International Journal of Scientific Reports
Aamir Z et al. Int J Sci Rep. 2023 Oct;9(10):329-337
http://www.sci-rep.com
pISSN 2454-2156 | eISSN 2454-2164

DOI: https://dx.doi.org/10.18203/issn.2454-2156.IntJSciRep20232912

Review Article

Support vector machines in neonatal mortality detection: a comprehensive scoping review with disease-specific emphasis

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Received: 14 August 2023
Revised: 18 September 2023
Accepted: 20 September 2023

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ABSTRACT

Neonatal mortality is a widely significant problem since diseases such as sepsis, apnea and jaundice have claimed the lives of 2.3 million neonates in 2021. As such, better tools need to be developed to reduce its rate. While traditional methods like Clinical risk index (CRIB) and Score for neonatal acute physiology (SNAP) have proven helpful in predicting neonatal mortality, there is a need for more efficient measures. One such approach is support vector machine (SVM), a supervised machine-learning algorithm that is primarily used for classification. SVM can perform both linear and non-linear classification; it conducts the latter with the assistance of the kernel trick and functions such as polynomial, gaussian, RBF and sigmoid functions. This narrative review aims to explore the potential and limitations of SVM in predicting major global causes of neonatal mortality. We searched through articles employing SVM to predict different diseases and symptoms such as sepsis, seizures, fetal heart rate, low birth weight, hypoxic-ischemic encephalopathy, apnea, jaundice and neonatal respiratory distress syndrome, and concluded that while SVM has its merits and has shown promising results in many aspects, it also has its demerits such as requiring an extensive training time to achieve higher accuracy and precision.

Keywords: Support vector machines, Neonatal mortality, Disease-specific emphasis

INTRODUCTION

The death of a newborn baby in the initial 28 days of its life is designated as neonatal mortality. This period is considered to be extremely crucial as the risk of death is greatest during the first hours to the first days of life as the newborns are highly vulnerable to multiple causes of mortality during this period such as newborns with low birth weight, premature delivery, or any other health problems are even more likely to have a greater risk of death in the neonatal period.[1]

The rate of neonatal mortality varies across countries and regions, depending upon the disparities in healthcare infrastructure, access to quality care, socioeconomic conditions, and other factors that may influence infant survival rates. There has been a notable reduction in neonatal deaths from 5.0 million to 2.4 million between 1990 and 2019 according to the data provided by the WHO. However, it is concerning that in 2019 alone, nearly half (47%) of neonatal deaths took place within the first 28 days of their lives. In conclusion, reducing the number of neonatal deaths remains a serious challenge.[1] There are many causes of neonatal deaths, such as prematurity, congenital anomalies, intrapartum hypoxia etc. The most common are sepsis, respiratory distress syndrome/hyaline membrane disease (HMD), pulmonary haemorrhage, trisomy 18, Potters syndrome, low birth weight, pneumonia, meningitis, health problems in the mother, such as high blood pressure, diabetes, infections, structural or functional abnormalities present at birth. It has been seen that socioeconomic factors like poverty, malnutrition, and poor living conditions can also lead to an increasing rate of neonatal mortality. Recently it has been observed that developed machine-learning models can be used as a valuable tool to help physicians predict deaths of the neonates with the help of a range of variables, such as patient demographics, clinical characteristics, and data provided by the laboratory. In the modern era, machine learning methods are used to categorize information that may remain undetected through traditional approaches.[3]

