Indonesian Journal of Global Health Research
Volume 6 Number S4, August 2024
e-ISSN 2715-1972; p-ISSN 2714-9749
http://jurnal.globalhealthsciencegroup.com/index.php/IJGHR

HUMAN-IN-THE-LOOP (HITL) APPLICATION DESIGN FOR EARLY DETECTION OF PREGNANCY DANGER SIGNS

Ery Hadiyani Puji Astuti
RSUD Awet Muda Narmada, Nyur Lembang, Narmada, Lombok Barat, Nusa Tenggara Bar. 83371, Indonesia
eryhadiyanipujiastuti02@gmail.com

ABSTRACT

Maternal mortality is still a problem in all countries in the world, especially in developing countries like Indonesia. Several factors causing death are case detection, the risk of danger signs in pregnant women is still low, resulting in late case handling. Detection of danger signs of pregnancy is currently still done manually, but several studies have developed it machine learning Because it provides high accuracy, in this study researchers classified the detection of danger signs of pregnancy using an algorithm with techniques decision tree. Prediction of early detection of danger signs of pregnancy with 92% accuracy using comparative accuracy on 10 individual classifications (Nearest Neighbors, Decision Tree, Random Forest, Neural Net, AdaBoost, Gaussian Naïve Bayes, Bagging, Extra Tree, Gradient Boosting, Stacking) in this application a human in the loop was also developed for accuracy in providing recommendations. In predicting pregnancy danger signs, several studies use machine learning, because it has been proven to provide higher accuracy, interaction in providing predictions based on machine learning combined with expert intelligence, so that it can utilize big health data to solve problems and provide diagnoses and treatments. Test results, obtained values $p<0.005$ which mean Ordinal regression models can be used to predict maternal risk. Patients who are older, have more parity, lower height, distance between children < 2 years, HB < 11 gr/dl, LILA < 23.5 cm, have HBS-Ag, have HIV, have a history of DM, have a history of HT, positive for urine protein, hypertension and other diseases have a greater chance of having a high maternal risk. Conclusion, Application HITL can be developed for early detection of danger signs in pregnancy and provide appropriate recommendations to pregnant women and can determine high-risk pregnancies correctly, making it easier to care for and plan the place of delivery.

Keywords: detection of danger signs of pregnancy; decision tree; human in the loop

First Received	Revised	Accepted
28 Juni 2024	30 Juni 2024	20 July 2024

Final Proof Received	Published
17 August 2024	22 August 2024

How to cite (in APA style)
Astuti, E. H. P. (2024). Human-in-the-Loop (HITL) Human-in-the-Loop (HITL) Application Design for Early Detection of Pregnancy Danger Signs. Indonesian Journal of Global Health Research, 6(S4), 153-164. https://doi.org/10.37287/ijghr.v7i1.4167.

INTRODUCTION

Maternal and child health is one of the priorities Sustainable Development Goals (SDGs) Reducing maternal mortality is an effort to achieve maternal and child health (Kemenkes. 2020). The main strategy implemented is strengthening basic health with prevention and health promotion efforts by developing technological innovations in the health sector to increase universal health coverage and to fulfill the right of every pregnant mother to obtain quality health services so that she is able to have a healthy pregnancy, give birth safely, and give birth to a healthy and quality baby. Health services during pregnancy are carried out through comprehensive and quality integrated antenatal services by carrying out prevention in maternal health through detection of danger signs in pregnancy (Putri, 2018 & Kemenkes, 2015). In Indonesia, 94.1% of access to health facilities is more than 5 kilometers from residential areas, this has become the basis for developing several telehealth care which can be accessed by the community directly, without having to meet with health workers and can be done anywhere, and at any time, can change the existing paradigm in the community to obtain health services and information about their health directly. real time, and get direct recommendations from experts according to their needs. One of the most widely used ways today is to develop applications that can be accessed easily and get accurate information about their condition (Wiweko et al, 2016), During pregnancy, the care needed by pregnant women is very important to access real time, because recommendations and detection can be implemented so as not to get into something dangerous, because care during pregnancy can be a continuation during labor and postpartum as well as newborns (Manuaba, 2015).

