Performance comparison of State-of-the-art Missing Value Imputation Algorithms on Some Bench mark Datasets

M. Naresh Kumar,
National Remote Sensing Centre (ISRO), India,
nareshkumar_jn@nrsc.gov.in

May 11, 2014

Abstract

Decision making from data involves identifying a set of attributes that contribute to effective decision making through computational intelligence. The presence of missing values greatly influences the selection of right set of attributes and this renders degradation in classification accuracies of the classifiers. As missing values are quite common in data collection phase during field experiments or clinical trails appropriate handling would improve the classifier performance. In this paper we present a review of recently developed missing value imputation algorithms and compare their performance on some bench mark datasets.
1 Introduction

The presence of missing values influences the selection of appropriate set of attributes that render degradation in classification accuracies of the classifiers. Missing values are a common problem in almost all real world data sets [1] used in knowledge discovery and data mining (KDD) applications. Specifically they are more frequent in clinical databases [2,3,4] and temporal climate databases [5,6]. Their presence would greatly affect the performance of classifiers [7].

The missing values in the databases may arise due various reasons such as the value being lost (erased or deleted) or not recorded, incorrect measurements, equipment errors, or possibly due to an expert not attaching any importance to a particular procedure. The incomplete data can be identified by looking for null values in the data set. However, this is not always true, since missing values can appear in the form of outliers or even wrong data (i.e. out of boundaries) [8].

There are numerous methods for predicting or approximating missing values. Single imputation strategies involve using the mean, median or mode [9] or regression-based methods [10] to impute the missing values. Traditional approaches of handling missing values like complete case analysis, overall mean imputation and missing-indicator method [11] can lead to biased estimates and may either reduce or exaggerate the statistical power. Each of these distortions can lead to invalid conclusions. Statistical methods of handling missing values depends on the application of maximum likelihood and expectation maximization algorithms [9,12,13]. Some of these methods would work only for certain types of attributes either nominal or numeric. Machine learning approaches like neural networks with genetic algorithms [14], neural networks with particle swarm optimization [15] have been used to approximate the missing values. The use of neural networks comes with a greater cost in terms of computation and training. Methods like radial basis function networks, support vector machines and principal component analysis have been studied for estimating the missing values. A new index and a distance measure was developed in [17,18] for imputing the missing values which have resulted in improved classification accuracies. For an extensive treatment of these methods we refer the readers to Marwala [16].

The following are the main objectives of the present work:

(i) a review on imputation algorithm (RNI-II) developed by Rao and Naresh [17,18];

(ii) to consider the case in which the attribute values are missing randomly in real world data sets;
(iii) to compare the performance of RNI-II algorithm with other well known im-
putation methods in improving the classification accuracies of the decision
ree classifiers such as C4.5 [19] and Genetic Algorithm-C4.5 [20];

These claims are realized through standard databases available University of
California Irvin (UCI) machine learning and the Keel data repositories [21, 22].

This paper is organized as follows: Section 2 describes the preliminaries of
different missing value handling methods. A review on some recently developed
missing value imputation algorithms (RNI-II) forms the core of Section 3. The ex-
periments on some benchmark datasets are described and the results are discussed
in Section 4. Conclusions and discussion of the results are present in Section 5.

2 Imputation Algorithms- A Review

The following are the main imputation algorithms popularly employed in handling
missing values in data sets:

- Imputation with K-Nearest Neighbour (KNNI) [23]: the algorithm com-
putes the k-nearest neighbour for each of the missing values and imputes a
value from them. For nominal values, the most common value among all
neighbours is taken, and for numerical values the mean value is computed.
To obtain the proximity the Euclidean distance (a case of an Lp norm dis-
tance) norm is considered;

- Weighted Imputation with K-Nearest Neighbour (WKNNI) [24]: the weighted
k-nearest neighbour method selects the instances with similar values (in
terms of distance) to the record having the MV. The estimated value takes
into account the distances among the neighbours, using a weighted mean or
the most repeated value according to the distance;