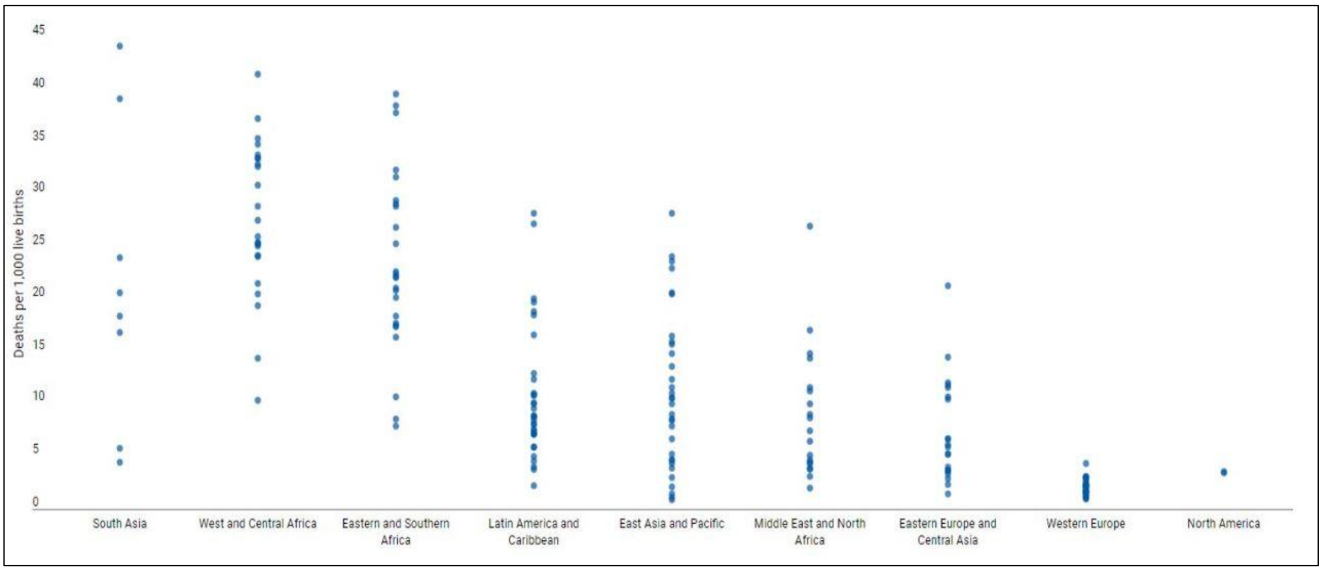

Figure 1: Neonatal mortality rates, by country and region, 2017.[2]

The support vector machine (SVM) is one of the machine learning classifiers used for the prediction of neonatal mortality.[4] It is a computer-based algorithm that utilizes training examples to understand patterns and assign appropriate labels to objects. The application of SVM analysis extends to a diverse range of biological data.[5] This study gives a broad assessment of the performance of SVM for disease prediction among neonates.

METHODS

We comprehensively searched for databases such as PubMed, Cochrane, Global Health Library (including Global Index by WHO), and Google Scholar to identify relevant studies published until 2023. We devised our search by focusing on certain keywords and phrases including terms such as 'machine learning,' 'artificial intelligence,' 'support vector machine learning', and 'support vector networks.' Additionally, we also used keywords such as 'approach to neonatal mortality,' 'data-driven approach to neonatal mortality rates,' and 'diseases associated with neonates and their causes' etc. We conducted a comprehensive study that analyzed articles utilizing machine learning algorithms to predict neonatal mortality especially SVM. We also utilized SANRA as an extremely useful resource to evaluate articles for the improvement of the quality of the manuscript.[6]

SUPPORT VECTOR MACHINES

SVM are examples of supervised machine learning algorithms that map input data to output data based on many sample input-output pairs specified while training the algorithm.[7] The algorithms create a plan that links inputs to desired outputs. One of the most famous derivations of the supervised learning task is the classification problem: the machine is required to learn the particular function that leads a vector into any of several determined classes by viewing many input-output examples of the function. Through classification, features attributed to a particular set of sample observations are used to train the decision function, enabling it to differentiate between the classes based on mere observations with a given accuracy.[8] Once the classifying criteria have been finalized based on observations, it can then automatically attach class labels to unseen observations using the patterns it has established in training. Support vector machines are one of the most popular supervised computer algorithms that can learn by examples to assign labels to objects, as mentioned earlier. It is a machine learning model used for classification, regression, and outliers detection.[9] SVM have been developed about statistical learning theories and have been successfully applied to several applications, comprising mass spectrometry for studying pollution, near-infrared analysis of food, thermal analysis of polymers, and UV/visible spectroscopy of polyaromatic hydrocarbons ranging from time series to face recognition and biological data processing for medical diagnosis.[10,11]

