PUSAT PENGAJIAN SAINS KOMPUTER

UNIVERSITI SAINS MALAYSIA

CPC251-MACHINE LEARNING AND COMPUTATIONAL INTELLIGENCE

PROJECT 1

Group Name : 6 Cardio

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Submission Date : 4 July 2021

Academic Session : Semester 2, 2020/2021

Video Link: https://youtu.be/Uwyzy535W2g

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1.0 Background Study

1.1 Cardiotocography

Cardiotocography (CTG) is a medical procedure that records the fetal heartbeat and uterine contractions during pregnancy. CTG reading will be very important in order to determine the condition of the baby and prevent any mortality whether to the baby or mother. The fetal heart rate is given more importance in the CTG because it reveals if the fetal is going through hypoxia or any distress which can lead to severe complications in delivery. Hence, CTG comes in handy in conditions where the women who are going to labour is in high-risk category or if the fetal heartrate is too low, too high or abnormal. It is a very controversial and problematic task. It because there are so many things that we need to look out in a CTG to correctly understand the fetal heart rate activity in accordance to the uterine contraction. Errors and pitfalls can cause doctors to receive incorrect reading which can endanger the fetus.

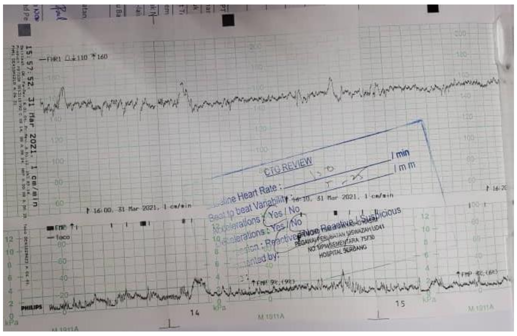

Figure 1.1.1: CTG of a Patient from Malaysian Hospital

There are few things we need to give importance on when interpreting the CTG such as the fetal heart rate, number of accelerations in the fetal heart rate, uterine contraction per second, variability in fetal heart rate and decelerations. The fetal is in normal condition if the heartbeat rate is between 110-160 beats per minute, there are accelerations present which lasts long for more than 15 seconds with a rise of 15 beats per minute in the fetal heart rate and there is a variability in the fetal heart rate more than 5 beats per minute. However, there must not be any deceleration present in the fetal heart rate. If it happened so, then the fetal is categorized as in the pathological state. There are 5 requirements for a fetal’s conditions to be categorized as normal. If one of the conditions is not met, then fetal condition will be categorized as suspect. If more than 2 condition is not met, then fetal condition will be categorized as pathological.

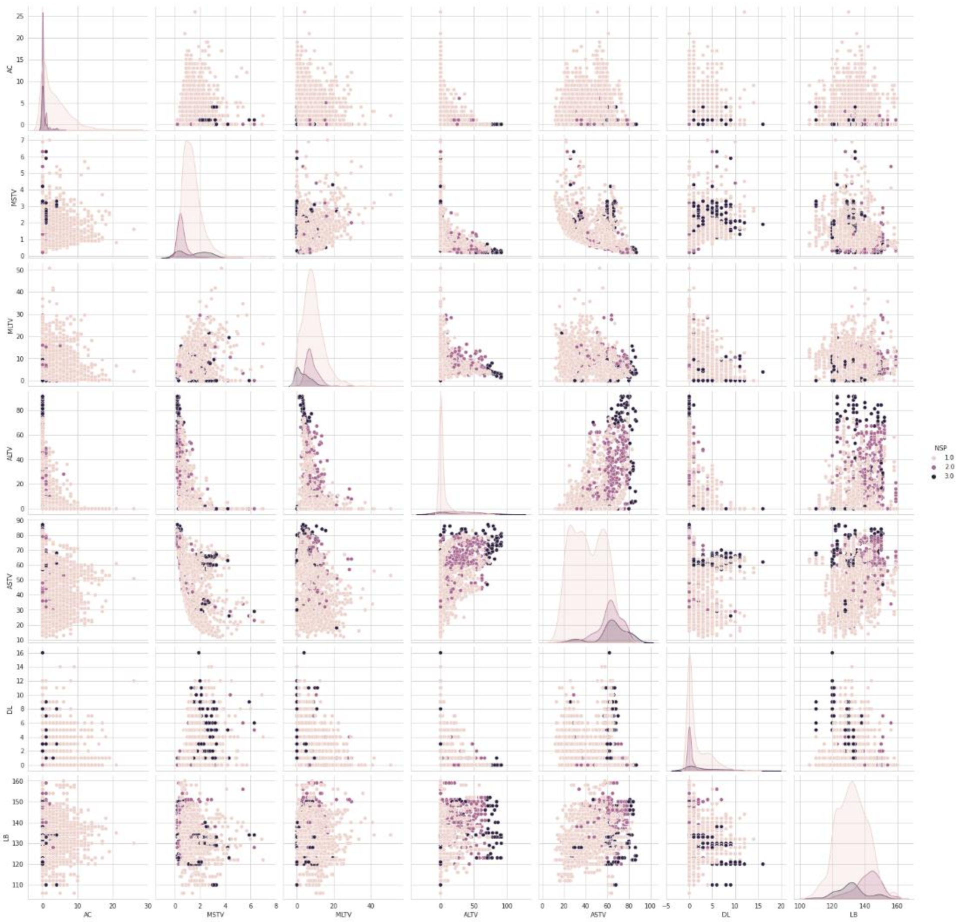

Figure 1.1.2: Pair Plot of Important Features in Dataset

The above pair plot shows all the features available in this dataset. All these features are part of CTG readings. In this project, we were very interested in building a predictive modal for cardiotocography. Our goal was to make a modal that can classify fetal heart rate reading into three categories which are Normal, Suspect and Pathologic.

1.2 Problem Definition

1) To reduce human interpretation error in CTG.

2) To build a cohesive computerised algorithm to interpret CTG readings with no human intervention.

3) To determine the best and optimal number of features to be used in the modal.

4) To choose the best modal for CTG reading interpretation.

5) To find the best parameters for each modal which are suitable for imbalance dataset. Then pick the best modal out of them.

Most fetal deaths occur in neonatal period are caused by preterm birth complications. CTG plays an important role in solving this problem as the readings can be used to determine fetal condition time to time. CTG interpretation can only be done by a trained medic or a computerised software. It is proven that computerised software helps reduce perinatal mortality more than traditional method. Although, it helps reduce fetal mortality, computerised software is still not performing to a level where we can fully rely on it. Further works need to be done to improve the computerised software for better CTG interpretation.

Artificial Intelligence is very useful to be used to build better computerised software. Artificial intelligence employs mathematical algorithms and many data points from the human body to make a diagnosis. This has been used in many other medical fields such as predicting cancer recurrence and mortality and cardiovascular risk prediction. The existing system does perform well in predicting fetus status, but it must be improved.

1.3 Aim

The project's objective is to create a machine learning and deep learning model that can accurately forecast foetal state, much like a highly trained obstetrician.

1.4 Problem Statement

The aim is to create a predictive modal that can classify fetal status into Normal, Suspect and Pathologic. The tasks involve in creating this modal are:

1. Standardising Data
2. Performing Data Cleaning
3. Feature Selection
4. Hyper parameter Tuning
5. Building final modal
6. Determine Number of Features for Fuzzy Logic Modal
7. Design and Optimize Fuzzy Rules

The final modal will be used to read all the non-discarded attributes in the dataset.

