DESIGN OF A NOVEL FUZZY INFERENCE CONVOLUTIONAL NEURAL NETWORK (FICNN) BASED MATERNAL AND EMBRYO RISK ASSESSMENT SYSTEM FOR FECG AND USG SIGNALS

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Abstract:
Objectives: To design an intelligent system to identify the eight different risk factors to determine the state of the maternal and embryo health. Methods: A hybrid approach namely Improved Genetic Ant Lion Optimization (IGALO) which combines Genetic selection operator such as tournament and Ant Lion Optimization is proposed for optimal feature selection in the process of Maternal and embryo risk factor classification. A novel strategy has been proposed to explore the potential benefits of combining Deep Learning (DL) with fuzzy-based fusion techniques. Specifically, introduce fuzzy layers to the DL architecture. Finally, on the basis of training details, a proposed FICNN classifier identifies a class of data. Findings: For the purposes of experimentation, the simulation of the proposed FICNN classifier utilizes fine pre-trained datasets. Based on metrics, such as Accuracy, TPR, TNR, PPV, NPV, HM, Kappa, AUC, PRAUC, LogLoss, Detection Rate, Prevalence, Detection Prevalence and Balanced Accuracy, the results of the proposed FICNN classifier are assessed. The results obtained affirm the utility of FICNN to classify records within maternal and embryo surveillance systems that are computer-aided. Novelty: Our results suggest that the system is able to predict risk factors during the maternal delivery and then it gives the best accuracy by the proposed technique as Fuzzy Inference Convolutional Neural Network (FICNN) is very useful to reduce the maternal and embryo morality. The proposed technique achieved better classification performance classified the risk factors with Accuracy, TPR and TNR of 98.89, 100 and 98.77 for D1 also same equivalent Accuracy, TPR and TNR achieved by the other seven risk factors such as Caesarean, Hypoxia, Indication of childbirth, Diabetes, Preeclampsia, Hypertension, Meconium, respectively being highly adaptable to different laboratory settings, and easy integration into clinical practice.

Keywords: FECG, USG, Meta-heuristics, Fuzzy Layer, Convolutional Neural Network, Performance Metrics.

1. Introduction

In the lack of additional health benefits with FECG upon admission, Owing to higher cost on machinery and materials, as well as the excessive use of the Cesarean Part and cascade of others procedures, it is likely to be less cost-effective than an auscultation with a USG system[29]. Labour Care Guide is developed to improve every woman's experience of childbirth, and to help ensure the health and well-being of women and their babies by facilitating the effective implementation of the WHO intrapartum care recommendations [30]. Fetal Electrocardiography (FECG) and Ultrasound Sonography (USG) includes the regulation of Fetal Heart Rate (FHR; bpm) and Uterine Contractions (UC; mmHg). A computerized method to assist clinicians is a potential solution to improve accuracy in the interpretation of FECG [1] and also that makes it more comprehensive, objective and independent of clinician experience in order to improve the precision of the FECG study. The sporadic Auscultation (IA) with a strict FECG or USG handheld device observing may raise the finding of FHR abnormalities which in turn, may decrease the risk of fetal heart rate. However, the party has decided that regulation of protocols was essential for the preparation of health care and medical-legal purposes [29]. Recent developments in machine learning, deep learning and fuzzy rule-based

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classification system might allow new relationships to be formed using large scale datasets between fetal heart rate characteristics and clinical outcomes [21]. ANFIS was applied source the FECG signal from two ECG signals verified in the thoracic and abdominal areas of the mother's skin. However the fuzzy method was more suitable to clarify the problem of pathological and normal fetal conditions and to include a qualitative analysis of FHR patterns [2]. The clinical study of the fetal heart rate trace is a challenge and is limited by the inability to represent uncertainty. The fuzzy logic system has improved and achieved the optimum overall efficiency of the crisp method [28].

1.2. Motivation and Justification

The main motivation of doing this research is to present a maternal and embryo prediction model using the optimized deep learning classification algorithms for the best prediction of embryo risk occurrence. Further, this research work is aimed towards identifying the best evolutionary based FICNN classification algorithm for identifying the possibility of embryo risk assessment in a maternal patient. The major contributions to the paper are as follows: i) An improved tournament based Evolutionary algorithm namely “Improved Genetic based Ant Lion Optimization (IGALO)” Algorithm which helps to achieve better classification accuracy with reduced set of features is proposed. ii) The proposed evolutionary algorithm is implemented and tested with 23 benchmark objective functions such as Unimodal, Multimodal and Fixed Dimensional Multimodal functions. iii) In addition to the proposed improved method, an attribute selection method is executed and the common attributes are identified is given into the proposed evolutionary algorithm and is evaluated using proposed optimized “Fuzzy Inference Convolutional Neural Network (FICNN)” classifier. iv) The time complexity of the test process of deep learning algorithms can be greatly reduced by fuzzy techniques, reducing the workload of deep learning algorithms.

2. Related Works

The ANN-based method for designing the FHR Fuzzy Membership Function (FMF) is introduced in the Fuzzy Unordered Rule Induction Algorithm and used towards describes the CTG (FURIA). The results attained suggest a significant enhancement in the classification of non-FMF [7]. Rough set approximations are exploited in extracting the uncertain information from the data set. The result reveals the importance of useful information present in the uncertain data during classification. In this paper, the overall highest accuracy is displayed by Random Forest classifier with 99.57% and a tree-based approach has shown its supremacy over other approaches [15]. Despite the different tools used, this study shows good accuracies in random forest, naïve Bayes of complete and reduced features (R-ML techniques), whereas naive Bayes, bagging and boosting are found to be showing good accuracies in reduced features (Python-ML techniques) with an accuracy of 91.88%–100% [25]. This shows that Fuzzy Logic System can be used to increase the efficiency of the clinician's position in precise diagnosis [27]. The results demonstrated the potential to support the FHR fetal assessment process by applying heuristic rules of inference to fuzzy signal processing algorithms [6]. The results show that the accuracy value, average F1 value and Area Under the Curve (AUC) value were 92.64 %, 92.01 % and 0.990 respectively in the external public data set, and were 91.64 %, 88.92 % and 0.9493 respectively in the internal private data set, which were the most excellent among all comparison models [31].

In order to track fetal health, cascade architectures of fuzzy neural networks can be implemented using cardiotocography data at a reasonable rate of classification [11]. The FECG portion of the maternal abdominal footage and the position maternal thoracic electrocardiogram (MECG) signal is extracted from the fluffy presumption of the counterfeit structure of the neural system (ANFIS). [20]. In order to evaluate the CTG [8], we are also seeking to involve clinicians with a distinct level of expertise. Based on the their latest review they conclude that combining different techniques and creating hybrid systems for FECG extraction might be the most promising direction in reaching an accurate fetal heart rate estimation [14].

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The swarm size has an effect on the accuracy of the prediction when it is increased. The obtained result showed that classification accuracy has been enhanced it was (81.843%) with all feature (21 feature) while subset selecting (8 feature) the result became (86.547%) [18]. The 4 feature selection methods have been applied (Correlation-based, Symmetrical Uncertainty, ReliefF, Information Gain, Chi-Square), and 4 classification algorithms such as Jrip, J48, KNN, NB have been used for enhancing the cardiotocography classification performance. The accuracy was found to be in a range of 86.78% to 98.73 % [3, 23]. In another study, the random forest using all features from SMOTE data shows specificity and sensitivity of 93% and 92% respectively. Similarly, the random forest using RFE from SMOTE data showed 90.79% and 91.35% respectively [24].