The pregnancy period is a time for mothers to empower themselves so that their pregnancy and birth are safe and comfortable. Pregnant women must seek information related to their pregnancy, including how to deal with discomfort during pregnancy, nutrition and nutrition, danger signs of pregnancy, and preparation for childbirth. Danger signs of pregnancy are warning signs that women encounter during pregnancy, child birth and postpartum. It is important for women and their health care providers to know these warning signs to rule out serious complications and begin treatment immediately. Lack of knowledge about the danger signs of pregnancy is one of the main factors causing maternal death (Dessu, 2018 & Kemenkes, 2013).World Health Organization stated that in 2018, 10% of maternal deaths were due to complications during pregnancy, the highest was due to hypertension in pregnancy, namely 31% and bleeding, 20% of research conducted in Tanzania 2019, 49% of deaths occurred during pregnancy and 44% and there was no preparation. families in labor, low levels of education cause a lack of knowledge about early detection to prevent complications in pregnancy, childbirth, postpartum, newborns and toddlerhood (WHO, 2019).

The death rate in Indonesia is one of the highest in Asia, where there were 305/100,000 maternal deaths in 2019. In West Nusa Tenggara (NTB) Province, one of the provinces in Indonesia experienced a decline in the MMR from 85/100,000 live births in 2017, increased in 2018 to 99/100,000 live births and decreased to 97/100,000 live births in 2019 (Herawati, 2019). Maternal mortality in NTB during pregnancy is 17.65%, with the largest age group being reproductive age. MMR in NTB can be reduced by developing programs to improve reproductive health, especially pregnancy services and creating safe pregnancies without high risks by using technology during the pandemic (Herawati, 2019). In adapting to new habits developed due to the impact of the Covid-19 pandemic, several service flows are carried out with policies that have been established by the Ministry of Health, including the use of technology and communication to facilitate services, because several routine services are eliminated, such as pregnancy checks which are carried out only if danger signs are found. in pregnancy (POGI, 2020). Currently, detection of danger signs of pregnancy is still done manually using maternal and child health (KIA) books, but utilization is still low, only 56%, and complete filling of MCH books is only 18% (2), so detection of danger signs of pregnancy is often late, So a new alternative is needed to speed up the detection of danger signs of pregnancy by utilizing health technology.

Utilization of health technology developed with machine learning, because it can provide high accuracy. Machine learning can help in image appearance and classification for predictions that are developed using algorithms. And currently many Android-based applications are being developed but no one has developed them yet human in the loop in the application and provide recommendations with artificial intelligence (Kemenkes, 2020 & Nurjasmi, 2020).Human-in-the-loop (HITL) is a useful approach in solving a problem computerized using an algorithm machine learning and combined with expert intelligence, in the form of a smartphone for telehealth (Holzinger et al, 2016).Detection of danger signs of pregnancy self-report by pregnant women can help early detection of danger signs, and use of applications human in the loop can help by using accessible technology real time (POGI, 2020 & Holzinger et al, 2016), Midwives can provide recommendations to pregnant women directly so that examinations are carried out quickly and at health facilities recommended by the midwife. So that case discovery and case management can be done quickly and precisely.

Classification in data sets for health research is very complex, and the data sets required are also very large and varied, besides that there are many languages in the world that make it difficult to carry out classification (Sutton, 2018). so that human in the loop can assist in conducting data analysis, providing recommendations (Holzinger et al, 2019), and inter collaboration to predict danger signs with artificial intelligence systems (Gross et al, 2017). Component human in the loop This is a doctor or other health professional who will provide analysis and provide relevant recommendations (Holzinger et al, 2016). Data processing is carried out using machine learning, with a grid model against the algorithm ((Holzinger et al, 2016).Current utilization smartphone in Indonesia is the seventh of all countries in the world, namely 2.34 billion users, and pregnant women use it smartphone to access information on her pregnancy (Wiweko et al, 2019), It is hoped that it can improve people's health status and change people's behavior in accordance with health recommendations.8 Research by Budi Wiweko et al, 2018 shows that the use of technology is based on mobile and the internet has proven effective in increasing mothers' knowledge in carrying out early detection of high risk so that cases can be discovered as early as possible and decisions can be made immediately by pregnant women and their families (Wiweko et al, 2019).The identification of the above problems caused researchers to be interested in researching Human-In-The-Loop in Early Detection of Danger Signs of Pregnancy to prevent morbidity and mortality of pregnant women as an effort to prevent the spread of Covid-19.