2.0 Feature Selection

In this experiment there are total of 23 features and 2126 CTG records. It is computationally expensive to build, train and test models with 23 features. Hence, to reduce the feature space we have performed feature selection to select relevant features in building the machine learning model. However, there are some data cleanings has been carried out before selecting the features.

2.1 Data Cleaning

Firstly, we have removed the columns that have least unique values. The reason why we do so is, because with least unique values the columns have, it is most probably not contributing much to predicting but just increase the feature space. Hence, we removed the DS, DP and NZeros.

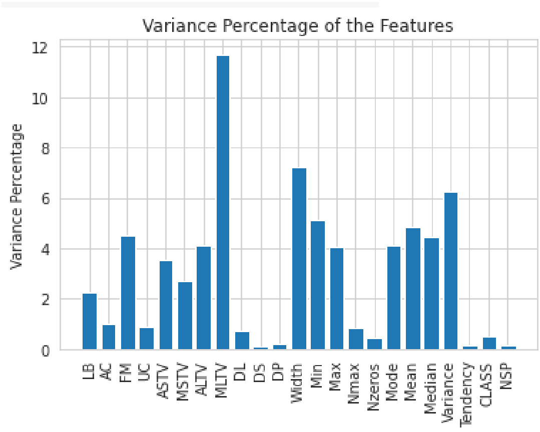

Figure 2.1.1 shows the variance percentage of features based on number of columns.

Secondly, we have removed all the duplicated rows that are present in the data because it paves the chance for information leak where the same record may present in both train set and test set. We have discovered a total of 12 duplicated rows, and we removed all of them.

	LB	AC	FM	UC	ASTV	...	Mode	Mean	Median	Variance	NSP
68	140.0	5.0	0.0	3.0	34.0	...	156.0	153.0	155.0	5.0	1.0
234	123.0	0.0	0.0	0.0	49.0	...	129.0	127.0	129.0	2.0	1.0
306	145.0	0.0	13.0	0.0	77.0	...	146.0	145.0	147.0	0.0	2.0
319	150.0	0.0	10.0	0.0	79.0	...	150.0	149.0	151.0	0.0	3.0
324	135.0	0.0	0.0	0.0	62.0	...	143.0	142.0	144.0	1.0	3.0
333	144.0	0.0	15.0	0.0	76.0	...	145.0	144.0	146.0	2.0	2.0
787	123.0	3.0	4.0	0.0	52.0	...	129.0	128.0	130.0	4.0	1.0
791	123.0	2.0	3.0	0.0	50.0	...	129.0	128.0	130.0	5.0	1.0
798	146.0	0.0	0.0	4.0	65.0	...	150.0	149.0	151.0	1.0	2.0
849	138.0	2.0	0.0	4.0	41.0	...	142.0	142.0	143.0	2.0	1.0
1113	122.0	0.0	0.0	0.0	19.0	...	120.0	120.0	122.0	3.0	1.0
1114	122.0	0.0	0.0	0.0	19.0	...	120.0	120.0	122.0	3.0	1.0
1115	122.0	0.0	0.0	0.0	19.0	...	120.0	120.0	122.0	3.0	1.0
1458	148.0	2.0	0.0	1.0	40.0	...	153.0	155.0	156.0	4.0	1.0

Figure 2.1.2 shows the duplicated rows.

Thirdly, we have imputed the missing data in the dataset instead of removing them, the reason why we do this is because every data matters. Hence, we perform KNNImputer to impute the missing values because it is a faster and efficient way to impute missing values instead of other statistical measures. Finally, we also removed the outliers that are present in the dataset or just introduced by previous imputation method as it can disrupt the prediction of model which will eventually lead to poorer results.

2.2 Feature Selection Process

2.2.1 Machine Learning Model

For this project, we are using wrapper method as the feature selection method. This is because the Cardiotocography dataset has both continuous and discrete data. It is not efficient to use Filter method for this dataset. We are using the Sequential Feature Selection technique in forward mode to select the best feature subsets. The reason why we chose forward method is because we give more importance for the features at the front as they are the important ones in determining the fetal state in a more conventional way.

When we perform feature selection, number of features chosen is very important. We performed feature selection using 2 to 17 features. So, we were able to find out subset with 2 best features to subsets with 17 best features for each of the modal. So, models of different machine learning algorithm will have different set of best features.

2.2.2 Fuzzy Logic Model

In this section of the report, we will discuss why we had to filter out certain variables from the dataset. As you can see from out work, we decided to only use variables from LB to MSTV. Firstly, using all the variables was making it hard for us to interpret it from our data set CTG, so we only used the data which is used to interpret the CTG model. By filtering that data, it also saved time and made it easy to define our fuzzy rules. Many features introduced noise into our dataset. In such a case our fuzzy algorithm was likely to overfit or produce an inaccurate result. The data that was filtered was deemed to be irrelevant because by removing it our model's prediction improved (Less ambiguous data means improvement of model accuracy.), and it also reduced the time complexity for our model as well. Then we create a fuzzy model we choose the 7 inputs in our fuzzy model after we filtered them using the feature selection mentioned above. We determined our fuzzy set by having 7 inputs and one output.

Our inputs included

- LB - FHR baseline
- AC - accelerations per second
- FM - fetal movements per second
- UC - uterine contractions per second
- ASTV - percentage of time with abnormal short-term variability
- MSTV - mean value of short-term variability
- DL - light decelerations per second

For the output it will be only one which will be divided into three sets which are

N(Normal), S(Suspect), P(Pathological)

3.0 Model Construction

3.1 Machine Learning Model

3.1.1 Training and Evaluating the model

For this project, we decided to create 5 modals which are K-nearest neighbour, Decision Tree, Perceptron, Support Vector Machine and Logistics Regression. We wanted to test all this model and choose the best model as the final machine learning model. Firstly, we train the model with some loose parameter and its best feature subsets which was selected using feature selection method to see how it performs. We plot the F1_weighted, accuracy, precision_weighted and recall_weighted score. We are also computing the weighted average for these scores because our dataset has imbalance class where most of the data are skewed into Normal class based on the figure 3.0. Moreover, to test the modal, we are using cross validation method with training set because we tried to avoid any information leak by using test set.

