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# Bayes Net Classifiers for Prediction of Renal Graft Status and Survival Period

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***Abstract*—**This paper presents the development of a Bayesian belief network classifier for prediction of graft status and survival period in renal transplantation using the patient profile information prior to the transplantation. The objective was to explore feasibility of developing a decision making tool for identifying the most suitable recipient among the candidate pool members. The dataset was compiled from the University of Toledo Medical Center Hospital patients as reported to the United Network Organ Sharing, and had 1228 patient records for the period covering 1987 through 2009. The Bayes net classifiers were developed using the Weka machine learning software workbench. Two separate classifiers were induced from the data set, one to predict the status of the graft as either failed or living, and a second classifier to predict the graft survival period. The classifier for graft status prediction performed very well with a prediction accuracy of 97.8% and true positive values of 0.967 and 0.988 for the living and failed classes, respectively. The second classifier to predict the graft survival period yielded a prediction accuracy of 68.2% and a true positive rate of 0.85 for the class representing those instances with kidneys failing during the first year following transplantation. Simulation results indicated that it is feasible to develop a successful Bayesian belief network classifier for prediction of graft status, but not the graft survival period, using the information in UNOS database.

***Keywords*—**Bayesian network classifier, renal transplantation, graft survival period, United Network for Organ Sharing

## I. Introduction

THE United Network for Organ Sharing (UNOS) database offers a list of tens of thousands of organ transplant records and as such is a valuable resource as a medical reference. Automated software tools that can extract this knowledge offer significant benefits to the renal patients in the waiting list for the renal transplantation. In that context, the inductive learning approaches from the machine learning domain are appropriate for empirical development of predictors for a given field or attribute in the UNOS dataset. For instance, Bayesian belief networks provide a promising means for empirical or data-driven development of predictors. Bayesian belief networks are probabilistic modeling tools and can approximate the posterior probability distribution of any chosen attribute in the domain. This type of information is poised to benefit medical professionals engaged in decision making and need data-driven or empirical classifier or regression models. In fact, Bayesian belief networks were already employed in a variety of ways for development of probabilistic inferencing or classification models in the medical organ transplantation domain [1, 2].

The relative scarcity of grafts available for liver transplantation, just as it is the case for nearly all other organ transplants, highlights the need to identify patients likely to have good outcomes after treatment. [1] used a Bayesian belief network (BBN) for prediction of graft survival period in liver transplantation. The author used transplant data from the UNOS to construct Bayesian network models to predict 90-day graft survival rates. The final model incorporated a set of 29 pre-transplant variables and achieved a performance of 0.674 through cross-validation, and 0.681 on an independent validation set for the area under the receiver operating characteristic (ROC) curve. The positive predictive value was 91%, however the negative predictive value was much lower at 30%.

J.-H. Ahn et al. [2] applied the Bayesian belief network to a large UNOS dataset to develop a predictor for renal graft survival period. The model was developed using a supervised, machine-learning approach, called the Advanced Pattern Recognition and Identification (APRI) system. The APRI system builds the Bayesian network model using entropy-based mutual information to select variables and indentify dependencies between selected variables. The model is built using the publicly-available data from UNOS with 35,366 records for kidney-transplants performed between 1987 and 1991. Each record contains 43 attributes (called variables in the paper) with information on characteristics of the donor kidney and the transplant recipients. The model was used to predict one-year graft survival rates. They illustrated the model's prediction for two hypothetical kidney-transplant patients. Patient A who is younger, never had a prior transplant, had fewer HLA mismatches, and a lower peak

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panel reactive antibody level was compared to those of patient B. Because of these favorable health characteristics, patient A had a much higher average predicted graft survival rate (91.2%) than patient B (78.4%). Finally, they claimed the performance in predicting 1-year graft survival rates showed promise for providing valid information to better allocate such scarce resources as transplant organs.

Researchers also investigated the predictive ability of multiple pretransplant comorbidities for graft and patient survival in renal transplantation [3]. They considered 25,270 transplants between 1995 and 2002, and examined the potential use of comorbidities not recorded in the organ procurement and transplantation network (OPTN) together with OPTN variables to predict long-term graft loss and patient death. Using the OPTN database they showed that patient survival is associated with cardiovascular conditions, diabetes and history of malignancy.