The highest accuracy of all scenarios is obtained by the Random Forest algorithm with Info Gain Feature Selection. The combination of these models produces accuracy with a percentage of 93.74% [21]. The non-fuzzy score of STV is then 0. But for the fuzzy scoring system, we could have observed that the membership value to the range [0, 6) was 0.5153 and to [6, 14) was 0.4844. Therefore, the total fuzzy score was equal to 0.9689 points [4]. On that basis two parameters describing the performance of classification were calculated. The results were as follows: SE = 51,85%, SP = 55,75% [22]. The rules were created basing on a new fuzzy clustering method. The achieved classification error at the level below 21% and sensitivity equal to 77% seem to be encouraging [12]. An evolutionary multi-objective genetic algorithm (MOGA) for extracting important factors causing fetal death by cardiotocographic analysis of fetal evaluation. Seven existing classification models are used to test its efficiency concerning fetal health classification in the dataset of most relevant features [19]. When evaluating the single recordings using the Apgar score the modified criteria provided the best classification results (SE = 100%, QI = 78.9%) [5]. The findings obtained show that the automated fetal state evaluation has increased efficiency in agreement with the position measures applied, fuzzy (c + p)-means clustering and Lagrangian support vector machines [13, 24]. Compared to conventional machine learning algorithms, the proposed algorithm was found to be as accurate as visual estimation.

Study of the effectiveness of FICNN algorithms against different metrics (Accuracy, TPR, TNR, PPV, NPV, HM, Kappa, AUC, PRAUC, LogLoss, Detection Rate, Prevalence, Detection Prevalence and Balanced Accuracy).The further work of the paper is prepared as: The dataset description and the preprocessing, feature extraction are explained in Section 3. For details in Section 4, the feature selection and proposed methods are explained, and in the Section 5 details about the deep learning and fuzzy approaches used for the proposed work are explained. The effects of experimentation, accompanied by the hypothesis and possible work in Section 6, are discussed in Section 7.

3. Materials and Methods

This work introduces the proposal and training of an innovative hybrid network architecture based on selected features using the proposed IGALO evolutionary algorithm then the input as fuzzy rules, ResNet50 architecture and a layer of convolutional neural network returns the output as shown in (Figure 1). Technically, the proposed FICNN algorithm anywhere within the DL architecture, a fuzzy layer may be mounted as long as it parallels the input layer and precedes the output layer.

3.1. Dataset Description

The CTU-UHB PhysioNet (https://physionet.org/content/ctu-uhb-ctgdb/1.0.0/), which has 552 raw signals but including latent class it has totally 634 records, is considered as a dataset of FECG and USG. Consisting of 634 records, the CTU-UHB database [3] is a subset of 9164 intrapartum FECG and USG records acquired between 2009 and 2012 at the UH in Brno, Czech Republic. The STAN and the Avalon instruments have been used to record FECG and USG. The scalp electrode (FECG 102 records), the ultrasound probe (USG 412 records) or a combination of the two is obtained (35 records).

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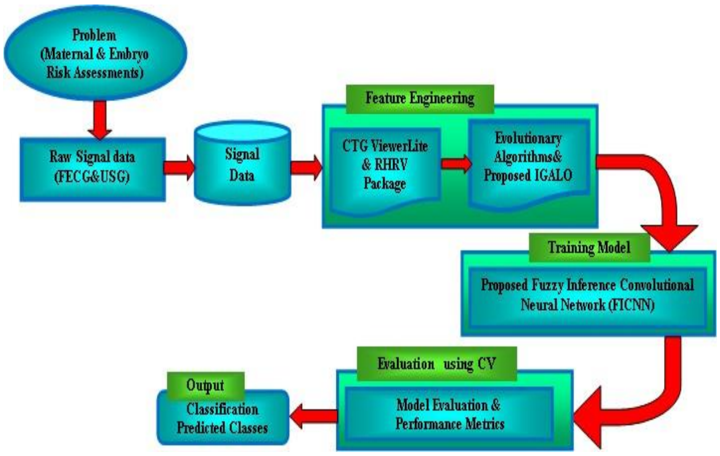

Figure 1. Overall Block Diagram for the Maternal & Embryo Risk Assessment

3.2. Pre-processing

In order to increase FECG and USG signal quality, as well as artifacts, missing beats are removed to get better findings caused by maternal and embryo movements. Signals are ready to be examined after the preprocessing stage and then the feature engineering has done to extract and improve the features with the reduced important features set to predict the maternal and embryo risk assessments.

3.3. Feature Extraction

Feature extraction is the great importance for signal representation. These characteristics are contrasted before and after the pre-processing process by visualizing all the changes made during the pre-processing process. Features are extracted using CTG ViewerLite, the latest Apgar rating, maternal age, sex, umbilical artery pH, base excess (BE) software has become an appreciated resource for FHR and UC signal classification (BDecf). In addition to the fact that some important relevant features are extracted they are morphological characteristics such by means of the baseline amount of ACC and DEC patterns and STV of the computed FHR and UC analysis, non-linear, time domain and frequency domain.

4. Feature Selection using Evolutionary Algorithm

Feature selection is substantially important in machine learning, deep learning, pattern classification, information retrieval, data analysis, and data mining applications. Utilized impressive classification results with classifier alone; during the method does well for a dataset which does not have many features and classification works using many features were yonder their consideration. The classification procedure with FS includes the input variable and the final output variable is the pattern of classification based on features that selected from the previous feature selection process

4.1. Ant Lion Optimizer

An ant lion optimization algorithm is a heuristic optimization algorithm inspired by the larval ant lion hunting techniques. While the antlion are larvae, they form a conical shape trap by drawing a circular path where the ants are located, and they ait for the ants at underneath of the conical shape trap. When the ants enter the trap, the ant lions start throwing sand in order to prevent the escape ants and slide them to the bottom of trap [26]. At last the ants are swallowed by the big jaws of the ants that they have moved to the bottom of the trap. After every hunting that has developed in this way, antlion make their trap ready for a new hunt.