- K-Means clustering Imputation (KMI) [25]: in K-means clustering imputa-
tion, the intra-cluster dissimilarity is measured by the addition of distances
among the objects and the centroid of the cluster which they are assigned
to. A cluster centroid represents the mean value of the objects in the cluster.
Once the clusters have converged, the last process in KMI is to fill in all the
non-reference attributes for each incomplete object based on the cluster in-
formation. Data objects that belong to the same cluster are taken as nearest
neighbours of each other, and a nearest neighbour algorithm is employed to
replace missing data;
• **Fuzzy K-Means clustering based Imputation (FKMI)** [25, 26]: in fuzzy clustering, each data object $x_i$ has a membership function which describes the degree which this data object belongs to a certain cluster $v_k$. In this process, the data object does not belong to a concrete cluster represented by a cluster centroid (as done in the basic k-mean clustering algorithm), because each data object belongs to all $k$ clusters with different membership degrees. The non-reference attributes for each incomplete data object $x_i$ based on the information about membership degrees and the values of cluster centroid;

• **Support Vector Machine Imputation (SVMI)** [27]: is a Support Vector Machine (SVM) regression based algorithm to fill in missing data, by setting the decision attributes (output or classes) as the condition attributes (input attributes) and the condition attributes as the decision attributes. Subsequently SVM regression is used to predict the missing condition attribute values. In the first step the values without missing values are considered. In the next step the conditional attributes (input attributes), some of those values among them are missing, as the decision attribute (output attribute), and the decision attributes as the condition attributes by contraries. Finally, SVM regression is used to predict the decision attribute values.

### 3 Imputation Algorithm (RNI-II) proposed in [18]

The authors in [17] have developed a mean imputation procedure based on a novel indexing measure to identify the best record that fits the missing value for imputation. As a further improvement the authors in [18] develop a imputation procedure considering the higher order statistics concerning the attributes with the following salient features:

- considers incomplete data sets as input and returns the completed data sets with all instances of missing attribute values filled with possible values;
- handles data sets with attributes of different types for example nominal or numeric;
- last attribute in the data set must be a decision attribute of the type nominal and may belong to multiple classes;
- the values to be imputed are obtained by using the data from within the data set;
• does not require additional parameters such as $k$ in KNN imputation.

The most popular metric for quantifying the similarity between the two records is the Euclidean distance. Even though this metric is simpler to compute, it suffers from the following drawbacks [28]:

• Sensitive to the scales of the features involved;
• It does not account for correlation between the features.

With this motivation the authors in [18] define a new indexing measure that accounts for the interaction between the features and their distribution. Based on the index we then compute the distances between the tuples.

### 3.1 Formalization of the distance measure

For the sake of completeness we present the measure in this section. For more details we refer our readers to [18].

Let $S$ denote the collection of all data records, represented $A_{ij}$ for $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n - 1$. The attributes can either be a nominal (categorical) or numeric type. Our objective here is to define a distance measure for all pairs of the elements of $S$.

In the first case the decision of the two tuples may be same $A_{in} = A_{kn}$. Let $A$ denote the collection of all members of $S$ that belong to the same decision class to which $R_i$ and $R_k$ belong. If the attribute to which the column $C_l$ belongs is nominal then the set $A$ can be written as a union of subsets of distinctive elements or collections of the attributes. That is $A = B_{\gamma_p1l} \cup B_{\gamma_p2l} \cup \ldots \cup B_{\gamma_psl}$. The index for column $C_l$ of $S$ for two tuples $R_i, R_k$ may be computed as

$$I_{C_l}(R_i, R_k) = \begin{cases} \min\left\{\frac{\gamma_{pi}}{\gamma}, \frac{\gamma_{qkl}}{\gamma}\right\}, & \text{for } i \neq k; \\ 0, & \text{otherwise}, \end{cases}$$

where $\gamma_{pi}$ represents the cardinality of the subset $B_{\gamma_pil}$, all of whose elements have first co-ordinates $A_{il}$, $\gamma_{qkl}$ represents the cardinality of that subset $B_{\gamma_qkl}$, all of whose elements have first co-ordinates $A_{kl}$ and $\gamma = \gamma_{pi} + \gamma_{qkl} + \ldots + \gamma_{psl}$ represents the cardinality of the set $A$.

If the attribute $C_l$ is of numeric type and for fractional numbers the set $P_l$ for $l = 1, 2, \ldots, n - 1$ may be considered as a collection of all the members of the column $C_l$. Based on the skewness of the dataset the index is computed as
In the above definition $\gamma$ represents the cardinality of the set $P_l$ and $\tau_l$ and $\rho_l$ be the cardinalities of the sets $M_l$ and $N_l$ where in $M$ and $N$ are subsets constructed out of the subset of elements belonging to skewness being less than or greater than zero.

