MINIMAL LOSS FUNCTION DETERMINATION ON FOUR MACHINE LEARNING ALGORITHM USING CHRONIC MYELOID LEUKEMIA CANCER DATASET

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ABSTRACT

In Artificial intelligence researches, machine learning (ML) algorithms are used to extract meaningful information from the datasets to aid prediction and in some cases diagnosis. The determination of loss function on the chosen machine learning algorithm(s) is discovered to be deficient in grouping or stratification of datasets. This paper used dataset of 1640 Chronic Myeloid Leukemia patients from Obafemi Awolowo University Teaching Hospitals Complex, Ile-Ife, Osun Sate, Nigeria. An experimental analysis was performed in Waikato Environment for Knowledge Analysis 3.8.0 using basophil count and spleen size values on four ML algorithms (BayesNet, Multilayered perceptron, Projective Adaptive Resonance Theory (PART) and Logistic Regression) to determine low and high risk patients. Two validation techniques (Holdout and 10-fold cross-validation) were used to evaluate the performance of the algorithms on correctly classified instances, time to learn, kappa statistics, sensitivity and specificity. Two algorithms (Logistic regression and PART) showed leading performances in stratifying the dataset; the loss function was minimized by finding the difference between the true output r and the predicted output $\hat{r}$. The results of the loss function of Logistic regression algorithm for low and high risk in holdout and 10-fold cross-validation showed 0.22%, 1.40% and -0.22%, -0.02% respectively. Similarly, PART algorithm yielded -1.58%, 1.40% and -0.22%, -0.26%. From the findings, Logistic regression algorithm had the loss function with minimum value in holdout technique. Therefore, the determination of minimal loss function is of high importance as it would enhance the choice of the algorithm to be used in grouping of dataset.

Keywords: Artificial intelligence, Data grouping, Empirical risk minimization, Loss function, Machine learning

1.0 Introduction

Utilization of scoring systems for stratification of Chronic Myeloid Leukemia (CML) disease into their risk group was used for cure and survival prolongation but these systems do not computationally handle very large datasets from clinical platforms, and are faced with the limitations of transforming the data due to noise and overfitting of the data, which led to the challenge of accurate stratification and prediction (Atul, Prabhat & Jaiswal, 2014). As a result, Machine Learning (ML) algorithms that understand, mimic and aid the information processing tasks had been applied over the years in diverse areas to extract meaningful information based on their performances. Evaluation of the ML algorithm performances had been carried out to measure the functionality, which helped to achieve great success in stratifying and predicting a given data instances of a problem domain (Safoora, Fatemeh, Mohamed, Coco, Joshua,

Congzheng & Lee, 2017). The selection of an optimal algorithm had been based on the existing performance benchmarks such as accuracy, speed, time to learn, number of features, comprehensibility, robustness, scalability and interpretability. However, these benchmarks alone do not guarantee the successful adoption of an algorithm for stratification and prediction since there may be an incurring loss or risk in its adoption (Meng, Zhaoqi, Xiang-Sun & Yong, 2015), due to the loss function that was not considered as a metric for evaluation. This had posed the question that after the learning of an algorithm and an optimal one was chosen, what guarantees that the optimal algorithm would not lead to a loss or cause a risk in prediction? (Jonathan & Steven, 2017). Hence, this paper focused on the determination of algorithm with minimal loss function using the Empirical Risk Minimization (ERM) technique on the four machine learning algorithms to determine the one with the minimal loss function (empirical risk) for stratifying chronic myeloid leukemia data.

2.0 Literature Review

Machine learning (ML) is central to many areas of interest in Computer Science and related large-scale information processing domains (David, 2012). ML entails data-driven methods capable of mimicking, understanding and aiding human and biological information processing tasks; and is closely related with Artificial Intelligence (AI), with ML placing more emphasis on using data to drive and adapt the model from large datasets (Ian & Eibe, 2005). The motivation in ML is majorly to produce an algorithm that can either mimic or enhance human/biological performance (Sepp, 2013). Machine Learning has been successfully deployed in variety of applications areas such as: morphological analysis in natural language processing, Optical Character Recognition (OCR), text or document classification, statistical parsing, named-entity recognition, medical diagnosis, speech recognition, speech synthesis, speaker verification, image recognition, fraud detection, network intrusion, robots, navigation, recommendation systems, search engines, information extraction systems, games, and many more (Mehryar, Afshin & Ameet, 2012). Hina, Syed and Harleen (2018) carried out a comparative survey of machine learning and meta-heuristic optimaization algorithms for sustainable and smart healthcare. The paper reviewed machine learning and its various optimization techniques in disease datasets which would help to avoid any kind of epidemic in algorithm selection. Alongside, an optimized sustainable healthcare framework that can use machine learning techniques and nature-inspired optimization algorithm was designed to be used in healthcare dataset. In machine learning, more complex models can be searched because the task is more focused to learning only one or few carefully defined models which predict the variable in question. In another paper by Oladejo, Oladele and Saheed (2018), two dimensionality reduction strategies (feature selection and feature extraction) were used to address the problems of highly correlated data and to obtain a robust and efficient dimensional space. Analysis of micro array data was carried out on Leukemia cancer dataset with the goal of finding the smallest quality subsets for precise tumor arrangement. One-way ANOVA algorithm was used to select relevant variables and Principal component analysis (PCA) algorithm was used to remove the most relevant variables out of the ones that were selected. The classification algorithms employed were support vector machine (SVM) and K Nearest Neighbour (KNN) and experimental analysis was performed in matlabR2015a (8.5.0.197613) environment. The result of performance metrics in terms of accuracy attained 90% of SVM and 81.67% of KNN algorithm.

