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A comparative predictive analysis of neural networks (NNs), nonlinear regression and classification and regression tree (CART) models

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Abstract

Numerous articles comparing performances of statistical and Neural Networks (NNs) models are available in the literature, however, very few involved Classification and Regression Tree (CART) models in their comparative studies. We perform a three-way comparison of prediction accuracy involving nonlinear regression, NNs and CART models using a continuous dependent variable and a set of dichotomous and categorical predictor variables. A large dataset on smokers is used to run these models. Different prediction accuracy measuring procedures are used to compare performances of these models. The outcomes of predictions are discussed and the outcomes of this research are compared with the results of similar studies.

Keywords: Neural networks; Regression; Classification and regression tree

1. Introduction

Classical statistical methods have been applied in industry for years. Recently, Neural Networks (NNs) methods have become tools of choice for a wide variety of applications across many disciplines. It has been recognized in the literature that regression and neural network methods have become competing model-building methods (Smith & Mason, 1997). For a large class of pattern-recognition processes, NNs is the preferred technique (Setyawati, Sahirman, & Creese, 2002). NNs methods have also been used in the areas of prediction and classification (Warner & Misra, 1996).

Since NNs was developed as generalizations of mathematical models of human cognition through biological neurons, it is regarded as an information processing system that has certain performance characteristics in common with human neural biology. The characteristics include ability for storing knowledge and making it available for use whenever necessary, propensity to identify patterns, even in the presence of noise, aptitude for taking past experiences into consideration and make inferences and judgments about new situations.

Statistical methods such as regression analysis, multivariate analysis, Bayesian theory, pattern recognition and least square approximation models have been applied to a wide range of decisions in many disciplines (Buntine & Weigend, 1991). These models are attractive to decision makers because of their established methodology, long history of application, availability of software and deep-rooted acceptance among practitioners and academicians alike. NNs are data dependent and therefore, their performance improves with sample size. Statistical methods, such as Regression perform better for extremely small sample size, and also when theory or experience indicates an underlying relationship between dependent and predictor variables (Warner & Misra, 1996). Classification and Regression Tree (CART) models use tree-building algorithms, which are a set of if-then (split) conditions that permit prediction or classification of cases. A CART model that predicts the value of continuous variables from a set of continuous and/or categorical predictor variables is referred as regression-type model. For the prediction of the value of categorical variable from a set of continuous and/or categorical predictor variables, classification-type CART model is used. One noticeable advantage of decision tree

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based models, such as CART, is that the decision tree based models are scalable to large problems and can handle smaller data set than NNs models (Marcham, Mathieu, & Wray, 2000).

Despite the apparent substantive and applied advantages of statistical models, Neural Networks (NNs) methods have also gained popularity in recent years (Ripley, 1994). These methods are particularly valuable when the functional relationship between independent and dependent variables are unknown and there are ample training and test data available for the process. NNs models also have high tolerance for noise in the data and complexity. Moreover, the software technologies, such as, SPSS-Clementine, SAS-Enterprise Minor and Brain Maker that deploy neural networks algorithm have become extremely sophisticated and user-friendly in recent years.

Our research objective was to compare the predictive ability of multiple regression, NNs method and CART model using a set of data on smokers that include mostly categorical variables. Comparison of predictive abilities of statistical and NNs models are plentiful in the literature. It is also widely recognized that the effectiveness of any model is largely dependent on the characteristics of data used to fit the model. Goss and Vozikis (2002) compared NNs methods with Binary Logit Regression (BLR) and concluded that NNs model's prediction accuracy was better than that of BLR model. Shang, Lin, and Goetz (2000) also concluded similarly. Feng and Wang (2002) compared nonlinear regression with NNs methods in reverse engineering application using all non-categorical variables in their study. Both models provided comparably satisfactory prediction, however, the regression model produced a slightly better performance in model construction and model verification. Brown, Corruble, and Pittard (1993) show that NNs do better than CART models on multimodal classification problems where data sets are large with few attributes. The authors also concluded that the CART model did better than the NNs model with smaller data sets and with large numbers of irrelevant attributes. For non-linear data sets, NNs and CART models outperform linear discriminant analysis (Curram & Mingers, 1994). In our research, a three-way comparison involving nonlinear regression, NNs and CART models is performed. The prediction errors of these three models are compared where the dependent variable is continuous and predictor variables are all categorical.

