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A Comparison between Linear and Non-Linear Machine Learning Classifiers

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Abstract

Data mining can be defined as searching for similarities and patterns in a huge amount of data in a certain knowledge field and to arrange them in classes and clusters. Many classification algorithms and clustering techniques are implemented to suit different types of data such as numeric, real, and nominal data types. Each classification and clustering algorithms are implemented in a certain approach. Some are linear and some are non-linear algorithms. In this paper, a comparison between some linear and non-linear classification algorithms has been conducted to study the performance of these classifiers with three different types of data set. The first data set is the collected MRI images of the brain tumor with type real, the second is diabetes data set with type numeric and the third is the breast cancer data set with type nominal. The linear classifiers chosen for this study are Lazy and Bayesian classifiers. While for the non-linear both Multilayer Perceptron (MLP) and Linear Vector Quantization (LVQ) are chosen. The results showed that the performance of the nonlinear classifiers was better than the linear classifiers with all data sets. In particular the accuracy rate of both MLP and LVQ with the real brain tumor data set is 91%, 83% respectively. On the other side, the linear classifiers showed comparable result with all datasets.

Keywords: data mining, classification, clustering, pattern, linear and nonlinear classifiers.

Introduction

Brain cancers are one of the fetal human brain diseases. Testing the human brain can be performed by using a special medical technique called Magnetic Resonance Imaging (MRI) as shown in Fig.(1). Using MRI images enables the specialist to decide whether the brain is normal or abnormal. The MRI scans the brain and produces up to 300 images for the brain in different plane directions such as axial plane (up to down), sagittal plane (from right to left and in opposite).these images are gray level and in three dimensions. To reduce the work pressure and improve the specialist performance these images can be segmented and classified using different computer techniques and algorithms.

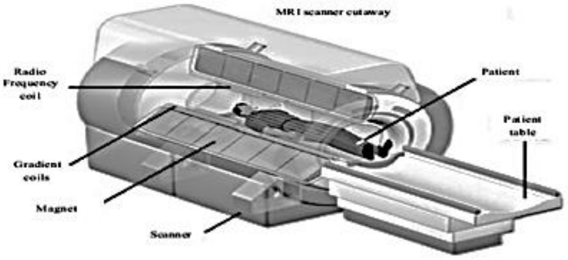


Fig.(1): MRI scanner [1].

These algorithms are used to classify the input data into two or more different classes and clusters. The input data can be divided into training and testing data sets in a certain percentage or number of folds. This technique is called data mining, which aims to classify the input data sets by seeking patterns and likelihoods. Neural networks, Logistic, SPegasos, SMO, Bayes Net, rules, lazy, tree and naïve are all classifiers which can be used with different types of data sets such as text files, customer profile, liver cancer, car plate, breast cancer, brain cancer, fabric texture and more.

This research aims to compare between the performances of all these classifiers to classify three data sets. The first data set is brain MRI images which is collected by the research for the research purposes. The second and the third are diabetes and breast cancer. These two data set are collected from UCI Machine Learning Repository.

Related Researches

This section presents a summarized discussion of some researches have been done to compare between the performances of different classification techniques.

In [2], Bayesian and Lazy classifiers algorithms were used to classify the files which are stored in the computer hard disk. In this research the researchers found that the performance of the Lazy classifier was more efficient than the Bayesian classifier.

The researchers in [3] study, used Linear classifiers (standard Naive Bayes, Linear logistic regression and multinomial logistic regression classifiers), Support Vector Machine (SVM) classifiers and Decision trees to automatically detect Twitter messages (tweets) that are likely to report cases of possible influenza like illnesses (ILI). The result of this research showed that the performance of SVM classifiers was better than Naïve byes classifiers.

The study [4] used a state-of-the-art machine learning based approach called averaged one-dependence estimators with subsumption resolution to solve the problem of predicting, from DNA microarray gene expression data, whether a particular cancer will recur within a specific timeframe (usually 5 years after the first treatment) or not. The researchers applied leave-one-out cross-validations (LOOCV) to classify the gens data set for three types of cancers breast cancer recurrence, Prostate cancer recurrence and CNS cancer recurrence. The study approach showed an average accuracy of 98.9% in predicting cancer recurrence over the three datasets.