2.1 Empirical Risk Minimization (ERM) Technique and Function

Empirical Risk Minimization (ERM) is a theory in statistical learning that defines a family of learning algorithms and is used to give theoretical bounds on the performance of learning algorithms. It is a natural choice for a learning algorithm that helps to determine a good classification and regression learning function from a bad one (Barnabas, 2012); and it is a common and useful technique with which good approximation of globally optimal classifier can be obtained to give good statistical classification result. ERM is mostly used in determining the loss or risk function in supervised learning problems, and the major interest is to minimize the risk of choosing a hypothesis of a learning algorithm (Liyang, 2016).

The ERM can be computed when the distribution $p(x,y)$ is known to the learning algorithm, and by averaging the loss function on the training set. Considering the situation in which the hypothesis h^* among a fixed class of function $\mathcal{H}$ for which the risk $R(h)$ is minimal. The risk in this hypothesis is to be minimized using the equations 1 to 3 as defined by Vapnik (2000):

$$h^* = \arg min_{h \epsilon H} R(h) \quad \text{(Equation 1)}$$

In order to minimize the risk, let X and Y be the learning function: $h: X \rightarrow Y$

Training set = $(x_1, y_1), \ldots (x_m, y_m)$ where $x_i \epsilon X$ is an input and $y_i \epsilon Y$ is the corresponding response (output) to give $h(x_i)$. Assuming there is a probability distribution $P(x, y)$ over x and y, and the training set consist of m instances $(x_1, y_1), \ldots (x_m, y_m)$ drawn independently and identically distributed (i.i.d) from distribution $P(x, y)$. This assumption allows the model of uncertainty in predictions. The loss function $L(\hat{y}, y)$ is required to measure the difference between the predicting $\hat{y}$ of a hypothesis and the expected or true outcome y (Ji, Jiang, Wang, Xiong & Ohno-Machado, 2014).

The risk associated with the hypothesis $h(x)$ is the expectation of the loss function:

$$R(h) = \mathrm{E}[L(h(x), y)] = \int L(h(x), y) dP(X, Y) \quad \text{(Equation 2)}$$

In this case, the learning algorithm chosen for prediction finds the hypothesis h^* among a fixed class of function $\mathbb{H}$ for which the risk $R(h)$ is minimal.

Empirical Risk Minimization Function

The ERM function is computed when the distribution $p(x,y)$ is known to the learning algorithm, and by averaging the loss function on the training set. It is an approximation that replaces $R(h)$. The empirical risk is introduced as:

$$R_{emp}(h) = \frac{1}{m} \sum_{i=1}^{m} L(\mathrm{h}(x_i), y_i) \quad \text{(Equation 3)}$$

Hence, the principles' interest is to choose a hypothesis $\hat{h}$ that minimizes the empirical risk

The ERM function is important in evaluating the performance of the function $R(h)$ by using non-negative Real valued loss function $L(\hat{y}, y)$, which measures how different the prediction $\hat{y}$ is from the true outcome y. ERM can also be used to compute M-estimators (Chaudhuri, Sarwate & Sinha, 2013) which is obtained as the minima of sums of functions of the data. A regularization

term $R(\cdot)$ on R_{emp} can be used to prevent overfitting to give regularized ERM. The regularization term is seen as stabilizer of learning algorithm and it explains the phenomenon that changing a data point in the training set does not affect the performance of output classifier too much. This indicates how to control the trade-off between empirical risk and the difference between the true and empirical risk. Lagrange duality indicates that when we want to find linear classifier *f* that minimizes ERM with bounded norm $\| f \| \leq C$ for some constant *C*, we can find *f by* minimizing the regularized ERM for a suitable choice of Lagrange coefficient λ (Mahdavi, et al., 2014; Poline, et al., 2012).

2.2 Chronic Myeloid Leukemia

Chronic Myeloid Leukemia (CML) is a type of leukemia characterized by the increased and unregulated growth of predominantly myeloid cells in the bone marrow and the accumulation of these cells in the blood (Besa, et al., 2013). It is a cancer of the white blood cells characterized by expansion of proliferating myeloid cell pool especially in the bone marrow, spleen and peripheral blood. The risk of getting CML increases with age as it occurs in the Caucasians from the median age of 65 to 75 years (Eric, et al., 2014) and in the Africans from the median age of 36 years (Range, 13-75) Based on the differences in the median age of occurrence, the Nigerian patients have their prognosis at an early age when compared with the Caucasians (Oyekunle et al., 2012). Chronic Myeloid Leukemia is a disease with three phases i.e. the Chronic-Phase (CP), Accelerated-phase (AP), and Blastic transformation Phase (BP) but emphatically, the interest of this study is the chronic phase of CML because approximately 90% of patients are diagnosed in this phase (Hasford, et al., 2011). In predicting chronic myeloid leukemia-chronic phase (CML-CP), some scoring systems are used for risk stratification but mainly three (3) of them are widely accepted to stratify the patient into low, intermediate or high risk groups namely: Sokal, Hasford and EUTOS (European Treatment and Outcome Study).