The rest of the paper is organized as follows: The Section 2 provides literature review on comparative analysis of NNs and statistical models. Section 3 provides a brief description and organization of data and the research model. Section 4 provides a brief discussion on NNs, regression and CART models and presents test hypotheses. In Section 5, we examine results of these three models and provide analysis. Based on the analysis in Section 5, conclusions are drawn and presented in Section 6.

2. Literature review

2.1. Classical statistical tools

Some of the widely used traditional Statistical tools applied for prediction and diagnosis in many disciplines are Discriminant analysis (Flury & Riedwyl, 1990; Press & Wilson, 1978), Logistic regression (Hosmer & Lemeshow, 1989; Press & Wilson, 1978; Studenmund, 1992), Bayesian approach (Buntine & Weigend, 1991; Duda & Hart, 1973), and Multiple Regression (Menard, 1993; Myers, 1990; Neter, Wasserman, & Kutner 1985; Snedecor & Cochran, 1980). These models have been proven to be very effective, however, for solving relatively less complex problems.

2.2. Neural networks models

An overview of NNs models is provided by Lippmann (1987). Fausett (1994); Freeman (1994); Hertz, Krogh, and Palmer (1991); Lawrence (1994); Mehrotra, Mohan, and Ranka (1996); Rumelhart, Hinton, and Williams (1986); Smith (1993); Taylor (1999) and White (1992) conducted research involving mathematical description of NNs models, Neural Net architecture, training algorithms such as supervised/unsupervised learning and backpropagation algorithm. It is also evident from the literature involving NNs models that the development and application of NNs is not limited to a specific area. The applications of NNs range from signal processing in telecommunications to pattern recognition (Lippmann, 1987) in Medicine, Business and Engineering. The following section provides a brief overview of the articles that applied Neural Networks in various disciplines.

2.2.1. Health

Numerous articles involving applications of NNs in medicine have been published over the years. NNs models are applied in cardiovascular studies by Baxt (1990) and also by Fujita, Katafuchi, Uehara, and Nishimura (1992). Fujita et al. concluded that their feed-forward neural network with a back-propagation algorithm performed better than radiology residents but worse than experienced radiologists. Poli, Cagnoni, Livi, Coppini, and Valli (1991) applied NNs models in hypertension diagnosis. NNs models are used to predict protein structures by Qian and Sejnowski (1988). Shang et al. (2000) used NNs and Regression to detect antibiotic-resistant pathogen infections in the US hospitals. The results obtained by Shang et al. are mixed; Regression model worked better for smaller test sets, however, NNs as a whole, provided slightly better prediction and less variation across different subgroups. Zhang and Berardi (1999) applied NNs in thyroid function diagnosis.

2.2.2. Financial

Lee and Jung (2000) compared predictive ability of Logistic regression and NNs to identify creditworthiness of urban and rural customers. The results were mixed; for urban customers, regression worked better and for rural customers, NNs methods provided better prediction. Tam and Kiang (1992) applied multivariate discriminant analysis model and NNs to examine the failure of banks. The authors concluded that NNs offered better predictive accuracy than discriminant analysis model. Applicability of NNs for cost estimation in building construction, is tested by Setyawati et al. (2002). The authors concluded 'Neural networks outperform regression linear models given the same training data and the same variables'. Other applications of NNs in finance can be found in article by Kimoto, Asakawa, Yoda, and Takeoka (1993). Applications of NNs models in Stock market performance prediction are provided by Hutchinson (1994) and Studenmund (1992).

2.2.3. Marketing and data minning

Numerous applications of NNs models in Marketing and data mining are available in the literature (Ainslie & Dreze, 1996; Groth, 2000; Kumar, Rao, & Soni 1995; Westphal & Blaxton, 1998). West, Brockett, and Golden (1997) observed that NNs provides better prediction than discriminant analysis and logistic regression in brand choice decision.

2.2.4. Business, manufacturing and engineering

Like other areas, applications of NNs in Business, Manufacturing and Engineering are plentiful. Wong, Bodnovich, and Selvi (1997) provided a comprehensive review and analysis of the literature involving NNs applications between 1988 and 1995. A survey by Zhang and Huang (1995) provides applications of neural network in manufacturing. Hurrion (1992) applied NNs metamodel to find optimal number of Kanbans in manufacturing systems. Liang, Markowitz, and Yih (1992) used NNs metamodel in Operations Management, Hill and Remus (1994) in Managerial Decision Making and Kaparthi and Suresh (1994) in quality control. Feng and Wang (2002) compared nonlinear regression and neural network models in computer-aided reverse engineering and automatic inspection applications. Coit, Jackson, and Smith (1998); Martinez, Smith and Bidanda (1994); Moon and Na (1997); Petri, Billo, and Bidanda (1998); Smith (1993) and Yarlagadda (2000), among others, used NNs in manufacturing processes and operations modeling. Yang and Lee (2000) applied NNs for data processing in reverse engineering. Zhou and Harrison (1999) used a fuzzy-neural based hybrid approach for error compensation in on-line inspection on a CNC machine tool. Smith et al. (1997) compared the predictive capabilities of NNs and regression methods in manufacturing cost estimation problems. Feng and Pandey (2002), in an experiment with a coordinate-measuring machine (CMM), used both regression and NNs models to study the effect of digitizing parameters on digitizing uncertainty. The authors concluded that the 'multiple regression method produced a better prediction in terms of both the root mean square error and the mean relative error'.

