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Enhancing Delivery Type Classification Using a Particle Swarm Optimized One-Dimensional Convolutional Neural Network

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ABSTRACT: Vaginal deliveries have linked to less respiratory issues in the newborn. Vaginal delivery and on-demand C-section showed better outcomes than operatory vaginal delivery and intrapartum C-sections. In this paper a Particle Swarm Optimization-based One Dimensional Convolutional Neural Network the delivery type is proposed. Initially, the data is pre-processed undergoing stages like handling missing values to analyse the missing values from input data, data encoding to convert unconditional variables into numerical representations. Then data balancing to balance the data and dimensionality reduction to visualize the data by enhancing data quality for detection. Next, the data are selected using the Chi square test score to extract independent variables from a large sample data for delivery type detection. Finally, a PSO based 1D-CNN framework is processed to enhance the classification accuracy of delivery type. Using python software the proposed framework shows an improved accuracy of 96% is expert when compared to other methods.

Keywords: Delivery type, Chi square test score, Particle Swarm Optimization (PSO), One Dimensional - Convolutional Neural Network (1D-CNN), C-section, Normal.

1. Introduction

The infant's birth technique shows a significant role in ensuring the mother and child's safety [1]. This study's objective is to examine the delivery method during childbirth based on specific maternal features. Based on the mothers' biological (age, previous delivery method), socioeconomic (marital status and education), and spatial (residence region) attributes. The World Health Organization (WHO) reports that in 1985 the C-section proportions above 10–15% in whichever given location cannot be right solely on the basis of medical considerations. However, throughout the older three eras, both in wealthy and emerging nations, the number of C-section in figure 1deliveries have steadily increased. After a dramatic increase since 16 million C-section births in 2000, an examination of data as of 169 countries, which account for 98.4% of all births worldwide, indicated that 29.7 million babes were born via C-section in 2015 [2]. In particular, it is clear that C-sections, particularly elective ones, have observable short-term impacts on neonates and also affect their long-term prognosis when taking into account the respiratory, immunological, and neuropsychiatric systems [3]. Globally, C-sections are growing more prevalent in both wealthy and developing nations [4].

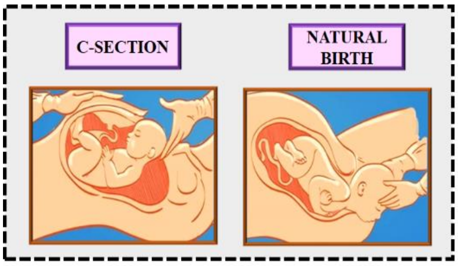

Figure 1: *Basic natural birth and C-section*

Moreover, the woman is still conscious following a spinal block or an anesthetic dose. After a C-section, recovery takes a few days. Whereas, normal delivery takes in a fraction of time to birth [5-6]. It is demonstrated that recent machine learning models with many algorithms are more accurately predict obstetric outcomes, such as shoulder dystocia and vaginal birth following cesarean delivery [7].

Random Forest classifier predicts birth modes more accurately as a caesarean section (C-section) or a Normal Vaginal Delivery (NVD). The process of the testing is slow, when dealing with large datasets [8–9]. Conversely, the methods used to predict the mother's delivery mode include Gradient Boosting Classifier (GBC), Logistic Regression, Linear regression and Extreme Gradient Boosting (XGB). For attempting to collect insights from complex data patterns in order to decrease the number of cesarean procedures birth [10].

Moreover, ensemble models predict from the combined output of the basis classifiers, combining individual machine learning techniques to increase accuracy. To create a voting ensemble model for the classification of the birth, base learners such as the Gradient Boosting Classifier (GBC), Bagging Classifier (BC), and Extra Trees Classifier (ETC**)** were utilized. It is computationally expensive when using large number of methods [11]. The modified Robson Classification is used to find delivery type. Subsequently controlling the potential variables, the Poisson regression of sandwich estimation is used to evaluate the relationship between women's migrant status and C-section rates. It needs the obstetric record, labor and delivery status before itself [12].

