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Innovation Article

Develop a web-based system using the Naïve Bayes algorithm to predict asphyxia neonatal

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ABSTRACT

Introduction: Most cases of perinatal asphyxia are caused by conditions unrelated to labor. When asphyxia occurs during childbirth, it is usually caused by an obstetric emergency that was not detected during pregnancy. It is essential to prevent asphyxia by identifying the incidence of asphyxia during pregnancy. Several studies have been conducted to identify asphyxia problems developing by predictive models. However, there has been no development of a system for predicting birth asphyxia during pregnancy and carried out in primary health facilities.

Purpose: Develop a web-based system using the Naïve Bayes (NB) algorithm to predict asphyxia neonatal using a dataset of antepartum risk factors in primary health facilities.

Methods: This study employed research and development, which consists of 4 stages, namely literature study, development stage, expert validity, and trial.

Results: A system that health workers in primary health facilities can use to predict asphyxia neonatal and recommend referrals for determining the place of childbirth has been successfully created. The system performance test predicted asphyxia neonatal with all NB evaluation values reaching more than 98%, and the prediction accuracy in the respondent test included in the High Accuracy category (MAPE value 9.06%).

Conclusion: The development of a web-based system using the NB algorithm has been proven to be able to predict asphyxia neonatal and can be implemented for health workers as an effort to anticipate delays in handling cases of asphyxia neonatal because of the predicted results along with recommendations for focusing mothers with the risk of babies born asphyxia to find out possible childbirth places.

INTRODUCTION

Asphyxia is one of the highest causes of neonatal death cases found in the world. Approximately 4 million (23%) of neonatal deaths occur each year due to asphyxia at birth.[1,2] Nearly all asphyxia-related deaths (98%) occur during the first seven days of life. Approximately 75% of these deaths occur within the first 24 hours of birth, and less than 2% occur after 72 hours of birth.[3] Every year, there are 6-15 million babies are born with asphyxia.[4,5] The World Health Organization (WHO) estimates that around 5-10% of newborns will need assistance to start breathing, including 3-6% who require ventilation with bags and masks.[6] In developing countries, it was found that 120 million newborns experience birth asphyxia, which causes 900 thousand infant deaths every yea.[1] his proportion is ten times greater than in developed countries.[2] The neonatal asphyxia mortality rate in Indonesia reaches 29.9% on the first day of birth and 75.6% after one week of birth.[7] In Indonesia, asphyxia is the second cause of neonatal death after Low Birth Weight (LBW), with an incidence of 5,464 cases (27.0%).[8,9]

Babies who grow after being asphyxiated have short-term impacts such as death, hypoxic-ischemic encephalopathy (HIE), and seizures. Apart from that, there are also long-term impacts such as cerebral palsy, hearing loss, visual

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impairment, increased support requirements, lower test scores, explosiveness and irritability in behavior, psychotic symptoms, and autism spectrum.[10] The impact of asphyxia at birth is not only limited to general clinical problems and death but also has an impact on the socio-economic burden on families, where families have to spend much money on treatment for babies born with asphyxia.[11]

Asphyxia is caused by fetal hypoxia in the uterus due to disruption of the exchange and transport of oxygen from mother to fetus so that oxygen supply to the fetus is reduced and carbon dioxide levels increase.[12] Difficulty in recognizing the problem is one of the causes of early death from perinatal asphyxia.[13] Most cases of perinatal asphyxia are caused by conditions unrelated to labor. When asphyxia occurs during the intrapartum period (during childbirth), it is usually caused by an obstetric emergency that was not detected during pregnancy.[14] Therefore, it is essential for health workers to prevent asphyxia by identifying the incidence of asphyxia during pregnancy or before childbirth.