These machines work on the theory of statistical learning. Statistical learning theory elaborates on the performance of learning machines using the restrictions of their ability to predict future data. It has been proven that training many local support vector machines instead of a single global one may lead to immense improvement in the performance of a learning machine. To simplify how it works, we elaborate on three models.[12]

Linear SVM

Given there is a standard domain with *n* data dispersed randomly, and that the input sample dataset can be divided linearly to separate classes in the original domain. Classifying is then simpler, and the steps in the linear support vector machine include mapping the data domain into a response set and dividing the data domain.

$$y = wx + \gamma$$

The above equation is manipulated for linear domain division.

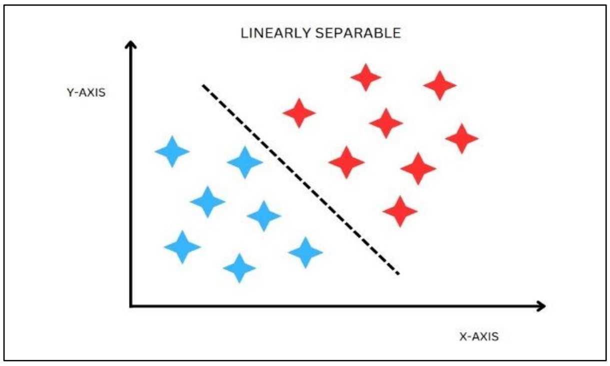

Figure 2: Linearly separable.

Non-linear SVM

However, the given standard domain with *n* data dispersed randomly cannot be divided linearly; classifying is a little complicated, but it may be transformed into a space called the feature space where the data domain can be divided linearly to separate the classes and the steps in the nonlinear support vector machines are the mapping of the data domain to a feature space using a kernel function, the mapping of the feature space domain into the response set, and then dividing the data domain.

$$y = w\varphi(x) + \gamma$$

The above equation was used manipulate a non-linear data domain.

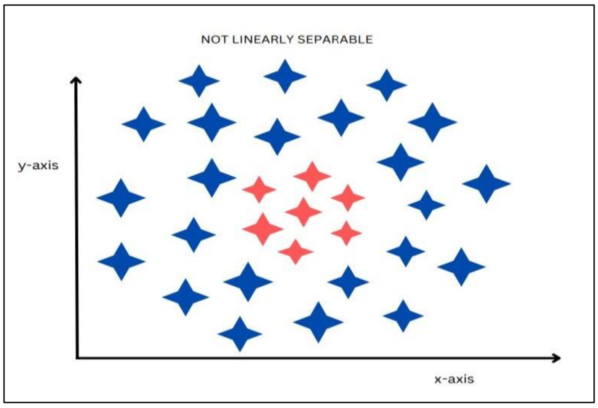

Figure 3: Not linearly separable.

Hyperplane

SVM are a representation of features as points in space, mapped in such a manner that the distinct classes are separated by a clear gap. A larger width of the gap reflects the precision of the SVM model. For instance, when a set of points belonging to either of any two classes, an SVM finds a hyperplane with the largest possible fraction of points of the same class on the same plane. This separating line is termed the optimal separating hyperplane (OSH) that serves to maximize the distance between the two parallel hyperplanes and can minimize the risk of misclassifying examples of the sample dataset. The margin is the distance between the hyperplane and the observations closest to the hyperplane.[13]

