Artif Intell Rev
https://doi.org/10.1007/s10462-018-9635-1

Neonatal intensive care decision support systems using artificial intelligence techniques: a systematic review

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Abstract A neonatal intensive care unit (NICU) provides critical services to preterm and high-risk infants. Over the years, many tools and techniques have been introduced to support the clinical decisions made by specialists in the NICU. This study systematically reviewed the different technologies used in neonatal decision support systems (DSS), including cognitive analysis, artificial neural networks, data mining techniques, multi-agent systems, and highlighted their role in patient diagnosis, prognosis, monitoring, and healthcare management. Articles on NICU DSS were surveyed, Searches were based on the PubMed, Science Direct, and IEEE databases and only English articles published after 1990 were included. The overall search strategy was to retrieve articles that included terms that were related to "NICU Decision Support Systems" or "Artificial Intelligence" and "Neonatal". Different methods and artificial intelligence techniques used in NICU decision support systems were assessed and related outcomes, variables, methods and performance measures was reported and discussed. Because of the dynamic, heterogeneous, and real-time environment of the NICU, the processes and medical rules that are followed within a NICU are complicated, and the data records that are produced are complex and frequent. Therefore, a single tool or technology could not cover all the needs of a NICU. However, it is important to examine and deploy new temporal data mining approaches and system architectures, such as multi-agent systems, services, and sensors, to provide integrated real-time solutions for NICU.

Keywords Neonatal decision support system · Neonatal outcome prediction · Multi-agent systems · Artificial intelligence · Neonatal intensive care unit management

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Published online: 22 May 2018

1 Introduction

The first month is the most important period for a child's survival. According to WHO (World Health Organization), 45% of deaths that occur in children less than 5 years old happen in the first 28 days of life. Over the past 25 years, the percentage of neonatal deaths has increased in all WHO regions. In recent years, there have been great improvements in the development and use of new tools, technologies, and neonatal monitoring techniques. These advances have caused the neonatal mortality rate to decrease, although statistics have shown no reduction in the mortality rate for preterm, low weight, and neonates born after labor complications (Frize et al. 2003).

In a NICU, treatment decision-making is a very complicated and critical task, as healthcare providers are concerned with allocating medical resources and treatment according to a patient's medical condition (Frize et al. 2011). Information technology has been widely used in medical diagnosis and treatment as a decision-making tool. Using artificial intelligence and data mining tools can increase the patients quality of care by providing early warnings for high-risk neonates (Frize et al. 2001, 2003). NICU decision support systems have been designed for two main reasons: to predict the risk of mortality and to measure the performance of medical services. Multi-agent systems are intelligent, autonomous, and collaborative system components that can be used to negotiate, manage, and improve healthcare processes. They are considered to be part of the distributed problem-solving solution and collaborate to achieve a common goal. Over the years, multi-agent systems have been widely used in healthcare modeling, process management, and DSS (Santos et al. 2011; Zhang et al. 2009). They have also been applied in intensive care units (ICUs) (Foster et al. 2005).

The main research question on this study is: "what are the current state-of-the-art artificial intelligence techniques used in NICU". Addressing this question would help designing and developing new tools and solutions for neonatal care at NICU. In this paper, articles that discussed the methods and technologies used in NICU DSS were reviewed. These methods included cognitive analysis, artificial neural networks (ANNs), data mining classification techniques, fuzzy Logic and biosensors (as DSS input media). A review of multi-agent systems, as a new approach for NICU DSS, was also performed.

2 Method

In this study, articles on NICU DSS were examined. Searches were performed in the PubMed, ScienceDirect, and IEEE databases. Only English articles published after 1990 were included. The overall search strategy was to retrieve articles that included terms related to "NICU DSS" or "Neonatal Decision Support Systems" in the title or abstract. PubMed articles published within the past 10 years included the terms "Artificial Intelligence" and "NICU" in the title or abstract were also included.

We categorized the resulting articles based on the main method and technology employed in the NICU DSS, which included cognitive analysis, ANN, classification techniques, multi-agent systems, fuzzy logic, and biosensors. A search for relevant articles in each category was then performed to enrich the discussion. A total of 90 articles were found in the initial database search of which 24 articles were excluded after a title review; 10 articles were excluded after their abstracts were read. Relevant articles in each category were then added. Articles were excluded if they concentrated on medical aspects without using information technology, studied metabolic modeling, used mechanical tools in the NICU, or used text