2.3. Comparison of statistical and NNs models

Numerous authors have compared performance of statistical and neural networks models on specific problems (Sarle, 1994; Schumacher, Robner, & Vach 1999; Wu & Yen, 1992). Hruschka (1993), for example, compared econometric techniques with NNs models applied in market response functions. The authors indicated that the back-propagation NNs model that they used might lead to better model fits than achieved by comparable econometric models. However, they also cautioned that more studies were necessary to establish general conclusion regarding the strengths and weaknesses of neural networks. Lee and Jung (2000) compared the forecasting ability of logistic regression analysis with that of NNs model to predict creditworthiness of urban customers. Werbos (1991) discussed the link between Artificial Neural Networks (ANNs) and Statistical models in pattern Recognition. Warner and Misra (1996) compared the performance of regression analysis with that of neural networks using simulated data from known functions and also using real-world data. The authors discussed the situations where it would be advantageous to use NNs models in place of a parametric regression model. They also discussed difficulties related to implementation of NNs models. Zahedi (1996) compared predictability of NNs with that of discriminant analysis in financial applications. Ainslie and Dreze (1996) compared predictability of logistic regression with that of NNs model. The authors concluded that logistic regression, in one case, outperformed NNs model, while both performed equally in another.

2.4. Hybrid models (combination of choice and NNs models)

The idea behind combined (Hybrid) models is to derive advantages of individual model's best features to obtain the best possible results in a given problem/situation (Papatla, Zahedi, & Zezic-Susac, 2002; Mojirsheibani, 1999). The practice of mixing models (classifiers) is not new, and have also been suggested by Xu, Kryzak, and Suen (1992). Larkey and Croft (1996) used combined (hybrid) classifiers for handwriting recognition and text categorization. Whitecotton, Sanders, and Norris (1998) combined statistical method with human judgment and argued that the combination could provide better accuracy. Smith, Palaniswamy, and Krishnamoorthy (1996); Wolport (1992) and Zhang and Beradi (2001) developed hybrid models by combining different NNs architectures and showed that the combinations provided improved performance compared to standalone NNs models. Hybrid models by combining statistical models (mixed regression models) were done by Breiman (1996); LeBlanc and Tibshirani (1996); Mojirsheibani (1999) and Stone (1974), among others. Results from these studies suggest that hybrid statistical models improve predictive performance when compared against the predictive performances of standalone models. The recent trend in hybrid model development is to mix classical statistical models with NNs models (Papatla et al., 2002). Papatla et al. proposed two classes of hybrid models: linear and nonlinear. The authors suggested that mixing models using NNs has a higher probability of resulting in a better performance. Supporting the findings of other researchers, they also indicate that hybrid models (combination of NNs and Statistical models) outperform standalone models.

3. Organization of data

In this study we have used a set of data on the smoking habits of people. The data set contained 35 variables and 3652 records. Among 35 available variables, initially we choose 10 variables considered to be most intuitively related to illness, and ran a correlation analysis. Based on the results of correlation analysis, the following variables (presented in Table 1), considered to be significant contributor towards the prediction of the dependent variable (Days in bed due to Illness), are selected.

4. Choice of research models and predictive accuracy procedures

4.1. Neural network model

We choose to use NNs method because it handles nonlinearity associated with the data well. NNs methods imitate the structure of biological neural network. Processing elements (PEs) are the neurons in a Neural Network. Each neuron receives one or more inputs, processes those inputs, and generates a single output. Main components of information processing in the Neural Networks are: Inputs, Weights, Summation Function (weighted average of all input data going into a processing element (PE), Transformation function and Outputs (Fig. 1).