There is currently substantial interest in developing decision making aids to help better manage the overall organ transplantation process starting with who should get the organ. Prediction of graft survival rate for a given pool of potential recipients for an organ transplant such as a kidney is helpful for decision makers [4, 5, 6]. It is the aim of this paper to investigate the feasibility of such a tool in the form of a Bayesian belief network classifier designed to predict the renal graft status and survival period for a given patient. This paper proposes the Bayesian belief network as an empirical classifier model for predicting the value of the "graft status and survival period" for renal transplantation.

The following sections present the details of the work accomplished. The UNOS data for University of Toledo Medical Center (UTMC) and the data-preprocessing applied are discussed next. This is followed by Bayesian belief network classifier development using Weka machine learning software [7]. Simulation study and testing results are listed and analyzed subsequently. Finally, conclusions are discussed.

## II. Data and Preprocessing

The study reported herein covers patients who received a kidney transplant at University of Toledo Medical Center (UTMC). The raw data file was obtained from UNOS for UTMC patients who received kidney transplantation from 1987 to 2009. This file entails general registration information data of patients just before the transplant survey, and it is supplied by the patients through the form entitled "Transplant Candidate Registration Form". There are 1,228 records for recipient registration for UTMC patients for this time period, and each patient record is made up of 128 fields or attributes.

The "Transplant Candidate Registration Form" entails the patient information and profile as deemed relevant for the renal transplantation within the context of UNOS. The information content of this file is used for prediction model development after removing some fields that were deemed to be not essential, not relevant or unusable. The UNOS dataset has high ratio of missing values for many attributes. Any attribute which had more than 95% missing values was removed. The values entered for the fields or attributes in the original UNOS data file were varied since apparently no standards were imposed on data entry and different people worked on it during the time period covered by this study. For example, there are many kinds of expressions (entries or values) in the dataset that are all intended to represent the concept of "unknown." Some examples for this include "unknown", "U", "UNK", and "UNKNOWN" etc. Accordingly, values of a given attribute had to be unified by standardizing the different values with the same meaning. Another preprocessing step entailed conversion of the continuous-valued attributes into discrete-valued attributes so that Bayes net classifier algorithm can be applied. This has been implemented with the specialist domain input mainly by the transplant surgeon and the transplant coordinator nurse on the research team. Discretized variables or attributes are presented in Table I.

A number of data fields or attributes were deemed to be not relevant given the focus of this study. Since patient anonymity is a very important concern, personal information such as social security number, last name, first name, and initials are all removed from the data file. Any fields or attributes that relate to co-morbidity conditions were retained. Any attribute or field that was for an explanation for a given attribute was excluded: for instance "Primary Diagnosis//Specify" is an auxiliary attribute for the main attribute "Primary Diagnosis" and as such was deemed not essential. There were many attributes with some form of "age" information incorporated, i.e. registration age, admission age, discharge age, previous transplant age, first dialyzed age and so on. Consequently, a total of 70 attributes out of the original list of 128 were included in the study. The list of 70 attributes except those already listed in Table I is shown in Table A-I in the Appendix.

The time-to-failure for the transplanted kidney is variable of interest for observation or prediction for this study. A field named "graft survival period" was added to track the periods of the survival time after the renal transplantation. In deciding how many classes for this attribute, we analyzed 1228 patients and identified that the data can support at most 4 classes assuming that each class should have approximately equal number of instances so that the classifier model can be constructed with reasonable accuracy. Given the original UNOS/UTMC data distribution as presented in Table A-II in the Appendix, a total of 4 discrete values (or classes) were identified as indicated in Table IIA. Since the number of instances in each class is still disparate, a special processing step or Weka filter (weka.filters.supervised.instance.resample with biasToUniformClass parameter set to 1.0) that resamples the original dataset to induce a uniformly distributed new dataset was applied [7]. Following application of this filter, the new instance counts for each class is shown in the same table. A second attribute of interest related to the query or prediction is if a graft will fail or survive following the surgery given the pretransplant profile of the patient. We formulated an additional class attribute “graft status” with two values of “failed” and “living”. Original instance distribution for class values are shown in Table IIB. The same uniform distribution filter was applied to this class attribute as well with results shown in the same table.