The [5] research paper studied the performance of number classification algorithms like C4.5, CART, Random Forest, LMT, ADT, Naïve Bayesian and Bayesian logistic Regression with various cancer datasets (Leukemia and colon datasets). The Bayesian logistic Regression classifier outperformed the other classifiers with both datasets.

The researchers in study [6], introduced a new method to discover many diversified and significant rules from high dimensional profiling data. According to the researchers the new method showed the essential role of the low-ranked features to improve the accuracy of the classifier over the top-ranked features. The results displayed highly competitive accuracy compared to the best performance of other kinds of classification models.

In [7], The randomized Steiner tree based method is proposed to combine microarray gene expression profiles and protein-protein interaction (PPI) network for biomarker discovery for breast cancer metastasis. The study have used three breast cancer microarray datasets. The results of this approach showed better identifying of substantial numbers of well-known biomarker genes for breast cancer metastasis.

In [8] study proposed functional trees (FTs), to achieve an Estrogen receptor (ER) prognosis of the breast cancer *via* an objective decision model. The used data set was 27 biopsy images. Image processing methods were applied on these images to extract features (including statistical, wavelet, co-occurrence matrix, and Laws' texture features). From the results, the researchers demonstrated that the FT could be used as a tool to support the decision of doctors by indicating consistent outputs.

In [9] study, the researchers have used the rough set approach to generate the classification rules of the breast cancer data. The study showed that the approach of rough sets appears to be a useful tool and a valuable aid for building expert systems.

The [10] study proposed the use of Bayesian approach to gene selection and classification using the logistic regression model. Gibbs sampling and Markov chain Monte Carlo (MCMC) methods were used to discover important genes of microarray based cancer for several data sets. The results of this study showed that the method can successfully detect important genes consistent with the known biological findings in addition to high classification accuracy.

Martials and Methods

The main brain MRI data set is collected by the researcher. Different image segmentation techniques are applied to extract the images features to be used later for classification. Image segmentation includes image enhancement, filtering, applying morphological operation and Gray Level Concurrence matrix (GLCM) for features extraction [1]. The classification techniques are demonstrated in the next sections.

Classification Techniques

In this paper, different machine learning techniques are used to classify brain MRI images. Some of these classifiers are linear and some are not linear. This section demonstrates a summarized discussion about each classification technique used in this research.

Bayesian Classifier

Bayesian networks are a reliable and well known probabilistic representation. Bayesian algorithms work by predicting the class biased on the probability of belonging to that class. A Bayesian network is a graphical model for probability relationships among a set of variables features [11].

This Bayesian Network contains two modules. First model is Directed Acyclic Graph (DAG). In this model the graph nodes are called the random variables and the edges between the nodes or random variables represents the probabilistic dependencies among the corresponding random variables [11].

Bayes Net

Bayes Net learns Bayesian networks made in nominal attributes and no missing values. The graphical representation (G) of Bays Net is as follow:

Given a finite set X={X1…Xn} of discrete random variables where each variable Xi may take values from a finite set represented by Val (Xi).

Each node is annotated with a Conditional Probability Distribution (CPD) that represents P (Xi | Pa (Xi)) where Pa (Xi) denotes the parents of Xi in G. The pair (G, CPD) encodes the joint distribution P(X1…Xn). A unique joint probability distribution over X from G is factorized as eq(1):- S. Vijayarani [2].

$$\mathbf{P(X_1 \ldots X_n) = \Pi_i (P\ (X_i \mid Pa\ (X_i)))} \quad \ldots\ldots. (1)$$

Naïve Bayes

Conditional probabilities is the base of Naive Bayes (NB) algorithm. It uses a formula to calculate the probability by counting the occurrence of values and combinations of values in the data. Bayes' Theorem concludes the probability of an event occurring by comparing it with a given probability of another event that occurred earlier [2].

Likelihood Class Prior Probability

$$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)}$$

Posterior Probability Predictor Prior Probability

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where:-

- P(c|x) is the posterior probability of class (target) given predictor (attribute).
- P(c) is the prior probability of class.
- P(x|c) is the likelihood which is the probability of predictor given class.
- P(x) is the prior probability of predictor.