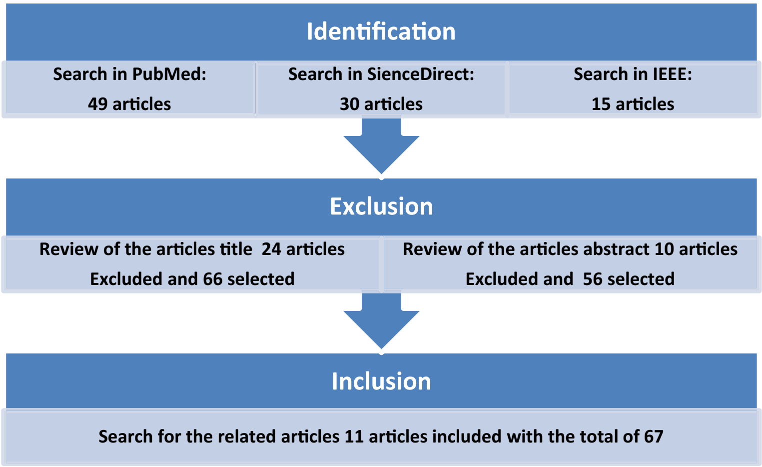

Fig. 1 Article selection according to the exclusion and inclusion criteria

Table 1 Number of articles on NICU DSS categorized into artificial intelligence branches

NICU DSS approach	Number
Cognitive task analysis	5
Classification techniques	
Support vector machines	11
Artificial neural networks	5
Decision tree	4
K-nearest newborns	2
Gaussian mixture model	3
Regression	3
Rule based	4
Fuzzy logic	4
Multi agent based approaches	1
Biosensors	4

mining techniques for knowledge extraction. Figure 1 illustrates the article selection and refinement methodology.

3 Results

Articles about NICU DSS were reviewed and categorized into five groups based on their artificial intelligence branch. Table 1 shows the number of articles reviewed in each category. DSS can be used during the prognosis, patient diagnosis, treatment, resource utilization, outcomes, or cost estimation. Tables 2, 3, and 4 shows the diagnosis, prognosis, and monitoring of the NICU DSS outcomes, as well as the analytical method, variables, and performance measures used.

Table 2 Diagnosis NICU DSS outcomes, analytical method, and variables and performance measures

Outcome	Method	Parameter's	Performance measures	Outcome estimation facts
Neonatal diagnosis at NICU				
Seizure detection	SVM and post-processing techniques (Temko et al. 2011a, 2015) Converting SVM outputs to posterior probabilities and filtered with a moving average filter (MAF) (Temko et al. 2011b; 2013) Basic Gradient Descent (BGD) Least Mean Squares (LMS) Newton Least Mean Squares (NLMS) (Thomas et al. 2008) Gaussian Mixture Model (GMM) With Linear discriminant analysis (LDA) and principal component analysis (PCA) increase the performance of the detector by reducing the dimensionality of the feature space (Thomas et al. 2010) Blending SVM and GMM (Temko et al. 2017) Analyzing the correlation between high-energetic segments of the EEG and detecting increases in low-frequency activities (Deburchgraeve et al. 2008). The model was improved using heuristic classifier and data driven post processing (Ansari et al. 2016)	EEG	Event-based metrics (good detection rate, false detection per hours) Receiver Operating Characteristic Area Under Curve (ROC AUC) Accuracy, sensitivity, specificity ROC AUC Positive Predictive Value (PPV) Accurcy and false alarm rate (FAR)	Average good detection rate of 89% with one false seizure detection per hour, 96% with two false detections per hour, or 100% with four false detections per hour Appling post-processing techniques by converting SVM outputs to probabilistic values, filtering and using thresholds increases the precision and the robustness of the system The largest overall ROC (96.3 ± 2.4) is obtained using MAF = 15 and collar = 40 s BGD (Sen:32.7, Spec:91.85, Acc:84.51, GDR:61.51, FD:9.73) LMS (Sen:36.01, Spec:91.23, Acc:84.72, GDR:60.54, FD:10.30) NLMS (Sen:28.09, Spec:92.39, Acc:84.02, GDR:59.69, FD:10.20) Using Gaussian mixture model with LDA transform leads to the highest ROC area of 95.6% SVM and GMM blended model resulted in AUC = 97.03% Sensitivity of the combined algorithms (correlation analysis and detecting low frequency activities) was found to be 88%, Positive Predictive Value (PPV) 75% Using post processing they archived GDR = 80% and FA = 1.3