TABLE I
LIST OF DISCRETIZED VARIABLES IN UNOS/UTMC DATA

| Attribute | Discrete Values | Discrete Value Ranges |
|---|---|---|
| Serum Creatinine at time of Tx | Nominal R1, R2, R3, R4, R5 | R1 in the range of 0 to 1.0, R2 in the range of 1.0 to 4.0, R3 in the range of 4.0 to 8.0, R4 in the range of 8.0 to 12.0, and R5 as greater than 12.0 |
| TCI Right KI//Total Cold ischemia Time Right KI(OR EN-BLOC) (if pumped include pump time) | Nominal R1, R2, R3, R4, R5 | R1 in the range of 0 to 5 hours, R2 in the range of 5 to 10 hours, R3 in the range of 10 to 15 hours, R4 in the range of 15 to 20 hours, and R5 as greater than 20 hours |
| TWI Right KI//Total Warm Ischemia Time Right KI (OR EN-BLOC) (incl. anastomotic time) | Nominal R1, R2, R3, R4 | R1 in the range of 0 to 30 minutes, R2 in the range of 30 to 60 minutes, R3 in the range of 60 to 120 minutes, and R4 as >120 minutes |
| TCI Left KI//Total Cold ischemia Time Left KI (if pumped include pump time) | Nominal R1,R2, R3,R4, R5 | R1 in the range of 0 to 5 hours, R2 in the range of 5 to 10 hours, R3 in the range of 10 to 15 hours, R4 in the range of 15 to 20 hours, and R5 as greater than 20 hours |
| TWI Left KI//Total Warm ischemia Time Left KI (include Anastomotic time) | Nominal R1, R2, R3, R4 | R1 in the range of 0 to 30 minutes, R2 in the range of 30 to 60 minutes, R3 in the range of 60 to 120 min., and R4 in the range of >120 minutes |
| Most recent Serum Creatinine prior to discharge | Nominal R1, R2, R3, R4, R5 | R1 in the range of 0.0 to 0.5, R2 in the range of 0.5 to 2.0, R3 in the range of 2.0 to 4.0, R4 in the range of 4.0 to 6.0 and R5 as greater than 6.0 |
| BMI | Nominal R1,R2,R3, R4,R5,R6, R7 | R1 in the range of 0.0 to 15.0, R2 in the range of 15.0 to 20.0, R3 in the range of 20.0 to 25.0, R4 in the range of 25.0 to 30.0, R5 in the range of 30.0 to 35.0, R6 in the range of 35.0 to 40.0, and R7 as greater than 40.0 |

## III. Simulation Study

### A. Weka and Bayes Net

The machine learning software workbench Weka [7] will be used for performing the simulation based analysis. The BayesNet classifier algorithm in Weka (Version 3.5.5) will be leveraged to develop the Bayesian belief network (BBN) [8] classifier model of the data. The options that must be addressed in Weka include the *estimator* that computes the conditional probability tables of the Bayes network, the *searchAlgorithm* that implements a user selected structure learning algorithm and the *useADTree* that facilitates savings in learning time at the expense of increased memory usage. The estimator will be set to *SimpleEstimator* with the default alpha value of 0.5, while the *useADTree* parameter will be set to false.

TABLE IIA
CLASS ATTRIBUTE GRAFT SURVIVAL PERIOD DISCRETE VALUES

| Discrete Value | Survival Period | Number of Instances | Instances After Resampling |
|---|---|---|---|
| LTE-1-Year | Up to 1 year | 94 | 359 |
| LTE-5-Years | More than 1 year but less than or equal to 5 years | 467 | 290 |
| LTE-10-Years | More than 5 years but less than equal to 10 years | 332 | 288 |
| GT-10-Years | More than 10 years | 335 | 335 |

TABLE IIB
CLASS ATTRIBUTE GRAFT STATUS DISCRETE VALUES

| Discrete Value | Number of Instances | Instances After Reseampling |
|---|---|---|
| Failed | 221 | 650 |
| Living | 1007 | 578 |

The *searchAlgorithm* option with Weka BBN algorithm will be set to a number of choices (as elaborated upon below) in order to adequately explore the structure learning space. The structure learning algorithms as implemented in Weka (through the so-called *searchAlgorithm* option) are presented in three groupings: local score based structure learning (i.e., minimum description length principle), conditional independence based structure learning, and global score based structure learning (i.e., cross validation). The local score based structure learning algorithms are desirable for computation cost savings purposes. We employed five of these algorithms, which included K2, hill climber, tabu search, Genetic Algorithm and Simulated Annealing. The set of local score based algorithms and associated option settings are presented in Table III. The conditional independence based structure learning option was also explored and its realization within Weka, the CISearch, was experimented with through the settings indicated as in Table III. Additionally, the naïve

Bayes classifier algorithm (through default parameter values) was tested on the UNOS UTMC dataset to serve as the minimum standard or benchmark to compare against.

