In-birth CPR in neonates; Predictable or Unpredictable?

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Abstract

Background: Anticipating on in-birth Cardiopulmonary Resuscitation(CPR) in neonates is very important and complex. Timely identification and rapid CPR in neonates in the delivery room significantly affect reducing the mortality and other neurological disabilities. The aim of this study is to create a prediction system for identifying the need to in-birth CPR in neonates based on Machine Learning(ML) algorithms.

Methods: In this study, 3882 neonatal medical records were retrospectively reviewed. Records were extracted from the maternal, fetal, and neonatal registry of Valiasr hospital in Tehran. A total of 60 risk factors were extracted, and five ML algorithms including J48, Naïve Bayesian, Multilayer Perceptron (MLP) Support Vector Machine (SVM) and Random Forest were compared to predict the need to in-birth CPR in neonates. Also, using 10 feature selection algorithms, the features were ranked based on the importance, and using the ML algorithms, the important risk factors were identified.

Results: In order to predict the need to in-birth CPR in neonates, SVM using all risk factors reached the accuracy of 88.43% and F-measure of 88.4%, while MLP using the 15 first important features reached the accuracy of 90.86% and the F-measure of 90.8%. The most important risk factors included gestational age, delivery type, presentation, steroid administration, macrosomia, prenatal care, infant number and rank, mother addiction, maternal chronic disease history, fetal hydrops, amniotic fluid, gestational hypertension, infertility and placental abruption.

Conclusions: The proposed system can be useful in predicting the need to CPR in neonates in the delivery room.

1. Background

Annually, around 1 million neonates die because of birth asphyxia worldwide(1). According to the WHO guideline on basic newborn resuscitation, although around one fourth of neonatal mortality is due to birth asphyxia, effective CPR at the childbirth moment can prevent a large number of these deaths(2). Most neonates enter from intrauterine to extrauterine life with no special assistance. However, less than 1% of all neonates (3) and around 0.1% of term neonates require advanced CPR at the moment of childbirth(4, 5). On the other hand, these statistics are very higher for preterm infants; 6–7% of preterm neonates (GA < 32 weeks) (6) and around 6–10% of Very Low Birth Weight (VLBW) and Extremely Low Birth Weight (ELBW) infants require advanced CPR, i.e. chest compression with or without injecting epinephrine (7). Many studies have been performed on CPR consequences, and it has been found that mortality, neurological morbidity, neurodevelopmental impairment, lower motor scores and ROP are more prevalent among the preterm infants who have received CPR(6, 8, 9). Thus, timely identification and rapid CPR of neonates in the delivery room can reduce the neonatal mortality and morbidity(7).

Currently, in-birth CPR is suggested for neonates with asystole, profound bradycardia (HR < than 60 per minutes), and pulseless electrical activity despite effective ventilation. Absence of heart rate or other vital signs, which is recorded as zero APGAR, can also be used as a guideline for decision-making on beginning CPR (8). Different studies have shown that the severity scoring systems have many limitations, and the systems based on machine learning have a better performance in prediction (10, 11). Accordingly, considering the importance of in-birth CPR, usage of ML based systems can be useful to help anticipating on the need to neonatal CPR. Application of ML algorithms in the medicine and especially in neonatal medicine has shown that these techniques have a very suitable performance in prediction and diagnosis.

Nevertheless, sparse studies have dealt with CPR in neonates, most of which have a small set of samples and risk factors because of the challenges in data collection (12–16). The aim of most of them is only identifying the risk factors affecting the need to CPR(12, 13, 17–19). Further, most studies have dealt with neonatal CPR in NICU, and fewer of them have addressed in-birth CPR, due to examine in-birth CPR, only maternal and fetal factors should be considered. To the best of our knowledge, no study has been performed on predicting the need to in-birth CPR in neonates using machine learning algorithms. Accordingly, our aim is to design a ML-based Clinical Decision Support System (CDSS) which predicts the need to in-birth CPR in neonates based on maternal and fetal factors.

2. Method

This retrospective study was conducted based on the maternal, prenatal and the fetal data, with the aim of predicting the need to in-birth CPR in neonates. In order to develop the prediction model, ML algorithms were used. Also, the models were evaluated to examine the performance and to determine the best model. The details related to the data, setting, method of development, and evaluation of the prediction models have been presented in this section.