This interesting hunting mechanism begins with random walks mathematically modeled as follows:

$$X(t) = \begin{bmatrix} 0 \\ cumsum(2r(t_1) - 1) \\ cumsum(2r(t_2) - 1) \\ \vdots \\ cumsum(2r(t_n) - 1) \end{bmatrix} \quad .. (1)$$

where n maximum iteration number, t is the step of random walk, cumsum is cumulative sum and r(t) is the stochastic function given below.

$$r(t) = \begin{cases} 1 & if rand > 0.5 \\ 0 & if rand \leq 0.5 \end{cases} \quad .. (2)$$

To keep the ants that start randomly walking in search space, you need to normalize these walks with the following formula:

$$X_i^t = \frac{(X_i^t - a_i)(d_i^t - c_i^t)}{b_i - a_i} + c_i \quad .. (3)$$

where i is the variable number, t is the iteration number, a is minimum random walk, b is maximum random walk, c and d are the minimum and maximum values of the antlion positions, respectively, updated in each iteration. The walks of ants are naturally affected by ant lions. When the ant

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enters the trap, the ant lion starts throwing sand to pull the trap down. Let i is the sliding ratio, and its mathematical model as follows:

$$c_i^t = Antlion_j^t + c^t \quad .. (4)$$

$$d_i^t = Antlion_j^t + d^t \quad .. (5)$$

$$c^t = \frac{c^t}{I} \quad .. (6)$$

$$d^t = \frac{d^t}{I} \quad .. (7)$$

The $_i$ sliding rate here increases during optimization process. The ants walk around the elite antlion and antlion selected by the roulette wheel. Thus the new positions of the ants can be found with the following equation:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad .. (8)$$

where Ant_i^t is t - th iteration i - th ant. When the ant lion eats the ants that slide into the pit, it updates the position. It is explained by the following mathematical expression.

$$Antlion_j^t = Ant_i^t iff(Ant_i^t) < f(Antlion_j^t) \quad .. (9)$$

where $Antlion_i^t$ is t -th iteration j -th antlion, Ant_i^t is t -th iteration i - th ant.

4.2. Improved Genetic Based Ant Lion Optimization Algorithm

In the original antlion optimization algorithm, the antlion which is selected by the roulette wheel method was not random but always first index taken in the negative fitness values. This problem solved by the using tournament selection. The selection of roulette wheel gives the fitness values of all the individuals and then each person is put on a wheel based on the percentage value of the total fitness sum. On the tournament, it is chosen two random individuals and chooses the most appropriate individual among them, even in the worst case scenario, the second lowest matching individual participates in the mating pool.

The Ant Lion Optimizer (ALO) algorithm mimics the hunting mechanism of antlion in nature. Five main steps of hunting prey such as the random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building traps are implemented. Tournament selection is a variant of rank-based selection methods. Its principle consists

Input: Total number of ants and antlions, and number of Iterations (T_{max}).
Output: The elitist antlion and the corresponding fitness value.
Initialization: Initialize the random positons of all agents $x_i(i=1,2,\dots,n)$ inside $_{up}$ and $_{low}$ bounds.
Calculate the fitness of ants and antlions
Select and find the best antlions as the elite (determined optimum).
While (end condition is not met) do
for(each ant_i) do
Update Ants Position:
Select an antlion using Tournament.
Then update ants position based on random walk around selected antlion and elite. Furthermore, calculate the fitness of all ants.
Update the fitness value elite if an antlion becomes fitter than the elite
Merge all ants and sort them based on the fitness metric and return the elite as the optimal solution for given problem.
Update the elite ants Position steps if an antlion is better than the elite agent.

in randomly selecting a set of k individuals [16]. These individuals are then ranked according to their relative fitness and the fittest individual is selected for reproduction. In the equations (4-7) in 4.4, the ants slide by sliding ratio of i to feed the antlion. After that, the antlion position is being updated. This update process is constructed with the following mathematical model by randomly changing option parameter. This model updates the ant lion's position according to the state of the ants in the trap. The whole process is repeated n times for the entire population. In order to find the optimal solution, the implementation of IGALO can be performed according to the pseudo-code algorithm:

$$\left.\begin{aligned} c_i^t &= Antlion_j^t + c^t \\ d_i^t &= Antlion_j^t + d^t \end{aligned}\right\} if\ option > 0.75 \quad .. (10)$$

$$\left.\begin{aligned} c_i^t &= Antlion_j^t - c^t \\ d_i^t &= Antlion_j^t - d^t \end{aligned}\right\} if\ option > 0.5 \quad .. (11)$$

$$\left.\begin{aligned} c_i^t &= -Antlion_j^t + c^t \\ d_i^t &= -Antlion_j^t + d^t \end{aligned}\right\} if\ option > 0.25 \quad .. (12)$$

$$\left.\begin{aligned} c_i^t &= -Antlion_j^t - c^t \\ d_i^t &= -Antlion_j^t - d^t \end{aligned}\right\} if\ option > otherwise \quad ..(13)$$

Unlike the original antlion optimization algorithm, the following mathematical expression is used to prevent the ants from escaping the search space boundaries.

$$Ant_i^t = \kappa\ if(Ant_i^t > b_{up})OR(Ant_i^t < b_{low}) \quad ..(14)$$

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where κ allows the ants out of the border to stay in the search space at random and can be expressed mathematically as follows

$$\kappa = b_{low} + rand \times (b_{up} - b_{low}) \quad ..(15)$$

where rand is random number in [0,1] interval, b_{low} lower bound, b_{up} upper bound. In the original antlion optimization algorithm, ant and antlion populations are grouped together according to their cost value and are regarded as antlion by taking as much as the population size, regardless of whether they are ants or antlion. In the proposed algorithm, the cost sorting process is removed and if the cost values of the ants are better than the antlion, they are replaced by the antlion for each ant-antlion pair. This means ants have been consumed by antlion.

5. Classification

In this study, an end-to-end classification strategy is based on previous studies is carried out using the CNN and fuzzy rule-based system to determine the maternal and embryo state that has the ability to self-learn the useful characteristics of the FHR and UC input signals.

5.1. Fuzzy Rule-Based Classification System

As depicted in Figure 2, the primary segments of fuzzy logic are: (1) Fuzzification which is the process of translating crisp inputs into fuzzy values, (2) Rule base reasoning which is the process of applying a fuzzy reasoning mechanism to get a fuzzy yield by fuzzy rule utilization, and (3) Defuzzification which is the process of translating the latter output into a crisp value [23].

5.1.1. Fuzzification

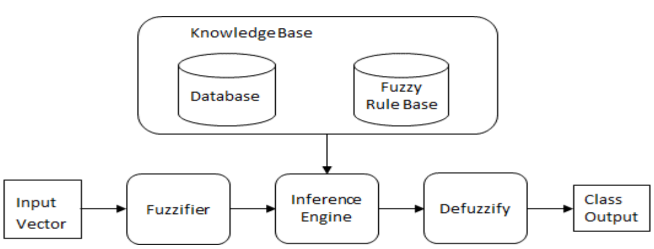

Figure 2. Modified diagram of a Mamdani-FRBS (Fuzzy Rule Based System)

The main purpose of fuzzification is selecting a membership function for transforming numerical valued inputs into corresponding membership values. Every input value may have one membership value corresponding to each linguistic set. The input is always characterized as a crisp value which is restricted by cosmos of the input variable and the output is a fuzzy membership degree in the appropriate linguistic set(s).

5.1.1.1. Types of fuzzy sets: Membership function

There are five shapes of membership functions implemented, namely TRIANGLE, TRAPEZOID, GAUSSIAN, SIGMOID, and BELL. They are represented by a matrix that the dimension is (5, n) where n is a multiplication the number of linguistic terms/labels and the number of input variables. The rows of the matrix represent: GAUSSIAN has two parameters (mean and variance).