For delivery type several deep learning is used as following. To enhance the classification performance a Deep Neural Network Model (DNN) is developed with higher accuracy. High demand for an enormous amount of training data when classifying delivery type [13]. Conversely, for predicting delivery type as c- section and normal a Gated Highway Multi-layer-perceptron (GHiM) model is used. It have good performance when predicting the delivery type. When the model is complicated or the training data is limited, GHiM are prone to over fitting [14]. However, to increase the accuracy of delivery type an Artificial Neural Networks (ANN) is used. In order to enhance simplicity and avoid over-fitting of ANNs, a set of Multilayer Perceptron (MLP) neural networks with the capacity to propagate errors backward have been trained to forecast the onset of labor in women who show signs of premature labor. Long training period when using huge datasets are handled [15]. To overcome the limitations on delivery type a PSO-1DCNN is used.

2. Related work

Sun *et al* [16] (2022) have proposed an Artificial Neural Network (ANN) for detecting the delivery type. Here delivery type is identified by using ANN for improving the detection performances. ANN increased computational burden, over fitting susceptibility for delivery type.

Hemalatha S. [17] (2023) have proposed a Multivariate Intensified Mine Blast Optimization (MIMBO) - Naïve Bayes – Random Forest (NBRF) for calculating the mode of child birth. The NBRF classifier estimates the likelihood parameter to produce the Bayesian rules using the Bird Mating (BM) optimization method. The classifier's performance is significantly enhanced with reduced computing load and higher prediction accuracy for MIMBO and BM optimization approaches. It increases time consumption and high error rate.

Nieto-del-Amor *et al* [18] (2021) have proposed a Genetic algorithm to determine the best feature subset for preterm labor prediction. With better average metrics and less variability between partitions, a basic aggregation ensemble classifier can produce preterm labor prediction systems that are more dependable than separate weak base classifiers. Slow convergence and local minima susceptibility are two drawbacks of genetic algorithm.

Islam *et al* [19] (2022) have proposed a Henry Gas Solubility Optimization-based Random Forest for C-Section prediction to identify the health issues with mother or conditions that hamper the development of the fetus. It identifies the high risk pregnancies timely when delivery. Low accuracy in complex issues, especially when working with high-dimensional search spaces.

Piri *et al* [20] (2022) have proposed a Crowding Distance-based Multi-Objective Ant Lion Optimization (MOALO-CD) to find the fetal health status. The MALO-CD method improves classification accuracy and decrease the computing time. Modified Ant Lion Optimization-CD algorithms have limitation that is stuck in local optima.

The contributions of the work are as follows:

- To effectively analyse missing values from input data by using handling missing values, data encoding convert unconditional variables into numerical representations.
- Then effectually balance the unbalanced data using data balancing and visualize the data using dimensionality reduction from the input caesarean data by enhancing data quality for detection.
- Chi square test score is used to extract independent variables from a large sample data for delivery type detection.
- The proposed work utilizes PSO-1DCNN for effective classification of delivery type detection.

3. Proposed work

The proposed block diagram in figure 2 shows for delivery type detection using machine learning technique is applied to caesarean datasets. The delivery type of normal and C-section is detected. At first the input data is processed using the data pre-processing stage that includes removing missing values from input data using handling missing values, convert unconditional variables into numerical representations using data encoding, balance the unbalanced data using data balancing and visualize the data using dimensionality reduction technique.

