Model Structure of Fetal Health Status Prediction

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Abstract - One of the issues of pregnant mothers in Indonesia is their access speed and accuracy services availability towards the prediction of fetus or baby conceived during pregnancy. Thus, the research aimed to obtain the ability to predict three ranges of a fetal target, namely normal, risk, and abnormal condition. This research emphasized the modeling aspect of supervised learning using seven different algorithms to obtain an optimal working score. Those are Decision Tree, Gradient Boosting, Random Forest, SVM, k-NN, AdaBoost, and Stochastic Gradient Descent (SGD). The structure process is mainly divided into two steps, pre-process model and the prediction model. An early data pre-process is needed before executing. Prediction output indicated that dataset test is valid, and can be proven by comparing between the testing data table and prediction and testing table diagram. The resulting model has described the sequence for simulating the training and testing data model to produce the highest working score from the seven selected algorithms. The simulated data based on the model created is proved its validity thru three main filter processes, which are missing data solution, outlier data control, and data normalization. The result obtained a working score that has data proximity with a low score range of 0.063 from model evaluation, confusion matrix, and prediction output.

Keywords: fetal prediction, pre-process model, prediction model, prediction output, supervised learning

I. INTRODUCTION

A woman's pregnancy condition bears health consequences towards herself or the conceived baby. Fetal health is affected by the expecting mother's adaptive changes during pregnancy with medical conditions based on several pregnancy attributes. Fetal health observation during this phase is crucial for the expecting mother and her baby [1].

Obstetricians and health workers in the obstetrics field wish to inform various clinical issues to expecting couples regarding their unborn baby's health, based on various case studies and previous experience. Hence, it is needed to create a clinical data prediction that gives benefit to fetal health during pregnancy and care.

This prediction can be obtained through the machine learning approach which is a subset of artificial intelligence technology. Machine learning could study numerous pregnant mother patient dataset as main criteria based on the data trained and tested previously [2-4].

The development of machine learning is vastly increased almost in every domain of technology application. This method allows researchers to solve various problems of diagnosis and prognosis in various medical domains [5]. Biomedical signal analysis, clinical examination sound, and image process, the discovery of new medicine are medical service that benefits from machine learning.

Several of the most prominent research projects for predicting pregnancy risk and fetal health are using machine learning techniques. Ref. [6] discovered that as an important indicator in fetal care, low birth weight risk in pregnancy can be predicted through machine learning. Using Bayes' minimum error rate classification on a healthcare dataset in India, researchers can predict fetal status as low birth weight or not with an accuracy number of 96.77%. Ultrasound images obtained from the lumbar spine of pregnant patients in other studies were used to determine the interspinous location generated using the Support Vector Machine (SVM) [7]. A model was generated with 880 images of 20 pregnant female subjects after training the dataset, and then the model testing process was carried out through 840 images of 16 pregnant patients. These testing processes create the best model with an accuracy level of 95%.

Ref. [8] researched various risk factor impacts such as age and red blood cells level during pregnancy. The main contribution of this research is that the known risk factors can impact differently towards gestational hypertension group (high blood pressure during pregnancy) and pre-eclampsia group (the rise of blood pressure with protein in urine). There are data of 412 pregnant mothers taken from 1874 medical records. Premature birth risk prediction is researched by [9]. They implemented an expert system in determining the risk of premature birth using 18,890 subjects and 214 variables.

Their system created an average test model accuracy of 53-88% in predicting premature birth that involved 9.419 pregnant patients. In the study of fetal health prediction, cardiotocography examination of vaginal bleeding (antepartum), eight machine learning methods were used. The highest accuracy is Random Forest (RF) with 99.2% [10].

These researchers utilize machine learning in diagnosis and medical prediction, including decision tree classification methods C4.5 and Naïve Bayes Kernel, which can predict and display gestational risk [11-12] as well as normal or abnormal conditions of pregnancy [13].

Ref. [14] created a prognosis for pre-eclampsia pregnancy deviation. They utilize genetic programming to confirm different plasma metabolism patterns of pre-eclampsia patients with 97 plasma samples. Ref. [15] researched to predict brain maturity and nerve development in babies, using various pattern analyses on functional Magnetic Resonance Imaging (MRI) data in the early life of babies (neonatal). The estimation of the SVM algorithm calculation at the gestational age that gave birth to an individual baby managed to achieve an accuracy of 84% [16]. The first step of fetal heartbeat classification is recognized through the fuzzy method. Moreover, using the Support Vector Machine (SVM) algorithm with the highest accuracy of 92% this research is used as follow up research from fetal brain development model, functional connectivity of brain with is examined in 105 premature babies [17]. Connection is expected to have an accuracy level of 80% using the SVM algorithm. The results obtained are some areas that cannot be fully interpreted by MRI analysis. Krupa *et al*. [18] utilized the decomposition empiric model and SVM algorithm in analyzing newly born babies' antepartum cardiotocography. Normal class prediction or risk prediction in 90 records are chosen randomly with 86% accuracy.

One of the issues of pregnant mothers in Indonesia is the availability of their access speed and accuracy services towards the prediction of fetus or baby conceived during pregnancy. Thus, the research is aimed to obtain the ability to predict three ranges of a fetal target, namely normal, risk, and abnormal condition.