Table 2 continued

Outcome	Method	Parameter's	Performance measures	Outcome estimation facts
hypoxic-ischemic e encephalopathy (HIE)	Automated multimodal prediction using SVM (Temko et al. 2015a) GMM supervectors and SVM (Ahmed et al. 2016) Scoring neonates into grades (Nevalainen et al. 2017)	Heart rate, EEG Somatosensory evoked potential (SEP), visual evoked potential (VEP)	Leave-one-patient-out (LOO), ROC AUC, Accuracy	LOO method was used to assess the performance the SVM method had 84% accuracy and 86% ROC GMM supervectors with SVM and post-processing using majority voting and probabilistic estimation techniques resulted in 87% accuracy Accuracy of outcome prediction was 98% with SEPs compared to 90% with EEG
Sepsis	SVM, Naïve Bayes (NB, Tree augmented naive Bayes (TAN), Averaged One Dependence Estimators (AODE), K-nearest neighbor, Cation and regression trees (CART), Random forests (RF), Logistic Regression (LR), lazy Bayesian Rules (LBR) And feature selection algorithms: SVM-BW, SVM-FBW, SVM-RFB, Hitton-MB, Hitton-PC	Seven hundred and eighty-one temporal variables from the laboratory dataset and 30 non-temporal variables (demographics, birth weight, gestational age, Apgar scores, mode of delivery etc.)	Sensitivity, Specificity	299 infants evaluated for late-onset sepsis AODE had the best sensitivity (88%) AODE had the best specificity (36%)

Table 2 continued

Outcome	Method	Parameter's	Performance measures	Outcome estimation facts
Neonatal jaundice	Multi attribute utility function using influence diagram (Gomez et al. 2007)	Mother RH Factor, Mother Blood group, is immunization, Mother age, Mother race, 1time-mother, mother illness, Mother cultural level, mother residence, New born weight, gestational age, age in hours, blood group, RH factor, bilirubin, hemoglobin, Apgar, Cord-PH, skin color, instrument usage, resuscitation	Match between experts and system proposals	Decision analysis based on medical expertise and patient preferences instead of using decision trees, expert systems and formal logic-based approaches. 6% mismatch reported
Plus disease	Image analysis using a two-component Gaussian Mixed Model (GMM) (Campbell et al. 2016)	Retinal images	Accuracy	77 wide-angle retinal images Accuracy was highest (95%)

Table 3 Prognosis NICU DSS outcomes, analytical method, and variables and performance measures

Outcome	Method	Parameter's	Performance measures	Outcome estimation facts
Neonatal prognosis at NICU				
Mortality	Evidence-based estimation using Neural Network techniques and case base reasoning ANN (Frize et al. 2005) C5.0 decisions tree (Gilchrist et al. 2011) ANN (MLP) and k-Nearest neighbors (Frize et al. 2013; Townsend and Frize 2008) ANN (Frize et al. 2015) Fuzzy Logic (Safdari et al. 2016; Chaves and Nascimento 2014) ANN and SVM (Cerqueira et al. 2014) Logistic regression (LR), classification random forest (cRF), regression random forest (rRF) and BART (Liu et al. 2015) ANN (Saadah et al. 2014)	Sex, Respiratory rate, PO2, PCO2, White blood cell count, Sodium, Glucose, Serum pH, Mean Blood Pressure, heart rate, absolute neutrophil count, immature/total neutrophil ratio, blood hematocrit, platelet count, Birth Weight, Gestational Age, Apgar Score, Neonate's Status in Delivery, Mother's Age, Previous Multiple, Diabetic Mother, Malformation, Base Excess, Previous Stillbirth, PO2-FIO2 ratio, seizures, urine output	Accuracy, sensitivity, specificity, positive predictive value, Classification Range AUC	Evidence-based estimation using Neural Network techniques resulted in mortality Classification Rate of 91.3% Using Decision Trees had less sensitivity (63%) and specificity (94%) compared with Multi-Layer Perceptron sensitivity (63%) and specificity (99%) Managing missing values with K-Nearest Neighbors Case base reasoning techniques MLP Neural Networks with automated knowledge extraction for real-time outcome prediction resulted in 81% sensitivity and 98% specificity Using Fuzzy Rule base system resulted in sensitivity = 83%, specificity = 97% Using SVM Accuracy = 79%, Sensitivity = 100%, Specificity = 75% and using ANN Accuracy = 84%, Sensitivity = 83%, Specificity = 84% LR = 0.93, cRF = 0.94, rRF = 0.94, BART = 0.95 Using ANN sensitivity of 82% and specificity of 100%
Discharge	Natural Language Processing using Bag of words Matrix Model and Random Forest Classifier (Temple et al. 2016)	NICU Notes	ROC AUC	AUC of 0.74, 0.77, 0.81, and 0.86 at 10, 7, 4 and 2 days until discharge

Table 4 Monitoring and health management NICU DSS outcomes, analytical method, and variables and performance measures