METHOD

Data retrieval

We used data on pregnant women from Village Health Post in the West Lombok Regency area. This data was taken from a cohort of pregnant women from the examination period from December 2020 to February 2021 totaling 5,324 pregnant women. The data taken for the data set included parity, birth interval, upper arm circumference, height. body, blood pressure, history of diabetes mellitus, hypertension, hepatitis B and HIV, to predict danger signs for pregnant women using this data set.

System design

The data set taken will be classified in a machine learning system using several steps. System design is the initial stage of designing all processes in artificial intelligence. There are two processes, namely the training stage and the testing stage. Data that has been collected by researchers manually in Excel will be processed and run using the Anaconda Version 3.7 program. Data testing is 5313 after data clearing. The data was folded 10 times with a result of 0.911 and increased to 0.912, an increase of 0.1%. With data systems

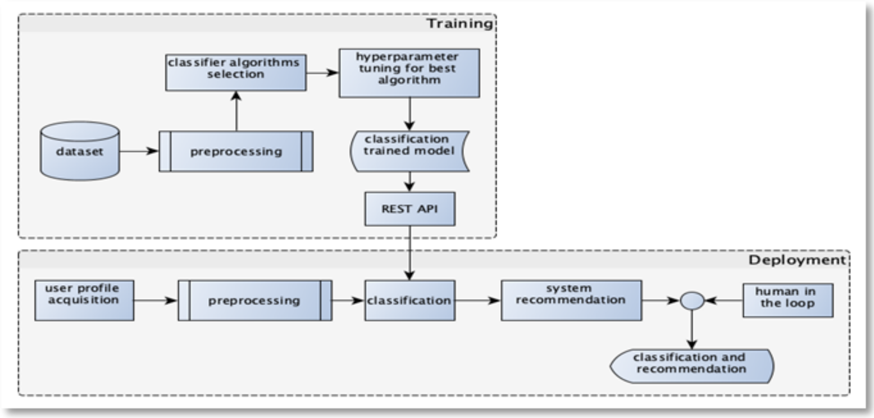

Figure 1. System design

Data processing

Several studies have used the prediction of danger signs of pregnancy machine learning, because it is proven to provide higher accuracy, interaction in providing predictions based on machine learning combined with expert intelligence, so you can utilize big health data to solve problems and provide diagnosis and treatment. For data processing, first install the Anaconda application using the link: https://www.anaconda.com/products/individual by selecting the menu python 3.7.

Figure 2. Anaconda Command Prompt

After that is done clearing data set so that the data to be processed produces accurate data. After that do it coding and data analysis. In the data on the disease suffered, if there is none it is given the code: 0, if there is a comorbidity it is given the code: 1, and the mother's risk classification is coded as normal with code: 0, low risk with code: 1, medium risk with code: 2, and risk high with code: 3.