Dataset is taken from Fetal Health Classification (https://www.kaggle.com/andrewmvd/fetal-health-classification), and then restructured and confirmed also validated by obstetricians with 30 years of experience in Indonesia. This datas*et al*so runs pre-process before becoming a training and testing dataset. The data obtained from kaggle.com is an initial dataset that is large enough so that it can be used as a reference to form training data and testing data. For Indonesian conditions, some of the data attributes/ features obtained from kaggle.com are adjusted to Indonesian conditions so that not all data features can be used as research data.

This research aims to obtain an accurate model along with valid dataset features and targets so that it can be used as input for the next research to make a mobile application to predict fetal health. The contribution of this research can help some pregnant women who cannot access quickly and easily some health facilities, in the form of specialist doctors and expensive hospitals.

II. METHOD

The model structure is divided into two steps, which are pre-processed model and the prediction model. But a data pre-processing is needed before conducting these steps.

Data pre-processing is an early technique of data mining to change raw data available into much more accurate information with a standard to be used in the next process. This process is called early steps to obtain information available through filtering and combining the data [19]. The pre-processing model diagram is shown in Fig. 1.

There are three issues solved in pre-processing step, missing value, outlier data or noise, and inconsistent data [19]. Missing values are inaccurate data because of missing information that makes irrelevant. Missing value often occurs when there are problems in the data collecting process, such as wrong entry or issues with using biometrics. It is handled using a missing data solution. Data outlier contains wrong data and outlying data found in the data pool. This data contains meaningless information. Some of the causes of outlier data are mislabelling and other problems during data collection. This outlier data is handled through the outlier data handling process. Inconsistent data occurs when a person saves a file containing the same data in different formats. Some of the inconsistent data are duplication in different formats, errors in code names, and others. The process of reducing inconsistent data is carried out through data normalization efforts.

The final result of pre-processing data is clean and standard data, ready to be used in the training process and data testing on the predictive model structure. The data is a dataset that will be divided into two training datasets and testing datasets with the composition of the training dataset being larger than the testing dataset [20]. In this study, 80% of the training dataset and 20% of the testing dataset were made.

Fig. 1 Pre-processing model structure

In general, the structure of the prediction model is divided into 2 parts, namely:

1) Training model, is an effort to make a training dataset that contains labeled features and targets that can be processed by the 7 selected algorithms and measured the performance level of each algorithm to produce the best algorithm selected as the best model and make prediction outputs to be valid for testing dataset. The seven supervised learning algorithms selected were Decision Tree, Gradient Boosting, Random Forest, SVM, KNN, AdaBoost, and Stochastic Gradient Descent (SGD). Empirically, these algorithms have already tested on several different datasets, where each dataset consists of a combination of numerical and categorical data. All algorithms have characteristics that are suitable for classification problems in machine learning, and are quite reliable in handling large amounts of data, both in terms of features and data rows.

2) Testing model, is a dataset testing processing process that contains all the same features like the training dataset features but does not contain targets so that the target is generated in the model prediction output. The prediction model structure diagram can be seen in Fig. 2.

III. RESULT AND DISCUSSION

The model structure formed is then implemented in a detailed model diagram with the help of Orange Data Mining software version 3.30.2, an open-source and freeware software. Fig. 3 illustrates the implementation of the pre-processing data model structure can be compared between the results before and after the pre-processing, through the block diagram of the raw data table to the pre-processing results table.

The comparison of pre-processing results can be seen in Fig. 4. It showed the table image before pre-processing. There are still 2.8% missing data indicated by the number of question mark symbols in each data cell from a total of 2126 data lines and 22 features. Missing data was changed to no missing and the question mark symbol that disappeared after pre-processing is run and replaced with new numbers.

The implementation of the training model is shown in Fig. 5. The training dataset is divided into 2, namely features and targets. The processed features can be selected through its block diagram, while in the testing dataset there is only one feature. Furthermore, in the training process, the data in the training dataset is connected to the prediction output block, while the testing dataset is not connected because this is a training process that runs independently.

There are 1701 data lines or 80% of the total data lines resulting from pre-processing as many as 2126 data lines in the training model. In the measurement model, 3 blocks indicate model performance measurement, namely prediction output, model evaluation, and confusion matrix. The prediction output indicates that the prediction is valid, which can be proven by comparing the block diagram of the training data table with the prediction and testing table. Model evaluation is the process of using different evaluation metrics to understand a machine learning model's performance, as well as its strengths and weaknesses. Model evaluation is important to assess the efficacy of a model during the initial research phases, and it also plays a role in model monitoring. The confusion matrix shows a more detailed breakdown of correct and incorrect classifications for each class. A confusion matrix is useful to understand the distinction between classes, particularly when the cost of misclassification might differ for the two classes or having a lot more test data on one class than the other.