Outcome	Method	Parameter's	Performance measures	Outcome estimation facts
Neonatal monitoring and health management at NICU				
Mechanical ventilation	Flex System (Tehrani and Abbasi 2009) Mathematical Model (Tehrani and Abbasi 2012)	Sex, Gestational age, Age since birth, Weight, Diagnosis, Ventilation mode, set ventilation, Total breathing rate, Set FIO2, Set PEEP, Race (W/B/O), Major clinical problem	Comparison of estimated and measured values, Differences between measured and predicted PaCO2, SaO2 values	Recommended values were on the average within 25% of the measured values Differences between measured and predicted PaCO2, SaO2 values (2.56 ± 1.4 mmHg, 0.043 ± 0.014 mmHg)
Extubation failure	LR (Mikhno and Ennett 2012) ANN (Mueller et al. 2004)	Monocyte cell count, rapid shallow breathing index, fraction of inspired oxygen (FiO_2), heart rate, PaO_2/FiO_2 ratio	AUC Sensitivity Specificity	Using logistic regression AUC of 0.871 and sensitivity of 70.1% at 90% specificity Using ANN AUC = 0.87
Apnoea monitoring	SVM (Monasterio et al. 2012)	Oxygen saturation, heart rate, respiratory rate and signal quality	Sensitivity Specificity Accuracy	sensitivity of 86%, a specificity of 91% and an accuracy of 90%
Infant transportation instructions	Rule based forward chaining (Heermann and Thompson 1997)	Breathing status, blood glucose status and lab values	Structural and Functional Testing, all rules were carefully reviewed by experts and the knowledge engineers	System safety mean = 5.77, Standard mean = 6.33, scope mean = 6.98
Neonate health condition	Direct Acyclic Graph based Support Vector Machine (DAGSVM) (Agarwal and Pandey 2012)	Systolic Blood Pressure (SBP), Arterial Blood Oxygen Tension, PaO2, Cardiac Pulse Rate in Electrocardiograph (ECG), Pulse Oximeter Rate (POR), Capnography Monitor Data (CMD), Capnography Monitor Data (CMD), Body Temperature (BT)		Using a Prognostic Index based on seven vital parameters to identify neonate health condition. The ranges of Prognostic Index are used for supervised learning classification

Table 4 continued

Outcome	Method	Parameter's	Performance measures	Outcome estimation facts
Sleep state	RBF SVM (Koolen et al. 2017)	EEG	Accuracy, sensitivity, specificity	231 EEG recordings from 67 infants between 24 to 32 weeks 57 EEG features were extracted The features were reduced using greedy algorithms Accuracy = 85%, Sensitivity = 83%, Specificity = 87%
Plasma insulin	Integral-based fitting method (Le Compte et al. 2011)	Total plasma glucose, plasma insulin, body weight, brain weight, endogenous glucose clearance and insulin effect, insulin distribution volume per kilogram body weight, Total plasma glucose input, endogenous glucose production, glucose distribution volume per kilogram of body weight, non-insulin mediated glucose uptake by the central nervous system, saturation of plasma insulin disappearance, saturation of insulin dependent glucose clearance	Median absolute prediction error	The identified model had the median absolute prediction error of 2.4%
Parental nutrition recommendation	Guidelines for parental nutrition solutions (Peverini et al. 2000)	Newborn weight, daily fluids, lipids, dextrose, sodium, potassium, chloride, elemental calcium, phosphorus, magnesium	Prescription mistakes	Prescription mistakes

Table 4 continued

Outcome	Method	Parameter's	Performance measures	Outcome estimation facts
Brain state	Random Forest method classification (Chen et al. 2014)	Amplitude-integrated electroencephalography (aEEG)	Accuracy Sensitivity Specificity	Accuracy = 92.5, Sensitivity = 93.7, Specificity = 87.5
Brain maturation	support vector regression (O'Toole et al. 2016)	EEG	mean square error (MSE), standard deviation of the estimate (SD) and the percentage error (SE) between the known GA and estimated EMA.	MSE of 82 days, SD = 9.1 days and SE = 4.8%
EEG artifacts	Linear and Kernel based Support Vector Machines (Bhattacharyya et al. 2013)	EEG	Sensitivity Specificity	Sensitivity = 78%, Specificity = 72%
Diagnosis pain	PCA, LDA, SVMs and NNSOA (Brahnam et al. 2007) NIPE Index (based on continuous cardiac signal ECG or plethysmography waveform processing((Butruille et al. 2015)	Neonate photograph Heart rate variability (HRV)	Accuracy, Comparison with EDIN Score (Neonatal Pain and Discomfort Scale)	NNSOA (90.2%), SVM (82.35%), PCA (80.39%), LDA (76.96%) Accuracy The NIPE index was significantly lower in the "high EDIN" group compared to the "low EDIN" group ($P = 0.009$). Moreover, EDIN score and NIPE index were correlated ($P < 0.01$

Different artificial intelligence methods and technologies used in the NICU DSS were assessed. Cognitive analysis, with the main goal of improving system usability, was applied to NICU DSS, while an ANN was used as an evidence-based medical tool that used knowledge from past medical outcomes to make predictions about neonatal mortality, length of stay, and artificial ventilation duration. Data warehouse technology was used to create a multi-dimensional neonatal data repository of heterogeneous databases that could be used with a data mining platform. The real time, modular, proactive, and complicated nature of the NICU environment requires the use of new technologies and software solutions, such as service-oriented architecture (SOA) and multi-agent systems. Providing data analysis in a service-oriented fashion and the real-time monitoring of infants in the NICU were also addressed in some articles (Frize et al. 2001; Khazaei et al. 2015a, b).