3.0 Methodology

Hold-out (66%) and 10-fold cross-validation evaluation techniques were used to evaluate the performance of the four classification algorithms (supervised learning) to choose the best two algorithms. Hold-out was used on all the data points that are i.i.d (independently and identically distributed) because it is computationally easier to program and cross-validation was used to generate training and validation sets for the hyper-parameter tuning.

Evaluation of Classification Algorithm Performance

The model was built and evaluated in WEKA 3.8.0 using the hold-out (66% training data) and 10-fold cross-validation evaluation methods on BayesNet, Multilayered Perceptron, PART and Logistic Regression algorithms to train and test the classifiers. After the training process, the values of correctly classified instances, time taken to learn, kappa statistics, sensitivity and specificity were computed to compare their performances in which two algorithms with leading performances were chosen. The value of the Correctly Classified Instances (CCI) was determined by the percentage of correctness of outcome among the test sets, and that compares how close a new test value is to a value predicted by the rules. CCI was determined by dividing the sum of True Positive (TP) and True Negative (TN) values by the sum of TP, TN, False

Positive (FP) and False Negative (FN) values multiplied by 100% as defined by Frank and Witten (2011).

3.1 Empirical Risk Minimization Computation

While determining the empirical risk minimization function, the learning hypothesis h: $X \rightarrow R$ was set with the training set = (x_1, r_1), … (x_m, r_m) where $x_i \in X$ is the input, and $r_i \in \mathcal{R}$ is the output to give $h(x_i)$, while the probability distribution $P(x, r)$ over x and r is independently and identically distributed (i.i.d). The loss function $L(\hat{r}, r)$ was determined to measure the difference between the true or expected output r and the predicted output $\hat{r}$ of the hypothesis using: $R(h)$ = E[$L(h(x), r)$] = $\int L(h(x), r)dP(x, r)$ to find the hypothesis h^* among a fixed class of function $\mathbb{H}$ for which the risk $R(h)$ is minimal: $h^* = \arg min_{h \epsilon H} R(h)$; and empirical risk minimization was computed using $R_{emp}(h) = \frac{1}{m}\sum_{i=1}^{m} L(\mathrm{h}(x_i), r_i)$ on Logistic regression and PART algorithms, whereby Logistic regression which had the lowest and non-negative loss function value was selected as the optimal one.

Problem Definition

In order to obtain the desired results, some assumptions on the class of the dataset were made. Given a CML dataset $\mathcal{D}$ of n individuals, where each observation d_i lies in this domain, the classifier that had the minimum loss function (empirical risk) was computed by averaging loss function on the training sets. From this point, it was assumed that the CML dataset had been processed, and the learning data has the specification of two spaces: $X \equiv$ Input space and $R \equiv$ Output space.

Training Set of the dataset $\mathcal{D}$

$\mathcal{D}$ = {Input set; Output set} = {Basophil count, Spleen size; Risk score} = {B, S; R}

Input Set

$\mathcal{X} = \{\mathcal{B}, \mathcal{S}\} = \{x_1, x_2\}$

where $x_1 = \mathcal{B} = \{b_1, b_2, \ldots, b_n\}$

$x_2 = \mathcal{S} = \{s_1, s_2, \ldots, s_n\}$

Test Set: Output Set

$\mathcal{R} = \{r_1, r_2, \ldots, r_n\}$

There are two spaces of objects $\mathcal{X}$ and $\mathcal{R}$ which learn a function h: $\mathcal{X} \rightarrow \mathcal{R}$ in which:

Output $r \in \mathcal{R}$ given $x \in \mathcal{X}$

There is the training set (x_i, r_i), … (x_n, r_n), where $x_i \in \mathcal{X}$ is an input and $r_i \in \mathcal{R}$ is the corresponding output were the hypothesis h (x_i) was derived from. It was assumed that there is a joint probability distribution $P(x, r)$ over x and r, and the training set consist of m instances (x_i, r_i), … (x_m, r_m), drawn independently and identically distributed (i.i.d) from distribution $P(x, r)$.

3.2 Loss Function

The concept of loss function L was introduced and it was assumed that there are non-negative real-valued Loss function $L(\hat{r}, r)$ which measures how the expected or true outcome r is different from predicted $\hat{r}$ of a hypothesis. The risk associated with the hypothesis $h(x)$ is the expectation of the Loss function L using the equations 1 to 6 as defined by Vapnik (2000):

$$R(h) = \mathrm{E}[L(h(x), r)] = \int L(h(x), r) dP(x, r) \quad \text{(Equation 1)}$$

In order to determine the risk of the hypothesis h in Equation 2, the integration of the product of the loss function, input x and the output r on the data distribution was done. However, the ultimate goal was to find a hypothesis h^* among a fixed class of function $\mathcal{H}$ for which the risk $R(h)$ is minimal:

$$h^* = \arg min_{h \epsilon H} R(h) \quad \text{(Equation 2)}$$

Therefore Equation 2 gives the minimum hypothesis from the training set that has the minimum loss function.