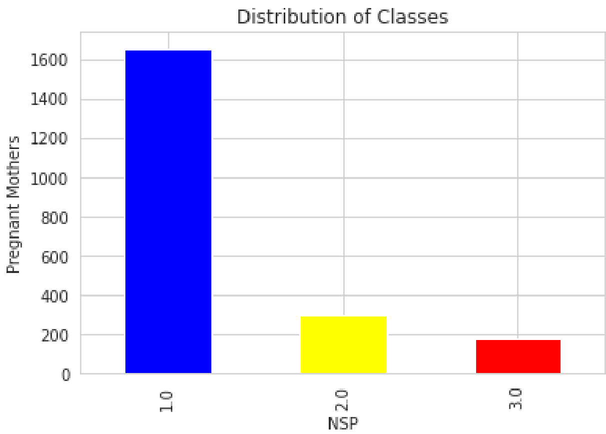

Figure 3.1.1.1 shows Distribution of Classes

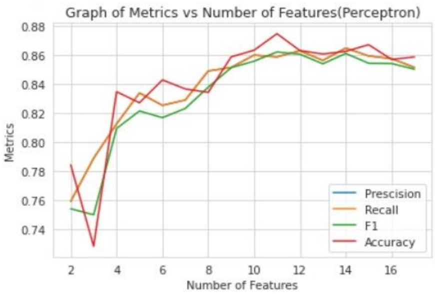

Figure 3.1 shows cross validation scores for Perceptron

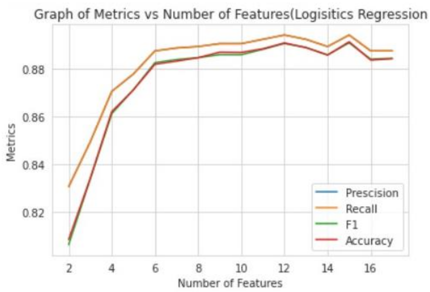

Figure 3.2 shows cross validation scores for Logistic Regression

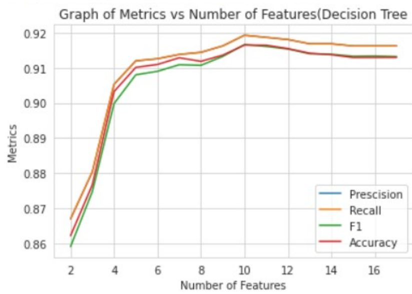

Figure 3.3 shows cross validation scores for Decision Tree

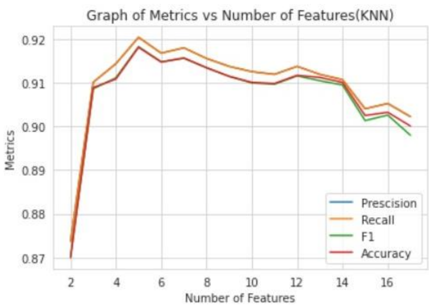

Figure 3.4 shows cross validation scores for KNN

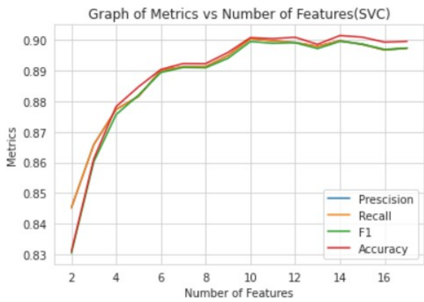

Figure 3.5 shows cross validation scores for SVC

3.1.2 Hyperparameter Tuning

Based on the graphs for each model in the training and evaluation we can see the F1, precision and recall fluctuate and none of them reached close to 100%. Moreover, we focus more on the precision and recall because the F1 score gives the optimal score if the precision and recall are similar. We can see that most of the models above their precision and recall almost reaching 100%. On the other hand, we are also not focusing more on the accuracy because it will not give optimal results for imbalance multiclass classification problems. Hence, we try to maximise the precision and recall score which will then eventually increase the F1 score. To do that, we are going to find the best parameters that the models can have along with the best features. We are going to run grid search for a couple of different set of parameters, to see which hyperparameter works the best for its respective best feature subset.

We did feature selection and hyper parameter tuning for all the modals. Then we chose the best modal based on the scores. The scoring that was used are f1_weighted, accuracy, precision and recall. So, when we compare all the 5 modals, decision tree performed the best and the train and test score difference is the lowest.

For perceptron model, we have used two parameters which are eta0 and max_iter. Eta0 is the initial learning state and we have set it to 0.01, 0.05, 0.1, 0.5 and 1.0. Next is max_iter which is the maximum number of iterations taken for the solvers to converge and we have set it to 100, 200, 300 and 400. The rest of the perceptron parameters are set to default.

For logical regression model, we have used three parameters which are solver, max_iter and C. Solver is the algorithm used in the optimization problem. There are 5 algorithm that can be chosen for solver but for multiclass dataset liblinear cannot be used. So, we decided to set solver to lbfgs, sag and saga. Lbfgs uses gradient evaluations to approximate second derivative matrix updates. For sag solver, the loss gradient is computed one sample at a time, and the model is updated at a constant learning rate along the way. Saga solver is the go-to solution for sparse multinomial logistic regression and can handle very large datasets. Next is max_iter which is set to 100, 200 and 300. Moreover, C parameter is the inverse of regularization strength. The smaller the number, the better the regularization. We have set C to 0.001, 0.01, 0.1 and 1.

For decision tree, pre-pruning process is very important as it helps to prevent over fitting by stopping tree-building process early, so that leaves with very small samples are not produced. Thus, all the parameters chosen are based on pre-pruning process. Criterion is the function used to measure quality of split. We have used gini and entropy where gini stands for Gini impurity, whereas entropy stands for information gain. Max_depth is the maximum depth of a tree which is set to 3, 4, 5, 6, 7 and 8. Next is min_sample_split which is the least number of samples required to split an internal node and it has been set to 2, 20, 2. Furthermore, min_sample_leaf is the bare minimum of samples that must be present at a leaf node which has been set to 1, 15, 1. Lastly, random state has been set to 10, 50 and 5 where random state controls the estimator's randomness.

For support vector classifier, three parameters have been used. There are kernel, C and degree. Kernel is set to poly, rbf and linear. Since this dataset contains non-linear values, poly and rbf kernels are given more importance. Poly allows non-linear models to be learned by comparing vectors of training samples in a feature space to polynomials of the original variables. RBF is used as it can overcome the space complexity problem as it only needs to store the support vectors instead of storing whole dataset during training. Next, C is set to 0.1, 1 and 5. Lastly, degree is used for poly kernel only. It is the degree of poly kernel function, and it has been set to 2, 3 and 4.

For k-nearest neighbour, two parameters have been used which are n_neighbours and metric. N_neighbors is the number of neighbours used for k_nearest neighbour model, which is set to 5, 10, 15 and 20. We decided to go with these values because based on our previous models we concluded that model only works well if n_neighbours is increased by 5 or else it starts to over fit. Next, metric is the distance metric used for the tree and it has been set to Minkowski, Euclidean and Manhattan. We included Euclidean and Manhattan as they are the only metric that we have studied. Minkowski metric was not included in the syllabus, but we still included it as it is the default metric value and we wanted to test all the metric to get better results.

3.2 Fuzzy Logic Model

3.2.1 Model Selection and Training

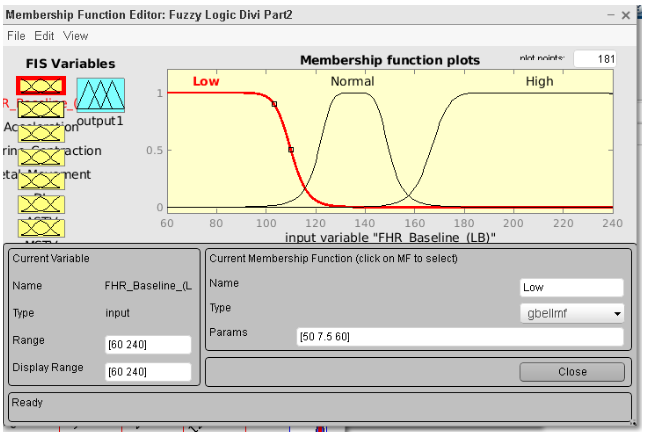

Figure 3.2.1.1

For the FHR Baseline, which is the first graph, it has 3 membership functions have been used a range of 60 to 240 and the graph type is Generalized Bell Shape membership function (gbellmf). The membership functions are Low, Normal and High. Low ranges from 60 to 115, Normal ranges from 115 to 160 and High ranges from 160 to 240. The ranges low is usually abnormal, normal is classified as assuring whereas when the baseline is high its non-reassuring.

