of a number of medical sensors that are connected to battery-operated MICOTT boards (Integration of NodeMCU with MCP3008) while all measured data is sent to a cloud computing system. The system has accelerometers, respiratory sensors, sensors for temperature, maternal and fetal heart rate sensors, pulse oximeters, and temperature sensors. The sensors collect data on the maternal characteristics (heart rates, body temperatures, blood pressures, glucometer, oxygen saturation), as well as the fetes parameters (heart rate), and send it to the cloud employing esp8266 WIFI transceivers. The hardware requirements employed for the IoT layers are shown in **Table 1**.

Table 1. Hardware requirements in the devices and IoT layers.

S. No	Hardware utilized	Specifics
01	MEMS accelerometer	Operating at 3.3 V, the three axis measurement has sensitivities of 28.6 LSB/g (x-axis), 31.2 LSB/g (y-axis), and 34.5 LSB/g (z-axis).
02	Maternal and fetal heart rate sensor	Simple optic heart rate sensors with electronics for noise elimination and amplification for quick, accurate pulse measurements. It also uses less power, drawing only 4 mA at 5 V, which makes it perfect for mobile applications.
03	Glucometers	The mother blood glucose level has been monitored employing with an OMRON Blood Glucometer.
04	Temperature sensor	A thermometer with a temperature-dependent analog voltage is the LM35. The output voltage is provided in Celsius, never Fahrenheit. There is no requirement for additional calibrating hardware. Sensitive to 10 mV/C, the LM35. Along with temperature, output voltage rises.
05	Pulse oximeters	Ambient light cancellation (ALC), a 16-bit sigma delta ADC, and a custom discrete temporal filter make up MAX30100. It operates at an extremely low power level, which makes it perfect for battery-powered devices. The operating voltage range for the MAX30100 is between 1.8 and 3.3 V. It can be utilized in wearable technology, fitness trackers, health monitors, and other devices. The MAX30100 may be turned down by software with very little standby current, allowing the power source to always be attached. It runs off of 1.8V and 3.3V power supplies.
06	Embedded CPU	In order to interface and upload data to the cloud, MICOT Boards are needed.

The only fetal signal that is monitored is the FHR, which is captured via a doppler ultrasonography sensor with a 4Hz sample rate and interfaced to MICOTT boards for cloud storage and monitoring.

3.4. Layers for feature extraction and data preprocessing

The data analysis module for maternal and fetal feature extraction is the 2nd component of the suggested framework. The FHR and maternal parameters are calculated using signal processing methods. Measurements are computed for the initial 15 min of signal capture while updated every 10 min in the cloud because the interpretation and scrutiny require several minutes of confirmation. The diagnostic prognoses of maternal, fetal, as well as every case were classified by the medical team into a total of 8 groups, which are shown in **Table 2**.

Table 2. A table of typical thresholds employed for data labeling and network training.

Sl.no	Thresholds	Descriptions
1	$MHR < 90$	MHR—Maternal Heart Rate
2	$MSBP < 140$	MSBP—Maternal Systolic Blood Pressure
3	$MDBP < 80$	Maternal Diastolic Blood Pressure
4	$MF < 99$	Maternal Temperature (In Fahrenheit)
5	$FHR < 100$	Fetal Heart Rate
6	$MBSL < 110$	Maternal Blood Sugar Level
7	$MO2 > 95$	Maternal Oxygen Saturation

3.5. Cloud prediction systems

The suggested structure employs a hybrid mixture of Gated Recurrent Unit for an efficient prediction system, and the Cuttle Fish Algorithm is used to optimize its hyperparameters. The hybrid framework has been offered as a solution to the overfitting issue and to lessen the likelihood of overfitting. The following is an explanation of how the model of hybrid learning functions.

After pre-processing data, Cuttle Fish optimized Gated Recurrent Unit (GRU) is used for the prediction of heart diseases from the patients.