Lazy Classifier

Lazy learners store the training instances until a query is sent to the system. The system generalize the training data pre receiving quires. Lazy learning has some advantages and disadvantages. The most important advantage is that the target function is locally approximated same as in K-nearest neighbor algorithm. This will enable the lazy system to work in parallel to solve multiple problems and handling any changes in the problem field at the same time [7]. On the other hand the disadvantages with using lazy learning represented by the large storage space requirement to store the whole training dataset.

IBL (Instance Based Learning)

IBL is a basic instance-based learner which finds the training instance closest in Euclidean distance to the given test instance and predicts the same class as this training distance.

IBK (K - Nearest Neighbour)

IBK is a k-nearest-neighbour classifier. A kind of different search algorithms can be used to speed up the task of finding the nearest neighbours. The distance function used with IBK is a parameter of the search method. The classifier keeps a limited number of training instances which is controlled by the window size option [7].

K star (K*)

K* is an instance based classifier, alike to K-Nearest Neighbour (K-NN).

The K* function can be calculated as:

$$K^*(y_i, x) = -\ln P^*(y_i, x) \quad \text{..........................} (3)$$

Where:-

- P*: is the probability of all transformational paths from instance x to y.
- x : represents the new data instances.
- yj,: the class that occurs most frequently amongst the k-nearest data points.
- where j = 1, 2…k.

Entropic distance is then used to retrieve the most similar instances from the data set. By means of entropic distance as a metric has a number of benefits including handling of real valued attributes and missing values [7].

Neural Networks (NN)

Neural networks are widely used due to their important characteristics. These characteristics are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data. The feed-forward network is the most commonly used neural networks for pattern classification tasks. This feed forward family includes multilayer perceptron and Radial-Basis Function (RBF) networks. Another popular network is the Linear Vector Quantization (LVQ), Self-Organizing Map (SOM) [12], which is mainly used for data clustering and feature mapping Nayef et al [1]. Artificial neural networks (ANNs) provide a new suite of nonlinear algorithms for feature extraction (using hidden layers) and classification (e.g. multilayerperceptrons, Learning Vector quantization (LVQ)) [11]. In this paper, the following NN are used:-

Multilayer Perceptron (MLP)

Multilayer perceptron (MLP) neural network is one of the most widely utilized neural networks. The architecture of MLP consists of:-

i- An input layer

ii- An output layer

iii- One or several intermediate layers(s) which contain hidden units.

The back-propagation learning algorithm is one of the most frequently used methods in training MLP neural networks. Because of that MLP is a supervised NN, the error is the difference between the output and desired response and calculated and propagated backwards from the output to the hidden layer(s) and then to the input [13].

Learning Vector Quantization (LVQ)

The LVQ neural network is a supervised version of the Self Organizing Map (SOM) algorithm, introduced by Kohonen in 1986 (Kohonen, 1990a) as a modified Labeled Vector Quantization. The LVQ neural network works by approximating the class distribution using the minimum number of codebook vectors that will reduce errors in the classification phase. The LVQ algorithm learns to classify the input vectors according to predefined classes [14].

An LVQ network comprises three layers of neurons: an input buffer layer, a hidden layer, and an output layer. The structure of an LVQ is shown in Fig.(2).

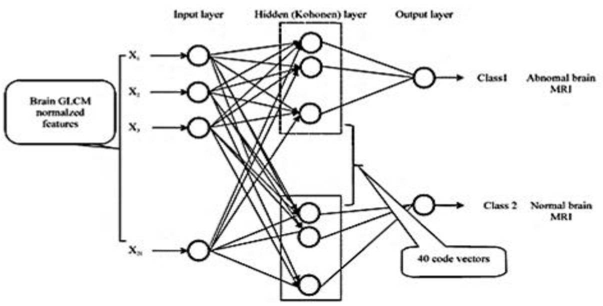


Fig.(2): LVQ structure [14].