umur	paritas	jarak_anak	tb	hb	lila	hbsag	hiv	dm	ht	protein	diastole	sistole	perdarahan	penyakit_lain	risiko_cat
20	00.00	999.00.00	150.00.00	09.06	24.00.00	2	2	2	02.00	02.00	120	90	2	0	1
30	03.00	48.00.00	151.00.00	11.02	28.00.00	2	2	2	02.00	02.00	120	80	2	0	0
28	01.00	77.00.00	150.00.00	12.03	26.00.00	2	2	2	02.00	02.00	110	70	2	0	0
30	02.00	60.00.00	151.00.00	11.00	28.00.00	2	2	2	02.00	02.00	110	70	2	0	0
33	04.00	03.00	148.00.00	13.01	26.00.00	2	2	2	02.00	02.00	130	80	2	0	3
16	00.00	999.00.00	155.00.00	12.08	24.00.00	2	2	2	02.00	02.00	100	70	2	0	1
30	01.00	72.00.00	152.00.00	14.07	28.00.00	2	2	2	02.00	02.00	120	70	2	0	0
31	02.00	72.00.00	145.00.00	13.00	26.00.00	2	2	2	02.00	02.00	120	80	2	0	1
33	05.00	24.00.00	150.00.00	16.00	22.05	2	2	2	02.00	02.00	130	90	2	0	0
22	02.00	03.00	160.00.00	10.06	25.00.00	1	2	2	02.00	02.00	120	70	2	0	2

Figure 3. Data clearing table display

Data Accuracy
From data processing tested with Nearest Neighbors, Decision tree, Random Forest, Neural Net, Adaboost, Gaussian Naïve-Bayes, Bagging, dan Extra Tree to get the best results, with the accuracy value of each algorithm (10-folding), namely:

1) Nearest Neighbors: 0.7568 (+/- 0.0577)
2) Decision Tree : 0.9117 (+/- 0.0351)
3) Random Forest: 0.7181 (+/- 0.0926)
4) Neural Net : 0.7037 (+/- 0.0808)
5) AdaBoost : 0.8690 (+/- 0.0470)
6) Gaussian Naïve-Bayes: 0.6674 (+/-0.2192)
7) Bagging : 0.7542 (+/- 0.0581)
8) Extra tree : 0.8524 (+/- 0.0312)
9) Gradient Boosting: 0.8728 (+/- 0.0511)
10) Stacking : 0.8428 (+/- 0.0895)

Application for Early Detection of Danger Signs of Pregnancy
In this application the accuracy results produce 0.9127 (+/- 0.0176). In this stage the user fills in the data set profile and continues with processing to get diagnosis results that match the profile data, then stored in the cloud or cloud computing with an architectural scheme.

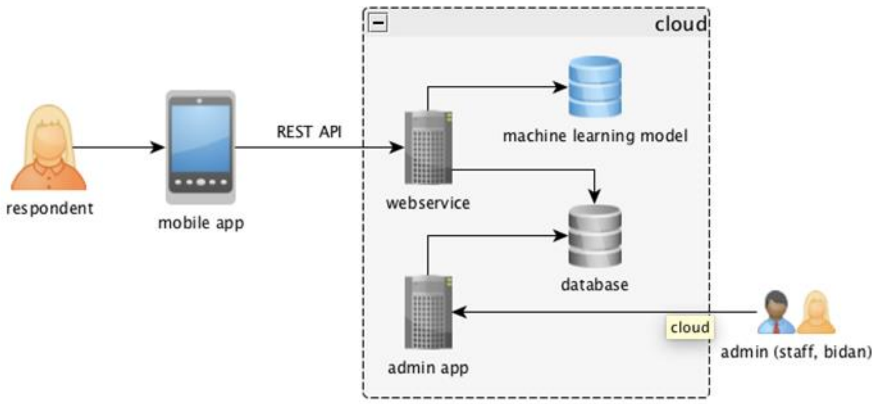

Figure 5. Application Architecture

After saving in cloud, the midwife appointed as human-in-the-loop can open in the admin application to check data, classify the suitability of the diagnosis, provide recommendations for patients according to the results of the classification of detection of danger signs of pregnancy, midwives as human-in-the-loop can also make diagnosis corrections if there are danger signs of pregnancy that are not in accordance with machine learning. In the machine learning results on profile 1 storage with normal classification, after human-in-the loop carry out a second clarification by saving the second profile data to refresh the data, then a second machine learning recommendation comes out with low risk classification results, in accordance with the results of the admin's clarification.