4 Discussion

4.1 Cognitive analysis in NICU DSS

Designing medical systems that represent knowledge require cognitive analysis to model a representation of a user's mental information and their attitude toward computer-based systems (Frize et al. 2011). One of the main goals of using cognitive analysis in a clinical DSS is to fill the gap between a user's mental attitude in a particular context with one presented by the DSS. Hence, cognitive analysis is used to integrate and adopt clinical decision systems into NICUs. However, as newly designed systems might not be accepted by healthcare providers and users, it is important to assess the usability of a system (Baxter et al. 2005).

Cognitive task analysis (CTA) was used to integrate a fuzzy logic based respiratory expert system (FLORENCE), into NICU workflow (Baxter et al. 2005). Using CTA, factors affecting the system's adoption and usefulness were obtained. CTA included analyzing the NICU workflow specifications and the user's tasks. System alarms had to be clear and understandable to users and the system had to have explanatory abilities so that it was reliable and acted as expected.

The critical decision method (CDM) was used in CTA for knowledge elicitation and for deriving user decision-making steps. The CDM was based on naturalistic decision-making and was used for case-based reasoning. For example, CDM was used to develop training materials for identifying neonatal sepsis (Hoffman et al. 1998; Patel eta l. 2001). Using CTA involved an analysis of the physical and social work using a light-weight rich picture representation to demonstrate the roles and responsibilities of people working with the system (Baxter et al. 2005). The final step involved observations, which provided further insight for the project.

Cognitive analysis was also used in the DSS for ordering antibiotics (Sheehan et al. 2012). The analysis was made using Norman's theory of action. The distance between the user's goal and the actions provided by the system was calculated in terms of semantic distance, articulatory distance, and issue distance. The cognitive study design involved two methods: a cognitive walkthrough and a think-aloud protocol. In order to identify the usability problems during the cognitive walkthrough, Nielsen's ten usability heuristics were applied.

Natural language processing (NLP) was applied on patient notes in order to identify a discharge cohort in the NICU. The results showed that combining classification algorithms with NLP improved the discharge prediction model (Temple et al. 2016).

The NICU workflows vary between hospitals. Cognitive analysis can reduce the conflict between what healthcare providers expect to see and what they actually see. One of the problems identified during DSS cognitive analysis was the availability of information while it was required by a healthcare provider. Another problem occurred when the system recommendations were not clear and understandable. Users must have enough skills, knowledge, and training to use the system to its full advantage.

4.2 Classification techniques in NICU DSS

An ANN gains knowledge through a learning process and stores that knowledge by updating the neuron interconnection weights. It learns the input/output relationship patterns from existing data and evolves by learning new available data. ANNs model existing data and predict outcomes based on new data (Walker and Frize 2004). A trained ANN is considered to be the knowledge base in DSS. ANNs can be applied to evidence-based medicine because they base their predictions on previous data (Mueller et al. 2004). ANNs are widely used in ICUs and in the field of neonatal care; they are mainly used to predict infant mortality and the length of stay in the NICU (Frize et al. 2001, 2010). An ANN can also be used in the ICU to predict medical outcomes. For example, the mortality, duration of artificial ventilation, and length of stay were predicted for adults using the back-propagation algorithm. Although it is a popular classification algorithm and is considered to be easy to use, the back-propagation algorithm has the problem of overfitting data. To overcome this problem, weight-elimination, adaptive parameters, and momentum have been used.