The set of options for the local score based search algorithms are *initAsNaiveBayes*, *MarkovBlanketClassifier*, *scoreType*, *maxNrOfParents*, *useArcReversal*, *randomOrder*, and *Runs*. The parameter *initAsNaiveBayes* has two settings. A value of true, which is the default, results in a naive Bayes network structure to be used as the initial network structure. On the other hand a false value will impose an empty network structure initially, i.e., the Bayes net has no arrows. The *markovBlanketClassifier* (set to false by default), if set to true, leverages a heuristic: when the search space is traversed completely, this heuristic is used to validate that each of the attributes are in the Markov blanket of the classifier node. If a node that is not already in the Markov blanket (i.e., is a parent, or child of sibling of the classifier node), an arrow is added. If the value of this parameter is set to false, then no action is taken. The *scoreType* parameter is used to identify the score metric to be used. The set of score metrics that were used in the simulations include Bayes, AIC, and MDL. The *maxNrOfParents* parameter establishes an upper bound on the number of parents for each node in the network. The *randomOrder* parameter has a default value of false, which implies that the order of the nodes in the dataset is used. If the *randomOrder* parameter is set to true, then the order of nodes in the network is randomly determined. The parameter *useArcReversal* has a default value of false, and when set to true results in arc reversal operation to be performed during the search. The parameter *Runs* has a default value of 10, and which sets the number of generations of Bayes network structure populations.

TABLE III
OPTION SETTINGS FOR BAYES NET STRUCTURE SEARCH ALGORITHMS

| WEKA Bayes Net Structure Learning Parameters | Local K2 | Hill Climber | Tabu Search | CI Search | Genetic Algorithm | Simulated Annealing |
|---|---|---|---|---|---|---|
| *initAsNaiveBayes* | false | false | n/a | n/a | n/a | n/a |
| *MarkovBlanketClassifier* | false | false | false | false | false | false |
| *scoreType* | {Bayes, MDL, and AIC} | {Bayes, MDL, and AIC} | {Bayes} | {Bayes} | {Bayes} | {Bayes} |
| *maxNrOfParents* | 3 or 4 | 4 | 3 | n/a | n/a | n/a |
| *Random Order* | false | n/a | n/a | n/a | n/a | n/a |
| *useArcReversal* | n/a | true | true | n/a | n/a | n/a |
| *Runs* | n/a | n/a | 10 | n/a | 10 | 1000 |

The genetic algorithm requires following parameters to be initialized or set: *descendantPopulation*, *populationSize*, *seed*, *useCrossOver*, *useMutation*, and *useTournamentSelection*. The *descendantPopulationSize* parameter, which was set to the value of 10, establishes the size of the population of descendants that is created each generation. The parameter *populationSize*, which was left with its default value of 10, sets the size of the population of network structures that is selected each generation. The parameter *seed* with the default value of 1 is the initialization value for random number generator. Setting the *seed* allows replicability of experiments. The parameter *useCrossOver* is set to true. It determines whether crossover is allowed. Crossover combines the network structure bit representations by taking at random first *k* bits of one, and adding the remainder of the other. The parameter *useMutation* which is set to true determines whether mutation is allowed: mutation flips a bit in the bit representation of the network structure. The parameter *useTournamentSelection* is set to true. It determines the method of selecting a population. When set to true, tournament selection is used (pick two at random and the highest is allowed to continue). When set to false, the top scoring network structures are selected.

For simulated annealing, it has several options to specify including *Tstart*, *delta*, and *seed*. *Tstart* has a default value of 10.0. It is the start temperature of the simulated annealing search. The start temperature determines the probability that a step in the "wrong" direction in the search space is accepted. The higher the temperature, the higher the probability of acceptance is. The parameter *delta* with the default value of 0.999 sets the factor with which the temperature and thus the acceptance probability of steps in the wrong direction in the search space is decreased in each iteration. The parameter *seed* also has the default value of 1. All parameters were used with their default values. Tabu search was used with the default value of 5 for its only additional parameter *tabuList*, which is the length of the tabu list.