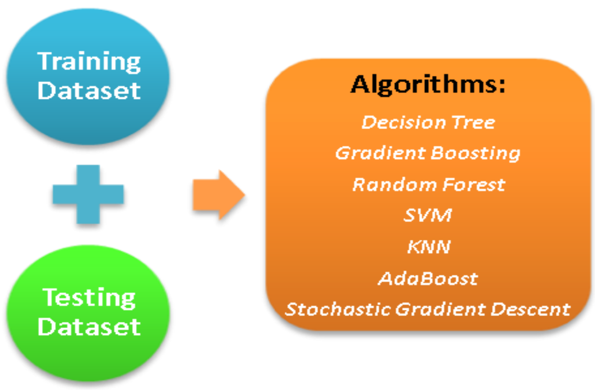


Fig. 2 Prediction model structure

The comparison can be seen in Fig. 6. Before the training model implementation, only features and targets were seen, while after its implementation, it was clear that there were scores for the algorithm used for each target category range, namely fetal health status, normal, risk, and abnormal (1, 2, 3). For example, Tree (1), Tree (2), Tree (3), all of which are the scores of the Decision Tree algorithm values in each of the predetermined target categories.

Furthermore, Fig.7 showed the block diagram of the evaluation model. 5 main performance scores distinguish the quality among the 7 existing algorithms.