The Medical Information Technology Group developed risk models of illness and complications and integrated these models for neonates, adults, and preterm births (Frize et al. 2005). The group introduced a multi-layer perceptron neural network to predict mortality, length of stay, and duration of ventilation. An interactive decision-making tool was also proposed to allow parents and specialists to be involved using a conceptual framework for NICU knowledge management (Frize et al. 2005). The outcome estimation was implemented using an ANN in an evidence-based estimation block; the correlation between the indicators and outcomes was analyzed using an ANN with diagnostic data to predict mortality, length of stay, and artificial ventilation. Information about the patient's condition, healthcare specialist, and parent perception was stored in a knowledge repository and enhanced the decision-making process by interacting with the parents. Design options for a NICU DSS with physician–parent involvement were discussed (Frize et al. 2011) and implemented (Frize et al. 2005), which resulted in a more complete web-based user interface and mobile-based interface. Drupal was used as an open source extensible tool for content management. Patient medical data were stored in a clinical data repository (CDR), which managed the admission/discharge and transfer of data, lab results, and medical measurements from patient monitors. The International Patient Decision Aids Standard (IPADS) was applied to the web-based DSS questionnaire to ensure that the DSS did not replace expert consultation. A physician and parent decision support tool (PPADS) was developed, which enabled the physician to view the patient's condition and the parents allowed to view neonate information activated by the physicians (Weyand et al. 2011). The tool improved decision-making efficiency in ethically conflicting situations and provided better family-centered care and usability (Frize et al. 2013).

An extubation DSS was introduced to predict extubation outcomes using an ANN (Mueller et al. 2004). The performance of the ANN was compared with statistical modeling using multivariate logistic regression (MLP) and with the clinician's expertise. The accuracy of the models was compared using ROC curves. In this model, a multilayer feed-forward neural network was used. Another study applied an ANN model to predict the effect of palivizumab on neonatal mortality, days of supplemental oxygen, and length of NICU stay during an outbreak of respiratory syncytial virus (RSV) (Saadah et al. 2014).

As the complexity of an ANN increases, it is important to reduce training, to increase performance, and to prevent the network from overfitting. The impact of misprediction must be considered when using ANNs to forecast clinical outcomes, for example, the impact of a misprediction of mortality is different from one about the length of stay in an NICU. Outcome predictions that involve patients' lives are more critical than those dealing with managerial issues.

One study classified the health condition of neonates and their vital parameters using SVM (Agarwal and Pandey 2012). In the research, a physiological data warehouse model was presented and utilized using data mining techniques. The data warehouse was built using a star schema with seven dimensions: systolic blood pressure (SBP), arterial blood oxygen tension (P_aO_2), cardiac pulse rate, scenography monitor data (CMD), ventilation data for the respiration rate and body temperature. Data preprocessing, which included signal preprocessing and feature preprocessing, and data fusion techniques were applied before loading the data to the warehouse.

A neonatal prediction model was developed using C5.0 algorithm to build a decision trees (Gilchrist et al. 2011). This model applied a probabilistic algorithm to handle the missing values. To predict mortality, 18 SNAP (Score for Neonatal Acute Physiology) attributes were selected. The results of this research showed that using data collected within 48 h of the patient's admission to the NICU produced the best results, while the use of large data sets with 12-h time segments had less specificity.

Classification techniques using a SVM classifier have been applied in neonatal seizure detection systems (Ansari et al. 2015; Temko et al. 2015b). The classifier was trained on normalized data and the output was converted to posterior probabilities and filtered with a moving average filter (MAF) (Temko et al. 2011a). In another study (Thomas et al. 2008), basic gradient descent (BGD), least mean squares (LMS), and Newton least mean squares (NLMS) were used to detect seizures, achieving 84.51, 84.72, and 84.02% accuracy respectively. Other studies used a combination of patient-dependent and patient-independent classifiers to detect seizures using SVM and Gaussian mixture models (Ahmed et al. 2012; Temko et al. 2017). A patient-independent system has no prior knowledge of the data from the patient being tested, while patient-dependent models use portions of the patient data for training. The blended adaptive model achieved 97.03% AUC.

SVM was also applied in a multimodal predictor of neurodevelopmental outcome in newborns with hypoxic-ischemic encephalopathy (Temko et al. 2015a) and an accuracy of 84% was reported. The severity of hypoxic-ischemic encephalopathy was predicted based on the electroencephalography (EEG) of neonates using SVM and achieved an accuracy of 87% (Ahmed et al. 2016). Kernel-based SVM methods were also applied for the classification of neonatal sleep states (Koolen et al. 2017). Random forest (RF) classification achieved the highest accuracy in amplitude-integrated electroencephalography (aEEG) classification for monitoring the functional state of the brain (Koolen et al. 2017). One study examined nine machine learning classification techniques for detecting late-onset neonatal sepsis, including SVM, naïve Bayes (NB), tree augmented naive Bayes (TAN), averaged one-dependence estimators (AODE), k-nearest neighbor, classification and regression trees (CART), RF, logistic regression (LR), and lazy bayesian rules (LBR) (Mani et al. 2014). The model used laboratory, clinical, and microbiological data and the AODE algorithms achieved the highest sensitivity (88%).

Old knowledge extraction methods takes advantage of the rule-based expert systems, In this way, an infant's clinical data can be captured and the necessary intervention is suggested with the help of the rule-based DSS (Heermann and Thompson 1997) or parental nutrition solutions can be prescribed for an infant in the NICU (Foster et al. 2005; Khazaei et al. 2015a).