2.1. Data source

The data were obtained through the neonatal registry system in Valiasr hospital affiliated to Tehran University of Medical Sciences (TUMS). This registry includes the information related to all neonates hospitalized in the NICU of Valiasr Hospital that has a grade of B3. The data related to the mother and fetus are recorded by pediatric residents in the data collection form, and are then entered into the registry by its person in charge. In this retrospective study, the data available in this registry were retrieved anonymously from March 2016 to March 2020.

Consent form has also been filled by the father or mother of the infants before loading the data into the registry.

The study was approved by the TUMS institutional review board (Approval ID: IR.TUMS.VCR.REC.1398.591).

2.2. Inclusion and exclusion criteria

All neonates hospitalized in NICU of Valisasr Hospital from March 2016 to March 2020 were included in this study. The post-delivery data such as Apgar score, height, and weight of the neonate were excluded.

2.3. Definition

In this study, delivery room CPR and CPR immediately after birth have been examined. CPR refers to any activity in the delivery room taken to simulate the cardiorespiratory activity of neonates who met the conditions of CPR according to the American Academy of pediatrics (AAP) guidelines(20, 21). These activities can be categorized into two groups: primary CPR (use of oxygen mask, Nasal continuous positive airway pressure (CPAP) and positive pressure ventilation(PPV)) and advanced CPR (primary CPR plus epinephrine injection, chest compression and intubation) (22).

2.4. Data extraction and preprocessing

After removing the any identifiers, the data was extracted from the registry as a .sav file and includes six groups:

- Gestational risk factors: prenatal care, chorioamnionitis, steroid administration, magnesium sulfate administration
- Maternal risk factors: age, hypertension (chronic, gestational, eclampsia), diabetes (chronic, gestational), addiction, HIV, chronic disease history, history of abortion (less than 20 weeks) and Intrauterine Fetal Death (IUFD)
- Female infertility: use of Assisted reproductive techniques (ART), name of ART
- Accreta status: decollement / placenta abruption, vasa previa, previa, placenta accreta
- Fetal Data: gender, gestational age, rank and number of infant, Intrauterine growth restriction(IUGR), congenital problems, fetal hydrops
- Delivery risk factors: mode of delivery, Prelabor rupture of membranes(PRoM), duration of PRoM, presentation, cord status, thick meconium, amniotic fluid status, Fetal Heart Rate (FHR)

The outcome variable is whether or not CPR is performed for a baby in the delivery room. The discrete and continuous missing values in the data set were imputed by the mode and mean of each variable, respectively.

2.5. Prediction models construction

In order to develop the prediction model for the need to in-birth CPR, ML algorithms were used including J48, MLP, SVM, Naïve Bayesian (NB) and Random Forest (RF). All of these algorithms were implemented for the original data set. Next, using Feature Selection (FS) algorithms, the importance of each feature in predicting CPR was examined. For this purpose, filter FS algorithms including Relief, Correlation-based feature selection (CFS), Pearson's Correlation, gain ratio, info gain, OneR and symmetrical uncertainty as well as wrapper methods using three classifiers SVM, J48 and NB were used (Table 1). Then, the risk factors were organized based on the total importance resulting from implementing 10 FS algorithms. Based on the ordered list of variables, various data subsets were created, and ML algorithms were implemented on both the original data set as well as these data subsets.

Table 1
Characteristics of feature selection methods

Type of FS method	Evaluation algorithm	Weka class name	Parameters tuning
Filter	Attribute Evaluation using RELIEF	ReliefFAttributeEval	
	Correlation-based feature selection (CFS) Evaluation	CfsSubsetEval	
	Attribute Evaluation using Pearson's Correlation	CorrelationAttributeEval	
	Attribute Evaluation using Gain ratio	GainRatioAttributeEval	
	Attribute Evaluation using Information Gain	InfoGainAttributeEval	
	OneR uses the accuracy of a single-attribute classifier	OneRAttributeEval	
	Attribute Evaluation using Symmetrical uncertainty	SymmetricalUncertAttributeEval	
Wrapper	Subset Evaluation by using a user-specified classifier and separate held-out test set	ClassifierSubsetEval	Classifier = SVM
	Subset Evaluation by using a user-specified classifier and internal cross-validation	WrapperSubsetEval - weka.classifiers.trees.J48	Classifier = J48
	Subset Evaluation by using a user-specified classifier and internal cross-validation	WrapperSubsetEval - weka.classifiers.bayes.NaiveBayes	Classifier = NB