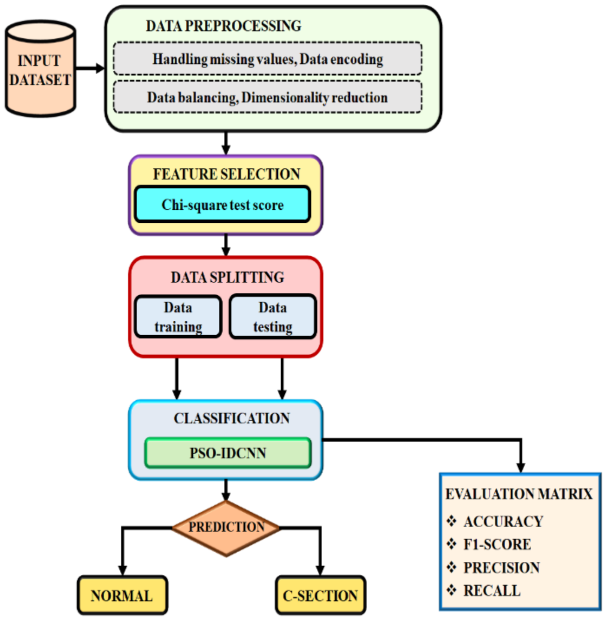

Figure 2: *Block diagram for proposed PSO-1DCNN*

Then the processed data is given as the inputs to Chi square test score extract large sample data for detection. At last model training is optimized using the featured data. To evaluate the methods accuracy and generalizability the dataset is split into training and testing data. In classification stage, a PSO-1DCNN is utilized to increase the accuracy and efficiency for the delivery type as normal and C-section.

3.1 Data pre-processing

In the delivery type detection the data pre-processing have four technique handling missing values, data encoding, data balancing and dimensionality reduction.

3.1.1 Handling missing value

For machine learning algorithms to remain accurate and avoid bias, missing values in datasets. A number of techniques including eliminating missing numbers are used in preprocessing.

3.1.2 Data encoding

The process of transforming categorical information into numerical representations is known as data encoding in delivery type. These algorithms are unable to directly analyze categorical data, which contain labels such as "red," "green," and "blue." In order to get around this, category data is frequently converted into numerical form.

3.1.3 Data balancing

Unbalanced data distribution is a crucial part of the machine learning process. One of the two classes occurs more frequently in an imbalanced dataset than the other; this technique is used to balance datasets by adjusting uneven data classes for delivery type.

3.1.4 Dimensionality reduction

The process of minimizing the number of features (or dimensions) in a cesarean dataset whereas preserving the greatest amount of information is known as dimensionality reduction. Subsequent to this the pre-processed data is given to the feature selection.

3.2 Feature extraction by Chi square test score

Chi square test score for delivery type is a statistical technique that selects data at random based on two factors and extracts independent variables from a large sample of data. In prediction systems, under fitting and over fitting training data are frequent problems. Over fitting occurs when a prediction model struggles to generalize to new data and becomes overly dependent on its training data. An overabundance of irrelevant characteristics in a dataset can lead to over fitting to training data and poor generalization. Therefore, it's critical to select pertinent features and eliminate noisy or irrelevant ones in order to improve the prediction methods performance.

To determine which features are dependent on the projected class, the Chi-Square value is used to each non-negative feature (xi). The feature is strongly dependent on the anticipated class when the Chi-Square score rises.

The perceived count (O) and the predictable count (E) are compared using the chi-square test. When two traits are independent, the actual and predicted numbers are extremely near. Let a, b, c, and d represent the measured values, and let Ea, Eb, Ec, and Ed represent the projected values. The expected value (Ea) then be found using Equation (1) if the two events are unconnected. The same is true for Eb, Ec, and Ed. Finally, Equation (3) is used to determine the chi-square score, which serves as the foundation for the universal chi-square test form seen in Equation (2).

$$E_a = (a+b) \times \frac{(a+b)}{t} \tag{1}$$

$$X^2 = \sum_{i=1}^{n} \frac{(o_t - E_t)^2}{E_t} \tag{2}$$

$$X^2 = \frac{(a-E_a)^2}{E_a} + \frac{(b-E_b)^2}{E_b} + \frac{(c-E_c)^2}{E_c} + \frac{(d-E_d)^2}{E_d} \tag{3}$$

Following feature extraction the extracted data is given to data splitting for delivery type.