3.6. Proposed model designs

As mentioned in Section 3.1.2, the simple cuttlefish methods are utilized to maximize the weight of GRU's dense networks. The main phrase employed in this instance for maximizing the weights and concealed layers of GRU is the cuttlefish reflection method. The GRU trained network receives a random selection of these hyperparameters at first. Equation (14) looks after the Fitness Functions (FFs) for the proposed network. Hyperparameters are determined for each iteration using Equation (15). Whenever the fitness function and Equation (9) agree, iteration ends.

$$Fitness\ Function = Average\{Max(Accuracy) + Max(Precision) + Max(Recall) \tag{14}$$

The suggested classification layer quickly and efficiently distinguishes between normal and cardiac disease after the input weights have been optimized by cuttlefish method. Algorithm 1 presents the proposed classification layers' operational mechanism. **Table 3** uses the specification of the training the proposed model. Hence the Modified GRU is used to extract the R-R intervals followed by the Cuttlefish Optimized Dense Classifier networks for an effective prediction of the heart diseases.

Algorithm 1 Pseudo Code for the Suggested Framework

1: Input: Bias weights, concealed layers, Epochs, rate of learning
2: Output: Prediction of Normal/Heart Diseases
3: Bias weights, concealed layers, epochs, as well as learning rate should be assigned at random.
4: Set the three parameters
5: Start the While loop
6: Use Equation (5) for calculating the result obtained from GRU cells.
7: Apply Equation (13) to FF to determine it.
8: Start the loop from 1 to maxi. Iteration
9: Bias weights and input levels should be assigned using Equations (11) and (12).
10: Utilizing Equation (14), determine fitness function.
11: Check for FF is equal to threshold
12: Go to step No. 17
13: Otherwise
14: Go to step no. 08
15: Halt
16: Halt
17: Check for output less than 1
18: # Normal is evaluated #
19: Otherwise check for output less than 2 and o greater than 1
20: # disease 1 is evaluated #
21: Otherwise check for output less than 3 and o greater than 2
22: # disease 2 is evaluated #
23: Halt
24: Go to step 09
25: Halt
26: Halt
27: Halt

Table 3. Optimized training parameters.

S. No	Parameters	Optimized parameters
01	No of Epochs	150
02	Learning Rate	100%
03	No of batches	30
04	Optimization Iterations	25
05	No of hidden nodes	100

3.7. Security algorithm

The complete Encryption process is detailed in the preceding section. To eradicate the complexity in employing the matrix in encryption technique, first byte's location of predicted inputs is taken into the consideration. Initially, logistic maps are generated randomly as mentioned by Sarosh et al.[25]. The generated logistic maps are used to form the AES (advanced encryption Schemes) with the two S-boxes. The intermediate S-box is formulated using the 3D logistic maps (I) and predicted results (K). The permutations and diffusions are adopted to produce the secured intermediate. S1-Box sequences. The formulation of S1 is depicted in Algorithm 2.

$$\text{I}= 3d\ logistic\ maps(X, Y, Z) \text{ for J=1, 2.... L} \quad (15)$$

$$S1 = mod(byte\{(I) permutation\ K(input)\}) \text{ For i = 0, 1, 2, L} \quad (16)$$

where X, Y and Z are the input predicted inputs from the proposed model.

Algorithm 2 Formulation of Intermediate S1-Box

1: Input: Input Sequences of the 3D logistic Maps/Input predicted results K
2: Output: S1-box with size (16X16)
3: Start
4: Generate the Random Sequences as initial conditions for 3d Logistic maps
5: Generate the 3D Logistic maps using Equation (15)
6: Identify the missing values in K sensor bytes and replace it with zeros
7: Rescale the maps and k-bytes to 16
8: Formulate the intermediate S1-box using the Equation (16)
9: End

In the next step, again 3D logistic maps are formulated, this time using the output sequences from the S1-box. The intermediate S2-box is generated using the last bytes of predicted (O) and 3D logistic maps (M). In this formulation, all permutations are adopted to form the new encoding to formulate the light weight and deployable, still possess the powerful defensive characteristics against any attacks. The formulation of S2 is depicted in Algorithm 3.