2.6. Statistical analysis and performance measurements

For the continuous data, mean and standard deviation, while for discrete data, frequency and percentage have been reported. To investigate the distribution of variables in the two groups (neonates receiving CPR vs those not receiving CPR), independent samples t-test, chi-square, Fisher exact and Mann-Whitney tests have been used. The significance level in all tests was considered $p < 0.05$. All statistical analyses were performed by SPSS 20. After analyzing the role of risk factors in predicting the outcome and developing the prediction models for the need to in- birth CPR, the performance of the developed models was evaluated based on the accuracy, precision, sensitivity, specificity and F-measure criteria and using the 10-fold cross validation method. The role of variables was analyzed using the FS algorithms in WEKA software. Development and assessment of models were also performed using R v3.4.1.

2.7. Clinical decision support system design

After selecting the best algorithm in the predicting the need to delivery room CPR in neonates, the system user interface was designed based on the best algorithm in Visual Studio platform 2015.

3. Results

A total of 3882 infants were included into the study according to the inclusion/exclusion criteria, out of them 2011(51.8%) had received delivery room CPR. The efforts were taken for the CPR, in the order of frequency, were: nasal CPAP (n = 1120, P = 28.8%), PPV (n = 891, P = 22.9%), Oxygen mask (n = 723, P = 18.6%), intubation (n = 494, P = 12.7%), chest compression (n = 86, P = 2.2%) and epinephrine injection (n = 68, P = 1.7%). Data statistics are shown in Tables 2 and 3.

Table 2
Descriptive statistics of discrete risk factors

Variable name	Values	Frequency	Percent	P-Value
Gestational risk factors				
Prenatal care	Yes	3426	88.25	.000
	No	456	11.75	
Chorioamnionitis	Yes	71	1.83	0.958
	No	3811	98.17	
Steroid administration	Yes	933	24.03	.000
	No	2949	75.97	
Magnesium sulfate administration	Yes	333	8.58	.000
	No	3549	91.42	
Maternal risk factors				
Hypertension	Yes	184	4.74	0.00752
	No	3698	95.26	
Gestational hypertension (Ghypertension)	Yes	654	16.85	0.0005595
	No	3228	83.15	
Diabetes	Yes	105	2.71	0.7826
	No	3777	97.29	
Gestational diabetes (Gdiabetes)	Yes	600	15.46	0.5829
	No	3282	84.54	
Mother addiction	Yes	63	1.62	0.006855
	No	3819	98.38	
Mother HIV	Yes	28	0.72	0.848
	No	3854	99.28	
Cardiac diseases	Yes	304	7.83	0.06417
	No	3578	92.17	
Blood diseases	Yes	187	4.82	0.8656
		3695	95.18	
	No			
Kidney diseases	Yes	63	1.62	0.9263
	No	3819	98.38	
Thyroid Disorders	Hyperthyroidism	15	0.39	0.2737
	Hypothyroidism	694	17.88	
	Thyroidectomy	2	0.05	
	No	3171	81.68	
Respiratory diseases	Yes	28	0.72	0.8509
	No	3854	99.28	
Mental diseases	Yes	21	0.54	0.9576
	No	3861	99.46	
Infectious diseases	Yes	16	0.41	0.885
	No	3866	99.59	

Variable name	Values	Frequency	Percent	P-Value
Brain diseases	Yes	62	1.6	0.211
	No	3820	98.4	
Cancer diseases	Yes	33	0.85	0.5051
	No	3849	99.15	
Skin diseases	Yes	7	0.18	0.6354
	No	3875	99.82	
Liver diseases	Yes	63	1.62	0.8716
	No	3819	98.38	
Autoimmune diseases	Yes	64	1.65	0.771
	No	3818	98.35	
Uterus diseases	Yes	41	1.06	0.5801
	No	3841	98.94	
Digestive diseases	Yes	34	0.88	0.3677
	No	3848	99.12	
Eye diseases	Yes	4	0.10	0.9424
	No	3878	99.9	
Other chronic disease (Mother)	Yes	12	0.31	0.1073
	No	3870	99.69	
(Pre)Eclampsia	Eclampsia	8	0.21	0.192
	Preeclampsia	198	5.10	
	No	3676	94.69	
Abortion history	Yes	17	0.44	0.925
	No	3865	99.56	
Intrauterine Fetal Death (IUFD)	Yes	10	0.26	0.1671
	No	3872	99.74	
Infertility				
Female infertility	Yes	214	5.51	.000
	No	3668	94.49	
Assisted reproductive techniques (ART)	Yes	144	3.71	0.0009746
	No	3738	96.29	
Name of ART technique	No	3738	96.29	0.000333
	Drug administration	26	0.67	
	IUI	18	0.46	
	IVF	100	2.58	
Accreta status				
Decollement / Placenta abruption	Yes	41	1.06	0.03364
	No	3841	98.94	
Vasa Previa	Yes	1	0.03	0.3347
	No	3881	99.97	