Example of steps involving NNs process is as follows:

4.2. Initialization

- Set network topology for neighborhood parameters to determine adjacent nodes

Table 1
Variables

Variable	Description
Y	Days in bed due to Illness
X_1	Gone to Clinic/Doctor/Health Center
X_2	Currently work indoors
X_3	Gender
X_4	Ever smoked 100 cigarettes in life

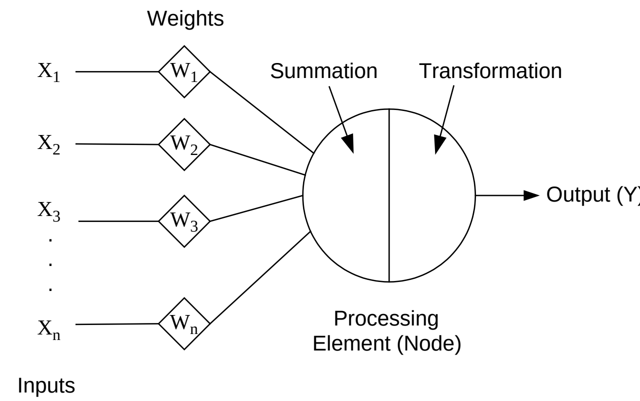


Fig. 1. Neural networks.

- Set initial weights, w
- Set parameters for learning rates, α

4.3. Iterative loop

1. While exit condition is false, DO:
2. Select an input vector $\mathbf{x}$
3. For each $\mathbf{j}$, compute the square of the Euclidean distance (ED) of $\mathbf{x_i}$ from the weight vector $\mathbf{w_{ij}}$ associated with each output node.

$$ED(j) = \sum_i (w_{ij} - x_i)^2$$

4. Select the index $\mathbf{J}$ so that $ED(j)$ is a minimum.
5. Update weights to all nodes within a topological distance of $\mathbf{J}$ using the following update rule for all $\boldsymbol{i}$:

$$w_{ij}(\text{new}) = w_{ij}(\text{old}) + \alpha[x_i - w_{ij}(\text{old})]$$

where, α = learning rate, a decreasing function of time
6. Update α
7. Reduce topological distance (radius)
8. Exit if the condition is true

4.4. Regression model

'Days in bed due to Illness' is chosen as dependent variable (Y) and others as independent variables. Applications of logistic regression approach can be found in Lee and Jung (2000) and Shang et al. (2000), among others. However, the requirement for Logistic Regression is that the dependent variable has to be binary (0 or 1). Even though we have binary variables in the list of variables selected for the study, the numeric variable, Days in bed due to Illness, is considered to be most suitable for the dependent variable. Application of nonlinear regression models can be found in Feng and Pandey (2002); Setyawati et al. (2002) and Nguyen and Cripps (2001), among others. We have constructed the following nonlinear multivariate regression model: $Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j X_{ij} + \sum_{k=5}^{10} \beta_k (X_{i1}X_{i2} + X_{i1}X_{i3} + X_{i1}X_{i4} + X_{i2}X_{i3} + X_{i2}X_{i4} + X_{i3}X_{i4})$.

4.5. Classification and regression tree (CART) model

CART model is developed by Breiman, Freidman, Olshen, and Stone (1984). Regression-type CART mode is a non-parametric procedure for predicting continuous dependent variable with categorical and/or continuous predictor variables where the data is partitioned into nodes on the basis of conditional binary responses to questions involving the predictor variable, $\boldsymbol{y}$. 'CART models use a binary tree to recursively partition the predictor space into subsets in which the distribution of $\boldsymbol{y}$ is successively more homogenous' (Chipman, George, & McCulloch, 1998). For example, CART procedure derives conditional distribution of $\boldsymbol{y}$ given $\mathbf{x}$, where $\mathbf{x}$ represents a vector of predictors [$x = (x_1, x_2, x_3, \ldots, x_n)$]. A decision tree Π with $\boldsymbol{t}$ terminal nodes is used for communicating the classification decision. A parameter $\Phi = (\varphi_1, \varphi_2, \varphi_3, \ldots, \varphi_t)$ associates the parameter value $\varphi_i (i = 1, 2, 3, \ldots, t)$ with the ith terminal node. The partitioning procedure searches through all values of predictor variables (vector of predictors) to find the variable $\mathbf{x}$ that provides best partition into child nodes. The best partition is the one that minimizes the weighted variance. The distribution $f(y|\phi_i)$ of $\boldsymbol{y}|\boldsymbol{x}$ represents the situation that $\mathbf{x}$ lies in the region corresponding to the ith terminal node. Although numerous articles have compared NNs models with linear, non-linear and hybrid Regression models, very few have compared the predictive ability of CART model with NNs and/or regression models. Brown et al. (1993) compared NNs with CART model. Since CART is a non-parametric procedure for predicting continuous dependent variable with categorical predictor variables, we find this model a natural fit for prediction with the variable set chosen for this study. For a thorough discussion of CART model, readers are referred to Breiman et al. (1984) and Chipman et al. (1998).