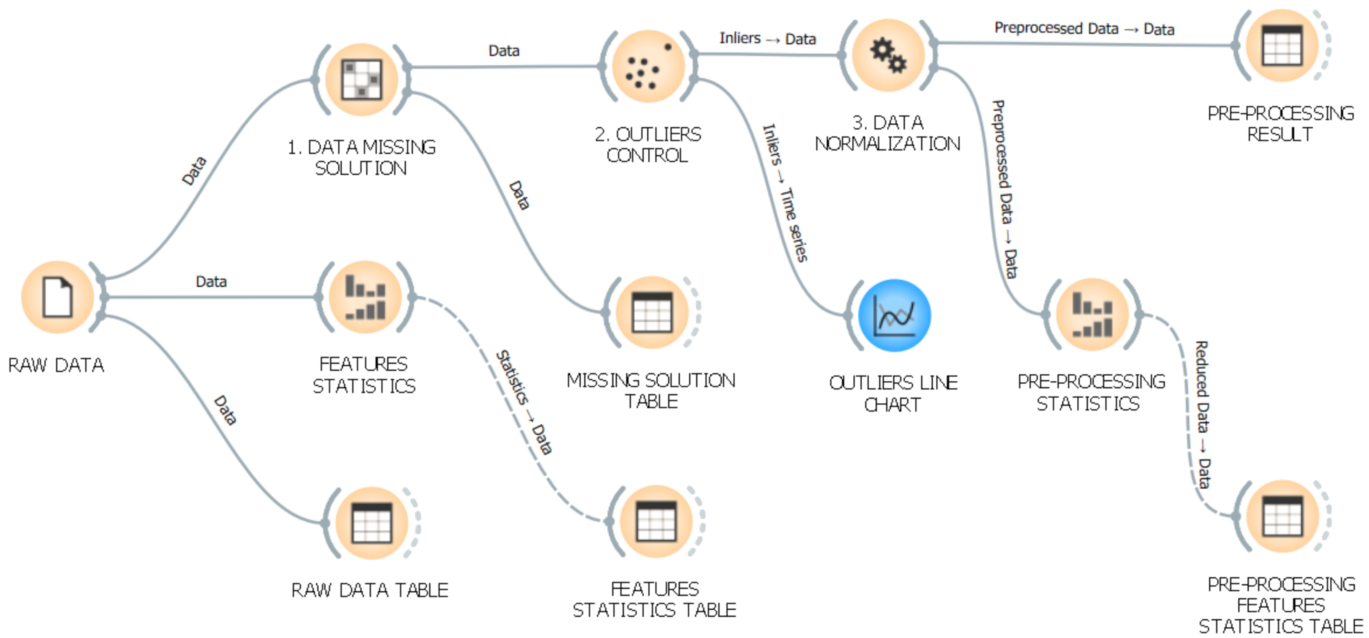


Fig. 3 Pre-processing model

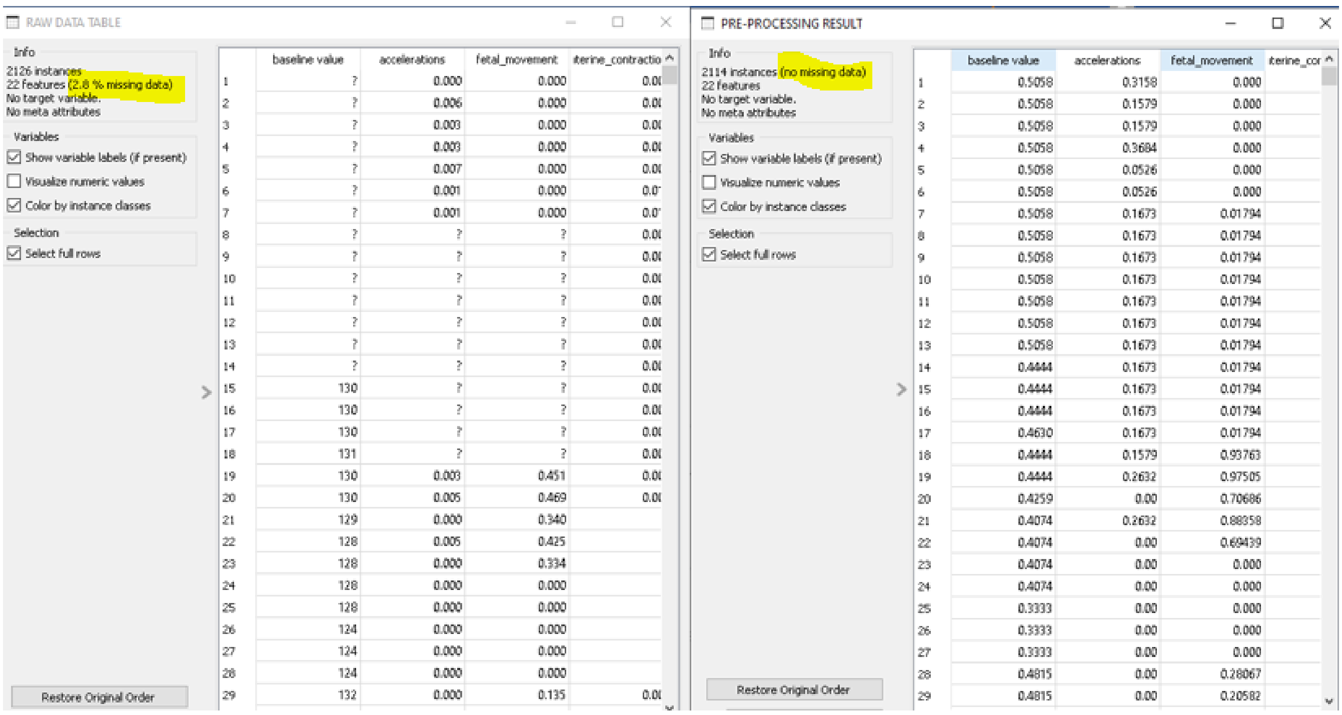


Fig. 4 Before and after pre-processing

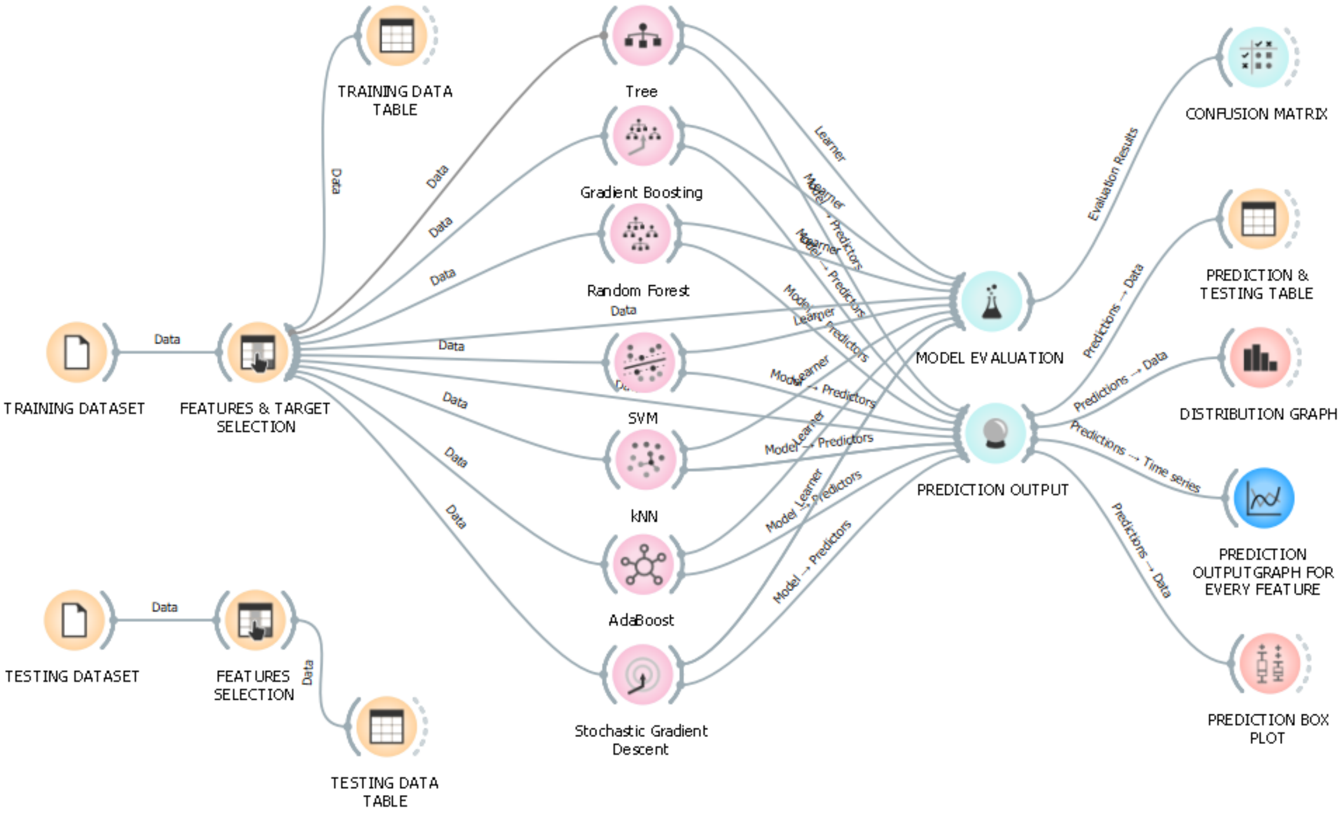
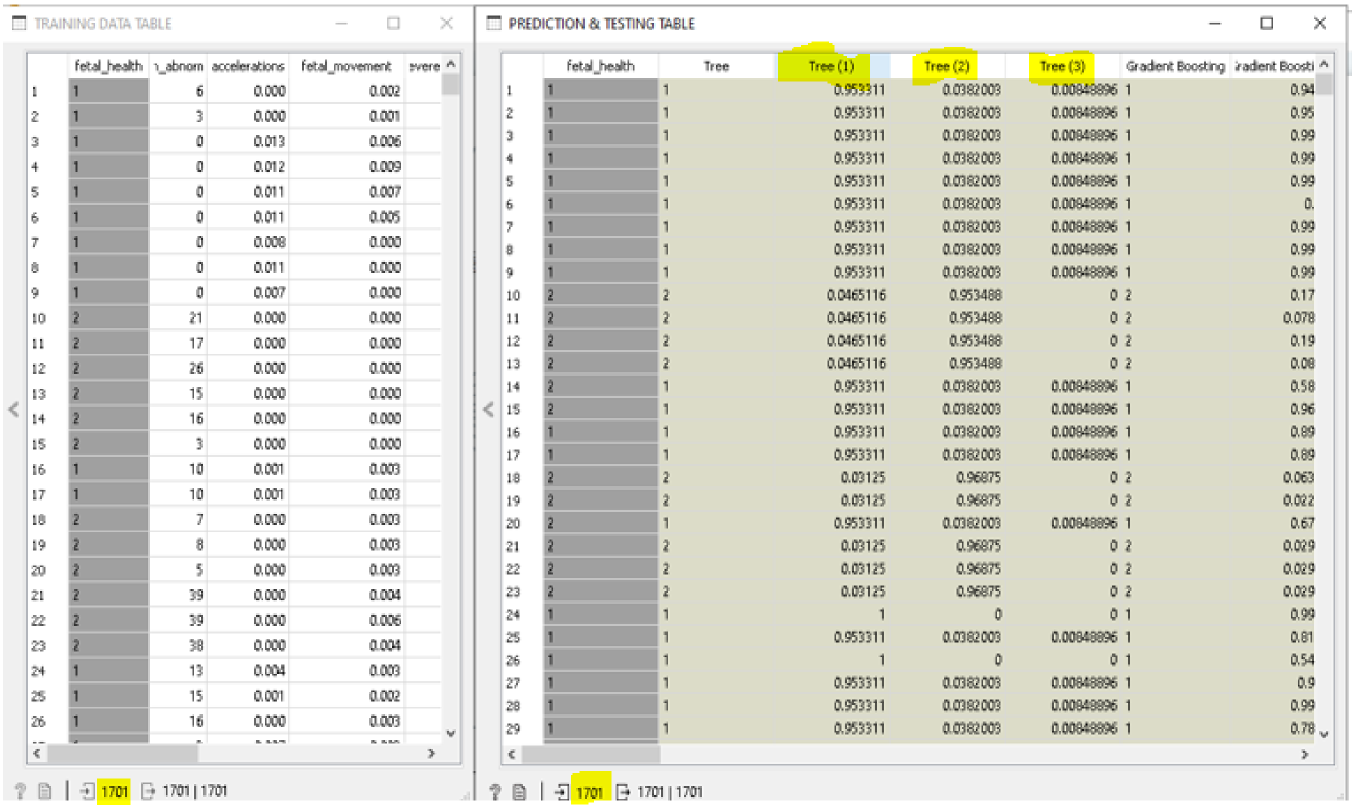


Fig. 5 Training model



TRAINING DATA TABLE

	fetal_health	ı_abnom	accelerations	fetal_movement	evere
1	1	6	0.000	0.002	
2	1	3	0.000	0.001	
3	1	0	0.013	0.006	
4	1	0	0.012	0.009	
5	1	0	0.011	0.007	
6	1	0	0.011	0.005	
7	1	0	0.008	0.000	
8	1	0	0.011	0.000	
9	1	0	0.007	0.000	
10	2	21	0.000	0.000	
11	2	17	0.000	0.000	
12	2	26	0.000	0.000	
13	2	15	0.000	0.000	
14	2	16	0.000	0.000	
15	2	3	0.000	0.000	
16	1	10	0.001	0.003	
17	1	10	0.001	0.003	
18	2	7	0.000	0.003	
19	2	8	0.000	0.003	
20	2	5	0.000	0.003	
21	2	39	0.000	0.004	
22	2	39	0.000	0.006	
23	2	38	0.000	0.004	
24	1	13	0.004	0.003	
25	1	15	0.001	0.002	
26	1	16	0.000	0.003	