3.3 Expected Risk

The expected risk was used to measure the expected performance of the algorithm with respect to L1-regularized logistic regression solver. With a given function f, loss function L, and a probability distribution $P(x, r)$, the expected risk or true risk of f was given to minimize the loss of test data.

$$R_{L,P}(f) = \int_{x*r} L\big(x, r, f(x)\big) dP(x, r), \; \mathrm{d}P(x, r) = P(x, r)\, \mathrm{d}r\, \mathrm{d}x$$

$$= \mathrm{E}[\mathrm{L}\big(\mathrm{X}, \mathcal{R}, \mathrm{f}(\mathrm{x})\big)] \quad \text{(Equation 3)}$$

where $L\big(x, r, f(x)\big)$: Loss function

$P(x, r)$: Distribution of the data

The expected risk of the loss function and distribution of the data was computed by finding the integration of the product of input x and output r, in which the derivative was done to give $dr\, dx$ i.e. the output (risk group) as shown in equation 3.

3.4 Empirical Risk Minimization Function

The ERM was used to choose the hypothesis (rule) that minimizes the empirical risk $\hat{h} = \arg min_{h \epsilon H} R_{emp}(h)$. In equation 4, the empirical risk of the hypothesis is averaged by $\frac{1}{m}$ where m is the number of inputs considered in the training set.

$$R_{emp}(h) = \frac{1}{m} \sum_{i=1}^{m} L(\mathrm{h}(x_i), r_i) \quad \text{(Equation 4)}$$

Where n($\mathcal{m}$) = {$\mathcal{B}$, $\mathcal{S}$} = 2

$\therefore \mathcal{m}$ = 2

$R_{emp}(h) = \frac{1}{2}\sum_{i=1}^{2} L(\mathrm{h}(x_i), \mathcal{r}_i)$ _____(Equation 5)

Therefore, equation 5 gives the empirical risk function on the hypothesis. However, the interest was to choose a hypothesis $\hat{h}$ that minimizes the empirical risk as shown in equation 6.

$\hat{h} = \arg min_{h \epsilon H} R_{emp}(h)$ _____(Equation 6)

In equation 6, the mathematical operator 'argmin' returns a value minimizing the argument function, hence, the learning algorithm defined by the ERM principle consists in solving the above problem in equation 6. The ERM was tested on the Logistic regression and PART algorithms, and Logistic regression which had the minimum loss function (risk) was identified as the accurate algorithm for grouping the dataset.

3.5 Dataset Description

Chronic Myeloid Leukemia data obtained from Obafemi Awolowo University Teaching Hospitals Complex (OAUTHC) was used and it contained 1640 patients' data from 2003 to 2017. The input variables (Basophil (x_1) and Spleen size (x_2)) were used as the training inputs to generate the risk score (r) as the output, which informed the grouping of the patients to either low risk or high risk groups. The dataset was converted into Comma Separated Values (.csv) format and a data repository that interfaces with Waikato Environment for Knowledge Analysis (WEKA) was created for the data.

4.0 Result

The four classification algorithms namely BayesNet, Multilayered perceptron, PART and Logistic Regression were built in WEKA 3.8.0 and evaluated with the holdout (66%) and 10-fold cross-validation techniques for training and testing on the CML dataset. The performance of the four (4) algorithms were measured based on five (5) existing performance benchmarks: correctly classified instances, time to learn, kappa statistics, sensitivity and specificity. Figures 4.1 to 4.8 depict the screen shots of the explorer view of the algorithms implemented in WEKA.