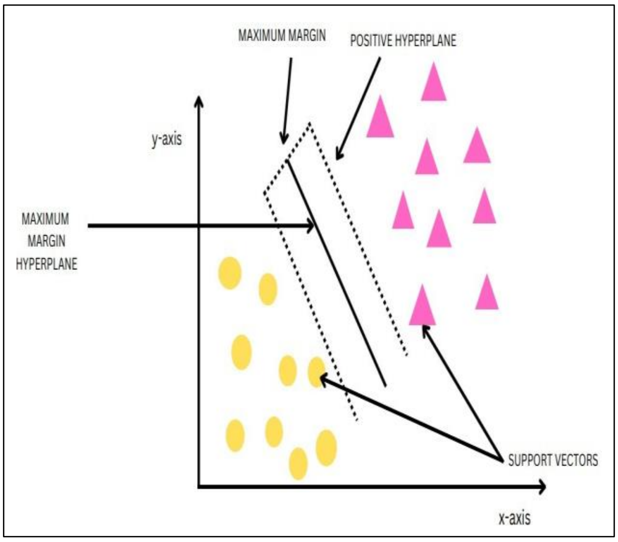

Figure 4: Hyperplane.

Support vectors

Support vectors, by definition, are the points closest to the hyperplane. They are assumed so because they may be thought of as 'supporting' the optimal hyperplane. The classification line will then separate with the help of said data points.

Kernel trick

The usefulness of the kernel trick technique is exemplified through non-linear classification. Assume datasets in classes that are not linearly separable in one dimension. If we transform them to a three-dimensional feature space using the following transformation, then we can attain a linear separability and render it eligible for the support vector machine technique to be applied to this higher dimensional space, and a hyperplane can be derived as a classifier.

Types of Kernel

Types of kernels are as follows- (a) Linear kernel: Kðxi; xjÞ¼ðxi xjÞ; (b) polynomial kernel: Kðxi; xjÞ¼ðxi xj þ 1Þ p; (c) Gaussian kernel: Kðxi; xjÞ ¼ e xi x k kj 2 2r2; (d) RBF kernel: Kðxi; xjÞ ¼ ecðxixjÞ 2; and (e) Sigmoid kernel: Kðxi; xjÞ ¼ tanhðgxi xj þ mÞ.[14]

DIAGNOSTIC BENEFITS

Support vector machines (SVMs) successfully meet high accuracies due to their kernel-based engines and greatly accomplish good explanations for their diagnosis due to their adaptable nature. These two approaches help train the algorithm to attain higher accuracies. Kernel-based engines output better classification results, and adaptability helps with a better runtime due to its reduced training set. A combination of these strong features enables the SVM to classify data efficiently. SVMs have proven to successfully classify diabetes, provide an accurate description of major depressive disorder, identify imaging biomarkers of neurological and psychiatric disease, and diagnose coronary heart disease.[15-20]

EXISTING GUIDELINES TO PREDICT NEONATAL MORTALITY

A sick neonate, at the triage area in the health facility and during admission, must be assessed for the severity of the illness, planning the management, and also prognosticating for the neonate's family. These scoring tools include the clinical risk index for babies (CRIB), the score for neonatal acute physiology (SNAP, SNAP-II), the extended sick neonatal score (ESNS), and the modified sick neonatal score (MSNS), etc. They perform with respect to data regarding birth weight, gestation, admission temperature, perfusion, arterial blood gas analysis, and blood sugar estimation. These scores may also be used frequently for quality assessment among various neonatal intensive care units (NICUs) and hospitals.

Precise, accurate, and reliable scores of the severity of illness are much needed for unbiased comparisons and specifically for comparative quality improvement care studies. The tools are a means of quantification of physiologic and pathologic aspects of the illness and, therefore, can be used as predictors of mortality and increased morbidity.[21]

Score of neonatal acute physiology (SNAP)

Multiple regression analysis on three variables- including birth weight, gestational age, and SNAP- was conducted, where SNAP was found to show the best correlation with mortality. Upon linking SNAP with the duration of hospital stay, 76.8% of the surviving neonates with SNAP<16 stayed for<15 days- while the rest stayed longer despite low SNAP. All nine babies with SNAP >15 who survived stayed for >15 days.