The decision attribute of the tuples may be different i.e $A_{ik} \neq A_{kn}$. Under this condition clearly $R_i$ and $R_k$ belong to two different decision classes. Consider the subsets $P_i$ and $Q_k$ consisting of members of $S$ that share the same decision with $R_i$ and $R_k$ respectively. Clearly $P_i \cap Q_k = \emptyset$. The members of the column $C_l$ of $S$ i.e $(A_{1l}, A_{2l}, \ldots, A_{ml})^T$ are of nominal or categorical type then the indexing measure between the two records $R_i$ and $R_k$ is defined as

$$I_{C_l}(R_i, R_k) = \begin{cases} \min\{\frac{\beta_{il}}{\delta_{il} + \beta_{il}}, \frac{\delta_{il}}{\delta_{il} + \beta_{il}}\}, & \text{for } i \neq k; \\ \frac{\beta_{il}}{\delta_{il} + \beta_{il}}, & \text{otherwise,} \end{cases}$$

where $\beta_{il}$ represents the cardinality of the subset $P_{\beta_{il}}$ all of whose elements have first co-ordinates $A_{il}$ in set $P_l$ and $\delta_{il}$ represents the cardinality of that subset $Q_{\delta_{il}}$, all of whose elements have first co-ordinates $A_{kl}$ in set $Q_l$. The set $P$ and $Q$ are sets having elements matching with the decision attribute of $R_i$ and $R_k$ If the members of the column $C_l$ of $S$ i.e $(A_{1l}, A_{2l}, \ldots, A_{ml})^T$ are of numeric type and for fractional numbers the index $I_{C_l}(R_i, R_k)$ between the two records $R_i$, $R_k$ is defined as

$$I_{C_l}(R_i, R_k) = \begin{cases} \min\{\frac{\beta_{il}}{\delta_{il} + \beta_{il}}, \frac{\delta_{il}}{\delta_{il} + \beta_{il}}\}, & \text{for } i \neq k; \\ \frac{\beta_{il}}{\delta_{il} + \beta_{il}}, & \text{otherwise,} \end{cases}$$

In the above definition $\beta_{il}$ and $\delta_{il}$ represents the cardinalities of the sets $R_i$ and $S_i$ respectively where $R$ and $S$ denote the sets with skewness equal to zero and greater than zero. The sum of the cardinalities of the sets $P_l$ and $Q_l$ is represented by $\lambda$.

The elements of set $D$ consisting of the distances between the tuples in an ascending order is constructed. To identify the nearest tuples the score $\alpha(x_k) = \frac{(x_k - \text{median}(x))}{\text{median}|x_1 - \text{median}(x)|}$ where $\{x_1, x_2, \ldots, x_n\}$ denote the distances of $R$ from $R_k$ is defined. The data records in set $S$ whose distances from the record $R$ satisfies the condition $\alpha(x_k) \leq 0$ is collected and is designated as $P$. For nominal type the frequency of each categorical value of the categorical attribute is computed.
and the highest categorical value of the frequent item set is imputed. If the type of attribute is numeric and non-integer for each element in set $B$ compute the quantity $\beta(j) = \frac{1}{\beta(j)}$ $\forall j = 1, \ldots, \gamma$ where $\gamma$ denote the cardinality of the set $B$ is computed. The weight matrix is computed as $W(j) = \frac{\beta_j}{\sum_{i=1}^{\gamma} \beta_j}$ $\forall j = 1, \ldots, \gamma$. The value to be imputed may be taken as $\sum_{i=1}^{\gamma} P(j).W(j)$ $\forall j = 1, \ldots, \gamma$.

4 Experiments and Results

4.1 Description of the Data sets

We have selected nine(9) data sets having missing values ranging from 2.19% to 70.58% in different types of attributes(integer, real (fractional or non-integer) and categorical(nominal)) from the Keel and UCI machine learning data repositories [21, 22].