### *B. Simulation Results and Analysis*

The Bayesian belief network structure learning algorithms in Table III and the naïveBayes algorithm were trained and tested on the revised UNOS UTMC dataset (with uniform class distribution) that had 70 attributes and 1,228 instances. The BBN classifier models on the dataset are built and tested by means of 5-fold cross-validation. The JavaHeap size was set to 1.5 GB for WEKA. The simulation platform is an Intel™ core duo 2 processor system with 3 GB RAM under Microsoft

Windows Vista™ operating system. There were two class attributes, graft survival period and graft status, and a separate classifier model was generated for each one.

Simulation results in Table IV for the classifier intended to predict the graft status indicate that the Bayes net classifiers generally demonstrated very high prediction accuracies for both class values of "failed" and "living". The version with hill climber structure learning and Bayes scoring function performed at 97.8% prediction rate with true positive rates of 0.967 and 0.988 for the two class values as seen Table V. The confusion matrix for this Bayes net classifier supports these observations as well, Table VI. This classifier demonstrated a very good performance indicating that it is able to predict the status of the graft with high accuracy for either value of the class attribute. Three other leading machine learning classifiers were trained on the same dataset through five-fold crossvalidation, and their prediction accuracy values are presented in Table VII. These results suggest that the Bayes net classifier performs at par with other leading machine learning classifiers.

TABLE IV
BBN CLASSIFIER MODELS FOR GRAFT STATUS ATTRIBUTE

| Search Algorithm (*including options in WEKA format*) | Prediction Accuracy in % | Build Time (sec) |
|---|---|---|
| Naïve Bayes | 79.6 | 0.02 |
| CISearch (-S BAYES) | 75.1 | 0.02 |
| Tabu Search (-R –N –U 10 –P 3 –S BAYES) | 75.2 | 1.69 |
| Hill Climber (-P 3 –N –S BAYES) | 97.8 | 67.09 |
| Hill Climber (-P 3 –N –S MDL) | 97.0 | 25.48 |
| Hill Climber (-P 3 –N –S AIC) | 96.7 | 39.42 |
| Local K2 (-p 3 –N –S BAYES) | 96.0 | 10.91 |
| Local K2 (-p 3 –N –S MDL) | 97.5 | 1.09 |
| Local K2 (-p 3 –N –S AIC) | 95.7 | 1.22 |
| Local K2 (-p 4 –N –S BAYES) | | 46.34 |
| Local K2 (-p 4 –N –S MDL) | 94.8 | 0.81 |
| Local K2 (-p 4 –N –S AIC) | 94.9 | 1.18 |
| Genetic Algorithm (-L 10 –A 10 –U 10 –R 1 –M –C –O -S) | 89.4 | 12383.07 |
| Simulated Annealing (-A 10 –U 1000 –D 0.999 –R 1 –S BAYES) | 84.9 | 0.19 |

TABLE V
COMPREHENSIVE PERFORMANCE PROFILE OF BAYES NET WITH HILL CLIMBER

| TP Rate | FP Rate | Precision | Recall | F-Measure | ROC | Class |
|---|---|---|---|---|---|---|
| 0.967 | 0.012 | 0.986 | 0.967 | 0.976 | 0.994 | Living |
| 0.988 | 0.033 | 0.971 | 0.988 | 0.979 | 0.994 | Failed |

TABLE VI
CONFUSION MATRIX OF BAYES NET WITH HILL CLIMBER

| Living | Failed | ←Classified as |
|---|---|---|
| 559 | 19 | Living |
| 8 | 642 | Failed |

TABLE VII
PERFORMANCE OF LEADING MACHINE LEARNING CLASSIFIERS FOR GRAFT STATUS PREDICTION

| Search Algorithm *(including options in WEKA format)* | Prediction Accuracy in % | Build Time (sec) |
|---|---|---|
| J48 (-U -M 2) | 98.04 | 0.13 |
| SMO (-C 1.0 -L 0.0010 -P 1.0E-12 -N 0 -V -1 -W 1 -K "weka.classifiers.functions.supportVector.RBFKernel -C 250007 -G 0.01") | 98.37 | 21.19 |
| IBk -K 10 -W 0 -A "weka.core.neighboursearch.LinearNNSearch -A \"weka.core.EuclideanDistance -R first-last\"" | 92.75 | 0.01 |