3.3 Data splitting

Data splitting involves dividing the cesarean dataset obsessed by training and testing sets. ML algorithm is trained on the training set, and the model's performance is assessed on the testing set. However, the caesarean data is splitted as 80 trained and 20 testing samples. Next by data splitting the delivery type data is given to the proposed PSO -1DCNN technique.

3.4 Classification

In this proposed work Deep Learning method called PSO based 1D- CNN is utilized for effective detection of delivery type. A 1D-CNN is trained and Particle Swarm Optimization (PSO) is initiated on the idea that a collection of individuals, such as insects, herds, fish, or birds, will swarm in search of food in a cooperative manner.

3.4.1 One Dimensional –Convolutional Neural Network

1D-CNNs have lately become more popular in a range of medical-processing applications such as delivery type because of their special ability to combine feature mining and labeling processes inside a single learning frame. CNN is easy to train and optimize, and it offers a high level of resilience and fault tolerance. The input layer, convolution layer, pooling layer, fully connected layer, and output layer make up the fundamental CNN design. The model used in this study is displayed in Figure 3.

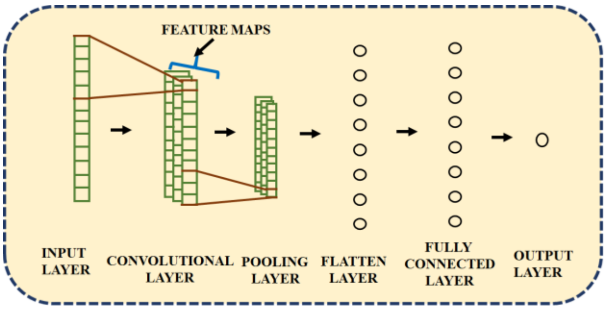

Figure 3: *One Dimensional –Convolutional Neural Network*

In order to create the fully connected layer, two convolutions and max pooling layers were used, followed by a layer that flattened the 1D-CNN. Ten neurons and one neuron each made up the two dense layers, which were fully coupled. In terms of binary classification, the output layer classified the input into normal and pathological classes using sigmoid activation. Rectified Linear Unit (ReLU) activation were used at the convolution layer. The two key parameters of the convolution layer, the sum of filters (represented by the variable n_filters) and the kernel size (represented by the variable kernel_s), were changed. The deep neural network's overall stability and training duration were improved by batch normalization.

3.4.2 Particle Swarm Optimization

The population-based stochastic optimization method known as Particle Swarm Optimization (PSO) is initiated on the idea that a collection of individuals, such as insects, herds, fish, or birds, will swarm in search of food in a cooperative manner. In search mode, the algorithm iterates its own experience and that of neighboring members to maximize the computation of each particle's internal velocity and position. In addition to its strong optimization capabilities, the PSO approach offers a quicker approximation of the global optimal solution.

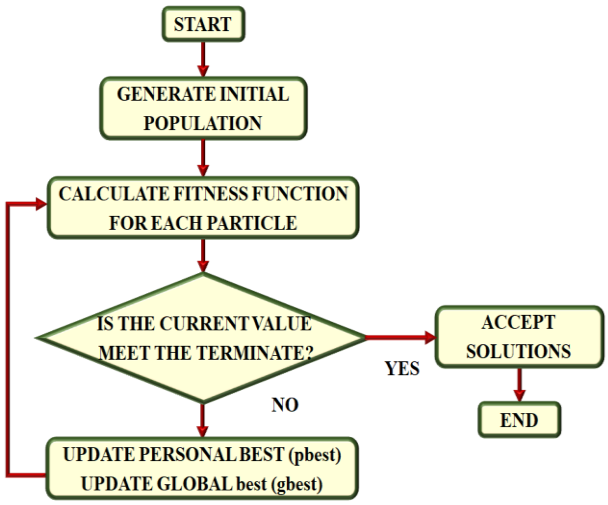

Figure 4: *PSO algorithm*

The position of the i^{th}particle in the n-dimensional space is represented by xi, and the velocity is represented by v_i, assuming that all n particles are free to look for the optimal position in the n-dimensional space. Each particle in figure 4 will receive a fitness value for the objective function of the current work based on the requirements, and it will be continuously informed of the global optimal value (p_g) and the individual optimal value (p_i) based on its current position (x_i). Consequently, the subsequent location update is carried out. The following formula represents each particle's position update:

$$V_{ij}^{k+1} = \varepsilon V_{ij}^{k} + c_1 r_1 \left(p_{ij} - x_{ij}^{k}\right) + c_2 r_2 \left(p_{gj} - x_{ij}^{k}\right) \quad (4)$$

$$x_{ij}^{k+1} = x_{ij}^{k} + V_{ij}^{k+1} \quad (5)$$

Where ε is the inertia weight, k is the number of iterations, p_{ij} is the best position for each particle individually, p_{gj} is the global best position for all particles, and i, j are the particle and its search direction (from 1 to J). In the chosen particle population, the two acceleration constants, $r_1 and\ r_2$, which are randomly chosen between [0, 1], represent the global population and individual particles, in table 1 respectively.

Table 1: *PSO algorithm for delivery type*

Algorithm 1: Particle Swarm Optimization (PSO) Input: N, Output: A size N (N position vectors) swarm S Set S to its initial value and produce each particle's position X at random with respect to the objective function's bonds; Adjust all velocities u to zero; Set i=0; Initialize While i< do Calculate inertia; = For each particle in S, the value for iteration I are: 1. Update velocity: 2. Update position: 3. Compute the value of the new position according to f; 4. Check/Update: (Optional) Check for convergence; Upgrade iteration: i=i+1 End return S;

4. Result and discussion

Dataset is taken from kaggle.com for delivery type detection using the Python software. Deep learning models are then applied to train caesarean data.

4.1 Dataset Collection:

The suggested model is evaluated on caesarean data consisting of normal and caesarean distribution. The dataset is distributed as 80% for training and 20% for testing.

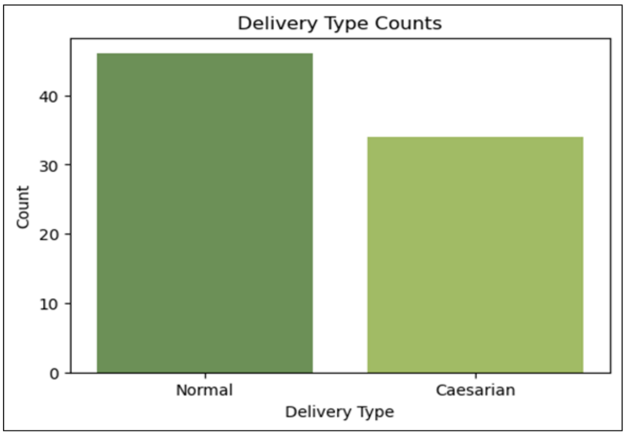

Figure 5: *Delivery type counts*

Figure 5 shows the delivery type counts for caesarean dataset from Python software. Here the delivery type is normal and caesarean is evaluated. For normal it is about 48 counts and caesarean it is about 35 counts.