We have selected the data sets pertaining to different problem domains such as: diagnosis of mammographic lesion-Mammographic (MAM), breast cancer identification-Breast (BRE), predicting erythemato-squamous skin diseases- Dermatology (DER), detect the presence of heart disease in the patients-Cleveland (CLE), data records pertaining to patients suffering from hyperthyroidism - Newthyroid (NTH), mitigating process delays due to rotogravure printing-Bands (BAN), classifying the U.S. House of Representatives Congressmen as Republican or Democrats based on the votes-House-votes (HOV), credit card applications approval-Australian (AUS), identification of different species of Iris plant-Iris (IRI). The details of the data sets are given in Table 1 with summary of their properties. The column labeled as “% MV.” indicates the percentage of the missing values in the data set. The column labeled as “% Ex.” refers to the percentage of examples in the data set which have at least one missing value.

4.2 Experimental Methodology

The experimental structure of our proposed methodology is shown in Figure 1. The data sets are considered one at a time and each of the data set is divided into training and testing data sets using a stratified $k$ fold cross validation method [29] with $k = 10$. For each fold, the training data set is considered for imputation using methodologies and the respective classifiers are built. The testing data sets that correspond to the training data sets are used in classifying the records.
Table 1: Data sets used in the experiments

| Data set          | #Attr. (R/I/N) | #Ex. | #CL | %MV | #DS(KB) |
|-------------------|----------------|------|-----|-----|---------|
| Dermatology(DER)  | 34  (0/34/0)   | 366  | 6   | 2.19| 442     |
| Mammographic(MAM) | 5   (0/5/0)    | 961  | 2   | 13.63| 194     |
| Breast(BRE)       | 9   (0/0/9)    | 286  | 2   | 3.15| 241     |
| House-votes(HOV)  | 16  (0/0/16)   | 435  | 2   | 46.67| 303     |
| Cleveland(CLE)    | 13  (13/0/0)   | 303  | 5   | 1.98| 253     |
| Iris(IRI)         | 4   (4/0/0)    | 150  | 3   | 32.67| 52.1    |
| Bands(BAN)        | 19  (13/6/0)   | 539  | 2   | 32.28| 649     |
| Newthyroid(NTH)   | 5   (4/1/0)    | 215  | 3   | 35.35| 70.4    |
| Australian(AUS)   | 14  (3/5/6)    | 690  | 2   | 70.58| 478     |

average accuracy is computed by taking the average of the classes that are predicted correctly relative to each classifier. The same methodology is followed for all the data sets considered in our experiment.

A non-parametric statistical test proposed by Wilcoxon [30] is used to benchmark the performance of the RNI-II algorithm with respect to other imputation algorithms in terms of the accuracies obtained using C4.5 and GA-C4.5. Wilcoxon signed rank non-parametric test is a popular measure generally employed to compare the results across multiple data sets [31, 32, 33, 34].

4.3 Parameters used in the study

The parameters used by each imputation method is given in Table 2. The values chosen are as recommended by the respective authors.
4.4 Experimental comparison of RNI-II with other imputation methods

In this section we present the analysis of our experimental results. The mean test accuracies of C4.5 and GA-C4.5 decision tree classifiers for all the 10 folds of the cross-validation data sets are computed and the results obtained invoking are tabulated in Table 3 and Table 4 respectively.

From the Table 3 we observe that the RNI-II algorithm has improved the test accuracies in all the nine data sets for C4.5 when compared with other imputation methods like FKMI, KMI, KNNI and WKNNI. In case of the data sets BAN,
Table 2: Methods and Parameters

| Method | Parameters |
|--------|------------|
| FKMI   | K=3        |
|        | error=100 |
|        | iterations=100 |
|        | m=1.5      |
| KMI    | K=10       |
|        | error=100 |
|        | iterations=100 |
| KNNI   | K=10       |
| WKNNI  | K=10       |

BRE, DER and MAM the accuracies of C4.5 classifier obtained using the RNI-II algorithm is comparable with the SVMI algorithm. In case of accuracies obtained using GA-C4.5 classifier Table[4] the RNI-II algorithm outperformed FKMI, KMI, KNNI, WKNNI for data sets AUS, BAN, HOV, IRM, MAM, CLE and NTH and equalled the accuracies in data sets BRE and DER. Our RNI-II algorithm outperformed SVMI for data sets AUS, BAN, CLE and MAM.