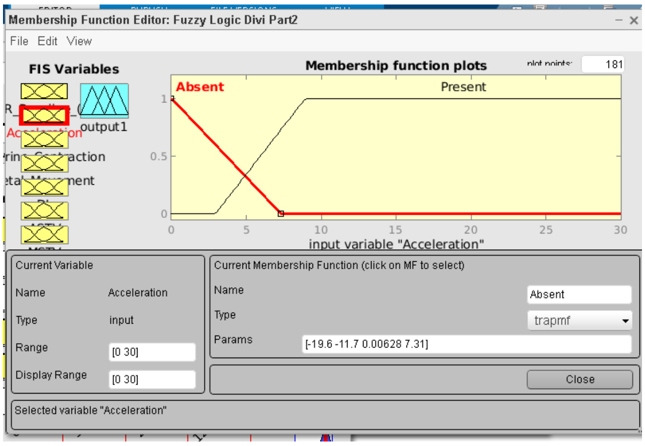

Figure 3.2.1.2

For the second graph which is acceleration it has 2 membership functions of types Trapezoidal membership function(trapmf). The first membership function ranges from 0 to 7 which if the value is in that limit will be declared as absent which will be too minimum. Second one is 7 and above for which if the value is 7 and above it will be declared as Present it will be considered more presence of acceleration.

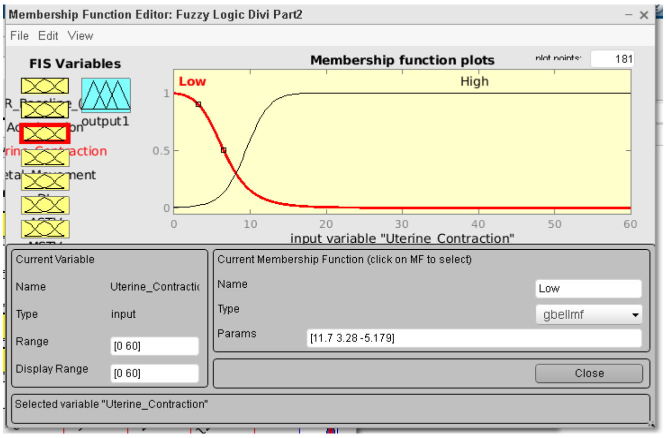

Figure 3.2.1.3

The third graph is Uterine Contraction which has 2 membership functions with the graph type as Generalized Membership function (gbellmf). The first membership which is called low it ranges from 0 to 17, there would still be contraction, but the number of contractions would be considered low. The second one which is high it ranges from 18 to 60, it would indicate that there is more contraction.

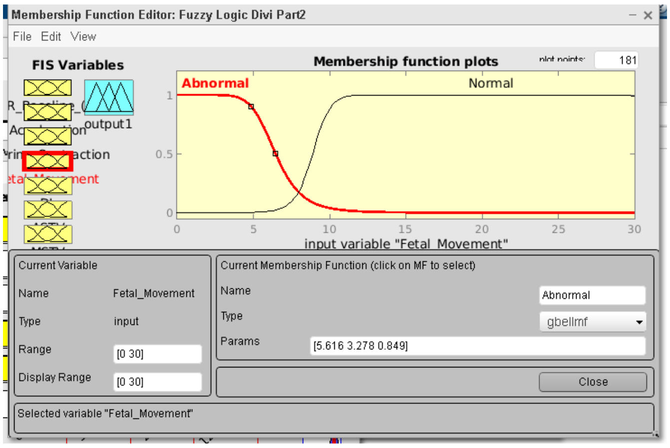

Figure 3.2.1.4

The fourth graph which is Fetal Movements Per Second, which is of the type Generalized Membership function (gbellmf) it has 2 membership functions first one being normal for which if the value is in the range 0 to 8 it will be declared as abnormal, which will also be considered as non-reassuring for the baby and if the value is in the range 9 and above it will be declared as normal, the values which are considered to be reassuring.

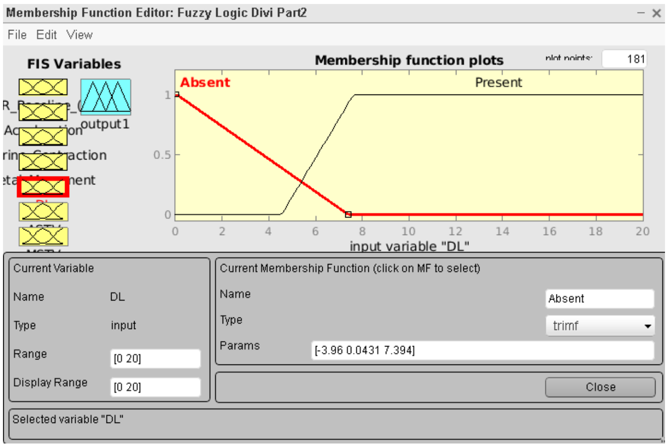

Figure 3.2.1.5

The fifth graph is DL, which has 2 membership functions of the type Triangular membership function(trimf) and Trapezoidal. It has 2 membership functions first one being absent, which the values range from 0 to 7.35 it will show that the deceleration is not present which is not an assuring sign, The second one is present for which the value ranges from 7.36 and above, which would be considered assuring for the baby.

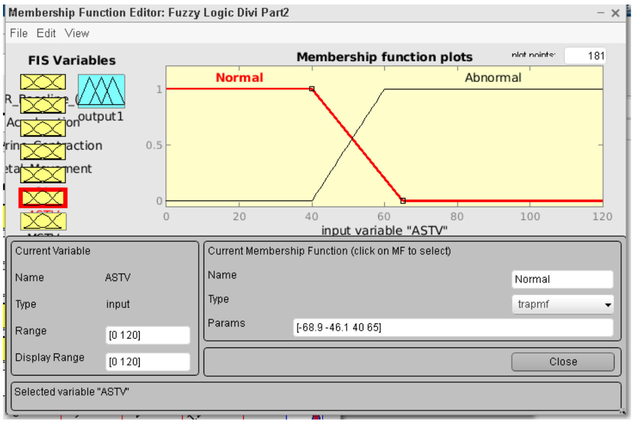

Figure 3.2.1.6

The seventh graph is ASTV which has 2 membership functions which are of the type Trapezoidal membership function (trapmf). The first one is normal the values of which ranges from 0 to 62 which is assuring for the baby and the second one is abnormal which ranges from 63 and above which is non reassuring.