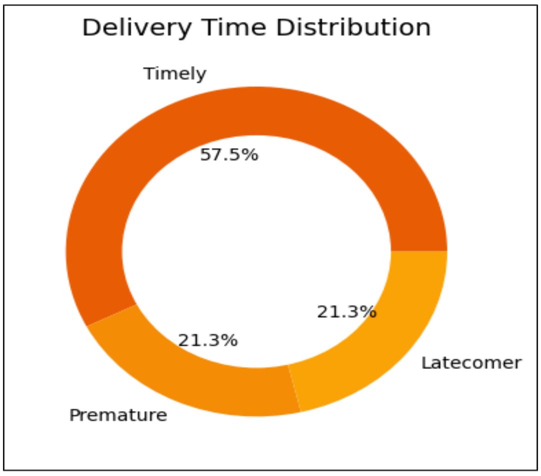

Figure 6: *Delivery time distribution*

In Figure 6 delivery time distributions for timely, latecomer and premature is calculated. Here the premature is 21.3% it means the baby deliver before the delivery date, latecomer is 21.3% it means the patient come after pain and timely is 57.5% it means patient present in the hospital at the time of delivery.

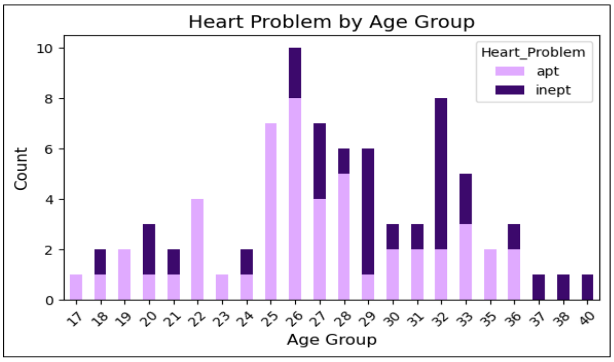

Figure 7: *Heart problem by age group*

In figure 7 heart problem by age group is calculated. Here from age 17 years to 40 years is grouped in that from age 17 years to 36 years it is approximate of heart problem and for age 37 to 40 years there is in approximate heart problem. In the age 17, 19, 22, 23, 25, 35 there is an approximate heart problem.

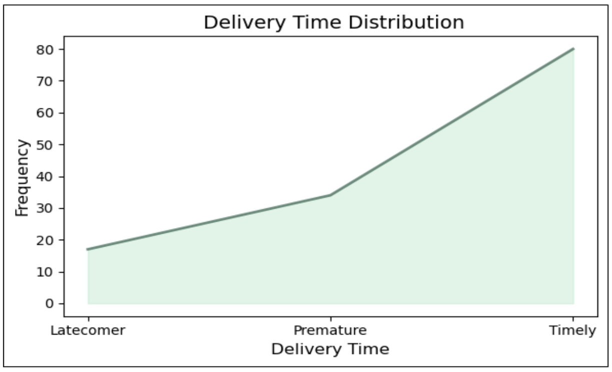

Figure 8: *Delivery time distribution*

The figure 8 shows the delivery time distribution for latecomer, premature and timely. Here, the delivery time distribution for latecomer, premature and timely is calculated. For latecomer frequency is about 40Hz, premature frequency is about 30 Hz and for timely the frequency is about 80 Hz which is high compared to latecomer and premature.

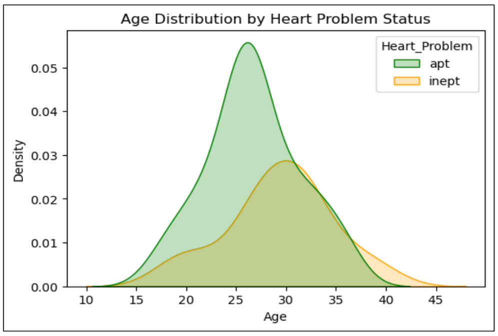

Figure 9: *Age distribution by heart problem status*

Figure 9 shows the age distribution by heart problem status is intended. Here, ages from 10 years to 45 years the heart problem is calculated, for ages from 12 to 40years it is approximate and the density is about 0.06. From age 13 to 45 years it is in approximate and its density is about 0.03 respectively.