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PREDICTION & TESTING TABLE

	fetal_health	Tree	Tree (1)	Tree (2)	Tree (3)	Gradient Boosting	ıradient Boosti
1	1	1	0.953311	0.0382003	0.00848896	1	0.94
2	1	1	0.953311	0.0382003	0.00848896	1	0.95
3	1	1	0.953311	0.0382003	0.00848896	1	0.99
4	1	1	0.953311	0.0382003	0.00848896	1	0.99
5	1	1	0.953311	0.0382003	0.00848896	1	0.99
6	1	1	0.953311	0.0382003	0.00848896	1	0.
7	1	1	0.953311	0.0382003	0.00848896	1	0.99
8	1	1	0.953311	0.0382003	0.00848896	1	0.99
9	1	1	0.953311	0.0382003	0.00848896	1	0.99
10	2	2	0.0465116	0.953488	0	2	0.17
11	2	2	0.0465116	0.953488	0	2	0.078
12	2	2	0.0465116	0.953488	0	2	0.19
13	2	2	0.0465116	0.953488	0	2	0.08
14	2	1	0.953311	0.0382003	0.00848896	1	0.58
15	2	1	0.953311	0.0382003	0.00848896	1	0.96
16	1	1	0.953311	0.0382003	0.00848896	1	0.89
17	1	1	0.953311	0.0382003	0.00848896	1	0.89
18	2	2	0.03125	0.96875	0	2	0.063
19	2	2	0.03125	0.96875	0	2	0.022
20	2	1	0.953311	0.0382003	0.00848896	1	0.67
21	2	2	0.03125	0.96875	0	2	0.029
22	2	2	0.03125	0.96875	0	2	0.029
23	2	2	0.03125	0.96875	0	2	0.029
24	1	1	1	0	0	1	0.99
25	1	1	0.953311	0.0382003	0.00848896	1	0.81
26	1	1	1	0	0	1	0.54
27	1	1	0.953311	0.0382003	0.00848896	1	0.9
28	1	1	0.953311	0.0382003	0.00848896	1	0.99
29	1	1	0.953311	0.0382003	0.00848896	1	0.78

1701 | 1701 | 1701

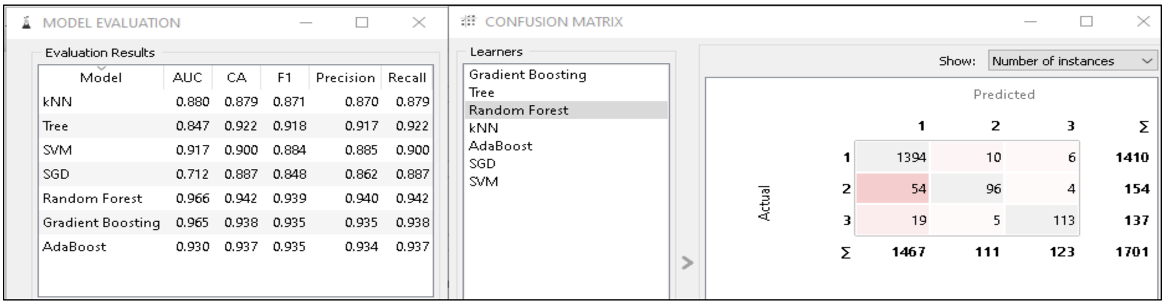
Fig. 6 Before and after training model implementation

They are Area Under Curve (AUC), Classification Accuracy (CA), F1, Precision, Recall. When it is viewed from only the CA indicator as to the main indicator of the accuracy of each algorithm, it appears that the score ranges between 0.879 (k-NN) and 0.942 (Random Forest). Thus, the difference is only about 0.063. This value is the range of accuracy values of the seven algorithms used. Mathematically, it is the largest difference in accuracy scores in the Random Forest algorithm (0.942) minus the lowest score in the k-NN algorithm (0.879). Sequentially based on fig. 7, the best performance of the 7 algorithms is Random Forest, Gradient Boosting, AdaBoost, Decision Tree, SVM, SGD, and k-NN.

It means that the accuracy score is not much difference between the minimum and maximum values. Intuitively, it can be said that the dataset that has undergone pre-processing produces a measurement of accuracy performance that tends to be homogeneous. While the confusion matrix block confirms various scores used as calculation material to determine each performance indicator in the evaluation model block.

In the final stage of implementation, which is the model testing in Fig. 8, it can be seen that the testing dataset is connected to the prediction output block, the training dataset automatically disconnects to the prediction output.

In the testing model, there are 425 data lines or 20% of the total data lines from the pre-processing results of 2126 data lines. Prediction output indicates that the testing of the dataset is valid, which can be proven by comparing the block diagram of the testing data table and the prediction and testing table. The comparison can be seen in Fig. 9. Only the features were seen before the implementation of the training model, while after its implementation, it was clear with scores for the algorithm used for each target category range, namely fetal health status, normal, risk, and abnormal (1, 2, 3). For example, SVM(1), SVM(2), SVM(3), all of which are the scores of the SVM algorithm values in each of the predetermined target categories.