4.6. Predictive accuracy procedures

It has been identified by Watts and Leftwich (1977) and Zhang, Cao, and Schniederjans (2004), among others, that a model with a solid goodness-of-fit measure may not perform as well in prediction. R^2 is a common criterion for goodness-of-fit for regression models, however, it does not work well for all data. The problem with goodness-of-fit procedure has been described by researchers as the 'descriptive-predictive paradox' or 'regression fallacy' (Lorek & Willinger, 1996; Zhang et al., 2004). In light of the above argument, instead of fitting a model with fundamental variables and measuring the goodness-of-fit, we estimate the predictive power of a model by comparing the forecast error for a relatively large sample of data.

A total of 3652 observations are used to forecast Days in bed due to Illness (Y) values. Mean Absolute Error (MAE) is used as one of the measurements of prediction accuracy. As used by Zhang et al. (2004), we also compute following three error metrics to measure prediction accuracy:

1. Mean Absolute Percentage Error (MAPE)$= \frac{1}{3652} \sum_{i=1}^{3652} |Y_i - \hat{Y_i}/Y_i|$
2. Mean Squared Error (MSE) $= \frac{1}{3652} \sum_{i=1}^{3652} (Y_i - \hat{Y_i}/Y_i)^2$

where, $\hat{Y_i}$ is the forecasted value of Days in bed due to Illness (Y).

3. Large Prediction Error (LPE): We set large forecast error as one that exceeds 100% as used by Zhang et al. (2004).

4.7. Hypothesis

In order to establish statistical significance, we carry out statistical tests to comparatively evaluate prediction accuracy between regression and NNs methods, between regression and CART methods and between NNs and CART methods on problems for the dataset of smokers. Following hypotheses are proposed:

H_{01}: There is no prediction accuracy difference in regression and NNs methods.
H_{02}: There is no prediction accuracy difference in regression and CART methods.
H_{03}: There is no prediction accuracy difference in CART and NNs methods.

Since regression models do not perform well with categorical predictor variables, we expect that both NNs and CART models will outperform the predictive ability of regression model.

5. Results and analysis

5.1. Regression

A stepwise regression procedure was conducted using SPSS. In the process, some of the variables and nonlinear interactions were thrown away by the procedure due to lack of significant contributions towards the prediction of the value of the dependent variable, Y. Multicollinearity among independent variables was also a factor in the final selection of the model. The final nonlinear regression model is as follows:

$$Y = 1.474 + 3.536X_2 + 5.856X_4 - 1.734X_1X_2 + 1.505X_1X_3 - 2.563X_2X_3 - 3.438X_3X_4$$

The following table shows the regression results of the prediction model. It shows that Current working conditions (X_2) and smoking intensity (X_4) have a significant impact on the Days in bed due to illness (Y) based on $\alpha = 0.05$.

Table 2
Output of regression model

Predictor	Coef (β)	SE Coef	T	P
Constant	1.474	0.461	3.197	0.001
X_2	3.536	0.532	11.007	0.000
X_4	5.856	0.645	−5.330	0.000
X_1X_2	−1.734	0.645	5.479	0.000
X_1X_3	1.505	0.623	−4.112	0.000
X_2X_3	−2.563	0.530	−3.272	0.001
X_3X_4	−3.438	0.602	2.499	0.012

Four interactions X_1X_2, X_1X_3, X_2X_3, and X_3X_4 also significantly affected Y for the same Alpha level (Table 2).

Analysis of variance

Source	DF	SS	MS	F	P
Regression	32092.131	6	5348.827	46.283	0.000
Residual Error	421241.6	3645	115.567		
Total	453334.6	3651			

5.2. Neural network model

Neural networks, through a network of functions, provide a non-linear mapping between dependent and independent variables. The network is supported by a set of inter-connected layers of processing elements. Table 3 provides statistics of neural network factors used in prediction.

5.3. Predictive accuracy results

Descriptive statistics and the graphs of $(Y_i - \hat{Y_i})$ for Regression, NNs and CART models are provided in Appendix A. All three models show almost same minimum and maximum prediction error. Regression model, however, shows lower standard deviation but higher mean of prediction error. All three graphs show that each model reacts similarly to outlier values of Y (please see graphs in Appendix A). Each model generates similar number of prediction errors where error is >40. However, upon close observation of graphs of these three models, it is evident that most errors for regression model are little higher than the errors generated by the NNs and CART models. Observations in this section are also supported by the predictive accuracy results explained below.