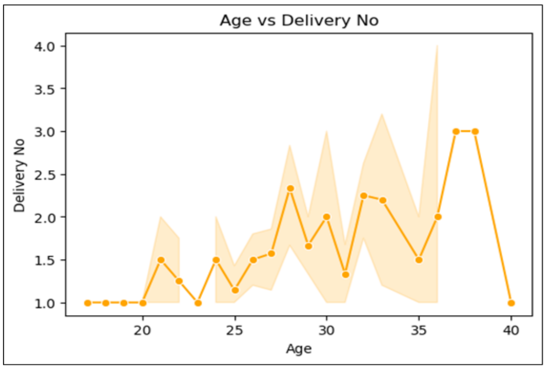

Figure 10: *Age vs delivery*

The figure 10 shows the age vs delivery is calculated. Here delivery is 1 means there is normal and delivery number is 2 means it is caesarean, from age 20 to 25 years it is about normal delivery.

4.2 Performance metrics

Using performance metrics the suggested method PSO based 1DCNN framework to training data is evaluated. And these metrics are accuracy, precision, recall, F1 score and AUC. Using the following equation each metrics are defined as

Accuracy:

$$Accuracy = \frac{(TN+TP)}{TS} \tag{6}$$

Precision:

$$Precision = \frac{(TP)}{(TP+FP)} \quad (7)$$

Recall:

$$recall = \frac{(TP)}{(TP+FN)} \quad (8)$$

F1 score:

$$F1 - score = \frac{(2*Prec*Recal)}{(Precision + Recal)} \quad (9)$$

At last, the performance across classification thresholds is estimated using the AUC, which describes the correlation between the true positive and false positive rates for delivery type as normal and caesarean.

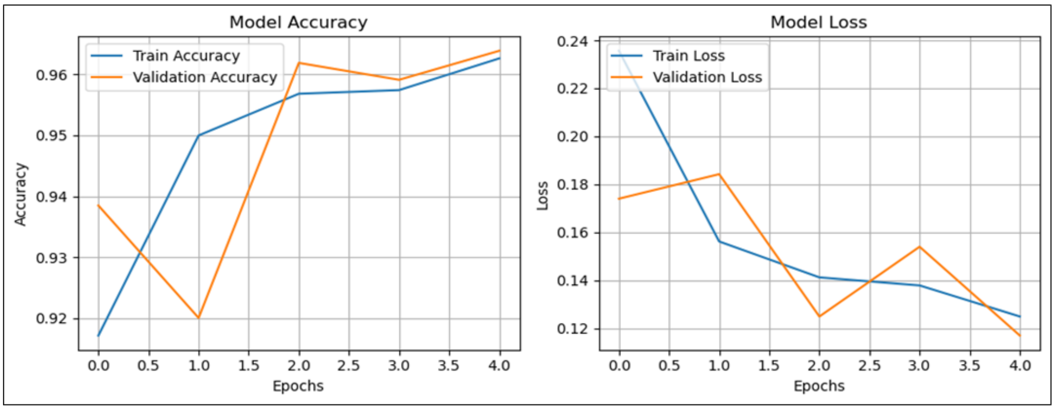

Figure 11: *Model accuracy and model loss*

The ratio of a model's accurate predictions to its total number of predictions is known as model accuracy. The accuracy for the proposed PSO-1DCNNmethod is 96%.The model's loss is demonstrated, which also shows loss value variations and the accuracy of the model is shown graphically in Figure 11.

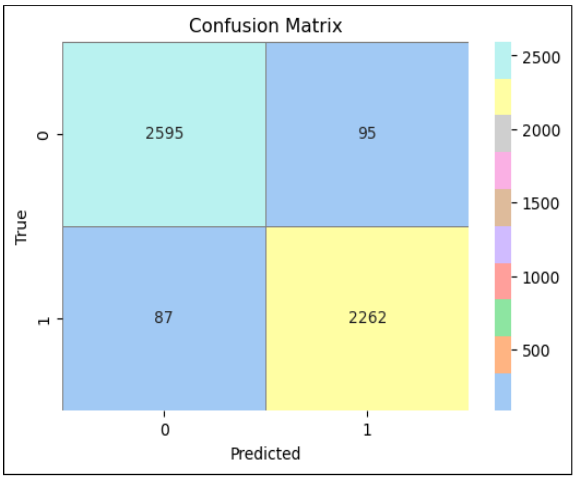

Figure 12: *Confusion matrix for PSO-1DCNN*

Figure 12 illustrates the confusion matrix for PSO-1DCNN. This matrix shows the values for true and predicted labels. Confusion matrices are commonly used to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances. Here the delivery type by normal and c-section are matrixes.