- This is the typical Gauss bell, defined by its mid value m and the value of σ > 0. The smaller σ is, the narrower the bell.

$$G(X) = exp\left[\frac{-(x-m)^2}{2\sigma^2}\right] \quad ..(16)$$

5.1.2. Rule Base

Fuzzy rule-based systems for control problems can be viewed as approximates of nonlinear mappings from non-fuzzy input vectors to non-fuzzy output values. Many approaches have been proposed for generating and learning fuzzy IF–THEN rules from numerical data for classification problems. Fuzzy IF–THEN rules with certainty grades are also used for our classification problem:

Rule R_j: If y_1 is L_{j1}….and $y_m$is L_{jm} then Class C_j with CF_j, j=1, 2, 3… N .. (17)

where y= (y_1,……y_m) m- dimensional feature vector, L_{ji} is the linguistic value, $C_j$is Consequent class, $CF_j$is certainty grade and N is the number of fuzzy rules. This mapping process provides the basis from which the inference or conclusion can be made. Features identified by the crisp system are fuzzified and assessed using new rule sets. The fuzzy rules can be written as (Table .1):

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Table 1. Evaluation of individual Embryo FHR parameters

Parameter	FHR (bpm)	Range (bpm)	Decelerations	Accelerations
Normal	110–160	≥ 5	none1	sporadic2
Suspicious	100–109 161–180	< 5 ≥ 40 minutes > 25	Early/variable dec. individual prolonged dec. up to 3minutes	present, periodical occurrence (with every contraction)
Pathological	< 110 > 180 sinusoidal3	< 5 > 90minutes	A typical variable dec. late dec. isolated prolonged dec. > 3 minutes	absent > 40minutes (significance still unclear, evaluation questionable)

- FHR = {110-160 small, 100-109 medium, <110 and >180 large}
- Decelerations (DEC) = {small, medium, large}
- Acceleration (AC) = {small, medium, large}
- A (pH) = {small, medium, large}

Fuzzy Rules:

```
$rule
     [,1] [,2]  [,3] [,4]     [,5]  [,6]
[,7] [,8]     [,9]  [,10] [,11] [,12]
[1,] "IF" "FHR" "is" "small" "and" "AC"
"is" "small" "and" "DC"  "is"  "small"
[2,] "IF" "FHR" "is" "small" "and" "AC"
"is" "small" "and" "DC"  "is"  "small"
[3,] "IF" "FHR" "is" "small" "and" "AC"
"is" "small" "and" "DC"  "is"  "small"
[4,] "IF" "FHR" "is" "small" "and" "AC"
"is" "small" "and" "DC"  "is"  "small"
[5,] "IF" "FHR" "is" "small" "and" "AC"
"is" "small" "and" "DC"  "is"  "small"
[6,] "IF" "FHR" "is" "small" "and" "AC"
"is" "small" "and" "DC"  "is"  "small"
     [,13] [,14] [,15] [,16]    [,17]
[,18] [,19] [,20]
[1,] "and" "A"   "is"  "small"  "THEN"
"C"   "is"  "1"
[2,] "and" "A"   "is"  "small"  "THEN"
"C"   "is"  "2"
[3,] "and" "A"   "is"  "medium" "THEN"
"C"   "is"  "1"
[4,] "and" "A"   "is"  "medium" "THEN"
"C"   "is"  "3"
[5,] "and" "A"   "is"  "medium" "THEN"
"C"   "is"  "2"
[6,] "and" "A"    "is"  "small"  "THEN"
"C"   "is"  "3"
```

A fuzzy rule set with crisp input provides overall classification based on the fuzzy variables Baseline, Variability, Accelerations, Deceleration and pH Class. The Final crisp output set as:

Classification output= {Normal, Suspicious, Pathological}

Matching degree, that is, the strength of activation of the if-part for all rules in the RB with the pattern x_p. To compute it we employ a product or minimum T-norm.

$$\mu_{A_j}(X_p)=T(\mu_{A_{j1}}(X_{P1}),\dots,\mu_{A_{jn}}(X_{Pn})),\quad j=1,\dots,L. \quad (18)$$

Classifications apply a decision function F over the soundness degree of the system for the pattern classification for all classes. This function will determine the class label l corresponding to the maximum value.

$$F(Y_1,\dots,Y_M)=\arg\max \arg\max_{k=1,\dots,M}(Y_K)$$

5.1.3. Fuzzy Inference Engine:

type.tnorm a value which represents the type of t-norm to be used:

- 1 or MIN means standard t-norm: $\min(x_1, x_2)$.
- 2 or HAMACHER means Hamacher product: $(x_1 * x_2)/(x_1 + x_2 - x_1 * x_2)$.
- 3 or YAGER means Yager class: $1 - \min(1,((1 - x_1) + (1 - x_2)))$.
- 4 or PRODUCT means product: $(x_1 * x_2)$.
- 5 or BOUNDED means bounded product: $\max(0, x_1 + x_2 - 1)$.

type.snorm a value which represents the type of s-norm to be used:

- 1 or MAX means standard s-norm: $\max(x_1, x_2)$.

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- 2 or HAMACHER means Hamacher sum:
  $(x_1 + x_2 - 2x_1 * x_2)/1 - x_1 * x_2$.
- 3 or YAGER means Yager class:
  $\min(1,(x_1 + x_2))$.
- 4 or SUM means sum:
  $(x_1 + x_2 - x_1 * x_2)$.
- 5 or BOUNDED means bounded sum:
  $\min(1, x_1 + x_2)$.

5.1.4. Defuzzification

Defuzzification is a process in which a quantifiable result in crisp logic is produced for a given fuzzy set and the corresponding membership degrees. Max-membership, mean-max, centroid method, center of largest area, and center of sums are some defuzzification approaches.type.defuz the type of defuzzification to be used as follows:

- 1 or WAM means weighted average method,
- 2 or FIRST.MAX means first maxima,
- 3 or LAST.MAX means last maxima,
- 4 or MEAN.MAX means mean maxima,
- 5 or COG means modified center of gravity (COG).

The fuzzy electrocardiogram model is a system for managing the sequences of events during the course of labor based on finite state machine principles and also adds memory to the model. This is an important feature of the model, since there are many cases during labor in which previous events and their series are told by the expert analysis of the electrocardiogram. The database is initially converted to a probabilistic index table, where data and attributes are represented in rows and columns. Then, the degree of membership of the unique symbols presentin each data attribute is found.

5.2. Convolutional Neural Network

Convolution is a feature extraction process, which is based on the concept of a receptive field, and is used by many traditional feature extractions. The fully connected part has been replaced by average pooling, which reduces the degree of over fitting and parameters required during training. As depicted in Figure 3, Convolution uses a convolution kernel mask of the sliding window on the input matrix. In each one, there is a collection $f_1$is 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 xth feature map, denote as $O_x^{(m)}$

$$O_x^{(m)} = W_x^{(m)} + \sum_{y=1}^{f_1^{m-1}} P_{x,y}^{(m)} * O_x^{(m-1)} \quad ..(20)$$