Table 3: C4.5 Classifier Test accuracies of decision tree classifiers

| Method | AUS    | BAN    | BRE    | CLE    | DER    | HOV    | IRM    | MAM    | NTH    |
|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| RNI-II | 86.38  | 69.40  | 74.83  | 51.75  | 95.64  | 97.02  | 94.00  | 83.04  | 93.92  |
| FKMI   | 82.03  | 68.29  | 74.83  | 51.45  | 95.64  | 96.80  | 87.33  | 82.42  | 88.81  |
| KMI    | 80.29  | 68.28  | 74.83  | 51.43  | 95.64  | 96.80  | 92.67  | 82.42  | 89.74  |
| KNNI   | 82.90  | 69.40  | 74.83  | 51.75  | 95.64  | 96.10  | 85.33  | 82.42  | 88.79  |
| WKNNI  | 80.43  | 67.90  | 74.83  | 51.75  | 95.64  | 96.10  | 85.33  | 82.62  | 89.26  |
| SVM    | 87.25  | 69.40  | 74.83  | 52.44  | 95.64  | 97.25  | 95.33  | 83.04  | 93.90  |

To establish the claim that the improvement in test accuracies obtained by the RNI-II algorithm when compared with other algorithms is not due to sampling errors, we performed the Wilcoxon signed rank test among the matched pairs. The test results at significance level $\alpha = 0.05$ are presented in Table[5] and Table[6].

The Table[5] depicts the Wilcoxon statistics generated for the test accuracies of C4.5 classifier generated from different data sets which are imputed using RNI-II and other methods. The performance of RNI-II is found to be superior to KMI and FKMI in terms of scoring positive rank sum of 28 with a p-value of 0.03. While
Table 4: GA-C4.5 Classifier Test Accuracies

| Method | AUS  | BAN  | BRE  | CLE  | DER  | HOV  | IRM  | MAM  | NTH  |
|--------|------|------|------|------|------|------|------|------|------|
| RNI-II | 85.65| 70.14| 75.50| 52.10| 95.09| 96.80| 94.00| 83.35| 94.37|
| FKMI   | 81.45| 66.80| 75.50| 52.44| 95.09| 96.57| 87.33| 82.42| 88.83|
| KMI    | 81.16| 68.65| 75.50| 50.10| 95.09| 95.88| 92.67| 82.42| 88.85|
| KNNI   | 81.74| 69.39| 75.50| 50.48| 95.09| 95.88| 85.33| 82.42| 88.81|
| WKNNI  | 81.30| 68.46| 75.50| 49.82| 95.09| 95.88| 85.33| 82.52| 89.31|
| SVMI   | 85.07| 65.32| 75.50| 49.49| 95.09| 97.25| 95.33| 82.00| 95.30|

RNI-II has shown higher positive rank sums with p-value ≤ 0.05 at a significance level of 0.05 when compared with other imputation algorithm.

It follows from the Table 6 that the test accuracies of GA-C4.5 have greatly improved when imputation is carried using RNI-II when compared with other imputation methods like FKMI, KMI, WKNNI and KNNI. The RNI-II has scored highest positive rank sum of 28 in relation to WKNNI, KMI and KNNI with a p-value of 0.01 at 0.05 significance level. In the case of SVMI the RNI-II imputation has scored a positive sum of 20 but could not meet the critical value to attain the required statistical significance level.

Table 5: Wilcoxon sign rank statistics for paired samples Results for C4.5 Classifier

| Method | Rank Sums (+, -) | Test Statistics | Critical Value | p-value |
|--------|------------------|-----------------|----------------|---------|
| FKMI   | 28.0, 0.0        | 0.0             | 3.0            | 0.02    |
| KMI    | 28.0, 0.0        | 0.0             | 3.0            | 0.02    |
| KNNI   | 15.0, 0.0        | 0.0             | 0.0            | 0.06    |
| WKNNI  | 21.0, 0.0        | 0.0             | 1.0            | 0.03    |
| SVMI   | 1.0, 14.0        | 1.0             | 0.0            | 0.12    |

The differences in the accuracies between RNI-II and other imputation algorithms are shown in Figures 2 to 6. In these figures vertical bars represent the difference in test accuracy obtained using RNI-II relative to other imputation methods for a variety of data sets. The positive values (bars above the baseline) represent the improvement in percentage accuracy obtained by using RNI-II method. It may be understood that the larger the bars indicate higher percentage accuracy between RNI-II method with the other base method, while a negative bar (below the baseline) indicates the decision tree classifier has a lower test accuracy for
Table 6: Wilcoxon sign rank statistics for paired samples Results for GA-C4.5 Classifier

| Method  | Rank Sums (+, -) | Test Statistics | Critical Value | p-value |
|---------|------------------|----------------|---------------|---------|
| FKMI    | 26.0, 2.0        | 2.0            | 3.0           | 0.04    |
| KMI     | 28.0, 0.0        | 0.0            | 3.0           | 0.02    |
| KNNI    | 28.0, 0.0        | 0.0            | 3.0           | 0.02    |
| WKNNI   | 28.0, 0.0        | 0.0            | 3.0           | 0.02    |
| SVMI    | 20.0, 8.0        | 8.0            | 3.0           | 0.37    |