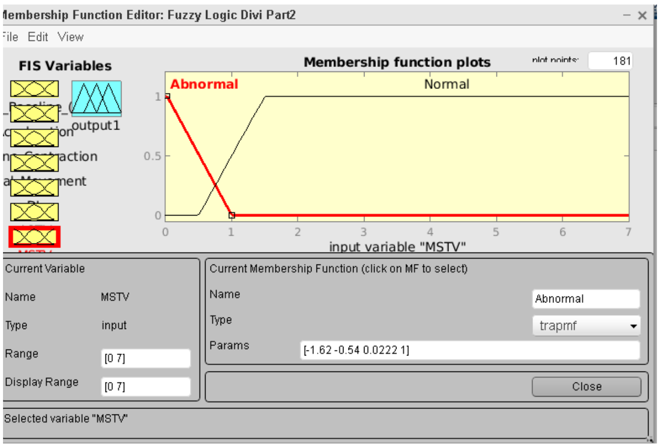

Figure 3.2.1.7

The eighth graph is MSTV which has 2 membership functions which are of the type Trapezoidal membership function (trapmf). The first one is Abnormal the values of which ranges from 0 to 2 which is not assuring for the baby, and the second one is normal which ranges from 2.1 and 10 which is reassuring.

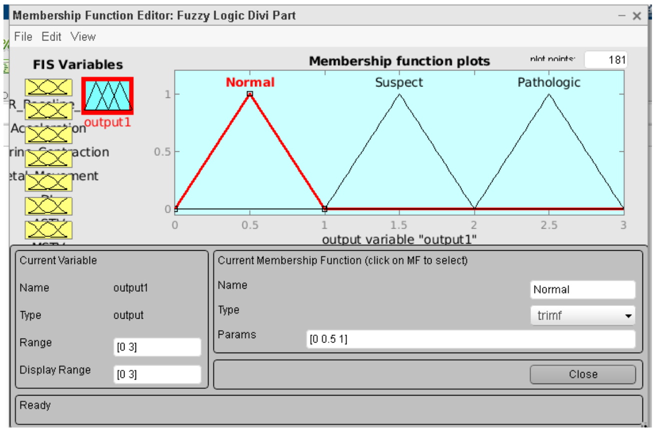

Figure 3.2.1.8

The output has 3 membership functions of the type Triangular, the first one which is Normal if the output is one its considered assuring and good for the baby, if the output is 2 it comes under suspect which is considered to be non-reassuring for the baby, and the third one which is 3 if the output comes under that it considered to be pathological for the baby

3.2.2 Rules

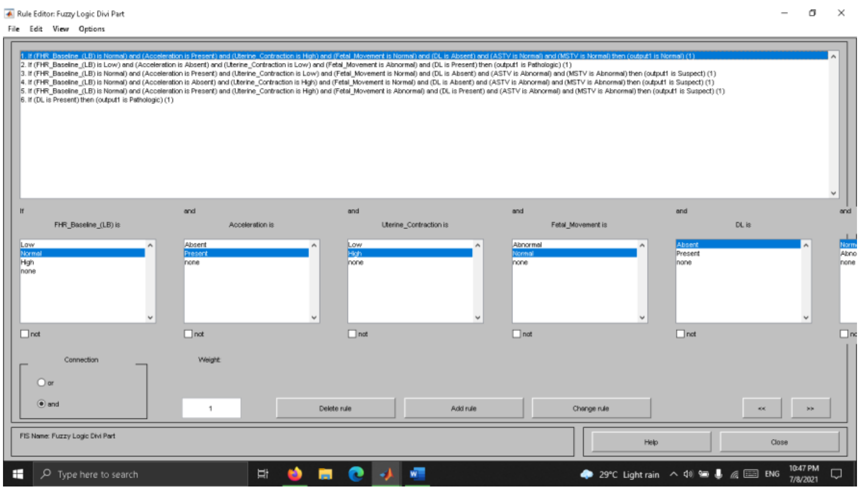

Figure 3.2.2.1

As Shown in the figure above there are 6 rules in the fuzzy logic that we created each rule have a different result based on the values and which range they are in i.e., the First rule which says that if the FHR_Baseline is normal simultaneously with the acceleration being present, uterine contraction being high, fetal movement being normal, DL being absent along with ASTV and MSTV being normal the NSP will be 1 which is the NSP we get if the output is normal. The second rule states rule which says that if the FHR_Baseline is low simultaneously with the acceleration being absent, uterine contraction being low, fetal movement being abnormal, DL being present the NSP will be 3 which is the NSP we get if the output is pathological. The third rule states rule which says that if the FHR_Baseline is normal simultaneously with the acceleration being present, uterine contraction being low, fetal movement being normal, DL being absent along with ASTV and MSTV being abnormal the NSP will be 2 which is the NSP we get if the output is suspect. The fourth rule which says that if the FHR_Baseline is normal simultaneously with the acceleration being absent, uterine contraction being high, fetal movement being normal, DL being absent along with ASTV and MSTV being abnormal the NSP will again result in NSP being suspect which is 2. The fifth rule which says that if the FHR_Baseline is normal simultaneously with the acceleration being present, uterine contraction being high, fetal movement being abnormal, DL being present along with ASTV and MSTV being abnormal the NSP will again result in NSP being suspect again which outputs in 2. The Sixth rule is if the DL is the only element present then the NSP will directly output Pathological which is 3

4.0 Results and Discussion

4.1 Machine Learning Model

After completing parameter tuning, we have used all the best parameters in testing model to test it with the test data. The results of the final model as shown below

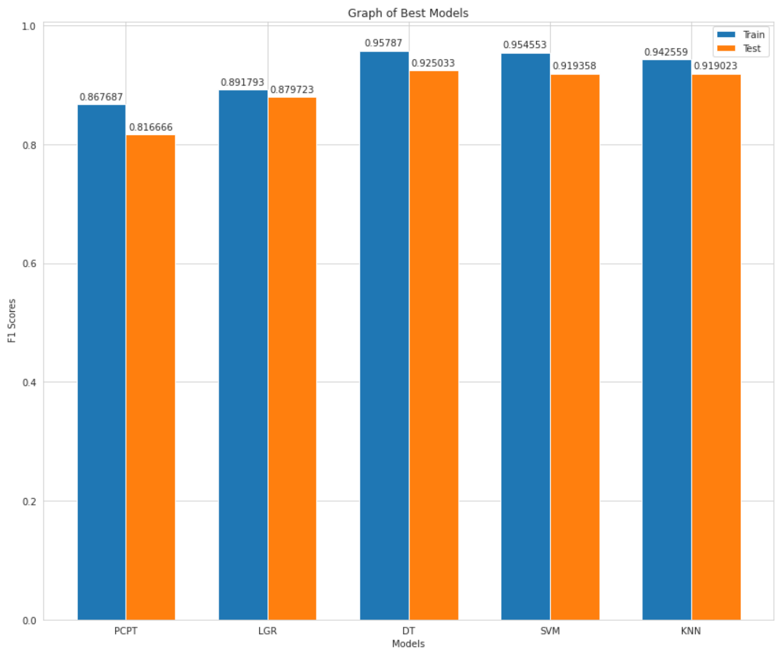

Figure 3.6 The training and testing F1 scores of the models

	accuracy	precision	recall	f1
PCPT	0.870913	0.870658	0.870913	0.867687
LGR	0.895810	0.890127	0.895810	0.891793
DT	0.958348	0.957899	0.958348	0.957870
SVM	0.955191	0.954398	0.955191	0.954553
KNN	0.943534	0.942454	0.943534	0.942559