Variable name	Values	Frequency	Percent	P-Value
Previa	Yes	113	2.91	0.5083
	No	3769	97.09	
Placenta Accreta	Yes	163	4.2	0.1257
	No	3719	95.8	
Fetal Data				
Number of infants	1	3407	87.76	.000
	2	419	10.79	
	3	55	1.42	
	4	1	0.03	
Sex	Female	1730	44.57	0.3964
	Male	2146	55.28	
	Ambiguous Genitalia	6	0.15	
Rank of infant	1	3628	93.46	.000
	2	235	6.05	
	3	19	0.49	
IUGR	Yes	223	5.75	0.01075
	No	3659	94.25	
Tumors	Yes	14	0.36	0.6887
	No	3868	99.64	
Genetic problems/ Anomaly	Yes	18	0.46	0.08225
	No	3864	99.54	
Macrosomia	Yes	19	0.49	0.001636
	No	3863	99.51	
Cardiac problems	Yes	31	0.8	0.983
	No	3851	99.2	
Surgery (Defect of the abdominal)	Yes (including Colonic atresia, diaphragmatic hernia, duodenal atresia, Esophageal atresia, Gastroschisis,	54	1.39	0.2758
	internal hernia, Intestinal atresia,	3828	98.61	
	Jejunal atresia,			
	Omphalocele)			
	No			
Blood problems	Yes	4	0.10	0.9424
	No	3878	99.9	
Pulmonary problems	Yes	12	0.31	0.1073
	No	3870	99.69	
Brain problem	Yes	25	0.64	0.9842
	No	3857	99.36	
Fetal hydrops	Yes	12	0.31	0.02858
	No	3870	99.69	
Other Problems(Fetus)	Yes	6	0.15	0.9295
	No	3876	99.85	

Variable name	Values	Frequency	Percent	P-Value
Delivery risk factors				
Delivery type	Cesarean	3617	93.17	.000
	Vaginal	265	6.83	
PROM	Yes	549	14.14	0.0708
	No	3333	85.86	
Presentation	Breech	106	2.73	0.07257
	Transverse	6	0.15	
	Hand	1	0.03	
	Normal	3769	97.09	
Cord	Absent Doppler	27	0.69	0.2395
	Cord prolapse	4	0.10	
	Reverse	1	0.03	
	No	3850	99.18	
Thick meconium	Yes	24	0.62	0.1438
	No	3858	99.38	
Amniotic fluid	Oligohydramnios	43	1.11	0.04057
	Polyhydramnios	26	0.67	
	Normal	3813	98.22	
Fetal Heart Rate (FHR)	Arrhythmia	1	0.03	0.3952
	BPP	2	0.05	
	Bradycardia	6	0.15	
	Tachycardia	10	0.26	
	Decreased FHR	269	6.93	
	Fetal distress	8	0.21	
	Sinusoidal	1	0.03	
	PVC	1	0.03	
	No	3584	92.31	

Table 3
Descriptive statistics of continuous risk factors

Variable name	Mean	SD	P-Value [95% confidence interval]
Maternal age (Year)	30.89	5.9	0.4742 [-0.1497735, 0.3219842]
Gestational age(day)	247.15	25.17	1.179099e-158 [19.21917, 22.09842]
PROM hrs.	7.84	62.41	0.0004639 [-10.95175, -3.09293]

In order to develop the prediction model for the need to in-birth CPR, ML algorithms were used. Figure 1 displays the results obtained from implementing these algorithms on the original data set.

Figure 1 shows that based on all performance criteria the SVM method has had the best performance in predicting the need to in-birth CPR. Also, J48 method reached comparable results. In the next step of simulation, FS algorithms were employed. For this purpose, seven filter FS algorithms including Relief, Correlation-based feature selection (CFS), Pearson's Correlation, gain ratio, info gain, OneR and symmetrical uncertainty as well as three wrapper methods using three classifiers SVM, J48 and NB were implemented (appendix A). Then, for each risk factor, the total importance resulting from implementing 10 FS algorithms was calculated. Table 4 presents the rank resulting from implementing the FS algorithms as well as the averaged rank for each variable. The averaged rank was calculated using the following relation, where r_i represents the rank of variable in the i^{th} feature selection algorithm.