How prevent asphyxia neonatal has been done with skilled birth assistance, asphyxia prediction with biomarkers,[15,16] and prediction models using systems such as hypoxia prediction fetus with a combination of feature selection algorithms and machine learning models using the intrapartum Cardiotocography (CTG) database,[17] predicting resuscitation needs using K-Nearest Neighbor (KNN) algorithm,[18] predicting the incidence of neonatal asphyxia using Rule Based Reasoning with Forward Chaining and Case-Based Reasoning (CBR)[19], and the prediction of apnea in neonates using the Multi-layer Perceptron (MLP).[20]

In previous asphyxia prediction system studies, a prediction system has not been found that predicts the incidence of asphyxia neonatal during pregnancy using risk factor datasets, and all studies were conducted in the hospital, even though the timely diagnosis and management of asphyxia is still considered lacking in primary health facilities.[21] In addition, referral services also need to be organized more effectively by focusing low-risk pregnancies on primary health services, and high-risk pregnancies on tertiary health services.[22] Therefore, implementing a prediction system accompanied by recommendations will be very useful if it is carried out in primary health facilities to determine the place of childbirth as a preventive effort as soon as possible.

Therefore, this research developed a prediction system using antepartum risk factors in primary health facilities with the help of the Naïve Bayes (NB) algorithm to produce predicted output for the level of asphyxia diagnosis and recommendations for childbirth places, which has never been done in similar research. System development is done on a web basis rather than mobile applications. Typically, web users access fewer systems because they receive sufficient support from long introductory pages.[23] This is suitable for health workers in health institutions that operate only during certain times when services are provided. Web applications are designed to have flexibility across mobile and non-mobile platforms so they can be used across multiple devices.[24] This research aims to develop a web-based system using the NB algorithm to predict asphyxia neonatal using a dataset of antepartum risk factors in primary health facilities.

METHOD

This study employed Research and Development (R&D) consisting of 4 stages: literature study, development stage, validity expert, and trial.

Stage 1 Literature Study

Researchers conducted literature studies and collected information data at the Kendal 1 Community Health Center to obtain data on the number of births of asphyxiated babies and antepartum data on asphyxia risk factors (based on the mother cohort, Antenatal Care register and birth register in January 2017-December 2021), also have interviews with midwives related to recommendations in the system to be built.

Stage 2 Application Development

The prediction system was built using Python programming language. The development system used AI algorithms. Several algorithms were tested for system performance, such as NB, KNN, Support Vector Machines (SVM), and Neural Networks (NN). The algorithm with the best performance results is used to develop prediction features. Meanwhile, for additional features, recommendations use Rule-Based Reasoning. The algorithm performance of the system is tested using the Confusion Matrix, Fold cross-validation, and the Area Under Curve (AUC)-Receiver Operating Characteristic (ROC).

Stage 3 Expert Validity

The expert validation test in this research did not use informatic technology experts to test the validity of the system being built; instead, it used a system acceptance test by users. User acceptance of the system was completed by filling out the System Usability Scale (SUS) questionnaire.

Stage 4 Application Testing

Application testing uses a pre-experimental design with a one-shot case study, in which one group (only intervention group without control group) was given one treatment and one measurement. The population was all third-trimester pregnant women in the working area of Kendal 1 Public Health Center, Indonesia. The sample size was determined to be 30 samples (adjust research time). Researchers limit research time by limiting the sample using specific criteria, such as pregnant women with gestational age ≥ 37 weeks, pregnant women who regularly make antenatal care visits, and pregnant women willing to be respondents. Midwives collect data and operate predictor systems on respondents. Furthermore, midwives assess the accuracy of predictions from the system by filling out the assessment sheet based on the Apgar Score.

Prediction accuracy results were analyzed using the Mean Absolute Percentage Error (MAPE) value. The scale for assessing prediction accuracy based on the MAPE value includes less than 10% (Highly Accurate), 11% to 20% (Good Forecast), 21% to 50% (Reasonable Forecast), and more than 50% (Inaccurate Forecast). The research carried out has received a letter of receipt for the implementation of the research from the Head of the National Unity and Politics Agency of Kendal Regency No. 070/0696/IV/2022 and has received a proper ethical statement from Poltekkes Kemenkes Semarang No.0345/ EA/KEPK/2022.