Critical risk index for babies- II (CRIB-II)

A large and well-balanced cohort of patients followed for a longer period is required to discern the importance of the CRIB-II scale in predicting outcomes in high-risk newborns. The mortality risk assessed with CRIB II in low birth weight newborns resulted in the Receiver Operating Characteristic curve with high sensitivity and specificity.[23] Therefore, this scoring tool could serve as an assistance to a personalized approach to severely sick children. The CRIB-II scale was adequate at identifying mortality rates, but not the outcomes.

Sick neonate score

303 extramural neonates were evaluated using sick neonate score (SNS) and were followed up until discharge or expiration. The score and its components were correlated with the outcome A receiver operating curve (ROC) was plotted to figure out the cutoff value for SNS in predicting mortality. The common causes of neonatal disease included sepsis (30.7%), birth asphyxia (17.5%), and respiratory distress (15.2%). As a result, sixty neonates (20%) expired and among them, 76% were hypothermic and 10% hypoglycemic at admission. The average SNS for all neonates was 10, but 6 for those who expired. A cutoff value of SNS $\leq$ 8 predicted neonatal mortality with a sensitivity of 58.3% and specificity of 52.7%.[24]

SVM-BASED MODELS FOR NEONATAL MORTALITY PREDICTION

In this section, we will discuss the various causes of neonatal mortality and the extent to which SVM has been effective in predicting them.

Sepsis

Late-onset sepsis is an issue that is frequently encountered in the NICU, especially in neonates with low birth weight.[25] It is estimated that 3 million neonates contract sepsis annually.[26] Sepsis is difficult to predict with traditional methods in neonates due to the variety of pathogens and diagnostic factors, so employing machine learning may prove useful.

One study that assessed the accuracy of different machine learning algorithms such as SVM, random forest (RF), artificial neural network (ANN), and decision trees reported that the accuracy of SVM with radial and hyperbolic kernels was 92%, while polynomial and linear kernels were slightly less accurate at 88%.[5] Another three-year study was conducted on 1095 neonates with clinically suspected sepsis, and multiple machine learning models were trained on the obtained data, such as SVM, k-nearest neighbour (k-NN), Random Forest (RF), and Treebag, with SVM having 74.75% accuracy.[27] Finally, a study that used data from a haematological analyzer showed that SVM had the second-highest mean accuracy at 72%, and while it had the highest specificity at 0.95, it had the lowest sensitivity compared to all other models. It also had a low value of area under the ROC curve (AUC-ROC), which may indicate that SVM is unsuitable for sepsis prediction.[27]

Seizures

From a neurological aspect, seizures are the most common symptom in neonates, with their rate of incidence being 1.5%.[28,29] Seizures are detected by EEG, and often there is not enough experienced staff available in NICUs that can monitor the EEG constantly and interpret the data correctly. Therefore, it will be of great benefit if ML techniques are used to interpret the data obtained from the EEG and convert it to a simpler form that is easier for inexperienced staff to understand. One study used a multi-channel patient-independent neonatal seizure detection system based on SVM and reported an average good detection rate of 89% with 1 false detection per hour and a 100% average good detection rate with 4 false detections per hour.[30] Another study used data obtained from 49 neonates to train the SVM model and then tested it on 13 neonates. It reported that the SVM model had a 92.3% accuracy.[31] Lastly, SVM can be used as a post-processor for multi-stage neonatal seizure detection to reduce the rate of false alarms by as much as 64%, although it does come at the cost of a 7% decrease in good detection rate.[32]