RNI-II relative to other imputation method in question. In case of C4.5 decision tree classifier the RNI-II algorithm has scored around 8% improvement in accuracies as compared to FKMI, KNNI, WKNNI imputation algorithms for IRM data set.

Figure 2: RNI-II vs FKMI

In the case of GA-C4.5 decision tree classifier we notice that our RNI-II method has achieved highest accuracy in the case of data sets AUS, BAN, and MAM while the performance of other methods (FKMI, KMI, KNNI, WKNNI and SVMI) are far below this accuracy.
Figure 3: RNI-II Vs KMI

Figure 4: RNI-II Vs KNNI

Figure 5: RNI-II Vs SVMI
5 Conclusions

In this paper a review on the missing values in databases and possible strategies for imputing missing values is discussed. A mathematical framework for computing an indexing measure is developed which in turn is used in the computation of the distance between the pairs of data records. The RNI-II procedure is presented and performance comparison on benchmark datasets is carried out. The new imputation procedure RNI-II has enhanced the test accuracies of the two decision tree classifiers (C4.5 and GA-C4.5) significantly in comparison to other imputation methods KMI, FKMI, WKNNI and KNNI with a $p$ value $< 0.05$ at significance level $\alpha = 0.05$.

References

[1] D. Pyle, Data preparation for data mining. Morgan Kaufmann Publishers, 1999.

[2] M. N. Colleen, A. G. William, L. K. Merril, C. D. Naylor, and S. L. Duncan, “Dealing with missing data in observational health care outcome analyses,” Journal of Clinical Epidemiology, vol. 53(4), pp. 377–383, 2000.

[3] G. Molenberghs and M. G. Kenward, Missing Data in Clinical Studies. Chichester: Wiley, 2007.
[4] K. J. Cios and W. Mooree, “Uniqueness of medical data mining,” *Artificial Intelligence in Medicine*, vol. 26, pp. 1–24, 2002.

[5] C. Glasbey, “Imputation of missing values in spatio-temporal solar radiation data,” *Environmetrics*, vol. 6(4), pp. 363–371, 1995.

[6] S. Antti, L. Amaury, C. Yves, and D. Eric, “An improved methodology for filling missing values in spatiotemporal climate data set,” *Computational Geosciences*, vol. 14(1), pp. 55–64, 2010.

[7] A. Farhangfar, L. Kurgan, and J. Dy, “Impact of imputation of missing values on classification error for discrete data,” *Pattern Recogn.*, vol. 41, pp. 3692–3705, December 2008.

[8] R. Pearson, *Mining Imperfect Data: Dealing with Contamination and Incomplete Records*. Philadelphia: SIAM, 2005.

[9] J. Schafer, *Analysis of Incomplete Multivariate Data*. Chapman & Hall, 1997.

[10] N. Horton and S. Lipsitz, “Multiple imputation in practise: comparison of software packages for regression models with missing variables,” *The American Statistician*, vol. 55(3), pp. 244–254, 2001.

[11] G. Heijden, A. Donders, T. Stijnen, and K. Moons, “Imputation of missing values is superior to complete case analysis and the missing-indicator method in multivariable diagnostic research: a clinical example;” *Journal of Clinical Epidemiology*, vol. 59(10), pp. 1102–1109, 2006.

[12] P. Allison, *Missing data Thousand Oaks*. Sage publications, 2002.

[13] J. L. Roderick and B. R. Donald, *Statistical Analysis with Missing Data, 2nd Edition*. Wiley, 2002.

[14] A. Mussa and M. Tshilidzi, “The use of genetic algorithms and neural networks to approximate missing data in database,” *Computing and Informatics*, vol. 24, pp. 1001–1013, 2006.