RESULTS

Result of Stage 1 Literature Study

Asphyxia data collected were 2,871 data consisting of 2,819 labeled normal, 33 labeled mild-moderate asphyxia, and 19 labeled severe asphyxia (the dataset was imbalanced). Then, data from interviews with midwives to obtain validity regarding antepartum asphyxia risk factors were the age of the pregnant mother, gestational age, parity, blood pressure, hemoglobin, antepartum hemorrhage, IUGR, malpresentation, condition of amniotic fluid, umbilical cord circumference, premature rupture of membranes, and fetal heart rate.

Result of Stage 2 Application Development

Datasets from Stage 1 were grouped and cleaned to overcome the imbalanced dataset. So, the data used was 2,153, which was 2.102 with the normal label, 32 with a mild-moderate asphyxia label, and 19 with a severe asphyxia label. The dataset is divided into data training and data testing (composition of 70% compared to 30%), so 1,507 for training data and 646 for test data. The dataset was processed to test its prediction performance system with several algorithms.

Table 1 shows that the algorithm with the best performance in the Confusion Matrix was NB and Neural Network (NN) with 99% Precision results, 98% Recall, and 98% F1-score. Based on the Fold Cross Validation test, the algorithm with the best performance was NB, with an average F1-score of 98.2%. Then, the AUC-ROC curve metric results in the algorithm with the best performance of NB with 99.4%. So it can be concluded that the best system performance was NB, so this research used NB to develop a prediction system.

This web-based system for predicting asphyxia neonatal can be opened via the website link https://asphyxia-checker.herokuapp.com/. The first step to operating this system is to create a new account (Figure 1). After that, the user (midwife/health worker) logs in by filling in the username and password that they created previously (Figure 2). After logging in, the user can start to input data consisting of patient identity data (patient's name, husband's name, last education, occupation, beliefs and address) and examination data in the form of risk factors for asphyxia neonatal (age of the pregnant mother, gestational age, parity, blood pressure, hemoglobin, antepartum hemorrhage, Intrauterine Growth Restriction (IUGR), malpresentation, condition of amniotic fluid, umbilical cord circumference, premature rupture of membranes, and fetal heart rate). After the user has entered all the data, click 'submit' on the blue icon at the bottom of this page (Figure 3).

The following page contains inspection result data along with predictions and recommendations. For "normal prediction" results, they recommend delivery at PONED Public Health Center and normal newborn handling. For "mild-moderate asphyxia prediction", they recommendations for delivery at the PONED public health center (if the resuscitation equipment is complete and the midwife is competent to carry out resuscitation) and resuscitation handling (if resuscitation is unsuccessful, make a referral); then "severe asphyxia prediction", they recommendations for hospital delivery (Figure 4). The final stage will display a list of patient names and their final data. Users can save and download this data by clicking the blue icon in the top right corner of the page. Data from this system will be saved in Ms. Excel format (Figure 5).

Result of Stage 3 Expert Validity

There were three users (midwives) in this research. From the SUS questionnaire distribution results, subtract one from the score for each odd-numbered question (X-1), while for even-numbered questions, subtract the score from 5 (5-X). The sum results of 10 questions were multiplied by 2.5 so that the SUS score for the predictor system that has been developed will be obtained. The usability test results were seen from the average SUS score of 82.5 (excellent/acceptable), indicating that users can understand the predictor system well and have met the usability standards that should be met from an application.

Table 1. System Performance Result

Algorithm	Confusion Matrix			Fold Cross Validation	AUC-ROC Curve Metric
	Weighted Average			Average Score	
	Precision	Recall	F1-Score	(F1-Score Weighted)	
NB	0.99	0.98	0.98	0.982	0.994
SVM	0.98	0.98	0.98	0.979	0.989
KNN	0.98	0.98	0.98	0.980	0.968
NN	0.99	0.98	0.98	0.981	0.989

Exp: F1-Score Confusion Matrix (comparison of weighted average precision and recall), AUC-ROC = Area Under *Curve (AUC)*-Receiver Operating Characteristic (ROC), Naïve Bayes (NB), K-Nearest Neighbor (KNN), Support Vector Machines (SVM) and Neural Network (NN)