Hypoxic ischemic encephalopathy

Hypoxic ischemic encephalopathy (HIE) is a type of brain injury caused by impaired blood flow (ischemia) or oxygen delivery (hypoxia) to the brain. 40-60% of neonates with HIE either die within 2 years after birth or develop serious disabilities such as cerebral palsy.[33] HIE is diagnosed by multiple methods, such as a CT scan, MRI, or ultrasound of the brain, ECG to detect irregularities in the heart, or an EEG to determine if a seizure took place.[34] In one study, a super-vector approach is used, where SVM is combined with a Gaussian mixture model, and a leave one out (LOO) cross-validation method is employed to assess the accuracy of the model. The overall accuracy was 87%.[35] Another study used data from EEG and ECG recordings taken on newborns 24 hours after birth, and a follow-up assessment taken 2 years later. 12 features were extracted from the data as input for the SVM, which turned out to be correct 73.68% of the time.[36] Lastly, long-term and short-term data from an EEG were extracted for input for a multi-class SVM classifier. It was 87% accurate for severe asphyxia, 78.3% accurate for mild asphyxia, and had an overall accuracy of 79.5%.

Apnea

Apnea is termed as cessation of breathing for more than 20 seconds which may be accompanied by bradycardia or cyanosis. It may be central when the central respiratory centre does not generate output; obstructive, when the airway is obstructed, or mixed, in which both central and obstructive apnea takes place. Mixed apnea is the most common in preterm neonates. Premature neonates are more likely to experience apnea as their mechanisms of respiration are not well-developed.[37] A study conducted on 15 premature newborns took data from an electrical impedance tomography (EIT) and used it in a hybrid classification model combining convoluted neural networks and SVM, resulting in an accuracy of 71% to 97%.[38] Another study collected data from 229 neonates who had apnea, with 23 features and processed it using decision trees and SVM. For the SVM-based model, a radial kernel was chosen with 10-fold cross-validation. This resulted in a 75% accuracy, however, the sensitivity was very low at 0.28 due to the data being imbalanced. By oversampling, the accuracy increases to 77%, and sensitivity increases to 0.61.[39] Finally, an Android application was developed to receive data from a wireless pulse oximeter and use an SVM with a radial function kernel to detect apnea. This resulted in an accuracy of 80.5% in the training set of 796 events and 64.6% in the test set of 663 events.[40]

Jaundice

Jaundice, or hyperbilirubinemia, is the accumulation of bilirubin in the blood, which is toxic to the CNS. It is the most common morbidity in neonates; 60% of all newborns get jaundice in the first week of their life. However, 5-10% of neonates that acquire jaundice need intervention.[41] Yellowing of the eyes and skin is considered the hallmark of jaundice. Typically, serum bilirubin is used as a laboratory test to diagnose jaundice, but SVM can be employed for a non-invasive and less time-consuming approach. One study did this by taking pictures of neonates with a smartphone camera and using various ML models such as multi-layer perceptron (MLP), SVM, decision trees, and random forest. SVM had the second-highest accuracy, with 65.95% when using pictures of the skin and 74.97% when using images of the eye.[42] A meta-analysis conducted in Tehran proposed an SVM model with the Gaussian kernel, and it had the highest F1 score or accuracy at 88% compared to other algorithms.[43]

Neonatal respiratory distress syndrome

Neonatal respiratory distress syndrome (NRDS) is a condition caused by scarcity of surfactant in the neonate's lungs. It mostly affects premature babies and is characterized by cyanosis, tachypnea, and nasal flaring. If untreated, it leads to respiratory failure. It is diagnosed by pulse oximetry, blood tests, and X-rays or ultrasounds[44]. One study took 2 ultrasound images each from 150 neonatal lung disease cases and then divided them into training and validation cohorts. Multiple ML algorithms were fed this data to decide if the neonate had NRDS. SVM had a training accuracy of 96.25% and a testing accuracy of 93.33%, which was second-best compared to random forest[45]. Another study assessed the cries of neonates to differentiate between those with sepsis from those with NRDS. They were analyzed from two perspectives; Harmonic Ratio (HR), the musical perspective, and Gammatone Frequency Cepstral Coefficients (GFCC), the speech-processing perspective.