MODEL EVALUATION

Evaluation Results

Model	AUC	CA	F1	Precision	Recall
kNN	0.880	0.879	0.871	0.870	0.879
Tree	0.847	0.922	0.918	0.917	0.922
SVM	0.917	0.900	0.884	0.885	0.900
SGD	0.712	0.887	0.848	0.862	0.887
Random Forest	0.966	0.942	0.939	0.940	0.942
Gradient Boosting	0.965	0.938	0.935	0.935	0.938
AdaBoost	0.930	0.937	0.935	0.934	0.937

CONFUSION MATRIX

Learners: Gradient Boosting, Tree, Random Forest, kNN, AdaBoost, SGD, SVM

Show: Number of instances

Actual \ Predicted	1	2	3	Σ
1	1394	10	6	1410
2	54	96	4	154
3	19	5	113	137
Σ	1467	111	123	1701

Fig. 7 Model evaluation and confusion matrix scores

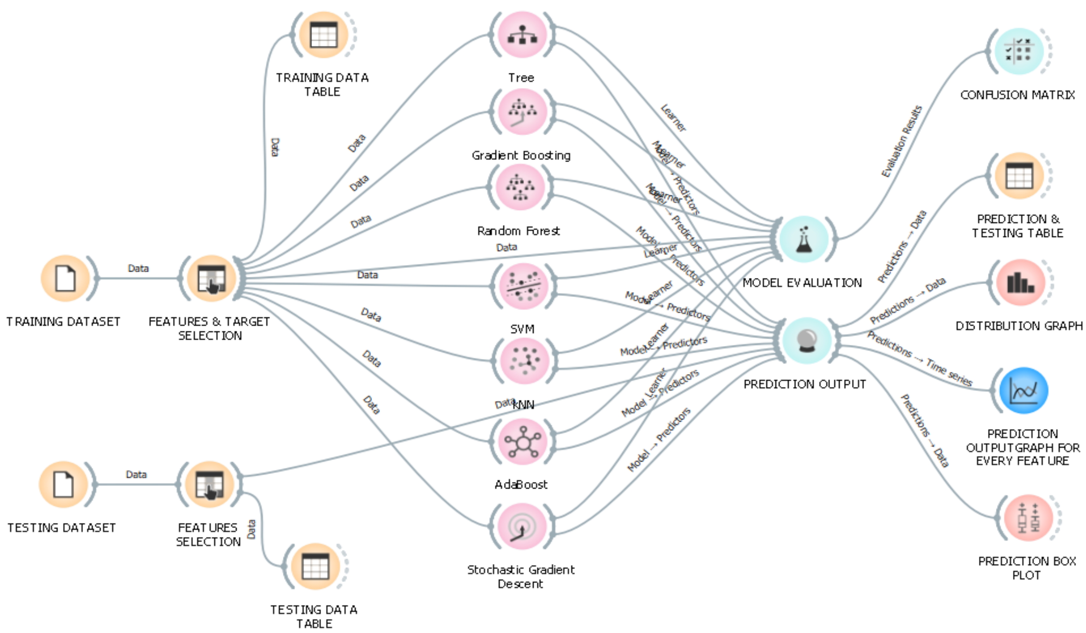
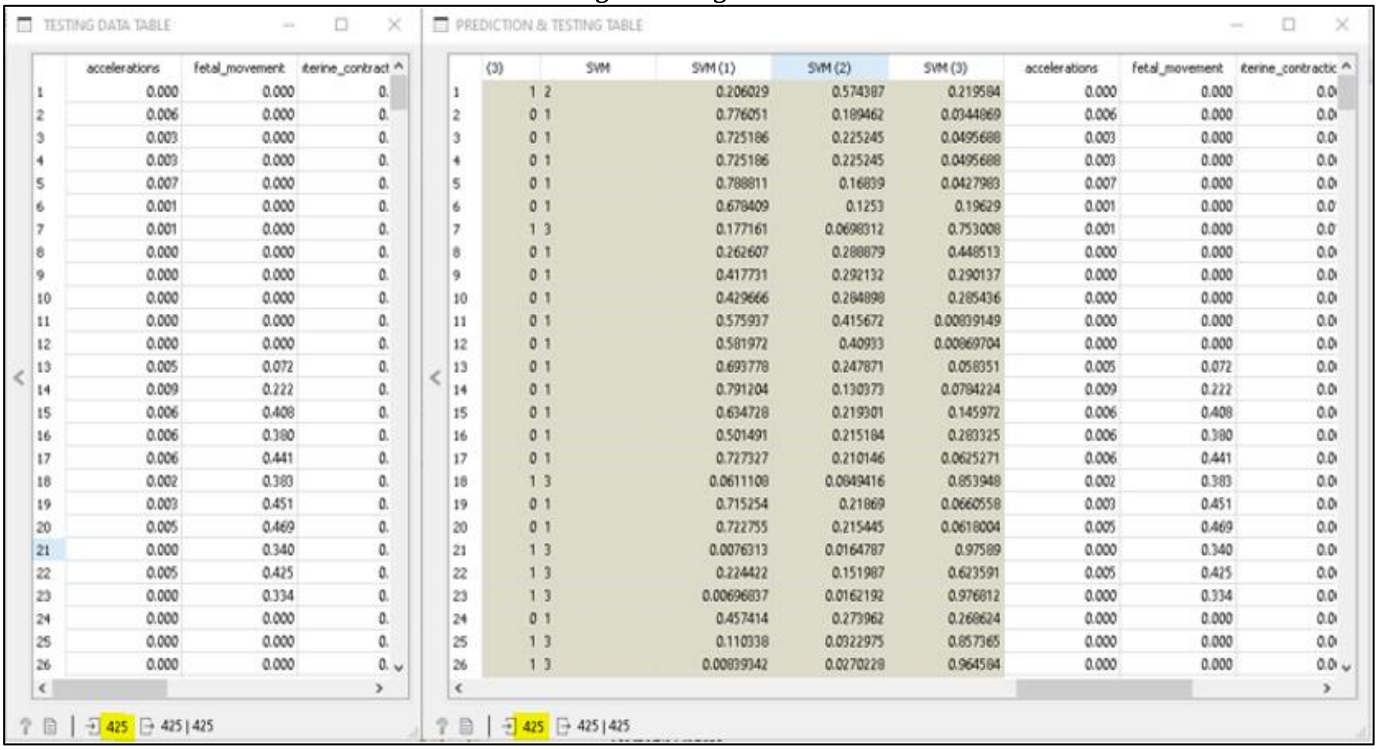