Table 4
Rank of attributes based on 10 feature selection methods

#	Variable names	Relief	CFS	Correlation	Gain ratio	Info gain	OneR	symmetrical uncertainty	Wrapper (SVM)	Wrapper (NB)	Wrapper (J48)	Averaged rank
1	GA	1	1	1	1	1	1	1	1	1	1	1
2	Delivery type	5	4	5	8	6	4	5	4	2	2	4.5
3	Presentation	10	7	17	21	15	6	14	6	17	8	12.1
4	Steroids administration	2	2	2	3	2	2	2	2	46	60	12.3
5	Macrosomia	22	18	13	2	13	9	11	9	3	24	12.4
6	Prenatal care	6	6	6	14	5	3	6	3	47	39	13.5
7	Infant number	8	3	3	5	3	5	3	5	58	45	13.8
8	Addiction	12	12	15	19	17	7	17	7	14	19	13.9
9	Fetal hydrops	32	16	19	4	20	18	20	21	6	15	17.1
10	Infant rank	11	15	7	11	7	23	7	15	59	31	18.6
11	Amniotic fluid	17	10	18	22	18	8	18	8	42	27	18.8
12	Ghypertension	9	14	10	28	10	21	16	25	10	59	20.2
13	Infertility	13	13	8	12	8	17	8	19	57	48	20.3
14	Decollement / Placenta abruption	27	11	20	20	23	30	23	31	4	14	20.3
15	Other Chronic disease (Mother)	29	23	26	10	28	28	26	32	5	6	21.3
16	Magnesium sulfate	3	5	4	6	4	52	4	60	55	46	23.9
17	IUFD	48	21	31	16	33	12	31	10	30	9	24.1
18	Hypertension	16	17	14	26	16	20	19	17	40	57	24.2
19	Genetic problems/Anomaly	26	36	25	15	26	29	23	33	11	25	24.9
20	IUGR	20	30	16	27	19	24	21	14	41	38	25.0
21	Vasa Previa	41	27	37	7	36	39	35	27	7	4	26.0
22	Surgery	28	34	34	31	35	14	34	13	18	23	26.4
23	Cardiac diseases	14	24	22	35	25	11	28	11	52	51	27.3
24	ART use	37	59	11	23	12	19	12	16	56	30	27.5
25	Cord	39	19	21	18	21	44	22	28	51	16	27.9
26	PROM hrs.	50	9	9	17	14	33	15	30	60	44	28.1
27	Pulmonary problems	34	26	27	9	29	31	25	35	31	35	28.2
28	ART name	23	22	12	13	9	51	9	49	50	47	28.5
29	Thick meconium	31	25	30	24	31	27	30	29	37	21	28.5
30	Brain diseases	56	33	33	29	34	15	33	12	9	43	29.7
31	Digestive diseases	38	41	36	30	37	13	37	24	29	33	31.8
32	Placenta Accreta	51	31	28	34	30	32	32	26	28	36	32.8
33	PROM	24	57	23	37	27	16	29	20	49	52	33.4
34	FHR	44	8	29	25	11	53	13	54	54	54	34.5
35	Sex	4	28	35	44	32	23	36	46	43	55	34.6