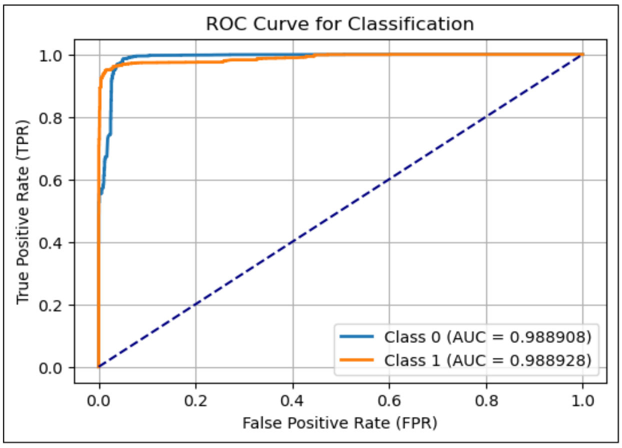

Figure 13: *ROC curve for classification*

According to the AUC results shown in Figure 13, the cesarean dataset significantly lowers the AUC value of PSO-1DCNN, class o of 0.988908 continues to have the highest AUC value for class 1 of 0.9889298, demonstrating the exceptional overview and flexibility of this approach.

4.3 Comparison for the proposed method

The comparison of the proposed method with existing method is presented in table 2. The Artificial Neural Network, Random Forest have the classification accuracy of 81.6% [16] and SVM have the accuracy of 90.9% [21]. The proposed PSO-1DCNN have the higher accuracy of 96% compared to the existing method.

Table 2: *Comparison for the proposed method*

Study	Method	Accuracy
Sun *et al*[16]	Artificial Neural Network, Random Forest	81.6%
Raja *et al* [21]	SVM	90.9%
Proposed approach	PSO-1DCNN	96%

4.4 Comparisons for precision and recall

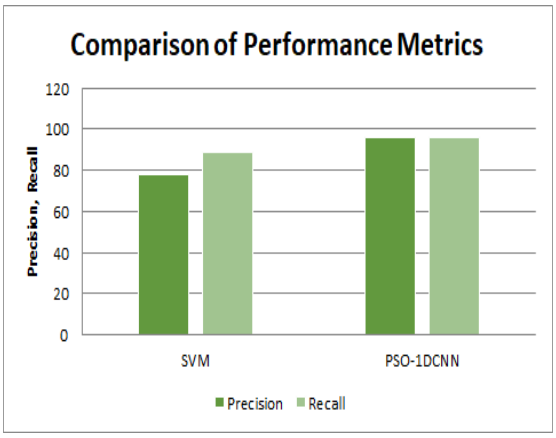

Figure 14: *Comparisons of performance metrics*

Comparisons of performance metric in figure 14 shows the precision value of 96% and recall of 96% for the proposed PSO based 1DCNN method predicted successfully when compared to the SVM [21].

5. Conclusion

In this paper, PSO-1DCNN model is proposed for classification of delivery type as normal and C-section. The data pre-processing stage effectively enhanced image quality using handling missing values, data encoding, data balancing and dimensionality reduction. Furthermore, Chi square test score based feature selection recognised the important feature from the large sample data for delivery type detection. The proposed PSO-1DCNN classifier demonstrates performance with state-of-the-art methods demonstrates its superiority. The improved accuracy of 96% is achieved as a higher accuracy using Python software when compared to the existing techniques.

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