SVM and MLP were both used - MLP outperformed as it had an accuracy of 92.49% for combined GFCC and HR, while SVM had 95.29% accuracy.[46]

Fetal heart rate

Fetal heart rate is recorded by cardiotocography during labour to determine the risk of symptoms such as metabolic acidosis and intrauterine growth restriction.

Metabolic acidosis is the reduction in serum bicarbonate concentration or excessive presence of hydrogen in the blood, which results in the accumulation of non-carbonic acid equivalents. The main causes of metabolic acidosis in neonates are birth asphyxia, sepsis, congenital heart and renal diseases, and inborn errors of metabolism such as defects in pyruvate metabolism or gluconeogenesis. If it goes untreated, it can lead to severe hypoxic injury which may cause cerebral palsy, development disorders, or death.[47] One study used 9 input parameters for the SVM and reached an 83% success rate with 70% accuracy. After further tweaking the machine and reducing the parameters to 7, it could make 78% correct classifications, while another study achieved a classification performance of 90%.[48,49].

Intrauterine growth restriction (IUGR) is decreased fetal growth due to an unfavourable uterine environment, causing the fetus to weigh below the 10th percentile for its gestational age. There are multiple reasons for it, such as smoking and alcohol consumption, abnormal uterine anatomy, and congenital or chromosomal defects. IUGR is associated with neonatal morbidity.[50] It has a prevalence of 8%.[51] In one study, a radial basis function support vector machine was used, with a Recursive Feature Elimination approach to improve classification accuracy, which ended up being 0.9208 in the training set and 0.8077 in the testing set.[52]

A systematic review and meta-analysis conducted recently reported that the random forest-support vector machine model achieves the best result- 97% accuracy- compared to other machine learning models.[53]

Low birth weight

A newborn weighing less than 2500 g is classified as having low birth weight. It is caused by IUGR or prematurity, and a neonate with LBW is 20 times more likely to die compared to a healthy neonate.[54] One study used different ML algorithms to develop a predictive model for low birth weight, and SVM had an 80.29% accuracy using a 10-fold cross-validation, coming second to logistic regression, which had an 80.30% accuracy. With the train-test split, SVM had the best performance at 81.67% accuracy.[55] A meta-analysis conducted on data obtained from the Indonesian demographic and Health Survey employed SVM with 4 different kernel functions, and the average predictive error was less than 10%, which indicates good predictive performance. The linear kernel function performed best, as it had a 7.1% confusion matrix error and an AUC value of 0.5495, the highest out of all the functions.[56] A retrospective cross-sectional study was conducted on 741 mother-newborn pairs, and 13 factors were taken into consideration. This data was fed into different ML models, and SVM had the 2nd highest accuracy at 92%, second to random forest, which had an accuracy of 93%.[57]

DISADVANTAGES AND LIMITATIONS

One of the drawbacks of support vector machines is their intense computational burden for artificially induced programming.[27] Support vector machines have proved to be a productive algorithm capable of competing with other learning machines but slower in terms of classification as the standard model is a little scale-sensitive and time-consuming. For higher accuracy and precision, SVM models require an extensive training period, and if not instructed correctly, there might be poor interpretability of results[58]. Increased efficiency in support vector machines is a requirement that demands a mechanism through which new data is easily interpreted and inserted into the technology as the numbers of training samples grow.

DISCUSSION

SVM is a type of supervised machine learning. It is a trained algorithm that works by linking given information to its ultimate output. SVM is primarily used for classification, regression, and outlier detection. Support vector machines use a hyperplane to separate two data classes. It is configured first linearly and then uses the non-linear decision functions to map the data domain to a feature space using a kernel function. Several applications are successfully analyzed and administered by support vector machines that work on the principle of statistical learning theory. In our study, we used SVM to determine various causes of neonatal mortality as it has been successful in the classification of diabetes, identifying imaging biomarkers for neurological and psychiatric diseases, and diagnosis of coronary heart disease, as mentioned in the main text.