The Experiment

In this paper, different types of classifiers are used some are linear classifiers and some are non-linear classifiers. Bayesian classifiers (Bayes Net classifier and Naïve classifier) and lazy classifiers (IBL, IBK, and K*) have been chosen for linear classifiers and Neural networks (MLP and LVQ) for non-linear classifiers.

The Classifiers Setting

With Bayesian and lazy classifiers, Weka application has been used to classify the brain data set. Simulated Annealing as an optimization searching algorithm (list length=5 and 10 runs) and simple Estimator algorithm with 0.5 alpha value have been used with Bayes Net. With IBK classifier the neighbour search algorithm used is the Linear Nearest Neighbour Search algorithm (using 1 nearest neighbor) and Euclidean Distance function. For K* classifier the global blending value is 15 and the missing attributes are treated using average column entropy curves.

According to the MLP and LVQ Neural networks, both are implemented using java Netbeans application. The number of hiding layers of MLP is 3, 0.3 is the learning rate and 500 learning iterations. Same for LVQ NN, 0.3, 2000, 40 for the learning rate, learning Iteration and number of codebook vectors in order.

Results and Discussion

Brain Tumor Data Set

The Brain tumor data set used in this paper consists of 200 with 40 attributes and two classes (52 normal images and 148 abnormal images) brain MRI images. Image processing techniques were applied to enhance and remove noise [1]. Grey Level Concurrence Matrix (GLCM) technique were used to extract the images Haralick texture features [15].

The results of the used classifiers are shown in Table 1 and Fig.(3). The lazy classifiers (IBL, IBK, and K*) in addition to Bayesnet showed higher positive predictive value (Precision) than the Sensitivity (Recall). This means that most of the instances are classified correctly. On the other side the implemented MLP and LVQ classifiers showed the best precision and recall than the lazy and bayesnet classifiers. Naïve classifier showed the least performance among the linear and non-linear classifiers. Among all the classifier Bayes showed the highest Mean Absolute Error (MAE) which is 0.331 as shown in Table (1).

Table (1)
The results of running linear and non- linear classifiers with brain tumor data set.

Classifier	*Precision*	*Recall*	*Accuracy%*	*MAE*
IBL	0.881	0.871	87	0.129
IBK	0.881	0.871	87.14	0.129
K*	0.845	0.829	82.9	0.183
Bayes	0.817	0.757	75.7	0.331
Naïve	0.726	0.757	75.7	0.245
MLP	0.923	0.914	91.4	0.158
LVQ	0.818	0.829	83	0.266

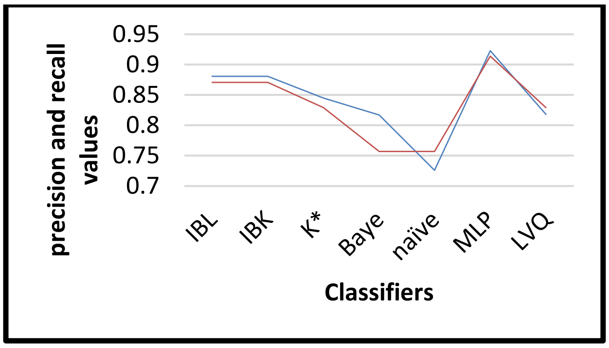


Fig.(3): The relation between precision and recall for each classifier with Brain data set.

The performance of the IBL and IBK is better than the performance of the K*.The results showed no difference between the accuracy rate of IBL (87%) and IBK (87.14%). Unlike K* (82.9%) which showed lower accuracy rate. For the bayesnet (75.7%) and naïve (75.7%) classifiers, both of them showed the same performance and less accuracy rate than the lazy classifiers. The highest accuracy rate gained from MLP (91.4%). The accuracy rate of LVQ classifier is (83%) which is better than K*, Bayesnet and naïve classifiers but less than IBL and IBK. As shown in Fig.(4).