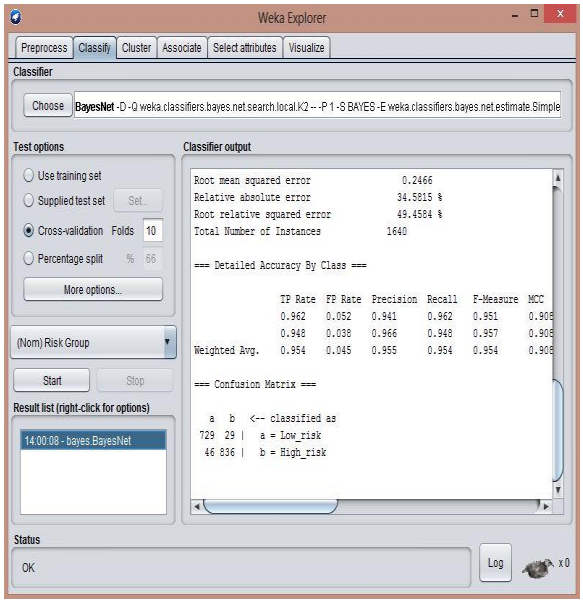

Figure 4.1: Screenshot of BayesNet in Cross validation

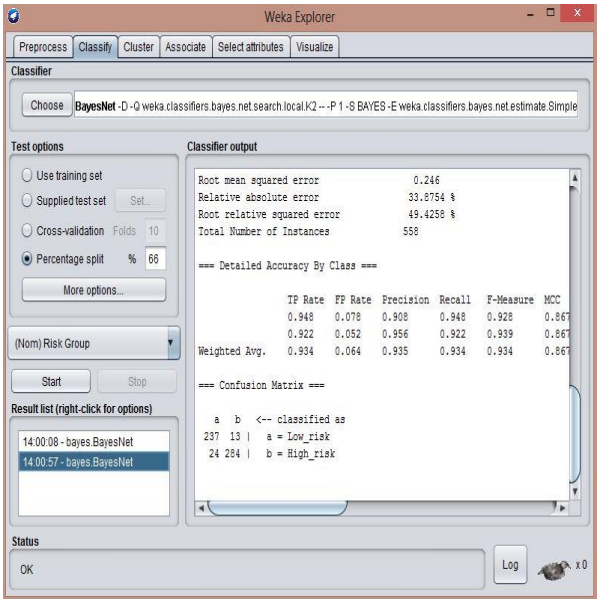

Figure 4.2: Screenshot of BayesNet in Holdout method

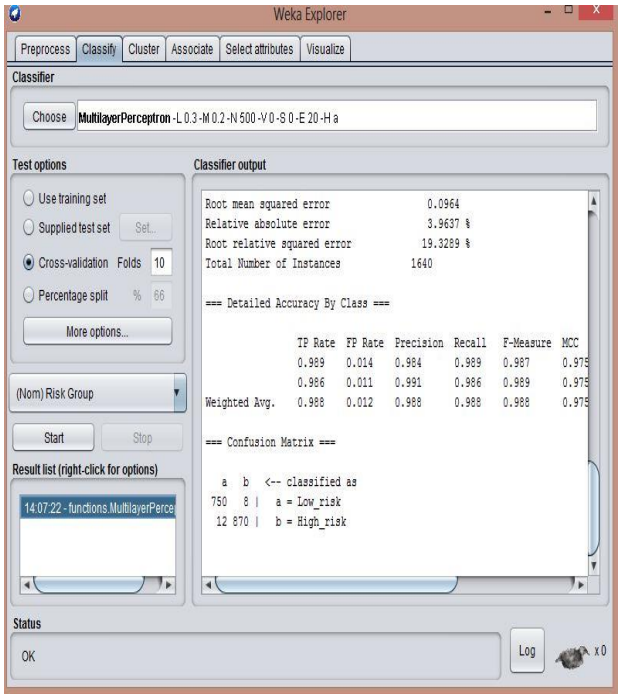

Figure 4.3: Screenshot of Multilayer perceptron in Cross validation

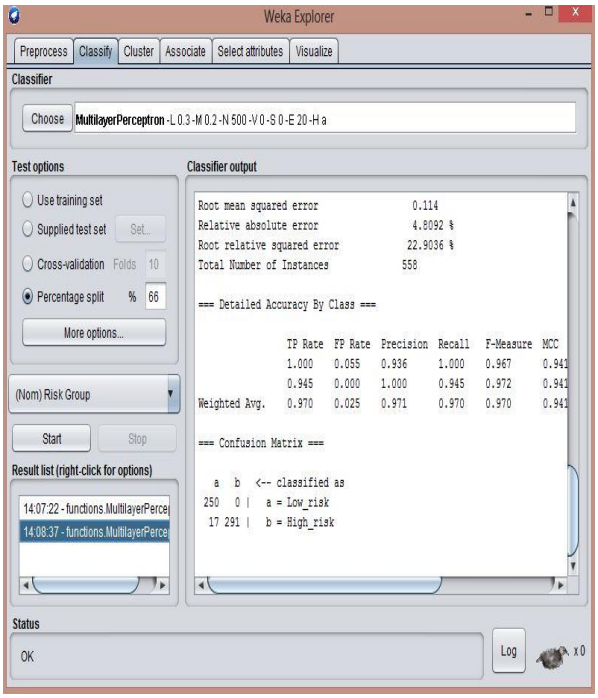

Figure 4.4: Screenshot of Multilayer perceptron in Holdout method

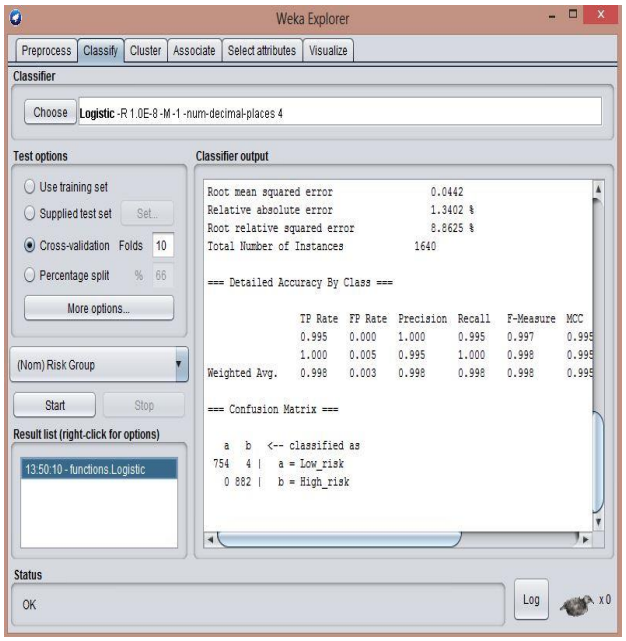

Figure 4.5: Screenshot of Logistic regression regression in Cross validation

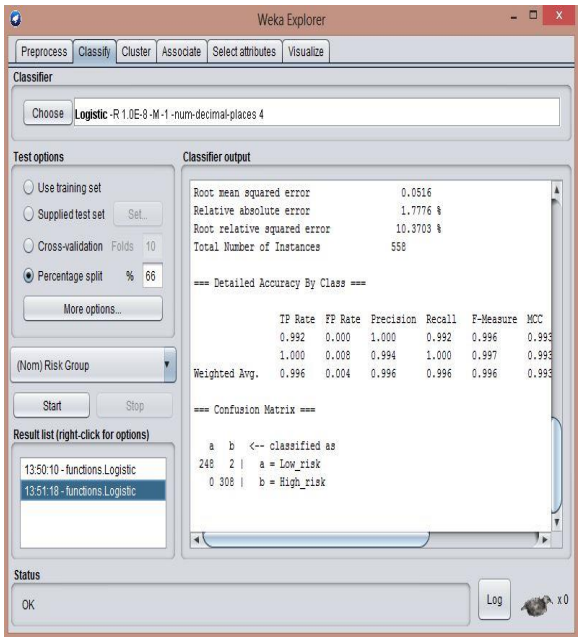

Figure 4.6: Screenshot of Logistic regression in Holdout method