Human-In-The-Loop

Human-in-the-loop (HITL) is a useful approach in solving a problem computerized using machine learning algorithms combined with expert intelligence, in the form of a smartphone to telehealth. In a systems approach human in the loop, humans are not only involved in pre-processing but also select data and features, making it easy to provide recommendations to pregnant women about danger signs and how to deal with them. Human thinking will interact with algorithms and interact with computational agents. Classification in datasets for research in the health sector is very complex, and the data sets required are also very large and varied, besides that, the many languages in the world will make it difficult to carry out classification, so human in the loop can help in carrying out data analysis.

Application Human-In-The-Loop

This human-in-the-loop application can provide diagnostic clarification whether or not it is in accordance with the data set that has been entered in the application, if the detection is appropriate then human-in-the-loop will provide clarification with code 1, namely appropriate, if not sesuai human-in-the-loop will provide clarification that does not match code 2, and the results can be saved in the admin application.

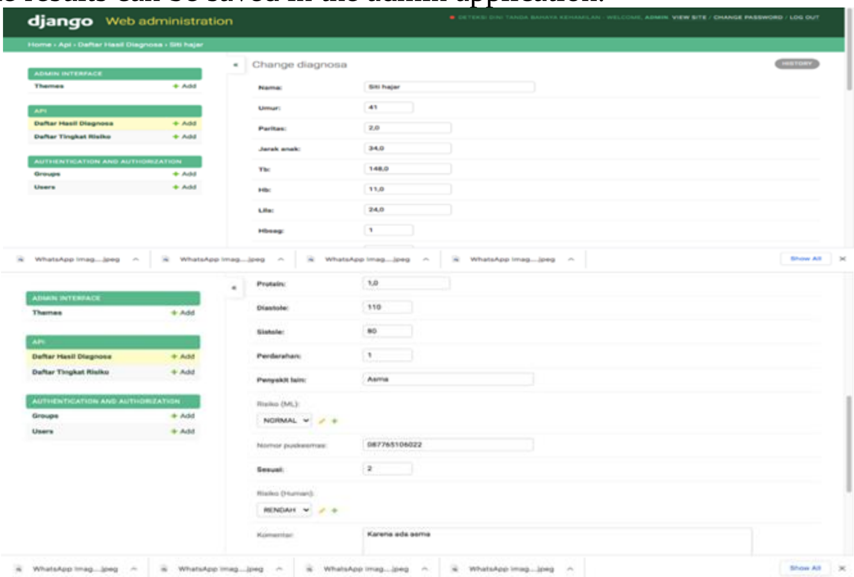

Figure 6. Human-In-The-Loop application

After receiving the results of the second machine learning clarification and recommendations, respondents can make an appointment with the referral midwife to carry out an examination so that there is no delay in referral if danger signs are found.

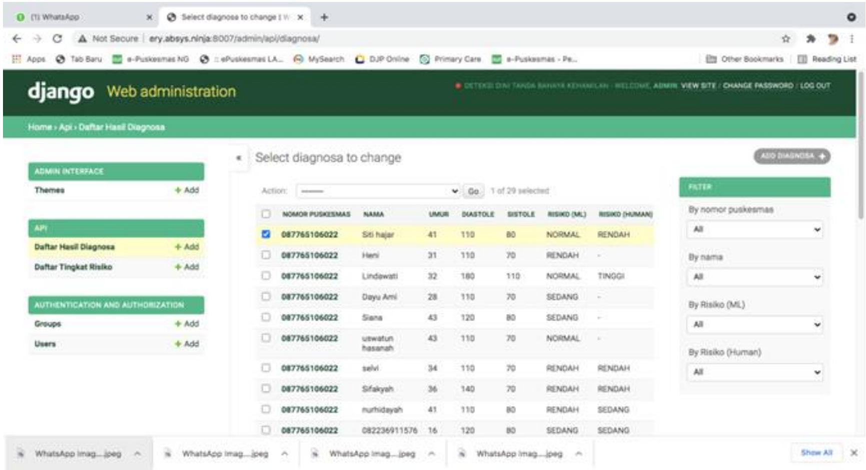

Figure 7. HITL Classification Results

This image shows that the human-in-the-loop application, apart from being able to clarify diagnoses, can also provide recommendations to pregnant women by refreshing them.