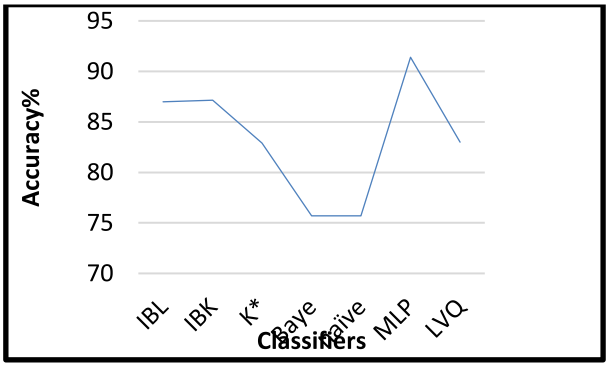


Fig.(4): Accuracy rate of the classifiers with brain data.

Diabetes Data Set

Diabetes data set consists of 768 numeric instances, 9 attributes and two classes (tested positive, tested negative). The source of this data set is UCI Machine Learning Repository. With this data set the performance of the classifiers as follow:

The accuracy rate of IBL, IBK and K* showed no difference in their performance. In which both IBL, IBK gained 72.5 % accuracy rate and 71.38% for K*. On the other hand naïve (79.6%) and bayesnet (78.1%) classifiers performed better with this data set than the brain tumor data set. But both have compatible performance. The performance of MLP (81%) and LVQ (77%) is less than their performance with the brain tumor data set as shown in Table 2 and Fig.(5). From the table it is clear that LVQ classifier collected the highest Mean Absolute Error (MAE) which is 0.3362.

Table (2)
The results of running linear and non- linear classifiers with Diabetes data.

Classifier	*Precision*	*Recall*	*Accuracy %*	*MAE*
IBL	0.727	0.725	72.5	0.275
IBK	0.727	0.725	72.5	0.276
K*	0.703	0.714	71.38	0.31٩
Bayes	0.791	0.796	79.6	0.300
Naïve	0.777	0.781	78.1	0.264
MLP	0.818	0.814	81.4	0.2٨٠
LVQ	0.774	0.773	77.3	0.336

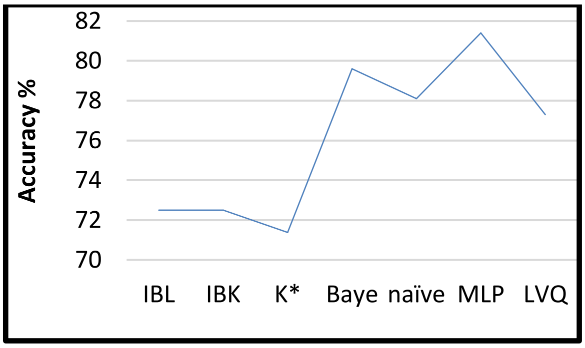


Fig.(5): Shows the performance (accuracy rate) of each classifier with diabetes data.

According to the Precision and the Recall measurements of the classifiers with diabetes data set are comparable in general. MLP also showed better precision and Recall among the classifiers with this data set too as shown in Fig.(6).

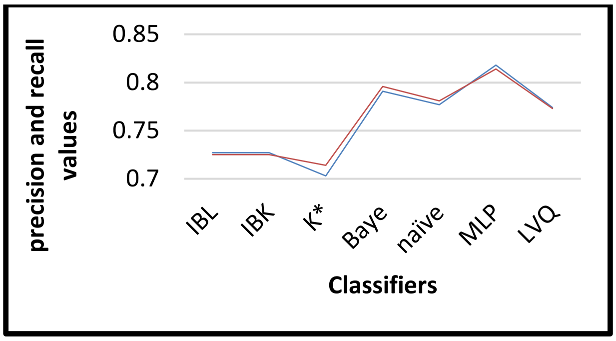


Fig.(6): The relation between precision and recall for each classifier with diabetes data.

Breast Cancer Data Set

The source of this data set is UCI Machine Learning Repository. It consists of 286 nominal instances with 10 attributes and 2 classes (no-recurrence, recurrence).