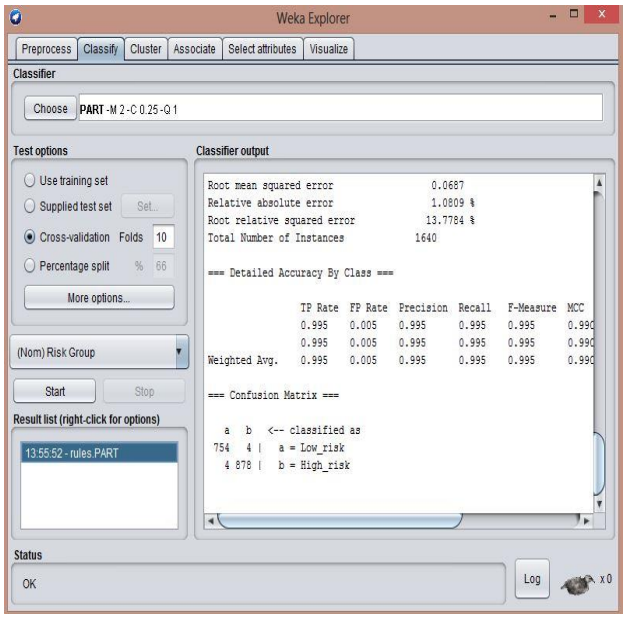

Figure 4.7: Screenshot of PART in Cross validation

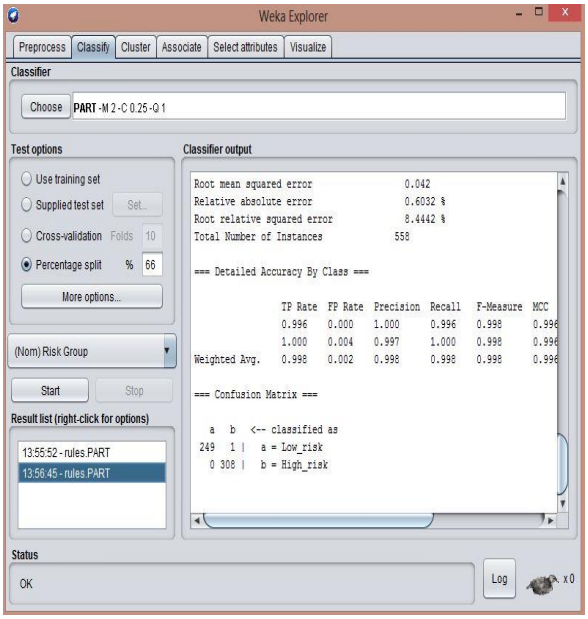

Figure 4.8: Screenshot of PART in Holdout method

4.1 Summary of Algorithm Performance Compared

The performance of the four classification algorithms (BayesNet, Multilayered perceptron, PART and Logistic Regression) were compared using correctly classified instance, time to learn, kappa statistics, sensitivity and specificity metrics. Logistic regression and PART algorithm had correctly classified instance values of 99.82% and 99.64% in holdout, and 99.76% and 99.58%