RESULTS

Table 1.
Descriptive Analysis of Categorical Variables

Variabel	f	%
Child Distance		
● < 2 tahun	249	4.68
● ≥ 2 tahun	5075	95.32
HB		
● < 11 gr/dl	721	13.54
● ≥ 11 gr/dl	4603	86.46
LILA		
● < 23.5 cm	1002	18.82
● ≥ 23.5 cm	4322	81.18
HBSAG		
● Ya	22	0.41
● Tidak	5302	99.59
HIV		
● Ya	3	0.06
● Tidak	5321	99.94
DM History		
● Ada	2	0.04
● Tidak Ada	5322	99.96
Protein Urine		
● Positif	8	0.15
● Tidak Positif	5316	99.85
Blood Pressure		
● Hypertension	20	0.38
● Not Hypertension	5304	99.62
Bleeding		
● Yess	0	0.00
● No	5324	100.00
History of other diseases		
● There is	7	0.13
● There is not	5317	99.87
Maternal risks		
● Normal	3497	65.68
● Low Risk	1466	27.54
● Medium Risk	304	5.71
● High Risk	57	1.07

Based on table 3, the distribution of respondents' characteristics based on child distance is 249 people (4.68%) who have a child distance < 2 years, and 5075 people (95.32%) have a child distance ≥ 2 years, 721 people (13.54%) have a HB < 11 gr/dl, and as many as 4603 people (86.46%) had HB ≥ 11 gr/dl, as many as 1002 people (18.82%) had LILA < 23.5 cm, and as many as 4322 people (81.18%) had LILA ≥ 23.5 cm, as many as 22 people (0.41%) had HBSAG, and as many as 5302 people (99.59%) did not have HBSAG, as many as 3 people (0.06%) had HIV, and as many as 5321 people (99.94%) did not have HIV, as many as 2 people (0.06%) had a history of DM, and as many as 5322 people (99.96%) had no history of DM, as many as 20 people (0.38%) had high blood pressure (hypertension), and as many as 5304 people (99.62%) did not have high blood pressure, as many as 8 people (0.15%) were positive for urine protein, and as many as 5316 people (99.85%) were not positive for urine protein, all of whom (100.00%) had never experienced bleeding in this pregnancy. Because the bleeding variable has no variance, it was not included in the ordinal regression analysis. Furthermore, as many as 7 people (0.13%) had a history of other diseases, and as many as 5317 people (99.87%) had no history of other diseases. From the data above, maternal risk as many as 3497 people (65.68%) were in the normal category, as many as 1466 people (27.54%) had low risk, as many as 304 people (5.71%) had medium risk, and as many as 57 people (1.07%) had high risk.

Table 2.
Test Results Forest Parameter Estimation and Hypothesis Testing

	Estimate	Std. Error	Forest	Df	Say.
[Maternal_Risk = .00]	-27.736	2.611	112.809	1	0.000
[Maternal_Risk = 1.00]	-25.093	2.604	92.869	1	0.000
[Maternal_Risk = 2.00]	-22.696	2.584	77.171	1	0.000
Age	0.079	0.006	159.389	1	0.000
Parity	0.285	0.029	97.287	1	0.000
Height	-0.025	0.006	14.678	1	0.000
[Child Distance=.00]	-0.529	0.135	15.331	1	0.000
[HB=.00]	-2.653	0.089	890.914	1	0.000
[LILA=.00]	-0.401	0.082	23.642	1	0.000
[HBSAG=.00]	-1.627	0.419	15.092	1	0.000
[HIV=.00]	-5.330	1.207	19.490	1	0.000
[DM History=.00]	-4.350	1.346	10.451	1	0.001
[Protein Urine=.00]	-2.793	0.747	13.976	1	0.000
[Blood Pressure=.00]	-2.468	0.467	27.922	1	0.000
[History of other Diseases=.00]	-7.673	1.187	41.821	1	0.000

Based on table 2 above, the following hypothesis testing results are obtained:

(1) The age variable obtained a p value = 0.000, which means there is a significant influence of age on maternal risk. The Age Coefficient which has a positive sign (0.079) indicates that the older the age, the higher the Maternal Risk.