Fig. 8 Testing model



TESTING DATA TABLE

	accelerations	fetal_movement	iterine_contract
1	0.000	0.000	0.
2	0.006	0.000	0.
3	0.003	0.000	0.
4	0.003	0.000	0.
5	0.007	0.000	0.
6	0.001	0.000	0.
7	0.001	0.000	0.
8	0.000	0.000	0.
9	0.000	0.000	0.
10	0.000	0.000	0.
11	0.000	0.000	0.
12	0.000	0.000	0.
13	0.005	0.072	0.
14	0.009	0.222	0.
15	0.006	0.408	0.
16	0.006	0.380	0.
17	0.006	0.441	0.
18	0.002	0.383	0.
19	0.003	0.451	0.
20	0.005	0.469	0.
21	0.000	0.340	0.
22	0.005	0.425	0.
23	0.000	0.334	0.
24	0.000	0.000	0.
25	0.000	0.000	0.
26	0.000	0.000	0.

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PREDICTION & TESTING TABLE

	(3)	SVM	SVM (1)	SVM (2)	SVM (3)	accelerations	fetal_movement	iterine_contractic
1	1 2		0.206029	0.574387	0.219584	0.000	0.000	0.0
2	0 1		0.776051	0.189462	0.0344869	0.006	0.000	0.0
3	0 1		0.725186	0.225245	0.0495688	0.003	0.000	0.0
4	0 1		0.725186	0.225245	0.0495688	0.003	0.000	0.0
5	0 1		0.788811	0.16839	0.0427983	0.007	0.000	0.0
6	0 1		0.678409	0.1253	0.19629	0.001	0.000	0.0
7	1 3		0.177161	0.0698312	0.753008	0.001	0.000	0.0
8	0 1		0.262607	0.288879	0.448513	0.000	0.000	0.0
9	0 1		0.417731	0.292132	0.290137	0.000	0.000	0.0
10	0 1		0.429666	0.284898	0.285436	0.000	0.000	0.0
11	0 1		0.575937	0.415672	0.00839149	0.000	0.000	0.0
12	0 1		0.581972	0.40933	0.00869704	0.000	0.000	0.0
13	0 1		0.693778	0.247871	0.058351	0.005	0.072	0.0
14	0 1		0.791204	0.130373	0.0784224	0.009	0.222	0.0
15	0 1		0.634728	0.219301	0.145972	0.006	0.408	0.0
16	0 1		0.501491	0.215184	0.283325	0.006	0.380	0.0
17	0 1		0.727327	0.210146	0.0625271	0.006	0.441	0.0
18	1 3		0.0611108	0.0849416	0.853948	0.002	0.383	0.0
19	0 1		0.715254	0.21869	0.0660558	0.003	0.451	0.0
20	0 1		0.722755	0.215445	0.0618004	0.005	0.469	0.0
21	1 3		0.0076313	0.0164787	0.97589	0.000	0.340	0.0
22	1 3		0.224422	0.151987	0.623591	0.005	0.425	0.0
23	1 3		0.00696837	0.0162192	0.976812	0.000	0.334	0.0
24	0 1		0.457414	0.273962	0.268624	0.000	0.000	0.0
25	1 3		0.110338	0.0322975	0.857365	0.000	0.000	0.0
26	1 3		0.00839342	0.0270228	0.964584	0.000	0.000	0.0

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Fig. 9 Before and after testing model implementation

IV. CONCLUSION

The resulting model has described the sequence for simulating the training and testing data model to produce the highest performance score from the 7 selected algorithms. The data that will be simulated based on the model formed has guaranteed validity because it has gone through 3 main filter processes, namely missing data solutions, controlling data outliers, and data normalization. Based on the model evaluation, confusion matrix, and prediction output, several performance scores have been produced which have data closeness with a fairly small score range of 0.063. Further research will examine the effect of various variations in the composition of the training and testing dataset on the model evaluation and the values of the confusion matrix.

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