Decision trees and some basic classification algorithms are not able to handle multiple time segmented data sets associated with one patient and, thus, it is hard to distinguish high-risk patient data from normal data. Other prediction techniques, such as an ANN, can overcome these barriers. Different classification techniques have been applied to detect neonatal seizures and it is believed that each classifier, if properly used by skilled practitioners, may reach similar levels of performance (Temko and Lightbody 2016).

4.3 Multi-agent systems in NICU DSS

Multi-agent systems are a subdomain of artificial intelligence; they are composed of agents that collaborate and negotiate with each other to solve a problem or achieve a goal. Multi-agent systems are used in two areas in ICU DSS: clinical management and clinical research (Foster et al. 2005). Clinical management multi-agent systems are used to identify specific medical conditions, diagnostics, and patient treatments, while clinical research-based multi-agent systems extract data, relationships, patterns, and trends. However, only a few proposed multi-agent systems are used in the NICU.

Multi-agent technology can be used for real-time warnings and alerts in the case of an abnormality in a wide range of neonatal data. An agent-based intelligent DSS was developed for a NICU (Foster and McGregor 2006), physiological data were analyzed and new trends were detected through an agent server architecture, which provided agent communication by passing requests between the service consumers and providers and validating the communication. The FIPA (Foundation for Intelligent Physical Agents) Agent Communication Language (ACL) and the Knowledge Query and Manipulation Language (KQML) standards were used. Access to multiple databases was managed by the agent server through a web service that acted as a database server in collecting and converting the data. The proposed architecture could be extended to support other ICUs.

4.4 Fuzzy logic in NICU DSS

Fuzzy logic has been widely applied to deal with the vagueness and uncertainty of medical data. Fuzzy logic has also been used to assess the risk of neonatal mortality (Nascimento and Ortega 2002; Nascimento et al. 2009; Safdari et al. 2016; Shimomura et al. 1994). In one study, a fuzzy expert computing model was designed to predict the risk of neonatal mortality; the model achieved a sensitivity and specificity of 83 and 97%, respectively (Safdari et al. 2016). In another studythe authors introduced a fuzzy model to estimate the possibility of mortality using few variables, including birth weight, gestational age, Apgar score, and report of stillbirth (Nascimento et al. 2009); the model had a sensitivity of 70% and a specificity of 98%. The fuzzy model used in (Nascimento and Ortega 2002) avoided the variability of parameters in the analysis of a newborn's condition and the model was compared with an expert opinion and there was a strong correlation between the results ($r = 0.96$).

A fuzzy linguistic model was also proposed to predict neonatal death, the model was tested using 100 cases and resulted in 81% accuracy, which was less than the accuracy obtained using other well-known neonatal severity scoring systems, such as CRIB and SNAP-PE, which had an accuracy of 90% (Chaves and Nascimento 2014). An expert system was built by applying fuzzy theory to Apgar scoring system (Shimomura et al. 1994); the system used three groups of knowledge (inexperienced, expert, and expert neonatologist) and the highest sensitivity belonged to the expert neonatologist knowledge base.

Fuzzy models are very simple and have a low computing cost, which makes them a good option for development of a prediction model (Nascimento et al. 2009). The inference method used in most fuzzy models is minimum of mamdanies. Mamdani fuzzy models are based on expert experience (Nascimento and Ortega 2002). One of the barriers to using fuzzy models is that the number of fuzzy rules grows exponentially, which affects the performance of the expert system. Another barrier is that the model outcome may change by adding variables. However, this approach has provided promising results in several medical applications.

4.5 Biosensors in NICU DSS

The NICU is a dynamically changing environment in which heterogeneous technologies interact with each other. Biosensors are widely employed in neonatal monitoring systems; multiple parameters of neonates are monitored in the NICU and are considered to be input data for DSS. These parameters include ECG, heart rate, respiratory blood pressure, blood oxygen saturation (O2Sat), body temperature, and cerebral function monitoring (CFM). The vital signs and physiological data of the patients are gathered through the interoperability of medical devices, personal health devices, and neonatal applications to make the clinical data available for medical decisions (Chen 2012). Thus, sensors, tools, and services need to interact with each other in a distributed environment, and these technologies must be able to provide integrated NICU solutions. One study introduced a new monitoring approach in which the NICU was considered to be an assembly of services and devices that had the ability to respond to the specific requirements of the setting (Piccini et al. 2008). The researchers developed a prototype platform that included a “BioBelt,” which was made of embedded sensors to monitor the heart rate, body movement, and temperature. They also introduced a graphical interface called “Assembly Browser” that allowed doctors to compare different parameters from different devices to obtain more accurate monitoring results.