$$\text{M}= 3d\ logistic\ maps(X, Y, Z) \text{ For J=1, 2.... L} \quad (17)$$

$$S2 = mod(byte\{(M) permutation\ O)(input), 16\}) \text{ For i=0, 1, 2, L} \quad (18)$$

Algorithm 3 Formulation of S2 Intermediate Box

1: Input: Output Sequences from S1-box/Input Sensors bytes
2: Output: Intermediate S2-box (16 × 16)
3: Start
4: Generate the Initial Conditions from the Output sequences of S1-box
5: Generate the 3D logistic maps using the Equation (17)
6: Identify the missing values in O sensor bytes and replace it with zeros
7: Rescale the maps and O-bytes to 16
8: Formulate the intermediate S2-box using the Equation (18)
9: End

Finally, the intermediates are concatenated to formulate the new hybrid s-boxes. After continuing the several time, input data as well as the hybrid S-box keys are then put through with XoR operation and it creates strong encrypted bytes that individually changes at each time. The complete encryption scheme using S-box is illustrated in Algorithm 4.

$$S = S1 - XoR - S2 \quad (19)$$

$$Encrypted\ Data\ Stored = Predicted\ Results(O, K) - XoR - S \quad (20)$$

Finally, the predicted outcomes are communicated to the user using their mobile Application developed in Android SDK.

Algorithm 4 Complete Encryption Process
1: Input: Input Sensor Sequences stored in CPU
2: Output: Encrypted data
3: Start:
4: Split the Data as K and O based on the byte locations
5: Generate the Random sequences for 3D logistic maps
6: Generate the 3D logistic maps using Equation (15)
7: Formulate the Intermediate S1-box
8: Generate the 3D logistic maps using initial conditions from output sequences of S1-box
9: Formulate the Intermediate S2-box
10: S-box(keys)=S1 concatenates S2
11: Encrypted Data=S-box XoR Input Sensor Sequences using Equation (20)
12: End

4. Results and discussions

The specifics of the datasets utilized in the investigational evaluation of the suggested framework are described in this section. The outcomes of the suggested framework are shown, and performance for various iterations is calculated. The outcomes of the suggested prediction system are then given and contrasted with the prior categorization method.

101 labor patients in total were monitored by the sophisticated devices for an average of ten hours. The test was conducted over a period of 30 days, with 150 days chosen at random to serve as a sample period for testing. 54 of the 101 patients in labor are antepartum, while 57 are at the intrapartum stage. Test results for the entire test bed have been gathered and saved in the AWS (Amazon on Web services) cloud. IoT sensors are implemented using embedded C, and the suggested learning method has been constructed with Python.

The partitioned datasets that were utilized to train as well as to test the network are shown in **Table 4**.

Table 4. Total quantity of data for testing and training.

S.no	Total quantity of data	Train data (%)	Test data (%)
1	9405	70	30

Parameters including "accuracy, sensitivity, specificity, recall and f1-score" are determined to evaluate the effectiveness of the suggested design. Algebraic expressions for the calculation of performance statistics to assess the suggested architecture are shown in **Table 5**.

Table 5. Algebraic expressions for the calculation of performance statistics.

Sl.no	Performance statistics	Algebraic expression
01	Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
02	Sensitivity or recall	$\frac{TP}{TP+FN}\times 100$
03	Specificity	$\frac{TN}{TN + FP}$
04	Precision	$\frac{TN}{TP + FP}$
05	F1-Score	$2 \times \frac{Precison \times Recall}{Precision + Recall}$

TP and TN: "True positive and True negative"; FP and FN: "False positive and False negative".

The proposed classifier's training performance with the optimizers is shown in the **Tables 6** and **7**. The effectiveness in training the current ADAM optimizer in foretelling different output level is shown in the **Table 6**. For 50 and 100 epochs, respectively, CNN performs between 80.5% and 84.5% with ADAM optimizer. According to the **Table 7**, CNN with an SGD base has achieved the lowest achievement (75.5% and 77.5%). Additionally, it is clear from the **Table 8** that the proposed approach has provided results with 96.5% accuracy over 100 epochs and 90.5% accuracy over 50 epochs. As a result, the new technique outperforms existing optimizers and finds use in the prediction of maternal and fetes status.