Bayes net classifiers for prediction of the graft survival period are presented in Table VIII. The naïve Bayes algorithm performance at 46% prediction rate serves as the minimum standard against which performances of other algorithm can be compared. A number of Bayes net classifiers performed better than the 60% prediction rate. The highest performing BBN models used versions of local K2 and hill climber for structure learning. The best performing classifier model (hill climber with Bayes scoring function) achieved a prediction accuracy of 68.2%. For a typical classifier, these numbers are quite low indicating that the data does not lend itself to a high-performing classifier model development. The Bayes net classifier with hill climber structure learning and Bayes scoring function was further analyzed to better understand and expose its performance characteristics through a number of measures. Set of performance measures included true positive rate, false positive rate, precision, recall, F measure, and area under the receiver-operating characteristic (ROC) curve as presented in Table IX. True positive (TP) value for LTE-1-Year is reasonably high but this appears to be an exception since the other classes have comparably much lower TP values. The same trend can be observed for the rest of the performance measures as well. This indicates that the developed classifier is performing well for the members of the class LTE-1-Year only. Supporting and correlated observations can be made through the confusion matrix presented in Table X.

TABLE VIII
BBN CLASSIFIER MODELS FOR GRAFT SURVIVAL PERIOD ATTRIBUTE

| Search Algorithm (*including options in WEKA format*) | Prediction Accuracy in % | Build Time (sec) |
|---|---|---|
| Naïve Bayes | 46.0 | 0.02 |
| CISearch (-S BAYES) | 46.5 | 0.01 |
| Tabu Search (-R –N –U 10 –P 3 –S BAYES) | 46.3 | 1.69 |
| Hill Climber (-P 3 –N –S BAYES) | 68.2 | 67.09 |
| Hill Climber (-P 3 –N –S MDL) | 29.7 | 25.48 |
| Hill Climber (-P 3 –N –S AIC) | 61.4 | 39.42 |
| Local K2 (-p 3 –N –S BAYES) | 54.2 | 10.91 |
| Local K2 (-p 3 –N –S MDL) | 29.8 | 1.09 |
| Local K2 (-p 3 –N –S AIC) | 60.9 | 1.22 |
| Local K2 (-p 4 –N –S BAYES) | 54.2 | 46.34 |
| Local K2 (-p 4 –N –S MDL) | 29.8 | 0.81 |
| Local K2 (-p 4 –N –S AIC) | 60.9 | 1.18 |
| Genetic Algorithm (-L 10 –A 10 –U 10 –R 1 –M –C –O -S) | 31.2 | 12383.07 |
| Simulated Annealing (-A 10 –U 1000 –D 0.999 –R 1 –S BAYES) | 54.2 | 0.19 |

TABLE IX
PERFORMANCE PROFILE OF BAYES NET WITH HILL CLIMBER

| TP Rate | FP Rate | Precision | Recall | F-Measure | ROC | Class Value |
|---|---|---|---|---|---|---|
| 0.858 | 0.043 | 0.893 | 0.858 | 0.875 | 0.967 | LTE-1-Year |
| 0.638 | 0.12 | 0.621 | 0.638 | 0.629 | 0.866 | LTE-5-Years |
| 0.542 | 0.14 | 0.542 | 0.542 | 0.542 | 0.824 | LTE-10-Years |
| 0.646 | 0.116 | 0.633 | 0.646 | 0.639 | 0.856 | GT-10-Years |

TABLE X
CONFUSION MATRIX OF BAYES NET WITH HILL CLIMBER

| LTE-1-Year | LTE-5-Years | LTE-10-Years | GT-10-Years | ← Classified as |
|---|---|---|---|---|
| 308 | 22 | 15 | 14 | LTE-1-Year |
| 12 | 185 | 63 | 30 | LTE-5-Years |
| 16 | 51 | 156 | 65 | LTE-10-Years |
| 9 | 40 | 54 | 188 | GT-10-Years |

Other prominent machine learning classifiers were also evaluated to validate that the Bayes net performance is competitive. Classifiers including C4.5 decision tree (J48 in Weka), support vector machine classifier (SMO in Weka), and instance based classifier were evaluated on the same dataset using Weka with default parameter values and settings. For classifier model development and performance testing, five-fold cross-validation was implemented on the entire (training) data set. Results of the simulations are presented in Table XI and indicate that Bayes net classifiers fail to demonstrate a competitive performance for the prediction of graft survival period on the UNOS/UTMC dataset.