A prototype application, called “BioAssembly,” was proposed in another study and consisted of a BioBelt prototype developed within the project (Grönvall et al. 2007). The prototype system relied on the SOA, which built up the system by self-contained units that solved tasks through interconnections. The open architecture was integrated with other standard medical devices for monitoring newborns.

Medical device data should be integrated and sharable with other health information systems in the NICU, and standard data formats should be defined for CDSS input and outputs. An XML schema with the capabilities of defining, detecting, and generating clinical alerts for NICU has been proposed (Catley et al. 2003). Sensor systems that evaluated and calibrated neonatal incubators were made using ANNs (de Araújo et al. 2013). The presented proposal reduces number of sensors, and the calibration necessity can be diagnosed in real time without the presence of technical professionals.

The ISO/IEEE 11073 family of medical/health device communication standards was proposed to provide device interoperability. The main architecture of this standard was divided into three models. The domain information model (DIM) embedded information inside the device agent by describing an abstract model composed of a set of objects that could be referenced in a communication. The service model (SM) provided methods to access data that were shared between agents and managed the interchange of the DIM data. The communication model (CM) described the network architecture in which agents communicated via a point-to-point connection (Chen 2012).

5 Conclusion

Neonatal technologies can save premature infants and infants with a low birth weight. Treatments for infants are normally based on an estimation of their health condition. In this study, a review of technologies that were used in neonatal NICU DSS was performed. These technologies included cognitive analysis, ANNs, and data mining techniques. There was also an emphasis on the use of multi-agent systems as a new approach for NICU DSS.

An ANN uses machine-learning techniques that are inspired by the natural nervous system; learning from past data makes ANN a great tool for evidence-based medicine. However, ANN may underperform statistical methods in comparison with other applications (Mueller et al. 2004).

Neonatal medical records at a NICU may consist of large paper files containing abnormal variations in measured parameters and medical data that may not be recorded in the notes. Currently, many NICU devices have the ability to output physiological parameters, such as vital signs and EEG signals, as high frequency multidimensional data streams, as the frequency and complexity of these data streams increase, it becomes more difficult to identify patterns and trends (Christina Catley et al. 2008; Moskovitch and Shahar 2005). Temporal abstraction (TA) is considered crucial for monitoring and performing diagnostic tasks, such as medical time-stamped NICU data analysis. NICU time series data features could be extracted as high-level abstract data views using expert rules or data mining approaches, such as hidden Markov models and SVMs with sequential kernels, to capture patterns (Ahmed et al. 2017; Temko and Lightbody 2016). The big data characteristic of medical data and the requirement of real-time data analysis in the NICU call for cloud-based analysis solutions and providing data analysis and live monitoring in a service-oriented fashion (Khazaei et al. 2015a, b).

Neonatal healthcare providers need to access guidelines and clinical DSS and, thus, there is a great predilection to use and adapt modern technologies. However, while there is a fear that CDSS is complicated and needs more working time, it is important to consider these barriers when designing neonatal CDSS.

Assessing healthcare outcomes, costs, and effectiveness can be performed using DSS that are based on scoring systems, such as the patient classification system (PCS) and the Acuity Index Method (AIM). In one study, the cost-related elements of care in the NICU were evaluated and the results showed that the PCS score was highly correlated with the length of stay, resource utilization, and hospital charges (Kotagal et al. 1995).

Predictions of medical outcomes and resource utilization can be made using case-based reasoning techniques in which the closest matching case to the newly admitted patient is selected. In one study, a case-based reasoning algorithm was adopted for a NICU and the results indicated that the inference engine selected the closest pattern at the case base to the new admitted infant (Frize and Walker 2000).

The differences between the outcome measures in the NICU should be considered, for example, prediction of the neonatal length of stay is used for economic and organization reasons, while predictions of neonatal mortality and duration of ventilation deal with a patient's life (Frize et al. 2001; Townsend and Frize 2008). Some DSS systems are not designed for real-time decision-making (Cerqueira et al. 2014), but can be used for the analysis and correlation of parameters and to determine how outcomes are influenced by the parameters.

It is difficult to compare neonatal decision support algorithms when there are no publicly available data sets and algorithms (Temko and Lightbody 2016).

The environment in a NICU is complicated and the data records that are produce are complex and frequent. Therefore, a single tool or technology could not cover all the needs of a NICU. It is important to examine and develop new temporal data mining approaches and system architectures, such as multi-agent systems, services, and sensors, to provide integrated real-time NICU solutions.

Acknowledgements The authors appreciate the support of the Maternal–Fetal and Neonatal Research Center of Tehran University of Medical Sciences for this project. This study was completed as part of a PhD thesis.

Compliance with ethical standards

Conflict of interest No potential conflict of interest relevant to this article was reported.

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