[15] W. Qiao, Z. Gao, and R. Harley, “Continuous online identification of nonlinear plants in power systems with missing sensor measurements,” in *In:IEEE International Joint Conference on Neural Networks*. Montreal: IEEE, 2005, p. 17291734.
[16] T. Marwala, *Computational Intelligence for Missing Data Imputation, Estimation, and Management: Knowledge Optimization Techniques* Information Science Reference, 2009.

[17] V. Sree Hari Rao and M. Naresh Kumar, “A new intelligence-based approach for computer-aided diagnosis of dengue fever,” *Information Technology in Biomedicine, IEEE Transactions on*, vol. 16, no. 1, pp. 112–118, 2012.

[18] V. Hari Rao and M. Naresh Kumar, “Novel approaches for predicting risk factors of atherosclerosis,” *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 1, pp. 183–189, 2013.

[19] J. R. Quinlan, *C4.5: programs for machine learning*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1993.

[20] D. Carvalho and A. Freitas, “A hybrid decision tree/genetic algorithm method for data mining,” *Information Sciences*, vol. 163, no. 1, pp. 13–35, 2004.

[21] A. Frank and A. Asuncion, “UCI machine learning repository,” 2010.

[22] A. Alcal-Fdez, A. Fernandez, Luengo, J. Derrac, S. G. J., L. Sánchez, and F. Herrera, “Keel data-mining software tool: Data set repository, integration of algorithms and experimental analysis framework,” *Journal of Multiple-Valued Logic and Soft Computing*, 2010.

[23] G. Batista and M. Monard, “An analysis of four missing data treatment methods for supervised learning,” *Applied Artificial Intelligence*, vol. 17, no. 5, pp. 519–533, 2003.

[24] O. Troyanskaya, M. Cantor, G. Sherlock, P. Brown, T. Hastie, R. Tibshirani, D. Botstein, and R. Altman, “Missing value estimation methods for dna microarrays,” *Bioinformatics*, vol. 17, pp. 520–525, 2001.

[25] J. Deogun, W. Spaulding, B. Shuart, and D. Li, “Towards missing data imputation: A study of fuzzy k-means clustering method,” in *4th International Conference of Rough Sets and Current Trends in Computing(RSCTC’04)*, ser. Lecture Notes on Computer Science, vol. 3066. Lecture Notes In Computer Science, 2004, pp. 573–579.
[26] E. Acuna and C. Rodriguez, *The treatment of missing values and its effect in the classifier accuracy*. Berlin-Heidelberg: Springer-Verlag, 2004, pp. 639–648.

[27] H. Feng, G. Chen, C. Yin, B. Yang, and Y. Chen, “A svm regression based approach to filling in missing values,” in *9th International Conference on Knowledge-Based and Intelligent Information and Engineering Systems (KES2005)*, ser. Lecture Notes on Computer Science, vol. 3683. Springer-Verlag, 2005, pp. 581–587.

[28] U. Tadashi, M. Yoshihide, K. Daichi, S. Masami, and K. Kenji, “Fast multidimensional nearest neighbor search algorithm based on ellipsoid distance,” *International Journal of Advanced Intelligence*, vol. 1(1), pp. 89–107, 2009.

[29] N. Littlestone, “Learning quickly when irrelevant attributes abound: A new linear-threshold algorithm,” *Machine Learning*, vol. 2(4), pp. 285–318, 1988.

[30] F. Wilcoxon, “Individual comparisons by ranking methods,” *Biometrics Bulletin*, vol. 1(6), pp. 80–83, 1945.

[31] R. R. Bouckaert, “Choosing learning algorithms using sign tests with high replicability,” in *AI 2003: Advances in Artificial Intelligence*, ser. Lecture Notes in Computer Science, T. D. Gedeon and L. C. C. Fung, Eds. Springer Berlin Heidelberg, 2003, vol. 2903, pp. 710–722.

[32] T. G. Dietterich, “Approximate statistical tests for comparing supervised classification learning algorithms,” *Neural Computation*, vol. 10, no. 7, pp. 1895–1923, 1998.

[33] J. Demšar, “Statistical comparisons of classifiers over multiple data sets,” *J. Mach. Learn. Res.*, vol. 7, pp. 1–30, 2006.

[34] S. Garca and F. Herrera, “An extension on ”statistical comparisons of classifiers over multiple data sets” for all pairwise comparisons,” *Journal of Machine Learning Research*, vol. 9, pp. 2677–2694, 2009.