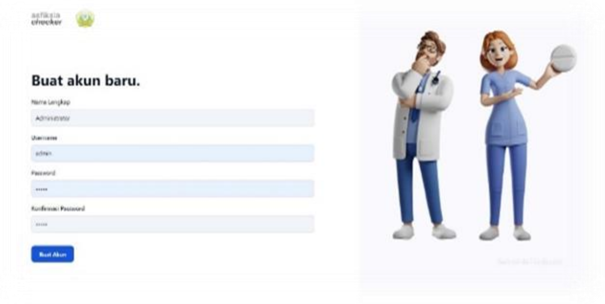

Figure 1. Register Page

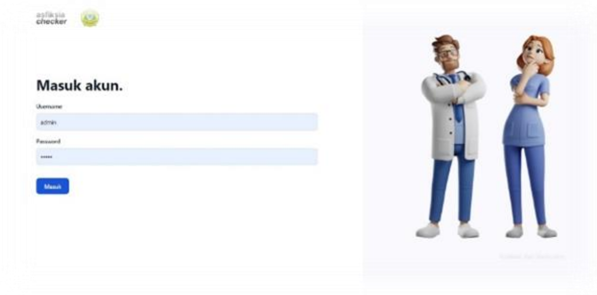

Figure 2. Login Page

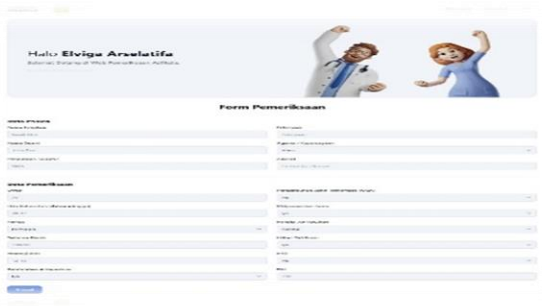

Figure 3. Main Page

Figure 4. Result Page

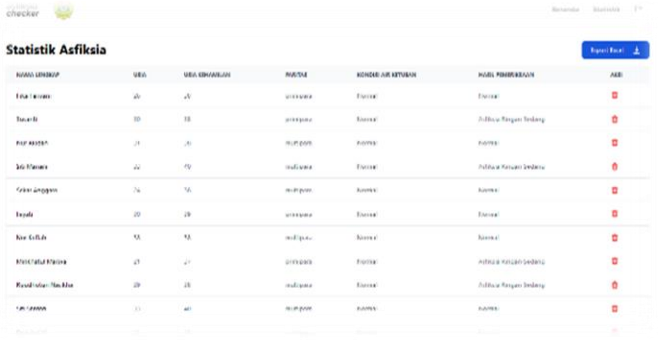

Figure 5. Statistic Page

Result of Stage 4 Application Testing

Based on the research results, there are 3 of 30 prediction errors, where the prediction results are obtained in the system "Mild-Moderate Asphyxia," however, it turns out that in real-time, the baby was born under normal conditions based on the APGAR assessment. The weekly MAPE assessment calculates the number of truths and errors in the system prediction results. Based on the results of calculations up to the fifth week (when 30 respondents have given birth to their babies), the MAPE value scale from the system trial results obtained 9.06%, which means the prediction accuracy value falls into the category of highly accurate (MAPE value less than 10%).

DISCUSSION

The features in this application are predictions of asphyxia neonatal with the output level of asphyxia (normal, mild-moderate asphyxia, or severe asphyxia) and additional features of recommendations for focusing on the place of childbirth and actions that health workers must carry out. Because this system predicts possible pathological cases, the user is not a pregnant woman but a health worker at a primary health facility in this study, namely a community health center midwife. It is because when the examination results are abnormal, pregnant women are not shocked, panicked, and stressed by the predicted results from the system so that it will not interfere with their pregnancy.[25] he prediction results are only known to the midwife who examines the pregnant woman (system user). Examinations are carried out on pregnant women with a gestational age of ≥ 37 weeks when carrying out ANC examinations so that midwives can simultaneously enter data on ANC examination results that are suitable for input into this system.