#	Variable names	Relief	CFS	Correlation	Gain ratio	Info gain	OneR	symmetrical uncertainty	Wrapper (SVM)	Wrapper (NB)	Wrapper (J48)	Averaged rank
36	Skin diseases	53	49	43	33	42	22	41	36	25	3	34.7
37	(Pre) Eclampsia	54	29	24	32	24	46	27	42	16	58	35.2
38	Thyroid Disorders	19	20	32	36	22	43	24	55	48	53	35.2
39	Eye diseases	33	32	53	40	52	40	52	37	12	7	35.8
40	Abortion	30	43	45	43	44	41	44	48	13	10	36.1
41	Infectious diseases	47	35	48	42	46	36	46	40	19	5	36.4
42	Cancer	35	38	40	39	39	26	38	23	38	49	36.5
43	Tumors	40	40	44	38	43	49	42	44	26	13	37.9
44	Gdiabetes	7	51	42	57	41	25	43	18	44	56	38.4
45	Previa	25	53	39	45	38	35	39	39	45	32	39.0
46	Uterus diseases	59	39	41	41	40	34	40	34	33	42	40.3
47	Blood problems	43	37	60	49	59	42	59	45	22	12	42.8
48	HIV	58	45	47	47	47	48	45	50	20	28	43.5
49	Other problems (Fetus)	49	48	55	46	54	37	54	47	34	11	43.5
50	Chorioamnionitis	15	58	58	58	56	38	55	53	27	26	44.4
51	Diabetes	55	56	46	56	45	59	47	57	15	18	45.4
52	Cardiac problems	36	54	50	48	48	57	48	52	24	37	45.4
53	Blood diseases	18	47	59	59	58	47	58	38	36	34	45.4
54	Maternal age	21	60	38	60	60	60	60	22	53	22	45.6
55	Mental diseases	57	52	56	53	55	50	57	43	8	29	46.0
56	Respiratory diseases	42	44	57	50	57	54	56	41	21	41	46.3
57	Liver diseases	45	46	52	55	51	56	51	59	32	17	46.4
58	Brain problem	46	42	54	51	53	55	53	56	23	40	47.3
59	Autoimmune	60	55	49	52	49	45	49	51	35	29	47.4
60	Kidney diseases	52	50	51	54	50	58	50	58	39	50	51.2

Averaged rank: $(r_1 + r_2 + \ldots + r_{10}) / 10$

According to Table 4, GA is the most important risk factor based on implementation of all FS algorithms. Also, the averaged rank of the "maternal kidney disease" variable was the lowest, suggesting that it is the least important risk factor. The variables have been sorted based on the averaged rank, then, 20 feature subsets were created, including 1, 2, …,10,15,20,25,30,35,40,45,50,55 and 60 important variables respectively. According to these subsets, 20 data subsets were created, and ML algorithms were implemented on these data subsets. Figures 2 and 3 reveal the results related to implementing the ML algorithms for 20 data subsets obtained from FS.

According to Figs. 2 and 3, MLP using 15 first important variables with accuracy of 90.86% and F-measure of 90.8% has achieved the best results. The first 15 most important variables are gestational age, delivery type, presentation, steroid administration, macrosomia, prenatal care, infant number and rank, mother addiction, maternal chronic disease history, fetal hydrops, amniotic fluid, gestational hypertension, infertility and placental abruption.

Table 5 provides the best results of every algorithm. Comparing Fig. 1 and Table 5, it is found that use of FS algorithms has caused increased accuracy and F-measure by 4.7% and 4.9% respectively on average.

Table 5
The best performance of each ML methods on various feature subsets

ML Method	Accuracy	F-measure	No of selected features
MLP	90.86	90.8	15
J48	90.29	90.2	6
RF	90.24	90.3	3
SVM	90.76	90.8	9
NB	89.37	89	15

Graphical user interface of the proposed CDSS was designed based on the best algorithm in Visual Studio 2015 and shown in Fig. 4.

4. Discussion And Conclusions

This paper dealt with a prediction system for the need to neonatal CPR immediately after birth in delivery room. In order to achieve a system with proper performance, various ML algorithms were compared with different sets of risk factors to identify the best system as well as the most effective factors in CPR predicting. According to the obtained results, in order to predict the need to CPR in neonates, SVM using all risk factors reached accuracy of 88.43% and F-measure of 88.4%, while MLP using the first 15 most important variables reached accuracy of 90.86% and F- measure of 90.8%.

Feature ranking was performed using 10 FS algorithms and the most effective risk factors were gestational age, delivery type, presentation, steroid administration, macrosomia, prenatal care, number of infant, mother addiction, fetal hydrops, rank of infant, amniotic fluid status, gestational hypertension, infertility, placental abruption and maternal chronic disease history, respectively.
According to the sixth's edition of the textbook of neonatal resuscitation(23) and the International Liaison Committee On Resuscitation (ILCOR) guideline(24), the risk factors of GA, delivery type, presentation, macrosomia, prenatal care, multiple gestation, fetal hydrops, amniotic fluid status, hypertension, placental abruption and maternal chronic disease history all may contribute to increasing the need to in-birth CPR in neonates. In the study by Afjeh et al. the risk factors affecting the CPR in neonates were examined, whereby placental abruption, multiple gestation, delivery type and infertility were identified as the risk factors which may contribute to increasing the need to delivery room CPR(17). Also, in the study by Jiang et al., it was found that diabetes, hypertension and delivery type affect the need to CPR in neonates (18).