Table 3
NNs factors used in prediction and analysis

Input layer:	4 neurons
Hidden layer	3 neurons
Output layer:	1 neuron
Relative importance of inputs:	
Gone to clinic/doctor/health center	0.039
Currently work indoors	0.039
Gender	0.013
Ever smoked 100 cigarettes in life	0.012

Table 4
Predictive accuracy procedures

	MAE	MAPE	MSE	LPE (%)
Regression	5.08	1.9	8.29	42.6
Neural Network	4.75	1.61	6.3	35.3
CART	4.79	1.62	6.8	32.5

The results of MAE, MAPE, MSE, and LPE for regression, Neural Networks and CART are provided in Table 4. The Neural Network method yields the lowest MAE, MAPE and MSE values (4.75, 1.61, and 6.3, respectively). However, the values of MAE, MAPE and MSE for CART model (4.79, 1.62, and 6.8, respectively) are close behind those of NNs method. Regression seems to provide consistently higher values of MAE, MAPE and MSE (5.08, 1.9, and 8.29, respectively) compared to other two procedures. It can be concluded that, across the three models, MAE, MAPE and MSE exhibit the same pattern. It was no surprise that the measure of large prediction error (LPE) for regression (42.6%) is higher that that of other two models. However, LPE shows opposite pattern between Neural Network and CART models. LPE for CART (32.5%) is significantly lower than that of Neural Networks model (35.3%). The implication is that, even though, CART model exhibit slightly higher values of MAE, MAPE and MSE, than the NNs model, it produces significantly lower percentage of large prediction error.

5.4. Hypothesis testing: regression vs NNs model

Since data used for prediction in all models are same, we carried out paired t-test (two samples for mean) on prediction accuracy $(Y_i - \hat{Y_i})$ to test all hypotheses. The results of paired t-tests are shown in Table 5. Detail results are provided in Appendix B.

Since $P<0.05$, H_{01}, H_{02} and H_{03} all are rejected. The evidence indicate that the average prediction error of regression model is significantly different from the average prediction error of NNs model (reject H_{01}). This conclusion, however, also indicate that the prediction error of regression model is higher than the NNs model. Similar conclusion can be drawn for the regression versus CART test (reject H_{02}) as well as for the NNs versus CART test (reject H_{03}). The implications of rejecting H_{02} and H_{03} are that mean

Table 5
Results of paired t-tests

Tests	df	t-Stat	$P(T \leq t)$	Conclusion
H_{01}: Regression vs NNs	3651	21.24	0	$\mu_R > \mu_{NN}$
H_{02}: Regression vs CART	3651	24.85	0	$\mu_R > \mu_{CART}$
H_{03}: NNs vs CART	3651	−3.61	0.000154	$\mu_{NN} > \mu_{CART}$

Where, μ_R, μ_{NN} and μ_{CART} are, mean prediction errors of Regression, Neural Networks and Classification and Regression Tree (CART) models, respectively.

prediction error produced by CART model is lower than that of Regression model and the mean prediction error generated by the NNs model is lower than that of CART model. However, it should be noted that *t*-Statistics for H_{03} test is quite low (-3.61) compared to $H_{01}(21.24)$ and $H_{02}(24.85)$.

6. Conclusion

In this research we perform a three-way comparison of prediction accuracy involving nonlinear regression, NNs and CART models. The prediction errors of these three models are compared where the dependent variable is continuous and predictor variables are all categorical. As mentioned before, many comparative studies have been done in the past, however, very few involved CART model in their studies.

NNs and CART models, in our study, produced better prediction accuracy than non-linear regression model. Even though NNs produced lower MAE, MAPE and MSE values than the CART model, the later model generated fewer LPEs than the former model. The advantage of decision tree based models, however, is that the decision tree based models are scalable to large problems and can handle smaller data set than NNs models (Marcham et al., 2000). Feng and Pandey (2002) compared nonlinear regression with NNs methods in reverse engineering application. However, variables used in their study were all non-categorical. The authors pointed out that, even though both models provided satisfactory prediction, the regression model yielded a slightly better performance in model construction and model verification. Brown et al. (1993) show that NNs do better than CART models on multimodal classification problems where data sets are large with few attributes. However, the authors also point out that CART outperform NNs models where data sets are smaller with large numbers of irrelevant attributes. NNs and CART models are shown to outperform linear discriminant analysis on problems where the data is non-linear (Curram & Mingers, 1994).