Table (3)
The results of running linear and non- linear classifiers with breast data.

classifier	*Precision*	*Recall*	*Accuracy%*	*MAE*
IBL	0.607	0.61	61	0.39
IBK	0.721	0.73	73	0.3065
K*	0.75	0.75	75	0.3329
Baye	0.717	0.73	73	0.3412
Naïve	0.721	0.73	73	0.3403
MLP	0.784	0.792	79	0.267
LVQ	0.77	0.782	78	0.3159

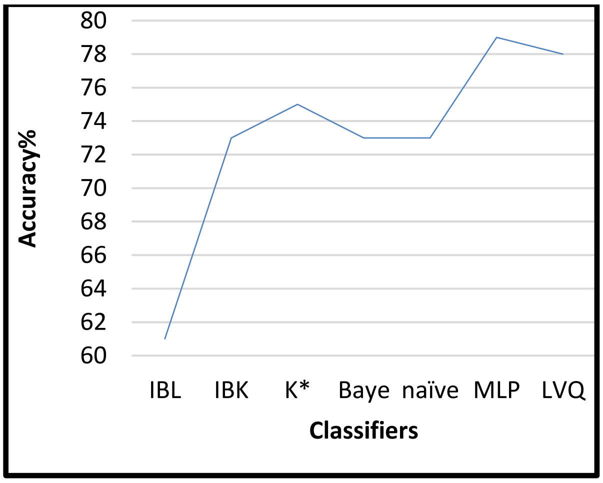


Fig.(7): Accuracy rate of the classifiers with breast data.

From Table (3) and Fig.(7), the least accuracy rate belongs to IBL classifier (61%). The rest of the classifiers are performed almost at the same level. IBK, Bayes and naïve performed equally with accuracy rate 73%. K* (75%) showed a little bit better accuracy rate than its likeness IBI, IBK. For MLP (79%) and

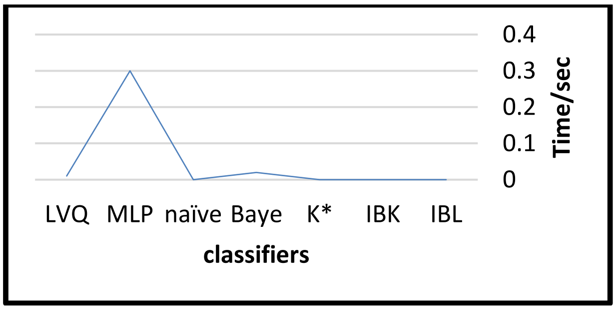
LVQ (78%) the accuracy rates are comparable. Also here MLP outperformed the non-linear classifiers.

The Precision and the recall measurements of the classifiers with the breast data are comparable. Also the MLP showed better precision than the other classifiers as presented in Table (3) and Fig.(8). The MAE of the bayesnets and naïve classifiers is higher than the other classifiers.

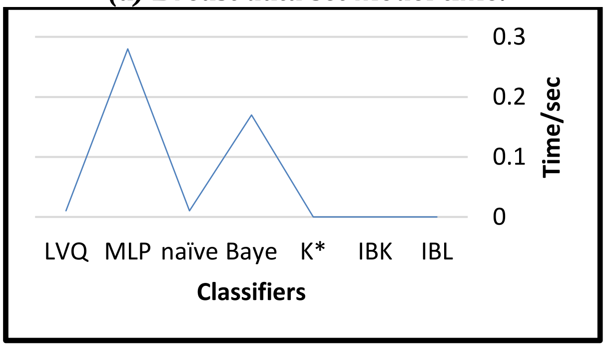
The time requested to build the classification model for each classifier is listed in Table (4).

Table (4)
Building model time.

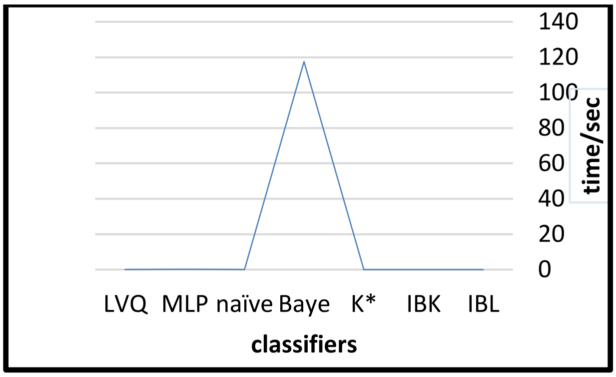
classifiers	*Data sets/seconds*		
	Breast data	*Diabetes data*	*Brain data*
IBL	0	0	0
IBK	0	0	0
K*	0	0	0
Baye	0.02	0.17	117.5
naïve	0	0.01	0.01
MLP	0.33	0.28	0.19
LVQ	0.01	0.01	0.01



(a) Breast data set model time.