The prevalence of mortality, neurodevelopmental impairment, respiratory support at 28 days, days to full oral feeds and length of stay are very high among the neonates who have received in-birth CPR (8, 25). Even the national institute of child health and developmental neonatal research reported that CPR in delivery room is a prognostic factor for morbidity and later complications up to 18 months of age (26). Thus, the healthcare system should be able to predict which neonates require CPR before delivery, so that the neonatal resuscitation team would present in time (27). Previous studies have shown that antenatal transfer of high-risk mothers reduces pre-discharge neonatal mortality (28, 29). Thus, predicting the need to in-birth CPR can be very effective, as it increases the preparation of the neonatal resuscitation team and provides the possibility of consultation with the family before delivery (27). Therefore, according to the results obtained from this study, use of the proposed system for predicting the need to in-birth CPR in neonates will have a great significance in reducing the adverse outcomes in childbirth and better preparation of the CPR team.

In addition, the coordination between the CPR team and obstetricians can lead to reduced adverse events in the delivery room and improve the care (27). In the Draper's study, intrapartum deaths in the UK were examined and it was found around 25% of mortalities have been due to lack of suitable communication between the multidisciplinary team during delivery (30). Thus, the proposed system can be used as an infant pre-resuscitation guide in order to ensure coordination between the CPR team and obstetricians.

In spite of the great significance of CPR prediction, very few studies have dealt with neonatal CPR, out of which mostly have addressed CPR in NICU (12–15), which have samples with a small sample size and few risk factors because of the challenges in data collection (12–16). However, in this study, in addition to considering a sample with suitable size, attempts were made to capture all fetal and maternal risk factors mentioned in credible guidelines which also had demonstrated their importance in previous studies.

The main limitation of this study, like most previous studies, was that the data related to only one center were examined. Thus, it is suggested to conduct studies with a more diverse sample extracted from multiple centers with different grades of NICU. Comparison of the results can be useful in identifying significant risk factors affecting the need to CPR and thus in its prediction.

List Of Abbreviations

CPR: Cardiopulmonary Resuscitation

ML: Machine Learning

MLP: Multilayer Perceptron

SVM: Support Vector Machine

GA: Gestational Age

VLBW: Very Low Birth Weight

ELBW: Extremely Low Birth Weight

FHR: Fetal Heart Rate

CDSS: Clinical Decision Support System

APGAR: Appearance, Pulse, Grimace, Activity, Respiration

AAP: American Academy of pediatrics

CPAP: Continuous Positive Airway Pressure

PPV: Positive Pressure Ventilation

IUFD: Intrauterine Fetal Death

ART: Assisted Reproductive Techniques

IUGR: Intrauterine Growth Restriction

PRoM: Prelabor Rupture of Membranes

NB: Naïve Bayesian

RF: Random Forest

CFS: Correlation-based Feature Selection

FS: Feature Selection

ILCOR: International Liaison Committee On Resuscitation

Declarations

Ethics approval and consent to participate: Our study was approved by the institutional review board of Tehran University of Medical Sciences and according to Helsinki declaration (Approval ID: IR.TUMS.VCR.REC.1398.591). All participants' parents gave their written informed consent before loading the data into the registry and for the participation in the study. Participants' data were considered confidential and no extra cost was imposed on our participants.

Consent for publication: 'Not applicable'

Availability of data and materials: The data that support the findings of this study are available from manager of maternal, fetal, and neonatal registry of Valiasr hospital in Tehran but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of manager of maternal, fetal, and neonatal registry of Valiasr hospital in Tehran.

Competing interests: The authors declare that they have no competing interests

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Authors' contributions: AO has participated in acquisition, analysis, interpretation of data; the creation of new software used in the work; MZ has participated in interpretation of data and substantively revised the work; AO and MZ have drafted the work. RM has participated in acquisition and interpretation of data. All authors read and approved the final manuscript.