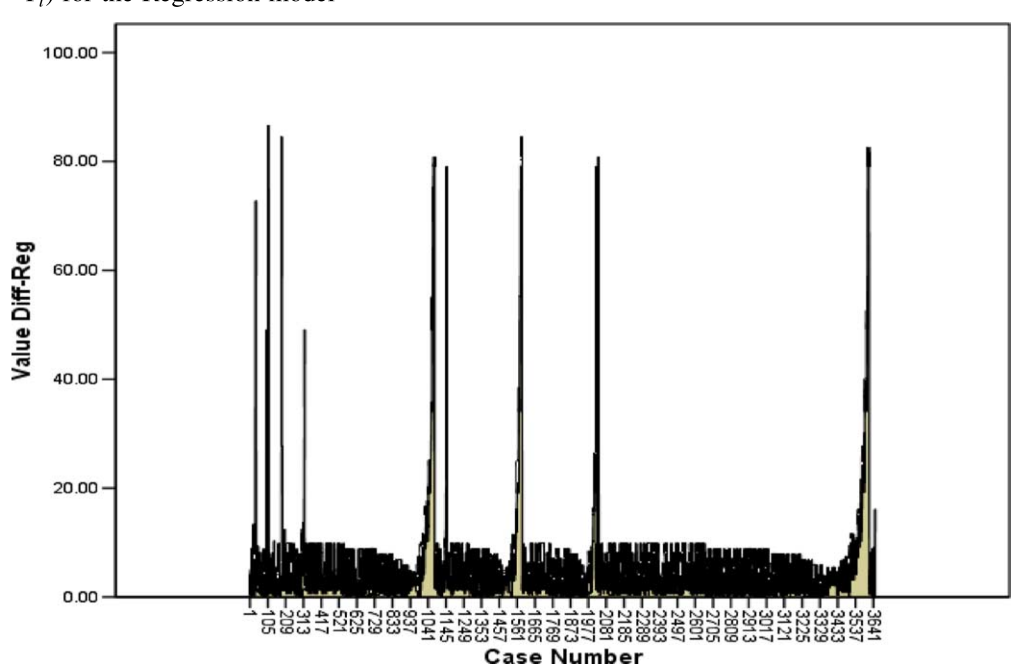
It is obvious from the study results that NNs and CART models provide better prediction compared to regression models when the predictor variables are binary or categorical and the dependent variable continuous. However, neither NNs nor CART model showed clear advantage of one over the other. For application standpoint, either one of NNs and CART models may be used for prediction and would provide better predictability over regression. However, oweverH-more studies and different scenarios/conditions need to be explored in order to establish a clear distinction of performance between CART and NNs models.