Figure 3.7 The training F1 score of the models

	acc	pres	recall	f1
PCPT	0.827670	0.816565	0.827670	0.816666
LGR	0.885922	0.879738	0.885922	0.879723
DT	0.924757	0.925624	0.924757	0.925033
SVM	0.922330	0.919762	0.922330	0.919358
KNN	0.922330	0.920256	0.922330	0.919023

Figure 3.8 The testing F1 score of the models

We can see the Decision Tree model outperforms other models where it records a higher training and testing score. Besides, models such as KNN and SVM also scores training and testing score higher than 90%. With these we can conclude that models such as Decision Tree, KNN and SVM performed well in our experiments. On the other side, we can perceptron and logistic regression model does not seem to perform well because the training and testing scores of perceptron and logistic regression model scores around 82 – 89% which is not really bad, but in the comparison of experiment it is bad. Also, the metric that we used to pick the final best model is the F1 score. As what we have mentioned earlier, we are trying to maximise the recall and precision score hence instead evaluating the models separately for precision and recall, we take the F1 the harmonic means as the metric to find the best final model. We can also say that none of our model overfits it's because the difference between the train scores and test scores is not very high as we can see it was around 3 – 5%. Hence, overall, the best final model that we picked is the decision tree. However, to be more precise on our decision we also compared the results obtained from the models. But this round of assessment we only chose the models that achieved scores more than 90% for training and testing. So, we are only going to choose Decision Tree, KNN and SVM in this comparison. This round of assessment we are going to refer to the classification report of these models. The diagram below shows the classification report of the models.

	precision	recall	f1-score	support
1.0	0.94	0.98	0.96	310
2.0	0.84	0.69	0.76	59
3.0	0.92	0.81	0.86	43
accuracy			0.92	412
macro avg	0.90	0.83	0.86	412
weighted avg	0.92	0.92	0.92	412

Figure 3.9 classification report for the SVM model

	precision	recall	f1-score	support
1.0	0.93	0.98	0.95	310
2.0	0.85	0.68	0.75	59
3.0	0.95	0.84	0.89	43
accuracy			0.92	412
macro avg	0.91	0.83	0.87	412
weighted avg	0.92	0.92	0.92	412

Figure 3.10 classification report for the KNN model

	precision	recall	f1-score	support
1.0	0.95	0.95	0.95	310
2.0	0.77	0.80	0.78	59
3.0	0.95	0.88	0.92	43
accuracy			0.92	412
macro avg	0.89	0.88	0.88	412
weighted avg	0.93	0.92	0.93	412

Figure 3.11 classification report
for the Decision Tree model

By looking at the diagrams above we can see that most of the models achieved a score of at least 70% for both precision and recall for each class. However, KNN and SVM, failed to achieve a score more than 70% for recall on the second class which is suspect. Which shows that these models fail to correctly predict all the suspect the suspect classes within the dataset. But that’s not the case for Decision Tree, where decision tree scored 80% recall for Suspect class which shows that the decision tree somehow managed to classify all the suspect classes in the test set correctly. On the other hand, it is clearly visible that decision tree model has higher F1 scores for each class compared to the other model. With all these models we can finally see that best model here is the Decision Tree model.

4.2 Fuzzy Logic Model

Normal Class

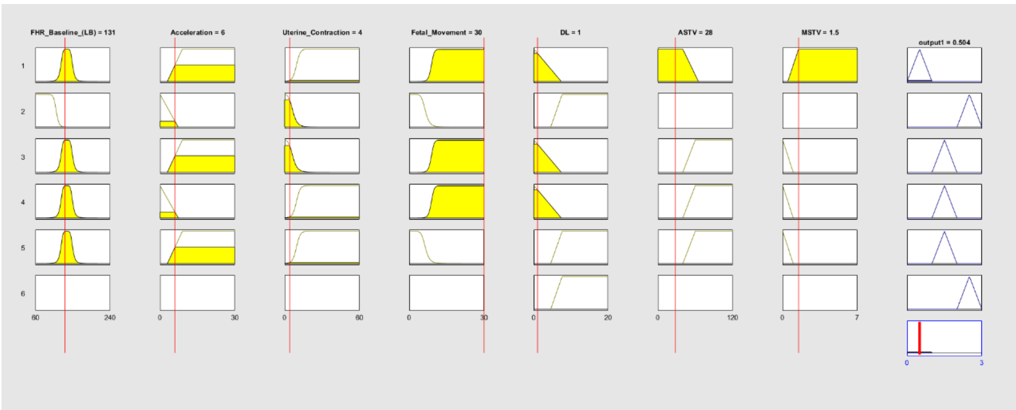

Figure 4.2.1.1

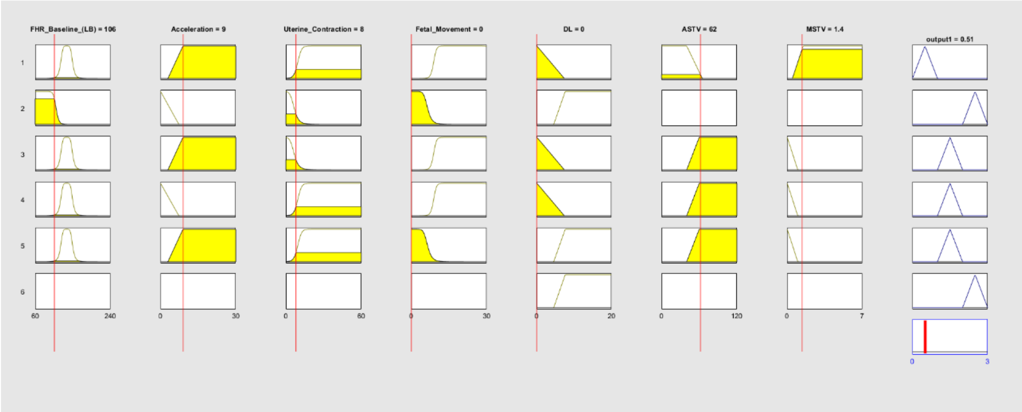

Figure 4.2.1.2

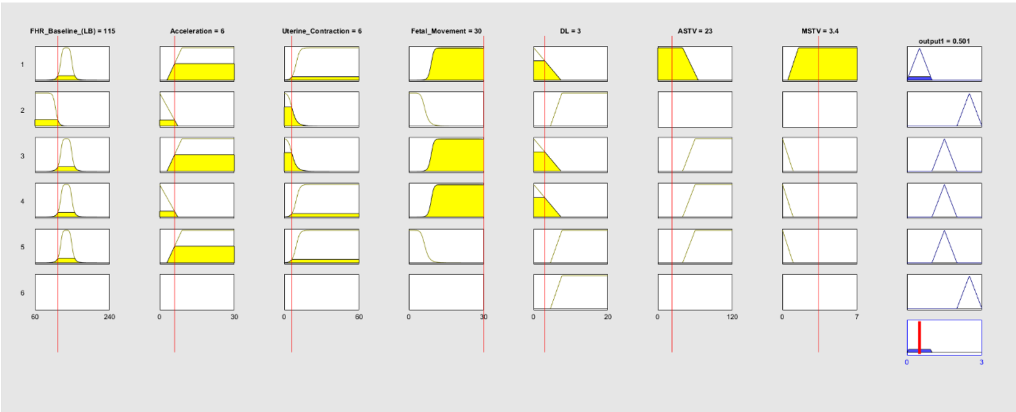

Figure 4.2.1.3

A Cardiotocography reading will be categorized as normal when the features of Cardiotocography will fall in the optimal range. Even though some of features are fall near the lower boundary or upper boundary of the optimal range, they also could be considered as the normal class of Cardiotocograph.