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

The purpose of the activation function is to obtain nonlinear outputs for linearly combined networks. However, when the network is deep and the number of layers is high, the sigmoid, which is used in earlier networks, appears and the gradient disappears during back propagation. Therefore, ReLU is used as the activation function in CNN. The definition of ReLU is as follows:

$$R_j^{(m)} = max\left(0, R_j^{(m-1)}\right) \quad .. (21)$$

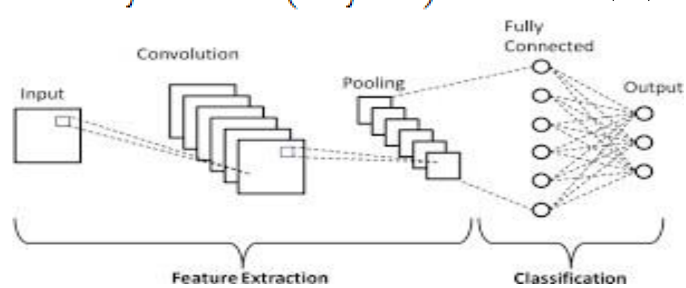

Figure 3. Convolutional Neural Network

After the convolution operation, the input feature map is compressed to simplify network computation complexity. Feature compression is performed to extract main features. Pooling is used to reduce the dimension. Pooling involves using a sliding window mask that operates on the input matrix; however, the mask does not overlap in the moving process. That is, the step is equal to the height of the convolution kernel to enable an N × N mask to reduce $1/N^2$ times of the input feature matrix and thereby reduce the dimension. Finally, the dense layer is used to classify using the fully connected layer using the softmax function. After passing through the fully connected layers, the final layer uses the softmax activation function (instead of

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ReLU) which is used to get probabilities of the input being in a particular class (classification).

5.3. Proposed Fuzzy Inference Convolutional Neural Network (FICNN)

FICNN consists of different layer types such as evolutionary algorithm, ResNet50, Convolutional Layer, Non-Linear Layer, Rectification Layer, Rectified Linear Units (ReLU), Pooling Layer, Fuzzy Layer (FRBCS.W), Dropout Layer and Output Layer. The FRBCS consists of a Knowledge Base (KB) and a Fuzzy Reasoning Method (FRM) that uses KB information to decide the class for any appropriate data pattern which enters the system.

Step 1: The raw training data are fed into IGALO evolutionary algorithm. Labeled training data as with the total number of classes.

Step 2: The reduced feature set is an input into Fuzzy to generate the fuzzy rules. The generated fuzzy rules is fed into the ResNet based CNN architecture.

Step 3: The residual module is a block of two convolution layers with the same number of filters and a small filter size, specifically a model of residual identity in which the output of the second layer is applied to the input of the first convolution layer. The input of the module is drawn as a graph, added to the output of the module and called a shortcut for a relationship.

Step 4: The convolutional layer is used to identify the local combinations of the preceding layer characteristics then to map their presence to a feature map. In a convolutional NN, a non-linearity layer that involves of an activation attribute that proceeds over as production the feature map produced by the produced and provides the activation function.

Step 5: Rectification Layer: The element-wise absolute value operation of the input volume is performed by means of a restructuring layer happen a convolutional neural network. ReLUs are special applications that integrate non-linearity and rectification layers into the Pooling Layer of the Convolutional Neural Network.

Step 6: Pooling Layer is the task of the pooling or down sampling network to reduce the actual dimensions of activation maps.

Step 7: Dropout is a technique used to enhance neural over-fitting with other techniques, such as L2 Regularization, which can be used through Dropout.

Step 8: Completely Connected Layer: In this classification layer instead of softmax method using the fuzzy algorithm for the classification. Because to improve the prediction rate the neural network makes the decision by the training data then using the decision the fuzzy makes the rules using the membership function.

Step 9: In a convolutional network, the completely connected layers are basically activation of the volume of the rule generation algorithm from the grouping of the earlier separate layers to the class likelihood distribution.

Step 10: Finally, the risk factors are predicted using the dense layer as the classification in the CNN. CNN makes the decision and fuzzy makes the rules with the CNN decision by the data.

Add a new layer to deep learning in this work: proposed optimized algorithm IGALO, Fuzzy Layer, Conv layer, pooling layer and fully connected layer, are usually the neural network architecture. In order to exploit the strong aggregation properties expressed by fuzzy methodologies the suggestion for the implementation of fuzzy layers in the deep learning architecture. To date, the implementation of various merger techniques at decision-making level to integrate outputs from state-of-the-art pre-trained models with ResNet-50 followed a fuzzy approach to deep learning, finally proposed a technique is namely called FICNN. Although these techniques have been shown to improve the accuracy of the classification tasks.

6. Experimental Results and Analysis

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This section explains the specifics of dataset description first with the continuation detail description about the parameters used in the implementation. Next, current performance measurements and the effects of the implementation of fuzzy layers in CNN are evaluated for different network configurations.

6.1. Experimental Result 1: Performance Based on Feature Reduction

Feature reduction is an important stage for maternal and embryo risk prediction, because high numbers of features are the great obstacle of the classification.

Table 2. Identification of best performing search evaluation method

Search Method + Fuzzy	No of selected features	Accuracy	Error rate	Elapsed Time
Fuzzy	Full features (46)	77.44	22.56	0.068614
MFO+Fuzzy	13	81.37	18.63	0.050125
DA+Fuzzy	15	79.61	20.39	0.058912
GA+Fuzzy	11	82.37	17.63	0.018628
ALO+Fuzzy	11	82.07	17.92	0.008188
Proposed IGALO+Fuzzy	8	87.25	12.75	0.004135

Table 2 shows the comparative analysis of different dimension reduction approaches. In this proposed approach we used improved tournament based ALO with fuzzy rule based classification system (IGALO+FRBCS) algorithm for feature reduction. When analyzing, using MFO with fuzzy for attributes reduction we obtained 13 attributes out of 45. When we use DA with fuzzy for feature reduction we obtained 15 attributes out of 45. When we using ALO with fuzzy for attributes reduction we obtain the 101attributes out of 45. Using GA with fuzzy based feature reduction approach we obtained 11 attributes. Compared to all the works, our proposed feature reduction approach selects only 8 attributes out of 45.

6.2. Experimental Result 2: Performance of the Proposed Optimization algorithm using Fitness Functions

Various objective functions are implemented for the proposed IGALO and is evaluated using FICNN classifier. The number of attributes selected for various benchmark objective functions together with the classification accuracy was shown in Table 3. For the proposed FICNN, the maximum number iteration is set to 100. The position of antlion (Xi) calculated using the following formula

$$Position(X_i) = rand(n, Dim) * (Upper\ Bound - Lower\ Bound) + Lower\ Bound \quad ..(22)$$

Where n refers to the population size (Number of Instances). In this research work, the

Table 3. Performance of various fitness functions for 45 attributes using proposed IGALO

Sl.No.	Fitness Functions	Range	CTU_UHB Dataset	
			No. of Featur es selecte d	Accuracy (FICNN) (%)
1	$f_1(x) = \sum_{i=1}^{n} x_i^2$	[-100,100]	8	95.60
2	$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-10,10]	**6**	**97.89**
3	$f_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{i} x_j^{\,2})$	[-100,100]	11	92.51
4	$f_4(x) = max_i\{\lvert x_i \rvert, 1 \le i \le n\}$	[-100,100]	19	88.00