While predicting neonatal mortality due to LBW, SVM achieved 2nd highest accuracy at 92%, second to the random forest, which had an accuracy of 93% in a study performed on 741 mother-newborn pairs considering 13 factors. SVM made 78% correct classifications, while another study achieved a classification performance of 90% in predicting mortality due to fetal heart rate.[48,49] The research was conducted to check whether neonates had NRDS or not using SVM with a training accuracy of 96.25% and testing accuracy of 93.33%, which was second-best compared to the random forest.[45] Another study assessed the cries of neonates to differentiate between those with sepsis from those with NRDS using SVM and MLP; MLP was outperformed by SVM with an accuracy of 95.29%.[46] Support vector machine also preserves the role of jaundice (accuracy of 65.95% when using pictures of the skin and 74.97% when using photographs of the eye), apnea (accuracy of 80.5% in the training set of 796 events and 64.6% in the test set of 663 events using SVM with a radial function kernel), and seizures in neonatal mortality obtaining a reasonable detection rate of 89% with 1 false detection per hour and 100% average good detection rate with 4 false detections per hour.[30,40,42]

Another study that used data obtained from 49 neonates to train the SVM model, and then tested it on 13 neonates, reported that the SVM model had a 92.3% accuracy.[31] One of the root causes of escalation in neonatal death rate is sepsis, with 3 million neonates contracting it yearly. Many studies were conducted on neonates with susceptibility to sepsis using different ML models, one of which was SVM. It had the lowest sensitivity compared to all other models. It also had a low value of area under the ROC curve (AUC-ROC), which demonstrated that SVM was not the best option for foreseeing sepsis in neonates.

Different guidelines exist such as scoring tools (SNAP, SNAP-II, ESNS, MSNS) which can be used to anticipate various pathologies associated with a disease so that it can be identified and treated at early onset. These tools are used widely for studying purposes and can play an important role in decreasing the neonate death toll by keen observation and correct management of frequently occurring illnesses in newborns. ML models have been proven to make such work more accessible and less time-consuming. SVM, being one of the types of ML models, was our prime subject for this study. Gathering data from different articles we have formulated a review in which we give the pros and cons of the algorithm straight. Support vector machines successfully classified most neonatal morbidity causes under scrutiny while they proved unsuitable for other maladies under investigation.

CONCLUSION

Support vector machines have proved to be a well-organized systematic algorithm for predicting neonatal mortality if proper data is collected, models are trained, and assessed. Multiple studies show how SVM has helped in the exposition of neonatal mortality rates in different countries after collecting datasets that include information on mortality rates. Classification techniques using an SVM classifier were applied to determine neonatal mortality rate due to seizures, a multimodal predictor of neurodevelopment outcomes in newborns with hypoxic-ischemic encephalopathy, and an accuracy of 84% was obtained. SVM was successful in predicting neonatal mortality rate via its most common causes, such as apnea, HIE, seizures and LBW, fetal heart rate, NRDS, and jaundice achieving the highest or second highest accuracy compared to other ML learning models. As mentioned in our study, it wasn't a very suitable option for sepsis prediction. SVM potentially impact clinical decision-making and resource allocation in healthcare facilities. In hospitals, due to the scarcity of resources and durable medical equipment, SVM models have helped doctors make correct decisions about the placement of their post-op patients managing available spaces alongside. Real-time operation in the classification phase, faster speed, high computational cost, handling multi-scale data, and maintaining the history of changes at each scale are some challenges that need to be overcome for effective real-world implementation of SVM. Further research in SVM-based prediction, including literature studies, observational studies, and clinical trials, is essential to maximize its effectiveness and real-world implementation, yielding better results for neonatal mortality prediction and improving medical outcomes for neonates.

Funding: No funding sources
Conflict of interest: None declared
Ethical approval: Not required

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Cite this article as: Aamir Z, Kasbati M, Hasan A, Hurjkaliani S, Imran R. Support vector machines in neonatal mortality detection: a comprehensive scoping review with disease-specific emphasis. Int J Sci Rep 2023;9(10):329-37.