(2) For the parity variable, the p value = 0.000. which means there is a significant influence of parity on maternal risk. The Parity Coefficient which has a positive sign (0.285) indicates that the more parity, the higher the maternal risk.

(3) For the height variable, the p value = 0.000. which means there is a significant influence of height on maternal risk. The Height Coefficient which has a negative sign (-0.025) indicates that the lower the height, the higher the Maternal Risk.

(4) For the child distance variable, the p value = 0.000. which means there is a significant influence of Child Distance on Maternal Risk. The Child Distance Coefficient which has a negative sign (-0.529) indicates that pregnant women who have a Child Distance of ≥ 2

years (code 0) have a lower Maternal Risk than pregnant women who have a Child Distance of < 2 years (code 1).

(5) For the HB variable, the p value = 0.000. which means there is a significant influence of HB on Maternal Risk. The HB coefficient which has a negative sign (-2.653) indicates that pregnant women who have HB ≥ 11 gr/dl (code 0) have a lower Maternal Risk than pregnant women who have HB < 11 gr/dl (code 1).

(6) For the LILA variable, the p value = 0.000. which means there is a significant influence of LILA on Maternal Risk. The LILA coefficient which has a negative sign (-0.401) indicates that pregnant women who have LILA ≥ 23.5 cm (code 0) have a lower Maternal Risk than pregnant women who have LILA < 23.5 cm (code 1).

(7) For the HBSAG variable, the p value = 0.000. which means there is a significant influence from HBSAG on Maternal Risk. The HBSAG coefficient which has a negative sign (-1.627) indicates that pregnant women who do not suffer from HBSAG (code 0) have a lower Maternal Risk than pregnant women who suffer from HBSAG (code 1).

(8) For the HIV variable, the p value = 0.000. which means there is a significant influence of HIV on Maternal Risk. The HIV coefficient which is negative (-5.330) indicates that pregnant women who do not have HIV (code 0) have a lower Maternal Risk than pregnant women who have HIV (code 1).

(9) For the DM history variable, the p value = 0.000. which means there is a significant influence of DM history on Maternal Risk. The DM history coefficient which has a negative sign (-4.350) indicates that pregnant women who have no history of DM (code 0) have a lower maternal risk than pregnant women who have a history of DM < 2 years (code 1).

(10) For the Urine Protein variable, the p value = 0.000. which means there is a significant influence of Urine Protein on Maternal Risk. The Urine Protein Coefficient which is negative (-2.793) indicates that pregnant women who are not positive for urine protein (code 0) have a lower Maternal Risk than pregnant women who are positive for urine protein (code 1).

(11) In the blood pressure variable, obtained p value = 0.000. which means there is a significant influence of Blood Pressure on Maternal Risk. The Blood Pressure Coefficient which is negative (-2.468) indicates that pregnant women who do not have low blood pressure (code 0) have a lower Maternal Risk than pregnant women who have high blood pressure / hypertension (code 1)

(12) For other disease history variables, a p value = 0.000 was obtained. which means there is a significant influence from history of other diseases on maternal risk. The coefficient for History of Other Diseases which has a negative sign (-7.673) indicates that pregnant women who have no history of other diseases (code 0) have a lower Maternal Risk than pregnant women who have a history of other diseases (code 1).

Thus, patients who are older, have more parity, lower height, children < 2 years apart, HB < 11 gr/dl, LILA < 23.5 cm, have HBSAG, have HIV, have a history of DM, have a history of HT, positive for urine protein, having high blood pressure (hypertension) and having other diseases have a greater chance of having a high maternal risk.