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5	$f_5(x) = \sum_{i=1}^{n-1}[100\,(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	[-30,30]	26	75.00
6	$f_6(x) = \sum_{i=1}^{n}([x_i + 0.5])^2$	[-100,100]	31	80.00
7	$f_7(x) = \sum_{i=1}^{n} i x_i^4 + random\,[0,1]$	[1.28,1.28]	19	92.40
8	$f_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	[-500,500]	22	75.00
9	$f_9(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$	[-5.12,5.12]	25	75.00
10	$f_{10}(x) - 20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	[-32,32]	15	90.00
11	$f_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x}{\sqrt{i}}\right) + 1$	[-600,600]	21	85.20
12	$f_{12}(x) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$	[-50,50]	14	83.00
13	$f_{13}(x) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2[1 + sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	[-50,50]	23	89.20
14	$f_{14}(x) = -\sum_{i=1}^{n}\sin(x_i).\left(\sin\left(\frac{i x_i^2}{\pi}\right)\right)^{2m}, \quad m = 10$	[0,	18	92.20
15	$f_{15}(x) = \left[e^{-\sum_{i=1}^{n}(x_{i/\beta})^{2m}} - 2e^{-\sum_{i=1}^{n} x_i^2}\right].\prod_{i=1}^{n} cos^2 x_i, \quad m = 5$	[-20,20]	16	84.00
16	$f_{16}(x) = \left\{\left[\sum_{i=1}^{n}\sin^2(x_i)\right] - \exp\left(-\sum_{i=1}^{n} x_i^2\right)\right\}.exp\left[-\sum_{i=1}^{n} sin^2\sqrt{\lvert x_i \rvert}\right]$	[-10,10]	19	78.32
17	$f_{17}(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10$	[-5,5]	12	89.23
18	$f_{18}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)]$ $* [30 + (2x_1 - 3x_2)^2 * (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	[-2,2]	11	90.20
19	$f_{19}(x) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{3} a_{ij}(x_j - p_{ij})^2\right)$	[1,3]	20	80.00
20	$f_{20}(x) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{6} a_{ij}(x_j - p_{ij})^2\right)$	[0,1]	19	83.33
21	$f_{21}(x) = -\sum_{i=1}^{5}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	[0,10]	21	78.40
22	$f_{22}(x) = -\sum_{i=1}^{7}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	[0,10]	22	76.20
23	$f_{23}(x) = -\sum_{i=1}^{10}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	[0,10]	24	75.00

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features size for CTU-UHB dataset is 46 and the CTU-UHB using FECG and USG dataset records is 634. Dim refers to Dimension that is total number of variables used. In this research work, the Dim ranges from 1 to 45 (Number of features); the upper bound and lower bound are the Range which was shown in Table 3.

Table 3 shows the results of 23 benchmark objective functions. Functions f_1 to f_7 be called as Unimodal benchmark functions. Functions f_8 to f_{13} be called multimodal benchmark functions and f_{14} to f_{23} be called as fixed dimensional multimodal benchmark functions. The performance of the 23 fitness functions with the proposed IGALO is evaluated using FICNN classifier and the accuracy is shown in Table 2. From Table 3, it is clear that the proposed IGALO algorithm works efficient with the objective function f_2 which shows an accuracy of 97.89 accuracy for CTU-UHB dataset.

6.3. Experimental Result 3: Fuzzy Membership Functions

In Table 4 shows the results of from the five Fuzzification functions identified the best fuzzification and in addition to that the identified the other fuzzy parameters also such as Defuzzification, Conjunction Operator (t-norm) and Disjunction Operator(s-norm). Among the five fuzzification Functions, the gaussian function creates the best fuzzy rules than others. In defuzzification, among the five functions the COG processed well than the other function, t-norm and s-norm is used with Min and Max function operator these functions are set to create the best fuzzy rules to predict the risk factors of the maternal and embryo health state.

Table 4. Identification of best performing fuzzy membership functions, defuzzification and operators evaluation method

Membership Function	Defuzzification	Conjunction Operator (t-norm)	Disjunction Operator (s-norm)	Accuracy
GAUSSIAN	WAM	MIN	MAX	74.40
		HAMACHER	HAMACHER	88.00
		YAGER	YAGER	89.52
		PRODUCT	PRODUCT	93.20
		BOUNDED	BOUNDED	91.94
	FIRST.MAX	MIN	MAX	94.40
		HAMACHER	HAMACHER	91.84
		YAGER	YAGER	94.00
		PRODUCT	PRODUCT	96.40
		BOUNDED	BOUNDED	95.92
	LAST.MAX	MIN	MAX	97.00
		HAMACHER	HAMACHER	90.40
		YAGER	YAGER	93.80
		PRODUCT	PRODUCT	87.80
		BOUNDED	BOUNDED	92.60
	MEAN.MAX	MIN	MAX	94.40
		HAMACHER	HAMACHER	88.00
		YAGER	YAGER	96.80
		PRODUCT	PRODUCT	89.20
		BOUNDED	BOUNDED	91.40
	COG	**MIN**	**MAX**	**97.58**
		HAMACHER	HAMACHER	96.23
		YAGER	YAGER	95.31
		PRODUCT	PRODUCT	94.90
		BOUNDED	BOUNDED	92.09

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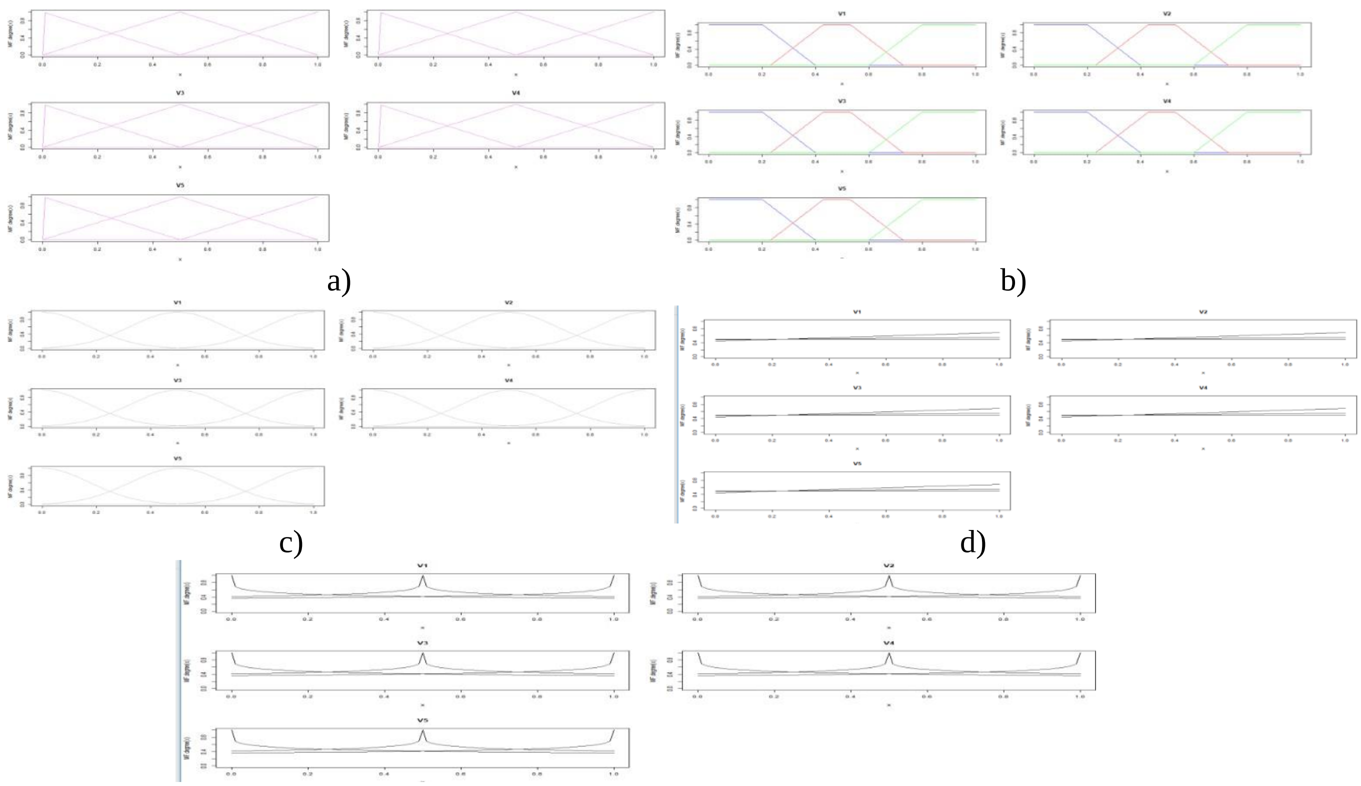
Table 5. Analysis of the above table with Identification of best performing fuzzy functions