TABLE XI
PERFORMANCE OF LEADING MACHINE LEARNING CLASSIFIERS ON UNOS/UTMC DATASET

| Search Algorithm (*including options in WEKA format*) | Prediction Accuracy in % | Build Time (sec) |
|---|---|---|
| J48 (-U -M 2) | 70.6 | 0.49 |
| SMO (-C 1.0 -L 0.0010 -P 1.0E-12 -N 0 -V -1 -W 1 -K "weka.classifiers.functions.supportVector.RBFKernel -C 250007 -G 0.01") | 73.8 | 82.72 |
| IBk -K 10 -W 0 -A "weka.core.neighboursearch.LinearNNSearch -A \"weka.core.EuclideanDistance -R first-last\"" | 76.4 | 0.01 |

## IV. CONCLUSION

Software tools are needed to help with the complex decision making process associated with the identification of a good transplant candidate for an available kidney. Predictors for renal transplantation graft status and graft survival period using Bayes net classifiers were developed using the University of Toledo Medical Center (UTMC) patient data as reported to UNOS. The Bayes net classifier for the graft status demonstrated very high prediction accuracy and true positive values for all classes suggesting that it can be readily employed in a clinical setting. The second Bayes net classifier for the prediction of graft survival period failed to demonstrate an acceptable level of performance.

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## APPENDIX

TABLE A-I
LIST OF ATTRIBUTES

| Attribute Label | Attribute Label |
|---|---|
| Gender | Incidental Tumor found at time of Transplant |
| Tx Age | |
| State of Permanent Residence | Resumed Maintenance Dialysis |
| Surgeon Name | Age of Graft Failure |
| Donor Type | Primary Cause of Graft Failure |
| Primary Diagnosis | Primary Cause of Graft Failure//Specify |
| Primary Diagnosis//Specify | Acute Rejection |
| Patient Status | Graft Thrombosis |
| Was patient hospitalized during the last 90 days prior to the transplant admission | Infection |
| Medical Condition at time of transplant | Surgical Complications |
| Functional Status | Urological Complications |
| Physical Capacity | Recurrent Disease |
| Working for income | Most Recent Serum Creatinine Prior to Disch.//ST= |
| Working for Income//If No. Not Working Due To | Kidney Produced > 40ml of Urine in First 24 Hours |
| Working for Income//If Yes | Patient Need Dialysis within First Week |
| Primary Source of Payment//Primary | Creatinine decline by quarter or more in first 24 hours on 2 separate samples |
| Secondary Source of Payment//Secondary | Did patient have any acute rejection episodes between transplant and discharge |
| Previous Transplant Organ 1 | Was biopsy done to confirm acute rejection |
| Previous Transplant Organ 2 | Biological or Anti-viral Therapy |
| Previous Transplant Organ 3 | If Anti-viral check all that apply//If Yes. check all that apply |
| Pretransplant Dialysis | Biological or Anti-viral Therapy1//Specify |
| CMV IgG | Biological or Anti-viral therapy2//Specify |
| CMV IgM | Other therapies |
| HBV Core Antibody | Are any medications given currently for maintenance or anti-rejection |
| HBV Surface Antigen | Did the patient participate in any clinical research protocol for immunosuppressive medications |
| Was preimplantation kidney biopsy performed at the transplant center | Did the px participate in any clinical research protocol for immunization medications//If Yes. Specify |
| Pretransplant blood transfusions//Did patient receive any pretransplant blood transfusions | HIV Serostatus |
| Any tolerance induction technique used | HCV Serostatus |
| Previous Pregnancies | EBV Serostatus |
| Procedure Type | Previous Pregnancies |
| Kidney(s) received on | |
| Received on ice | Graft Status |
| Received on pump | Graft survival period |

TABLE A-II
DISTRIBUTION OF FAILED KIDNEYS OVER THE YEARS

| Graft Survival Period | Number of Instances |
|---|---|
| 1 year (0-12 months) | 71 |
| 2 years (13-24 months) | 26 |
| 3 years (25-36 months) | 24 |
| 4 years (37-48 months) | 16 |
| 5 years (49-60 months) | 13 |
| 6 years (61-72 months) | 16 |
| 7 years (73-84 months) | 13 |
| 8 years (85-96 months) | 10 |
| 9 years (97-108 months) | 7 |
| 10 years (109-120 months) | 9 |
| 11 years (121-132 months) | 8 |
| 12 years (133-144 months) | 1 |
| 14 years (157-168 months) | 5 |
| 15 years (168-180 months) | 1 |
| 17 years (193-204 months) | 1 |
| Graft alive | 1007 |