in cross-validation respectively, which outperformed other algorithms. Considering the time taken in learning in relation to the performance of the algorithms, Multilayered perceptron consumed much time and computation resources, but it can be ascertained that Logistic regression and PART algorithms took shorter time and outperformed other algorithms relative to the accuracy level in this study with 0.02 and 0.09seconds in both holdout and 10-fold cross validation methods. In kappa statistics, PART and Logistic regression had the greatest result in both holdout and 10-fold cross validation methods. In holdout, PART had 99.64% and Logistic Regression had 99.57% while in 10-fold cross validation method PART had 99.82% and Logistic Regression had 99.71%. In sensitivity, Multilayered Perceptron and PART algorithm had the greatest value of 99.99% and 99.60% holdout method while PART and Logistic Regression have the same value of 99.47% in 10-fold cross validation. The specificity of the algorithms showed that PART and Logistic Regression had the greatest value of 99.99% each in holdout method, while in 10-fold cross validation method the two algorithms had 99.55% and 99.98% respectively. Therefore, it was deduced that Logistic regression and PART algorithms were the two good classifiers for stratifying patients' risk group as against other algorithms used in this study. Table 4.1 presents the summary of the performance of the models based on the benchmarks.

Table 4.1: Summary of the model performances in holdout and 10-fold cross validation method

	Hold-Out (66% train, remainder test)						**10-Cross Validation**				
S/N	**Classifier**	**CCI (%)**	**T (s)**	**KS (%)**	**S_e (%)**	**S_p (%)**	**CCI (%)**	**T (s)**	**KS (%)**	**S_e (%)**	**S_p (%)**
1	BayesNet	93.37	0.13	86.65	94.80	92.20	95.43	0.15	90.82	96.17	94.78
2	Multilayered perceptron	96.95	1.83	93.88	99.99	94.48	98.78	1.18	97.55	98.94	98.64
3	PART	99.64	0.09	99.64	99.60	99.99	99.58	0.09	99.82	99.47	99.55
4	Logistic Regression	99.82	0.02	99.57	99.20	99.99	99.76	0.02	99.71	99.47	99.98

Key: CCI = Correctly Classified Instances, T = Time to build, KS = Kappa Statistics, S_e = Sensitivity, S_p = Specificity

Thus, from the performance evaluation carried out on the algorithms, Logistic regression and PART algorithms were discovered to have the best performance based on their ability to correctly classify the chronic myeloid leukemia patient dataset within the lowest possible time of 0.02 and 0.09 seconds.

4.2 Determination of Minimum Loss Function of Algorithms

The decision of choosing the minimum loss function (i.e. the empirical risk) of Logistic regression and PART algorithms was defined by finding the difference between the predicted output and true output of the algorithms for high and low risk groups in the holdout and 10-fold cross validation methods as discussed in sections 4.2.1 and 4.2.2

4.2.1 Loss Function for Logistic Regression Algorithm

In determining the loss function for logistic regression, the delta Δ (i.e. differences) between the values of the true output and the predicted output were computed for both high and low risk patients. The values in the numerator and the denominator are derived from the confusion matrix in logistic regression output. In holdout method the numerators 259 is the total number of patients classified as low risk and 308 patients are classified as high risk, while the denominator 558 is the total number of instances. The predicted output $\hat{r}$ for low risk and high risk patients were determined by finding the percentage of the confusion matrix value divided by the number of instances in both holdout (66% split) and cross-validation methods as shown below. The true output r is 46.20% for low risk patients and 53.80% for high risk patients.

In Holdout Method

Predicted output $\hat{r}$ for low risk = $\frac{259}{558}$ x 100%

= 46.42%

and

Predicted output $\hat{r}$ for high risk = $\frac{308}{558}$ x 100%

= 55.20%

Loss function *L* in holdout method = $\Delta\ (\hat{r} - r)$

For low risk $\boldsymbol{L} = \Delta\ (\hat{r} - r)$ = (46.42 – 46.20)%

= 0.22%

For high risk $\boldsymbol{L} = \Delta\ (\hat{r} - r)$ = (55.20 – 53.80)%

= 1.40%

In 10-fold Cross-validation Method

In 10-fold Cross-validation method, determining the loss function for logistic regression, the delta Δ (i.e. differences) between the values of the true output and the predicted output were computed for both high and low risk patients. The values in the numerator and the denominator are derived from the confusion matrix in logistic regression output. In this method the numerators 754 is the total number of patients classified as low risk and 882 patients are classified as high risk, while the denominator 1640 is the total number of instances. The predicted output $\hat{r}$ for low risk and high risk patients were determined by finding the percentage of the confusion matrix value divided by the number of instances in both holdout (66% split) and cross-validation methods as shown below. The true output r is 46.20% for low risk patients and 53.80% for high risk patients.