Membership Function	Defuzzification	Conjunction Operator (t-norm)	Disjunction Operator (s-norm)	Accuracy
TRIANGLE	FIRST.MAX	BOUNDED	BOUNDED	96.40
TRAPEZOID	WAM	BOUNDED	BOUNDED	97.00
GAUSSIAN	**COG**	**MIN**	**MAX**	**97.58**
SIGMOID	COG	PRODUCT	PRODUCT	96.62
BELL	WAM	MIN	MAX	96.30



a) b) c) d) e)

Figure 4. a) Triangle Membership Function, b) Trapezoid Membership Function, c) GaussianMembership Function, d) Sigmoid Membership Function, e) BEL Membership Function

The performance of the fuzzification functions with the proposed IGALO is evaluated using FICNN classifier and the accuracy is shown in Table 5. From Table 5, it is clear that the proposed IGALO algorithm works efficient with the Gaussian fuzzification which shows an accuracy of 97.89 accuracy for CTU-UHB dataset. The five membership function plots are shown in the Figure 4 (a to e).

6.4. Implementation Details for Proposed Framework FICNN

FICNN is based on the reference network design seen in Table 6 of the proposed IGALO evolutionary algorithm with fuzzy rules using the Gaussian fuzzification membership function and ResNet50 Framework. The range of convolution layers and filters used on the proposed framework has been changed, but

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Table 6. Proposed Framework of the FICNN Parameters

Parameter	Description	Default
Evolutionary Algorithm	**Improved Tournament based Ant Lion Optimization Algorithm**	**IGALO**
Input	**Fuzzy rules using Gaussian**	**FRBCS**
Pre-trained	Transfer Learning	ResNet50
Filters	In the convolution process, the number of filters	9, 16, 32,64
Kernel size	Size of the Kernel of convolution	(3, 3), (5, 5)
Strides	Convolutional size for steps	(4,4)
Activation	Function of Activation	ReLU, Adam
Pool size	Size of the Pool	(2,2)
Padding	Whether zero padding works	Same, valid
Dropout	The proportion of neurons that are nonworking	0.25
Optimizer	Optimization function	Hybrid SGD+Adam (SAdam)
Epochs	Number of complete data set training samples	10, 20, 50, 100
Batch size	Number of samples of training by iteration	32, 64, 129,256
Output Layer	Classification :Dense Layer	Softmax

the ResNet50 paradigm is the inspiration behind the implementation of the template architecture.

6.5. Performance Evaluation of FICNN

The results of the experiment are discussed in this section. When the number of layers reached 10 layers, consisting of one ResNet50 input layer, two convolution layers, two pooling layers, two completely connected layers and one output layer as a fuzzy layer, including the normalization and ReLU layers accompanied by each convolution layer, the best result is achieved.

Confusion matrices show that FICNN algorithm performs marginally better than other current algorithms for eight different risk factors such as D1**:** FIGO Class, D2: Caesarean, D3: Hypoxia, D4: Indication of childbirth, D5: Diabetes, D6: Preeclampsia, D7: Hypertension, D8: Meconium and the performance is calculated in terms of Accuracy, TPR, TNR, PPV, NPV, HM, Kappa, AUC, PRAUC, LogLoss, Detection Rate, Prevalence, Detection Prevalence and Balanced Accuracy.

Table 7. Performance Measures Analysis for the Proposed FICNN

Risk Factors / Metrics	D1	D2	D3	D4	D5	D6	D7	D8
Accuracy	**98.89**	**98.52**	**99.01**	**98.90**	**98.36**	**98.52**	**98.20**	**98.19**
TPR	100	99.02	100	100	96.30	97.90	95.23	100
TNR	98.77	94.46	100	100	90.70	99.07	75.93	100
PPV	100	91.71	95.71	94.01	99.40	91.22	93.47	92.92
NPV	90	94.13	96.25	95.00	91.53	94.91	91.64	97.69
HM	92.30	94.20	71.59	95.23	93.53	94.17	91.29	99.63
Kappa	94.12	92.36	90.12	97.91	92.44	92.36	90.12	97.91
AUC	99.70	91.92	94.57	90.14	99.40	91.22	93.47	92.92
PR AUC	93.91	99.69	91.29	93.53	94.54	90.69	72.09	90.69
LogLoss	92.33	93.66	94.23	96.23	94.23	96.10	91.09	91.06
Detection Rate	88.89	94.33	92.23	97.02	93.25	95.20	90.93	90.57
Prevalence	90	92.69	93.25	96.63	95.23	96.23	92.95	91.47
Detection Prevalence	88.89	99.59	90.69	99	94.50	92.96	91.16	95
Balanced Accuracy	99.38	96.62	91.94	92.30	94.54	95.69	92.09	95.69
Note - D1: FIGO Class, D2: Caesarean, D3: Hypoxia, D4: Indication of childbirth, D5: Diabetes, D6: Preeclampsia, D7: Hypertension, D8: Meconium								