Appendix A

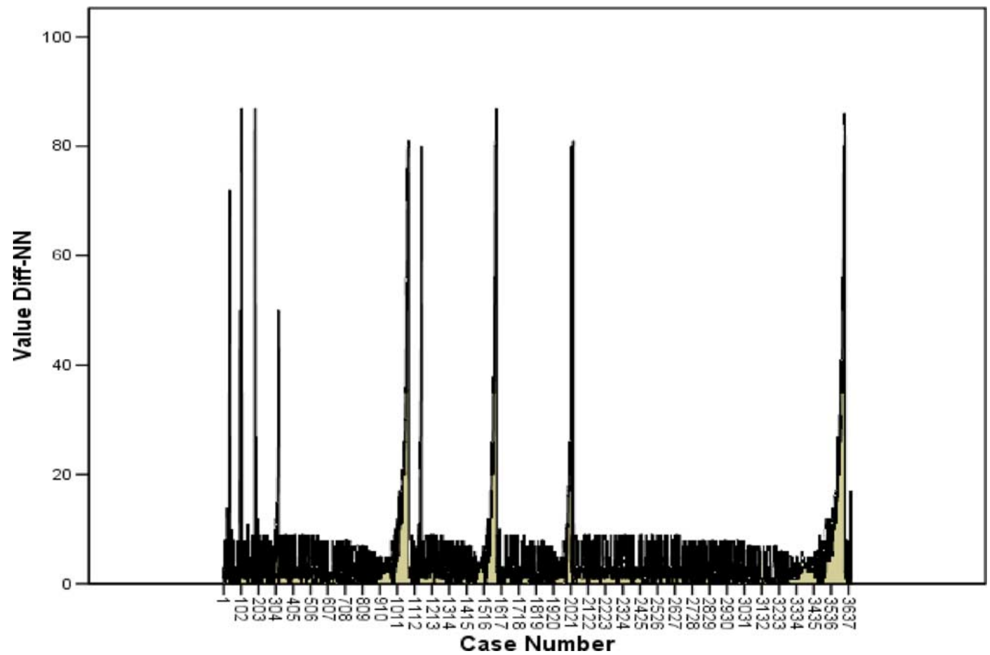
Descriptive statistics

	N	Minimum	Maximum	Mean	Std. deviation
Diff-Reg	3652	0.01	86.72	5.0864	9.46036
Diff-NN	3652	0	87	4.75	9.663
Diff-CART	3652	0	87	4.80	9.613
Valid N (listwise)	3652				

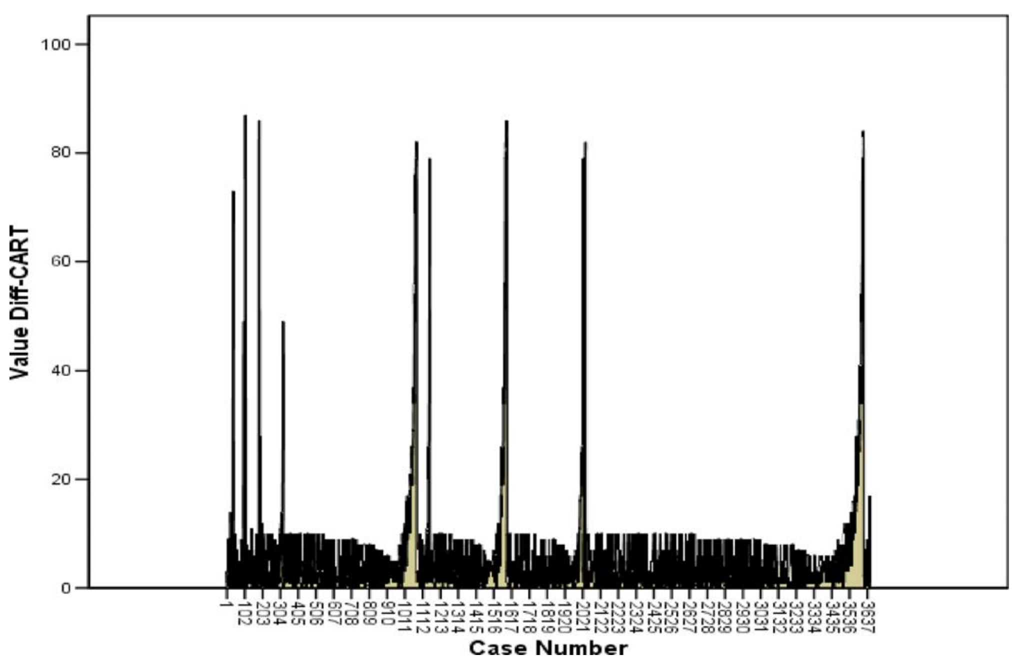
1. Graph of $(Y_i - Y_i)\hat{}$ for the Regression model



2. Graph of $(Y_i - Y_i)\hat{}$ for the NNs model



3. Graph of $(Y_i - Y_i)\hat{}$ for the CART model



Appendix B

Results of paired t-test

	Regression vs NNs		NNs vs CART		Regression vs CART	
	Variable 1	Variable 2	Variable 1	Variable 2	Variable 1	Variable 2
Mean	5.086396495	4.751916758	4.751916758	4.795180723	5.086396495	4.795180723
Variance	89.49843571	93.36653974	93.36653974	92.4039428	89.49843571	92.4039428
Observations	3652	3652	3652	3652	3652	3652

(*continued on next page*)

	Regression vs NNs		NNs vs CART		Regression vs CART	
	Variable 1	Variable 2	Variable 1	Variable 2	Variable 1	Variable 2
Pearson correlation	0.995269636		0.997192643		0.997369967	
Hypothesized mean difference	0		0		0	
d*f*	3651		3651		3651	
t Stat	21.23897452		−3.611781637		24.8497081	
$P(T \leq t)$ one-tail	8.69246E-95		0.000154096		2.252E-126	
t Critical one-tail	1.645271368		1.645271368		1.645271368	
$P(T \leq t)$ two-tail	1.73849E-94		0.000308193		4.5041E-126	
t Critical two-tail	1.960615919		1.960615919		1.960615919	

t-Test: paired two sample for means.

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