(b) Diabetes data set model time.



(c) Brain data set model time.

Fig.(8):(a,b,c) shows the building model time for all classifiers with breast, diabetes and brain datasets.

From both Table (4) and Fig.(9), the time requested to build a model for Lazy and naïve classifiers with the three data sets is almost equal to 0 which is very fast. Bayesnet classifier built the model with the three data sets 0.02, 0.19 and 119 seconds in turn. The difference in the building time due to the data set size, the number of attributes and the classifier structure. Where the number of attributes for the brain tumor is 40 unlike for breast cancer and diabetes which is equal to 10. For the nonlinear classifiers LVQ and MLP, both of them showed no big difference in time with all data sets.

Conclusion

In this paper three data sets where used to camper the performance of some linear and non-linear classifiers. For linear classifiers the LVQ and MLP were used while three linear classifiers from lazy family in addition to Bayesnet and Naïve classifiers. With all data sets the non-linear classifiers (MLP, LVQ) outperformed the performance of the linear classifiers (lazy and Bayesians). The highest accuracy rate (91%) gained by MLP with brain tumor data set then LVQ with 83% accuracy rate. The performance of the other classifiers with all data sets, in general was comparable. On the other side, the precision, recall and the MAE with brain tumor data set for the linear classifiers were clearly better than the linear classifiers.

In addition, the results showed that the performance of the linear and nonlinear classifiers with real data set values is much better than their performance with numeric and nominal data set (except Baye and naïve which showed higher accuracy rate than with real and nominal data types due to the classifier structure).

All the Lazy linear classifiers showed fast running in compare with the payesnet which took 117.5, 0.17, 0.02 sec to build the classification model with the brain dataset (real data), diabetes data (numeric) and breast data (nominal). Naïve classifiers works at the same speed with all data sets. The nonlinear classifiers, the LVQ showed a stable building time with all data sets and faster than all the different classifiers. While MLP classified the nominal data with 0.33 sec which is slower than building time of the numeric 0.28 second real data sets 0.19 sec.

In general MLP accuracy performance is higher than all classifiers but slower, due to its multi layers structure and the big number of iterations (500) and a hidden layers.

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الخلاصة

يمكن تعريف تنقيب البيانات على انه البحث عن المتشابهات والانماط في كمية ضخمة من البيانات في مجال معرفي معين وترتيبهم الى اصناف و مجاميع. تم اعداد العديد من خوارزميات التصنيف وتقنيات التجميع لتناسب مختلف انواع البيانات على سبيل المثال العددية, والحقيقة والرمزية. كل واحدة من خوارزميات التصنيف والتجميع تتطبق بطريقة معينة. بعض الخورزميات خطية وبعضها غير خطية. في هذا البحث, اجريت مقارنات بين بعض الخورزميات الخطية والغير خطية باستخدام ثلاث انواع من البيانات. مجموعة البيانات الاولى هي صور الرنين التي جمعت والمتعلقة بأورام الدماغ من نوع حقيقي, والثانية هي بيانات مرضى السكري وهي من نوع اعداد صحيحة, والثالثة هي بيانات المتعلقة بسرطان الثدي وهي من نوع رمزي. المصنفات الخطية المختارة لهذة الدراسة هي Lazy و Bayesian. بينما تم اختيارالمصنفات الا خطية وهي Multilayer Perceptron (MLP) و Linear Vector Quantization (LVQ). اظهرت النتائج بان اداء المصنفات الاخطية كان افضل من اداء المصنفات الخطية مع كل انواع البيانات. وعلى وجه الخصوص معدل الدقة لكلا من MLP و LVQ مع بيانات ورم الدماغ هي ٩١%, ٨٣% بالتعاقب. من الجانب الاخر اظهرت المصنفات الخطية نتائج متقاربة مع كل انواع البيانات.