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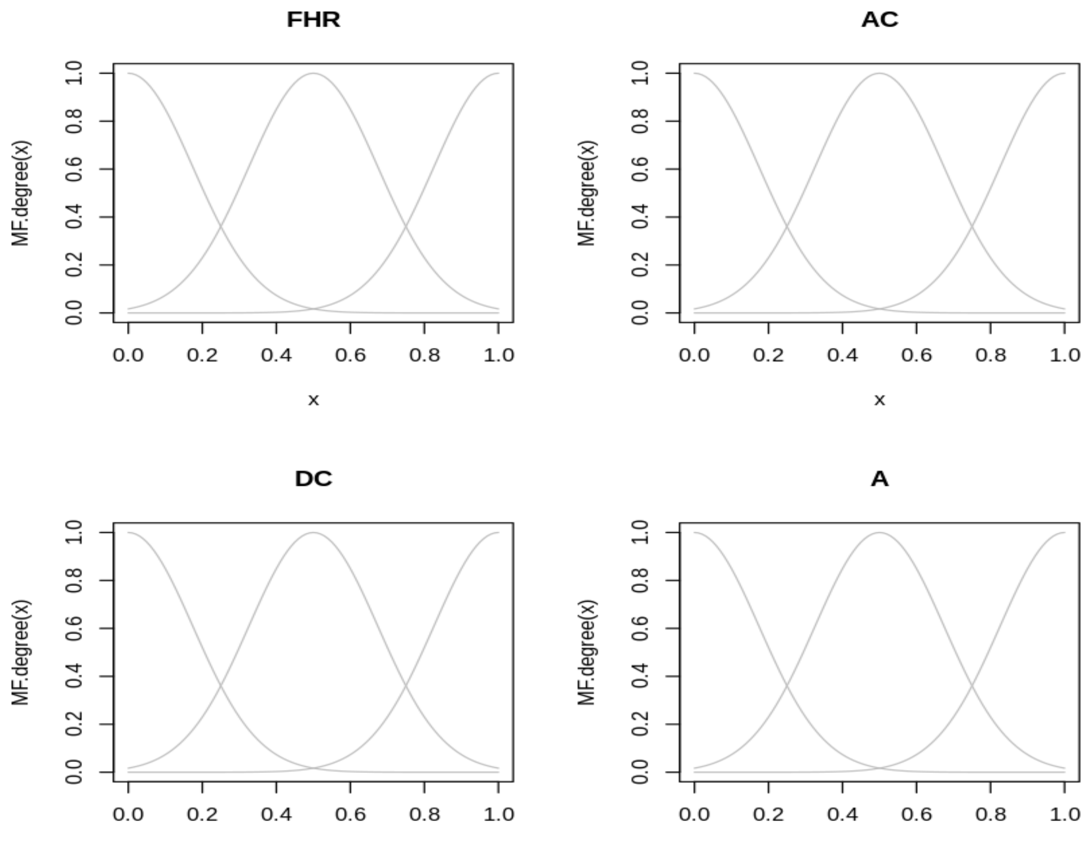

Figure 5. Performance analysis for the proposed technique FICNN with Gaussian Membership Function

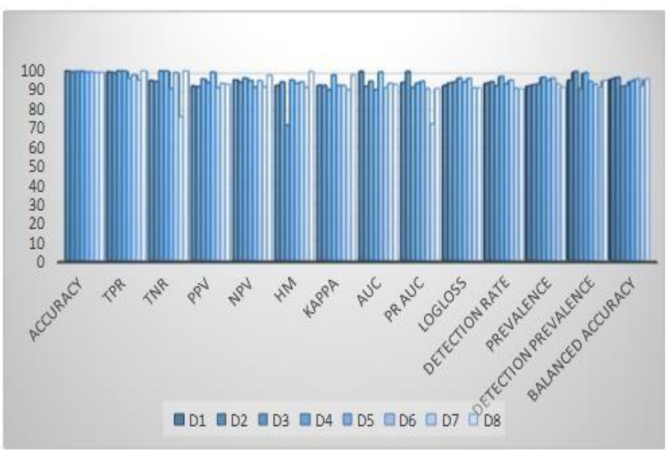

Figure 6. Overall Performance analysis for the proposed technique FICNN

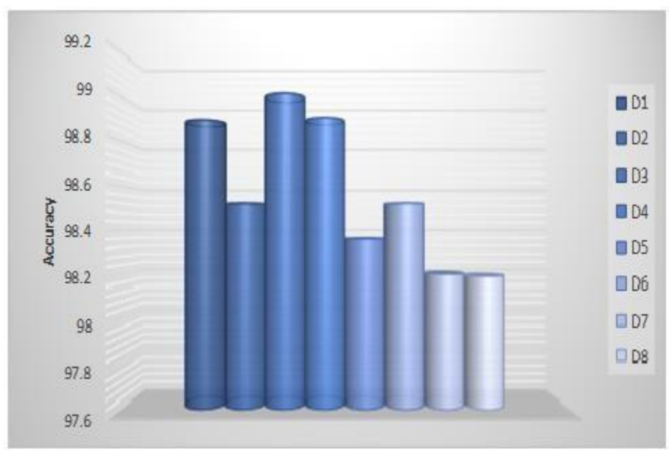

Figure 7. Accuracy analysis for the proposed technique FICNN

In addition, Table 7 shows that the several performance metrics derived from the uncertainty matrix, which are Acc, TPR, TNR, PPV, NPV, HM, Kappa, AUC, PRAUC, Log Loss, DR, Prevalence, DP and BA, have also been considered. In other words, the corresponding automated system could automatically recognize an unknown embryo irrespective of the number of layers once theproposed FICNN algorithm is successfully trained. In Figure 5 it shows the plot of the Gaussian membership function with relevant linguistic terms. The performance analysis is also shown as the bar chart representation in the Figure 6& 7.

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7. Discussion

In this paper, proposed an effective FECG and USG signals for maternal and embryo risk assessment classification method using fuzzy inference based convolutional neural network with the relevant extracted features from the FHR and UC. The testing scenarios carried out also implement several evolutionary algorithms to determine the performance of each model. The results of the accuracy and evaluation of the model can be seen in Tables 2-7. In the first experiment, the model is used to classify all features without and with evolutionary algorithms with fuzzy. In the proposed IGALO evolutionary algorithm using fuzzy inference system produces the highest accuracy with a percentage of 87.25%. The next scenario is to find the best membership, among the five membership function the Gaussian gives the best result than other membership functions. Finally, it can be concluded from this study that the combination of the proposed IGALO algorithm with Fuzzy rules gets the best results with an accuracy of 98.89%.

FICNN model is designed with considering important concepts such as proposed metaheuristic algorithm IGALO, Fuzzy rules, ResNet, regularization, k-fold cross-validation and mainly in the dense layer for classification with softmax. The proposed technique performs better than the existing techniques. The proposed technique achieved an accuracy of 98.89%. It also achieved 100 TPR, 98.77 TNR, 100 PPV, 90 NPV, 92.30 HM, 94.12 Kappa, 99.70 AUC, 93.91 PR AUC, 92.33 logloss, 88.89 detection rate, 90 prevalence, 88.89 detection prevalence and 99.38 balanced accuracy. The remaining seven risk factors also achieved the same range of values for the performance metrics respectively.

8. Conclusion

The FECG analysis model is compared to the fuzzy logic method and the findings suggest that better performance is given by the fuzzy logic approach. The first scenario is performed to determine the performance of the fuzzy without using feature selection and with feature selection. The highest accuracy obtained on the IGALO with a percentage of 87.25%. The second scenario is carried out to determine the effect of feature selection on improving the accuracy of classification results. Based on this research, the highest accuracy of all scenarios is obtained by the Gaussian Fuzzy membership function with proposed IGALO Feature Selection with the proposed FICNN. Overall the results demonstrated the effectiveness of our proposed FICNN achieved the overall results are 98.89% accuracy respectively, that can be implemented into clinical practice and critically assist obstetricians to make accurate medical decisions. Our FECG and USG classification result indicates that the detection of maternal and embryo risk factors with FECG and USG and FICNN model can be an effective approach to help the experts to diagnose the maternal and embryo state which can be predicted with FHR and UC values. Forthcoming work is expected in order towards explore how to construct a fuzzy membership for aggregation through fuzzy integrals with some other evolutionary algorithm.

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