For instance, based on the reading of Cardiotocograph in figure 4.2.1.1, the features of Fetal Heart Rate (LB), Acceleration (AC), Fetal Movement (FM), Light Deceleration (DL), Abnormal Short-Term Value (ASTV) and Mean Short Term Value (MSTV) are fall in the optimal range of Normal Cardiotocograph but the Uterine Contraction (UC) fall near the lower boundary of the optimal range of Normal Cardiotocograph but as other features are fall in the optimal range, the reading of Cardiotocograph is considered as normal.

Suspect Class

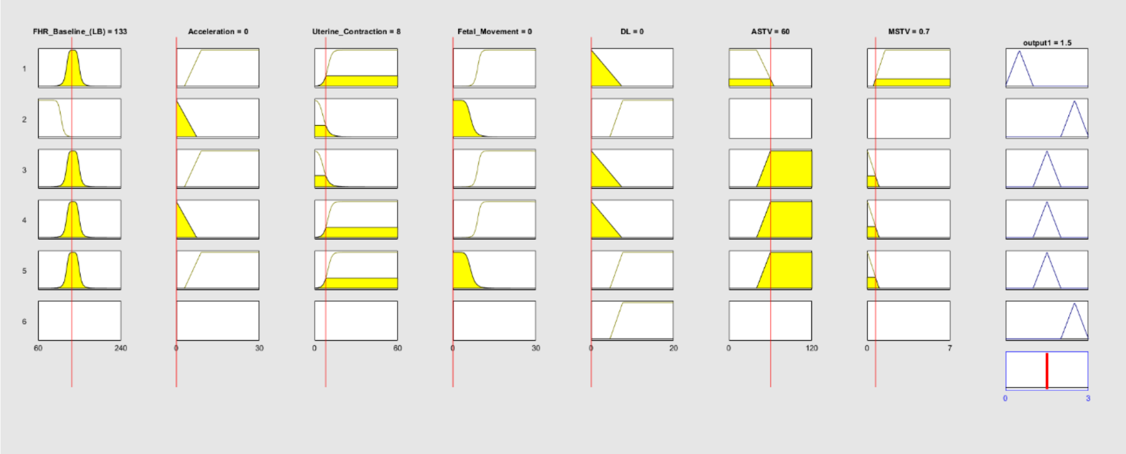

Figure 4.2.2.1

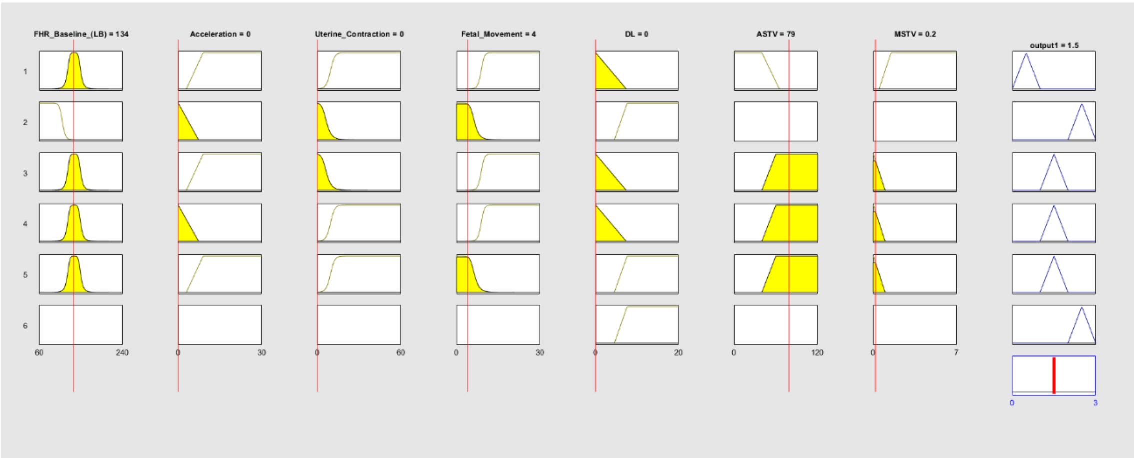

Figure 4.2.2.2

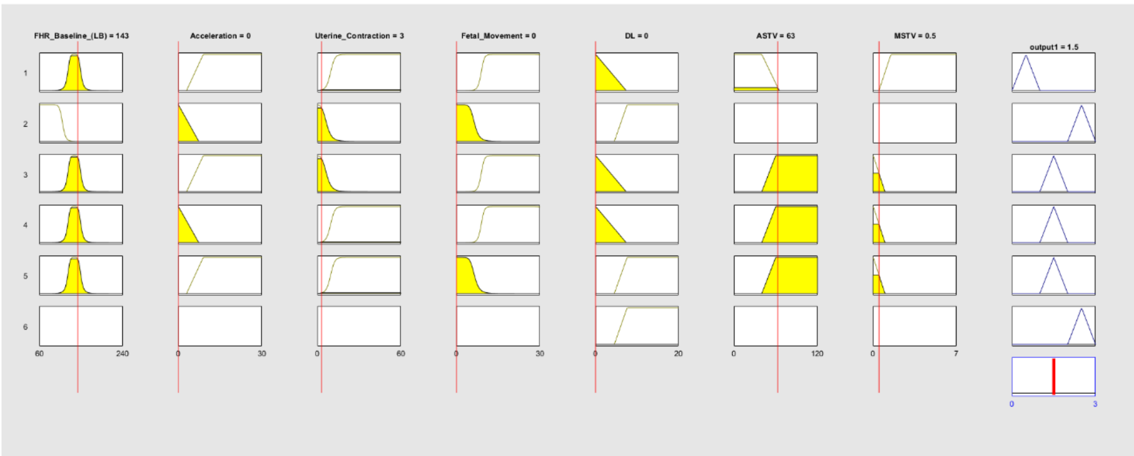

Figure 4.2.2.3

A Cardiotocography reading will be categorized as suspect when any of the features of Cardiotocography will fall outside of the optimal range.

For instance, based on the reading of Cardiotocograph in figure 4.2.2.3, the features of Acceleration (AC), Acceleration (AC), Fetal Movement (FM), Abnormal Short-Term Value (ASTV) and Mean Short Term Value (MSTV) are fall outside from the optimal range of Normal Cardiotocograph hence it is considered as suspect.