Predicted output $\hat{r}$ for low risk = $\frac{754}{1640}$ x 100%

= 45.98%

and

Predicted output $\hat{r}$ for high risk = $\frac{882}{1640}$ x 100%

= 53.78%

Loss function *L* in 10-fold cross-validation method = $\Delta(\hat{r} - r)$

For low risk $\boldsymbol{L} = \Delta(\hat{r} - r)$ = (45.98 – 46.20)%

= -0.22%

For high risk $\boldsymbol{L} = \Delta(\hat{r} - r)$ = (53.78 – 53.80)%

= -0.02%

Hence, the findings from the loss function in holdout method gave the loss function of 0.22% for stratifying patient into low risk and 1.40% for stratifying patient into high risk. In 10-fold cross-validation method, the loss function gave the empirical risk of -0.22% for stratifying patient into low risk and -0.02% for stratifying patient into high risk.

4.2.2 Loss Function for PART Algorithm

In determining the loss function for PART algorithm, the delta Δ (i.e. differences) between the values of the true output and the predicted output were computed for both high and low risk patients. The values in the numerator and the denominator are derived from the confusion matrix in PART output. In holdout method the numerators 249 is the total number of patients classified as low risk and 308 patients are classified as high risk, while the denominator 558 is the total number of instances. The predicted output $\hat{r}$ for low risk and high risk patients were determined by finding the percentage of the confusion matrix value divided by the number of instances in both holdout (66% split) and cross-validation methods as shown below. The true output r is 46.20% for low risk patients and 53.80% for high risk patients.

In Holdout Method

Predicted output $\hat{r}$ for low risk = $\frac{249}{558}$ x 100%

= 44.62%

and

Predicted output $\hat{r}$ for high risk = $\frac{308}{558}$ x 100%

= 55.20%

Loss function *L* in holdout method = $\Delta(\hat{r} - r)$

For low risk $\boldsymbol{L} = \Delta(\hat{r} - r)$ = (44.62 – 46.20)%

= -1.58%

For high risk $\boldsymbol{L} = \Delta\,(\hat{r} - r) = (55.20 - 53.80)\%$

= 1.40%

In 10-fold Cross-validation Method

In 10-fold Cross-validation method, determining the loss function for logistic regression, the delta Δ (i.e. differences) between the values of the true output and the predicted output were computed for both high and low risk patients. The values in the numerator and the denominator are derived from the confusion matrix in logistic regression output. In this method the numerators 754 is the total number of patients classified as low risk and 878 patients are classified as high risk, while the denominator 1640 is the total number of instances. The predicted output $\hat{r}$ for low risk and high risk patients were determined by finding the percentage of the confusion matrix value divided by the number of instances in both holdout (66% split) and cross-validation methods as shown below. The true output r is 46.20% for low risk patients and 53.80% for high risk patients.

Predicted output $\hat{r}$ for low risk = $\frac{754}{1640}$ x 100%

= 45.98%

and

Predicted output $\hat{r}$ for high risk = $\frac{878}{1640}$ x 100%

= 53.54%

Loss function *L* in cross-validation method = $\Delta\,(\hat{r} - r)$

For low risk, $\boldsymbol{L} = \Delta\,(\hat{r} - r) = (45.98 - 46.20)\%$

= -0.22%

For high risk, $\boldsymbol{L} = \Delta\,(\hat{r} - r) = (53.54 - 53.80)\%$

= -0.26%

The findings from the loss function in holdout method gave the empirical risk of -1.58% for stratifying patient into low risk and 1.40% for stratifying patient into high risk; while in cross-validation method, the loss function gave the empirical risk of -0.22% for stratifying patient into low risk and -0.26% for stratifying patient into high risk.

Interpretation

From the findings discussed in sections 4.2.1 and 4.2.2, the result showed that logistic regression had a minimal loss function with non-negative values in stratifying high and low risk patient in holdout method with values of 0.22% and 1.40% and respectively. In cross-validation method both logistic regression and PART algorithms had negative real valued loss function. In essence,

logistic regression is a good classifier with which the risk of the hypothesis was minimized, and that informs the decision of using Logistic regression algorithm in the model to stratify the dataset. Empirically, the loss functions of logistic regression and PART algorithm were compared, and the result showed that logistic regression in holdout method offered clear advantage in the presence of outliers.

5.0 Conclusion

Minimization of the empirical risk by finding the loss functions of logistic regression algorithm has played a big role in producing optimum and faster results for accurate predictions. The findings of this research in relation to other studies like Kamalika et al. (2011) showed how empirical risk minimization concept was used for privacy-preserving approximations of Logistic regression and Support Vector Machine classifiers to predict whether a network connection was a denial-of-service attack or not. Sensitivity method and objective perturbation algorithms were used by tuning algorithm and Michael and S´ebastien (2015) and Yuchen (2016) agreed with this assertion. The findings of this research agreed with other studies that employed empirical risk minimization technique to determine the loss function of classifiers before choosing and employing an algorithm for stratifying or predicting a dataset from any problem domain. The use of ERM had helped to determine the loss function of the two algorithms (Logistic regression and PART), that had great performance using some metrics (correctly classified instances, time to build, kappa statistics, sensitivity and specificity). Hence, logistic regression had the lowest non-negative loss function in holdout method, and it enhanced the decision of using logistic regression for CML data stratification into their risk group.

Therefore, determining the loss function (empirical risk) of machine learning algorithm is significant when building predictive or prognostic tools. This is important since it would aid the decision of choosing an algorithm for the dataset from the problem domain.

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