Table 6. Effectiveness of the suggested approach with the current CNN ADAM optimizer.

No of epochs	Sample size	Performance statistics (%)				
		Accuracy	Precision	Recall	Specificity	F1-score
50	30	80.5%	80.6%	81%	80.5%	80.2%
100	30	84.5%	84.3%	82.5%	81.4%	80.4%

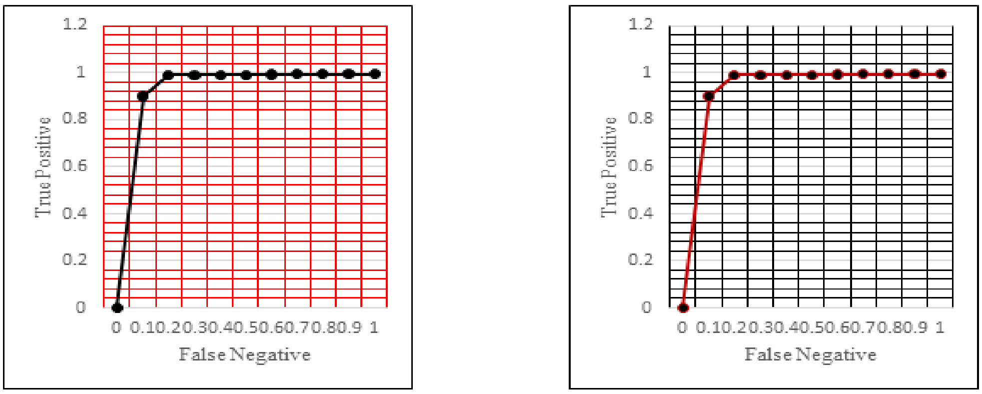
Table 7. Effectiveness of the suggested approach with Existing SGD optimizer in CNN.

No of epochs	Sample size	Performance statistics (%)				
		Accuracy	Precision	Recall	Specificity	F1-score
50	30	75.5%	70.6%	75%	74.5%	74.3%
100	30	77.5%	76.5%	75.5%	74.5%	75.3%

Table 8. Effectiveness of the suggested approach with suggested optimizer in CNN.

No of epochs	Sample size	Performance statistics (%)				
		Accuracy	Precision	Recall	Specificity	F1-score
50	30	90.5%	89.5%	88.45%	88.56%	88.6%
100	30	96.5%	95.5%	96.4%	96.0%	96.36%

The suggested algorithm's Receiver Operating Characteristics (ROC) for identifying normal and abnormal maternal and fetes conditions are shown in the **Figure 4**. According to the figures, the suggested algorithm's AUC (Area under curve) values are 0.934 and 0.95, respectively, making it suitable for identifying the usual and unusual condition of maternal along with fetes.



(a) **(b)**

Figure 4. (a) Normal **(b)** Abnormal.

Figures 5–7 demonstrate the validation curve for the proposed framework under different iterations. From these figures, it is clear that the proposed framework performance is better in terms of validation curve. To prove the superiority of the proposed model we evaluated the prediction system with several existing learning models, including existing GRU[26], PSO-GRU[27], and LSTM[28], 1D-CNN[29], K-Nearest Neighborhood[30] and Naïve Bayes[31], to demonstrate the superiority of the proposed approach.

Figures 8 and **9** illustrate how well the various learning models predict both maternal and fetal conditions. The suggested method has demonstrated the best performance in predicting the normal as well as abnormal condition of maternal along with fetes in each scenario (96.5% Accuracy, 96% Precision, and 96 % Recall, 96.5% F1-score, and 96.2% Specificity). The suggested framework outperformed 1D-CNN in terms of performance, although only marginally. The least accurate methods for predicting either normal or abnormal status are Nave Bayes and K-NN. In addition, it is clear that the suggested method has done better than other learning systems that are currently in use at predicting the various maternal and fetes statuses.