The prediction system for asphyxia neonatal was built using a dataset of 2153 risk factors for birth asphyxia during pregnancy (antepartum risk factors) using an artificial intelligence algorithm with the best performance that is System performance assessment using Confusion Matrix, Fold Cross Validation, and AUC-ROC Curve. These three tests are widely used to evaluate systems.[26,27] The assessment considers the F1 score results more than accuracy due to the imbalanced dataset of risk factors. One way to overcome imbalanced datasets is to choose the right metrics,[26] namely, metrics with a higher F1 score, even though their accuracy is lower than another metrics.[28] From the several AI algorithms used, such as SVM, KNN, NB, and NN, the highest performance results are the NB algorithm with FI-score Confusion Matrix (98%), F1-score Fold Cross Validation (98.2%), and AUC-ROC curve value (99.4%).

These results are supported by previous research on testing diabetes and depression prediction systems where the performance results of the NB algorithm also had the highest F1-score value compared to other algorithms.[28,29] So, it can be concluded that developing a prediction system by testing system performance (internal validation) got good results. These results are supported by similar research, such as predicting fetal hypoxia with a combination of feature selection algorithms and machine learning models using an intrapartum CTG database with a sensitivity of 77.40% and a specificity of 93.86%,[17] predicting the need for resuscitation using the KNN algorithm with sensitivity values of 90.871% and accuracy of 98.480%,[18] predicting neonatal asphyxia using Rule Based Reasoning with an average acceptance of the functional system and usability (92.73%),[19] then predicting the presence of apnea in neonates using MLP with an AUC value of 0.82.[20] However, the system performance in this research is superior to previous research because all evaluation performance values reached more than 98%.

In similar studies, no system testing was carried out on respondents (external testing). However, internal validation only plays a role in checking the algorithm's performance when developing the system rather than confirming the performance of the finished system. Therefore, additional external validation is needed to determine the performance of artificial intelligence algorithms.[30] In this study, external validation was carried out by testing pregnant women to determine the accuracy of the system in predicting asphyxia neonatal. In 30 trials, there were three prediction errors with the system output of "Mild-Moderate Asphyxia," but the baby was born in normal condition. However, this is not a big problem because all pregnancies should be considered risky,[31] but if the results are the opposite, the system has a problem.

MAPE calculations measured the system prediction results. MAPE was chosen as the standard for assessing prediction accuracy because it has been widely used in several studies and has proven effective in describing prediction accuracy.[32,33] The MAPE value scale from the system trial results obtained 9.06%, which means the prediction accuracy value is based on the MAPE value falls into the category of less than 10% (Highly Accurate), so this prediction system is proven to be accurate in predicting asphyxia neonatal.

In the system user test results, the user will use the web-based prediction system again; the user feels the system is easy and not complicated to use, the user does not need help from other people or technicians in using the system, the user feels the prediction system features work well, the user should assess the system as consistent and not confusing, the user feels that other people will also understand how to use it quickly, the user does not experience obstacles in using the system, and the user still needs to get used to using the system. It is based on the average SUS score of 82.5 (excellent/acceptable), showing that users can understand the web-based predictor system well.

The development of this prediction system is instrumental in health, especially in predicting asphyxia neonatal. Prediction models using systems or artificial intelligence help to provide fast decision-making.[34] In obstetrics knowledge, effective clinical decisions require artificial intelligence methods to optimize information delivery. Health workers cannot inform patients and prevent complications if information is too late. If information is presented too early, the patient may not yet be pregnant, so the information will not be helpful. If the system is optimized using artificial intelligence, patients can be given the correct information at the right time.[35] The existence of a prediction system for asphyxia neonatal is not a definite benchmark. However, the use of this system can be a preventive tool to help reduce the prevalence of neonatal deaths due to asphyxia.

CONCLUSIONS AND RECOMMENDATION

Development of a web-based system using the NB algorithm can predict asphyxia neonatal. The predictor system can be implemented for health workers as an effort to anticipate delays in handling cases of asphyxia babies because of the prediction results along with recommendations for focusing on mothers with the risk of babies born asphyxia to find out possible childbirth places. With good results from this prediction system, it is hoped that researchers and the health service can make promotive efforts by socializing this web-based predictor system with health workers in primary healthcare facilities.

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