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Figures

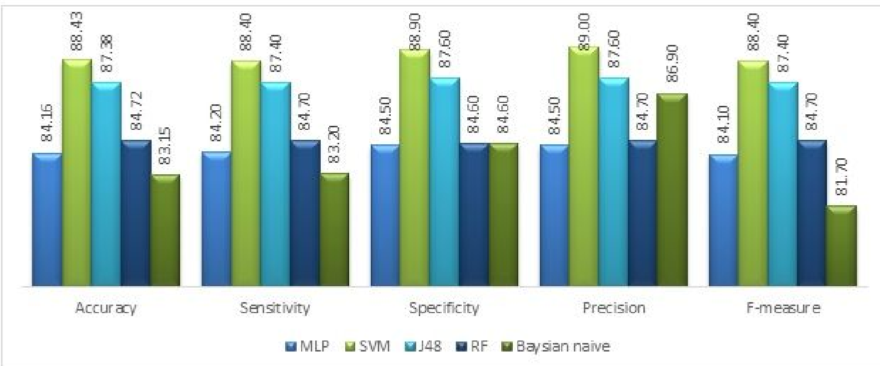

Figure 1

Performance metrics of ML algorithms for original dataset

Figure 2

Accuracy of ML algorithms for 20 feature subsets

Figure 3

F-measure of ML algorithms for 20 feature subsets

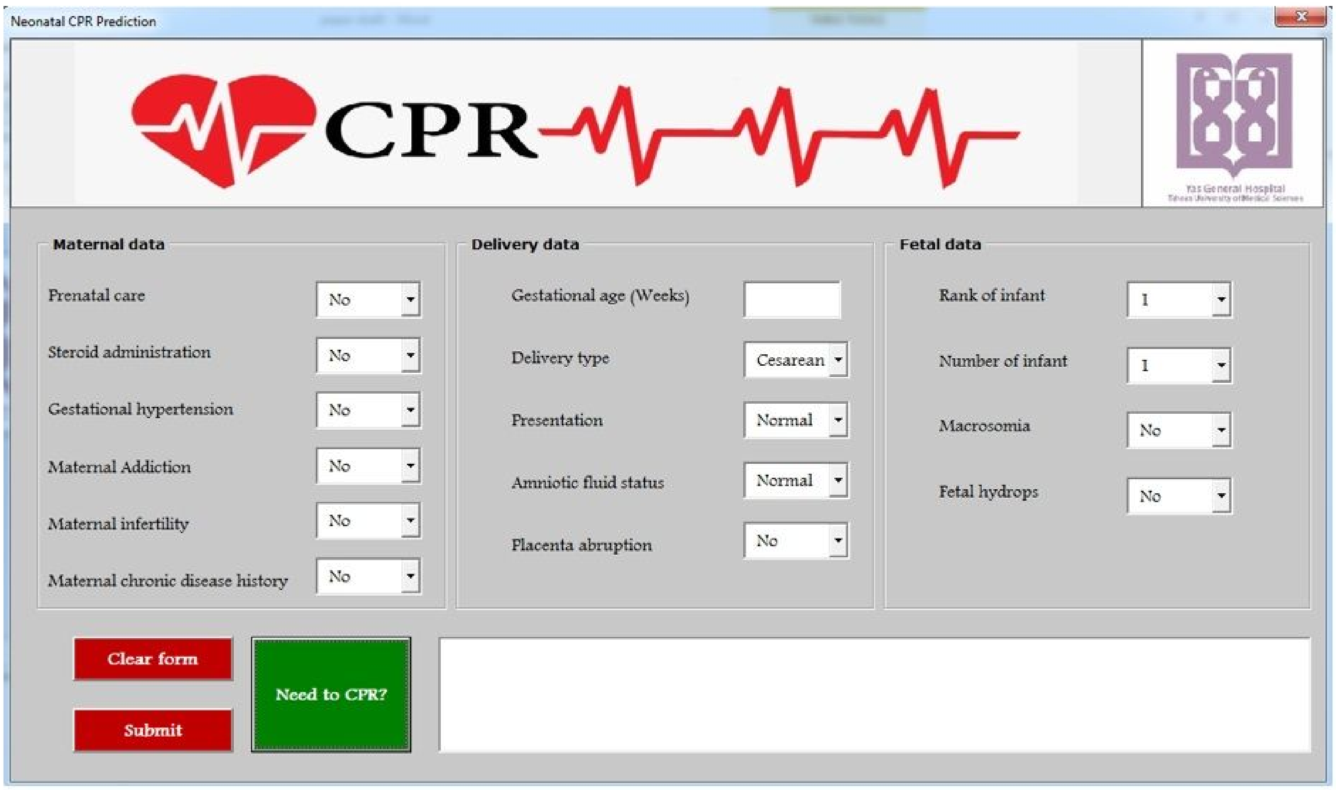

Figure 4

User interface of the proposed system

Supplementary Files

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- AppendixA.docx