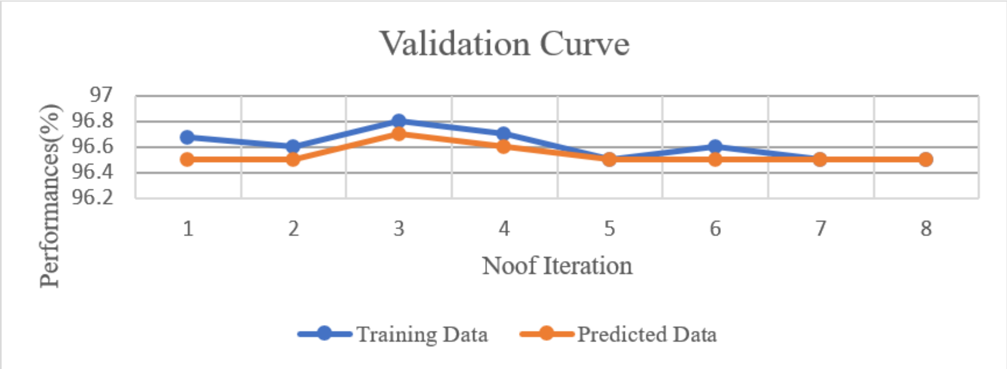


Figure 5. Validating performance in predicting the normal value for the suggested architecture.

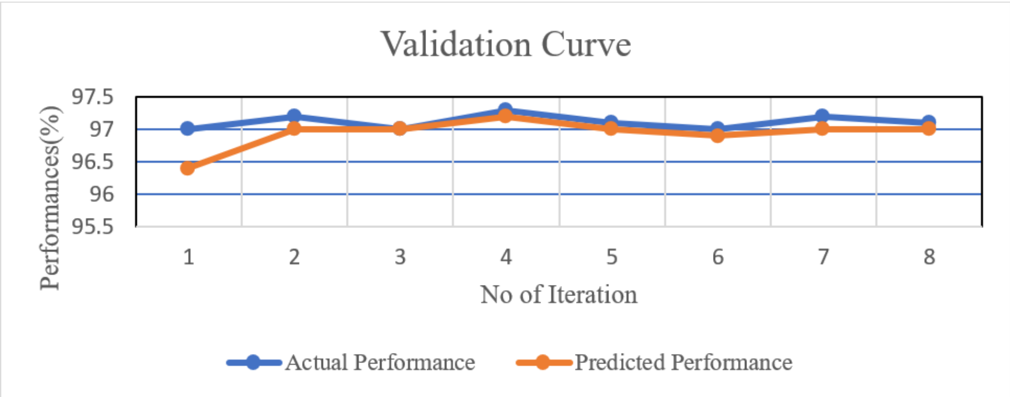


Figure 6. Efficacy in predicting the abnormal value for the suggested architecture.

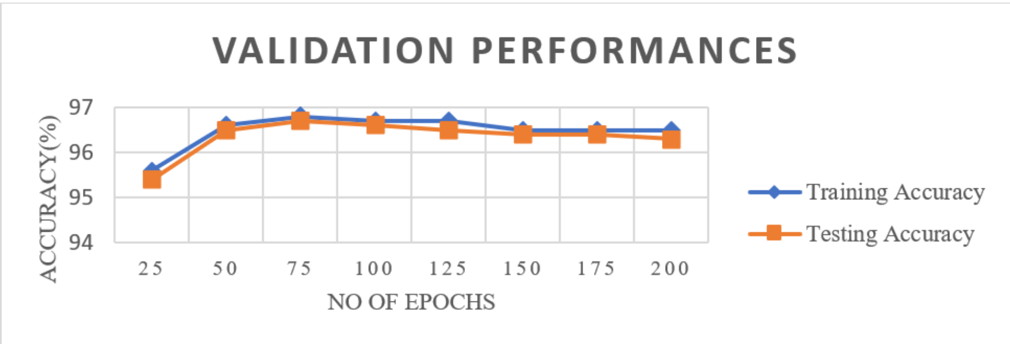


Figure 7. Validation Performance of the proposed model for the different Epochs.