Pathologic Class

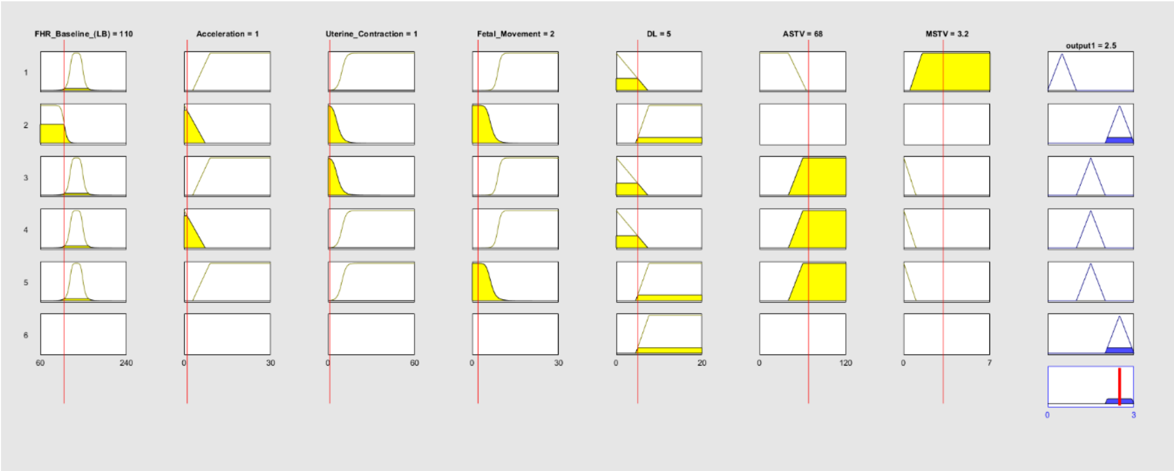

Figure 4.2.3.1

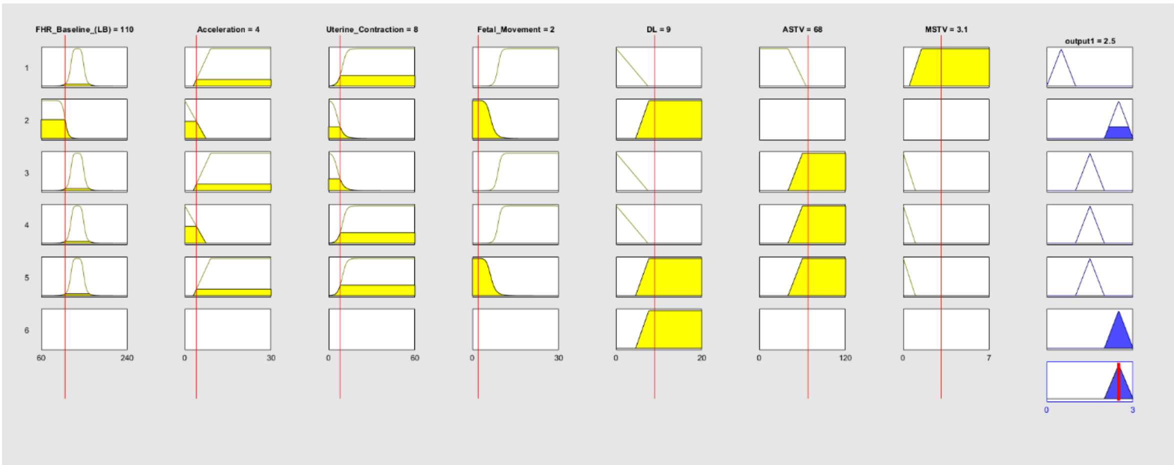

Figure 4.2.3.2

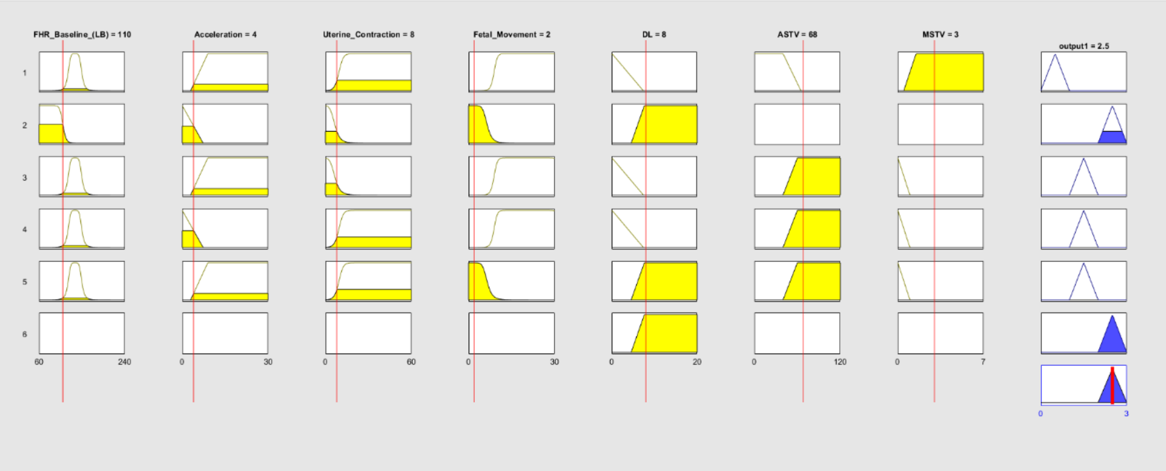

Figure 4.2.3.3

A Cardiotocography reading will be categorized as pathologic when all of the features of Cardiotocography will fall outside of the optimal range and if any light deceleration present.

For instance, based on the reading of Cardiotocograph in figure 4.2.3.1, all the features are fall outside from the optimal range except the Mean Short-Term Value (MSTV). As many features are fall outside of the optimal range, it is considered as pathological. Moreover, based on the Figure 6.3.3, the Light Deceleration (DL) present hence it is considered as pathological.

The fuzzy logic model is a human developed model where the parameters range will be self-created. Hence, some results from the dataset would not match with the dataset given and the model could not be used to define all the result in the dataset given. Moreover, the Cardiotocography dataset given has some outliers which is also could not defined by the fuzzy logic model. Apart from that, the model can work with most of the result in the given dataset so it can used to obtain final output of Cardiotocograph.

4.3 Comparison between Machine Learning Model and Fuzzy Logic Model

When we compare both models, we can say that both models have performed very well. For machine learning model, a successful prediction model has been created where the model was able to classify most of the dataset correctly. Especially, decision tree model was the best performing model and only few data were wrongly classified. For fuzzy logic model, we had to set membership function and fuzzy rules all by ourselves. Which means the rules are made based on our knowledge and the domain study we have done. The fuzzy logic model also worked well in classifying each data, but some data were classified wrongly. This is because fuzzy model does not have rules that can capture and overcome data points with ambiguous value.

Since we set rules for fuzzy logic ourselves, fuzzy model works best for some data and does not work well for others. Hence, we can get a best result from fuzzy logic if the data points are favoring the fuzzy rules. Because, it’s impossible to define a rule for every possibility as increasing the number of rules in fuzzy set reduces the efficiency the fuzzy logic model. The process of setting the rules is a try and error situation here.

However, the prediction that happens in machine learning model is more to a mathematical computation and not fuzzified. As the machine learning models able to capture the insights and trend based on the data and produce a mathematical function that able to accommodate all the data points from different possibilities. That is why we can see at times the machine learning model able to produce output efficiently if there are one or two feature is slightly ambiguous. But that is not the case for fuzzy logic model. It is because the membership function that we have defined may be not favoring the one or two slightly ambiguous values of the features

So, when we consider all of the facts, it can be said that machine learning models is a more dependable model than fuzzy logic model.

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5.0 References

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