Table 3.
Human In The Loop Recommendation Accuracy Results

Maternal risk	Recommendation		Total
	Not exactly	Appropriate	
Normal	0	3497	3497
Low	7	1459	1466
Currently	5	299	304

High	0	57	57
Total	12	5312	5324

The accuracy of the classification carried out by midwives can be seen from the recommendations given for the low and medium criteria

DISCUSSION

Detection of risk in pregnant women when carried out by screening using the KIA book (3) which contains instruments and maternal data, to determine risk classification using the Poedji Rochjati score will make it easier to provide planned referrals and even supervision carried out by the community such as health cadres (Widarta et al, 2015). Maternal deaths are currently still caused by 4 late cases, where late case discovery is still the cause of late management and referrals. The Poeji Rochjati score can also be used as a communication tool between cadres and midwives, where initial screening can also be carried out by non-medical personnel such as cadres who have been trained. when the mother knows about her condition by doing self-report which is carried out using an application and a midwife will provide recommendations regarding pregnancy care, so delays in case management do not occur.

Detection at the beginning of the examination also shows the effectiveness of the intervention, in addition to providing services with the 10 T standard, supporting examination services and doctor's examinations at the health center are carried out at least once during pregnancy to carry out early detection of preeclampsia. During the Covid 19 pandemic, examinations of pregnant women were carried out when there were complaints and danger signs. research on danger signs in pregnant women where sometimes the risks found are still considered extreme, so that mothers sometimes say they are still in normal condition, and this is also influenced by the age, education level and economic level of pregnant women, which are not the variables studied in this research. Only 18% of the KIA books were used as a communication tool for officers, which resulted in pregnant women not being monitored and found to be at high risk. In this application, the midwife will be determined human-in-the-loop is a midwife in the work area of the health center who provides recommendations for places for pregnancy care and recommendations for places of delivery according to the data self-report given by the patient, so that the examination can make an appointment in accordance with the examination provisions in the Covid 19 pandemic era that pregnant women are not recommended to carry out routine examinations, but to carry out minimum examinations according to predetermined standards and carry out examinations if there are danger signs.

Applications created to monitor and monitor maternal birth planning are considered more efficient because they can be filled in anywhere and get recommendations from health workers in real time. This is also in accordance with the middle-distance development plan that health technology is focused on maternal and child health by carrying out early detection as early as possible to provide quality services, so as to reduce morbidity and mortality rates. From the research results, it was found that, predicting high risk with Poeji Rochjati scores of respondents who were older, had more parity, lower height, children < 2 years apart, HB < 11 gr/dl, LILA < 23.5 cm, had HBSAG, had HIV, having a history of DM, hypertension, and having a history of other diseases have a greater chance of having a high maternal risk, so supervision and monitoring of pregnant women with several risks that have been predicted using the Poedji Rochjati score can be carried out by families, health cadres, health workers Relatedly, it is hoped that birth planning by the mother with the recommendations given can become a mutually agreed upon information, so that pregnancy care and birth plans can also be determined by the mother and family as early as possible.

Research carried out with predictions using an application developed by researchers had a good impact, because from 5331 data on pregnant women who detected danger signs using the application, the development of this application was carried out with 10 individual classification data-data tested using Nearest Neighbors, Decision tree, Random Forest, Neural Net, AdaBoost, Gaussian Naïve-Bayes, Bagging, dan Extra Tree To get the best results, with the accuracy value of each algorithm (10-folding), there is a data accuracy of 92% using the decision tree. However, there is data confusion in the results machine learning namely 25 data on high risk, this is because for high risk it is not based only on application predictions but also uses supporting examinations which will be carried out after human in the loop provides recommendations for places to provide pregnancy examination services and childbirth referrals.

CONCLUSION

This research developed a human-in-the-loop on pregnancy danger signs, with a system accuracy of 92% using k-folding 10 times to get an increase in accuracy of 0.1% using 10 individual classifications with Nearest Neighbors, Decision tree, Random Forest, Neural Net, Adaboost, Gaussian Naïve-Bayes, Bagging, and Extra Tree. For future researchers, we recommend that this application be equipped with GPS, making it easier to map pregnant women in real time

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