Figure 8. Comparative evaluation of the abilities of several algorithms to identify normal conditions.

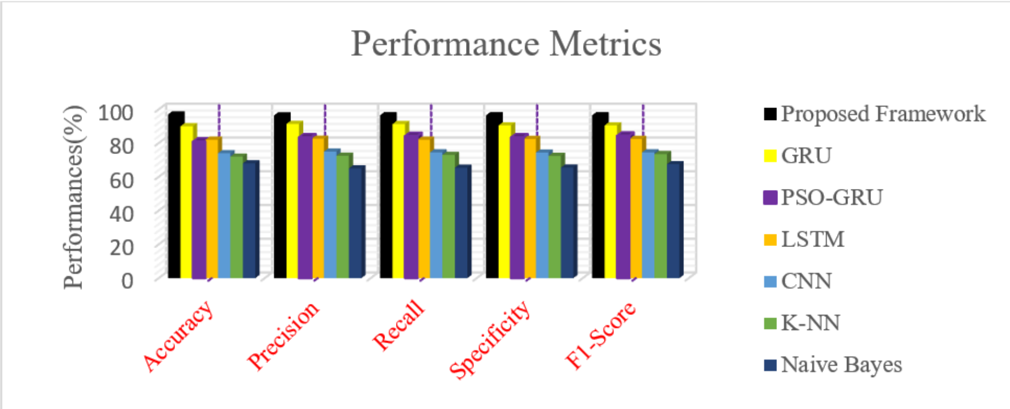


Figure 9. Comparative evaluation of the abilities of several algorithms to identify abnormal conditions.

4.1. Security analysis

To test the randomness of the output bits, NIST statistical investigations were conducted for the proposed encryption scheme. All the test results satisfied the NIST criteria and proved its randomness strength which can defend against any attacks in the networks. **Table 9** presents the complete performance of the suggested algorithm in NIST standard tests.

Table 9. Performance of the suggested algorithm in NIST standard tests.

S. No	NIST test specification	Status of test
1	DFT Test	PASS
2	Run Test	PASS
3	Long Run Test	PASS
4	Frequency Test	PASS
5	Block Frequency Test	PASS
6	Frequency Monotheist	PASS
7	Overlapping Template of all One's test	PASS
8	Linear Complexity Test	PASS
9	Matrix Rank Test	PASS
10	Lempel-ZIV Compression Test	PASS
11	Random Excursion Test	PASS
12	Universal Statistical Test	PASS

5. Conclusion

The hybrid solutions for high-risk continuous surveillance of mothers and babies are presented in this study. It is built on an IoT sensor and device networks and an artificial intelligence system that is cloud-centric and secure. For an effective prediction of maternal and fetes status, Cuttle fish optimized GRU networks suggested. Numerous experiments have been conducted utilizing various classifiers and predictors on around 12,400 real-time data points. The outcomes demonstrate that the suggested classifier has demonstrated effectiveness in predicting the various maternal and fetes statuses, which qualifies it for apps centered on the cloud that will improve diagnostic tools. Furthermore, the performance was taken as satisfactory by the medical specialists for an effective implementation of monitoring and diagnosis system. The technology will be extensively used in clinical practice in future works, which will provide further information. It is important to address performance and security issues including privacy of information and fault tolerance. In order to compare performance, different AI strategies need be taken into account for the categorization module.

We want to capture diverse bio-signals successfully in the future using contactless cameras and other video processing techniques. Furthermore, we intend to train the existing model using deep learning on as many pregnant instances as feasible. This will considerably improve the system’s accuracy and efficiency.

Author contributions

Conceptualization, SA and RA; methodology, SA; software, RA; validation, SA, RA; formal analysis, SA; investigation, SA; resources, SA; data curation, SA; writing—original draft preparation, SA; writing—review and editing, SA; visualization, SA; supervision, SA; project administration, SA; funding acquisition, RA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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