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Decision Making Support System for Medical Devices' Maintenance Using Fine-tuned kNN Classifier

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Abstract - This paper provides an improved decision support system for selecting the most appropriate maintenance strategy. Manually selecting the best maintenance strategy for medical devices requires a lot of expertise, therefore this paper suggests an efficient automated system based on fine-tuned k Nearest Neighbour classifier. Genetic Algorithm was used to select the best input weights and giving appropriate weights to each maintenance strategy. Several input variables were used that include device price, age, equipment management number, repair cost, availability, and utilisation. Accuracy of the modified k Nearest Neighbour model was compared to several well-known classifiers such as Decision Tree, Support Vector Machine, and Linear Discriminant Analysis based on collected data from 735 unique medical devices. Results shows that the simple yet fine-tuned k Nearest Neighbour model can choose the best maintenance strategy accurately and outperform other sophisticated classifiers.

Index Terms - Medical devices maintenance, k Nearest Neighbour, Genetic Algorithm, Maintenance strategy.

INTRODUCTION

Maintenance can be defined as a collection of activities needed to maintain a given system and its components in a good working condition or restoring the system after failure [1]. Maintenance strategies can be either corrective, preventive, condition based or predictive. Corrective maintenance is performed when sudden system failure occurs to restore the system to operation [2, 3]. Preventive maintenance tries to avoid the failure prior to its occurrence by taking care of the equipment through regular inspection to detect and correct the failures before occurring [3]. In condition-based maintenance, vital data is collected using sensors from the machine while operating. Studying the collected data reflects the machine working condition and therefore the service engineer performs any required actions before failure happens [4, 5]. Predictive maintenance foretells likely failures with the help of statistical tools and tests such as vibration analysis, thermograph, lubrication, and chemical analysis [6, 7].

Healthcare facilities must keep their medical devices in a good working order and maintaining their safety, accuracy, and reliability to provide better services [8]. Thus, the medical equipment management professionals must keep the medical devices in good and safe operational condition to fulfil the mission of the healthcare facility [9]. Inappropriate maintenance can lead to unreliable medical devices and might lead to unnecessary scrapping. The maintenance activity should be checked for applicability and feasibility by taking several factors into considerations such as machine lifetime, status, cost, safety, and priority of the devices. Deciding to replace or repair is also one of the most significant challenges in the maintenance management of medical devices [10]. As the complexity and the cost of biomedical maintenance is increasing particularly in the last decade, special emphasis is required when maintaining medicinal devices [11]. As a result, healthcare facilities have started to apply cost effective and efficient maintenance programs. For example, hospitals in Canada and USA developed a database that collects comparative data on maintenance for most critical devices [12].

Several studies focused on the selection of appropriate maintenance strategy for medical and non-medical equipment. For example, Analytic Hierarchy Process (AHP) was employed in [13, 14] for radiology medical equipment maintenance. A nonlinear integer programming model was used in another study to support the selection of maintenance strategies [15]. A multi-criteria decision-making models was also used to select an adequate maintenance strategy for public building [16]. Other tools such as Decision Tree (DT), Support Vector machine (SVM), Linear discriminant Analysis (LDA) was also used to support maintenance decision-making process [17, 18].

CLASSIFICATION TOOLS

This section will give a brief introduction about the most common classifiers in general. It is worth noting that many other heavy computational classifiers can be used, however using a simple yet accurate classifier is preferable. Therefore, *k* Nearest Neighbour (*k*NN), LDA, SVM, DT will be discussed here.

kNN

A kNN classifier predicts the output class labels depending on the closest training example based on a specific number of closest neighbours (k) [19]. The nearest neighbours measure can be as simple as Euclidean distance (d) between two points $x(x_1, x_2,\ldots, x_n)$ and $y(y_1, y_2,\ldots, y_n)$ in n-dimensional space using the following equation.

$$d = \left(\sum_{i=1}^{n}(x_i - y_i)^2\right)^{1/2}$$

To improve the traditional kNN classifiers weights can be introduce to each dimension (i.e., price, age, etc.) to increase or decrease the effect of certain input [20] and therefore the resulting distance can be represented as

$$d = \left(\sum_{i=1}^{n} w_i(x_i - y_i)^2\right)^{1/2}$$

Where w_i $(w_1,w_2,\ldots, w_n)$ represents the given weight for each input, $0 \leq \boldsymbol{w_i} \leq \mathbf{1}$.

When applying voting schemes, more weights can be given to a specific class (cw $(cw_1,cw_2,...,cw_n)$, Selected maintenance strategy in this case, $0 \leq \boldsymbol{cw_i} \leq \mathbf{1}$). Thus, after finding the k nearest neighbour the resulting distance is modified by applying a specific weighted based on the class of each nearest neighbour. Therefore, favouring certain class over other even if they are further away from the training example.

A. Other Classifiers

A classifier is a tool that can differentiate between available outputs given a set of given inputs. Some are based on very simple concepts such as DT, while others are more sophisticated and require more computational time. Supervised classifiers considered in this study include DT, SVM and LDA.

B. Genetic Algorithm

Genetic Algorithm (GA) is a random population-based search methodology inspired by evolution theories that imply the survival of the fittest. It mimics the idea of creating and evolving a collection of possible solutions (called population) through mating and manipulation operations. The evolution process starts with generating a random population. Each population member (chromosome) is represented by a collection of variables (genes) that relate to the solution [21, 22]. The best members in the population (parents) will have a higher chance to produce a new generation (children) by combining two parents at a time through mixing operation (crossover). Additionally, there is also a small chance to obtain new mutant member through (mutation) operator. This mutant member is created by introducing a small modification to one of the parents [23].

DATA COLLECTION

Information from over 3000 devices was collected from one of Jordan's largest hospitals. The following information was gathered: name, type and model of the device, installation date, and the department in which the device is found. Devices studied include MRI machines, C-arms, CT scans, ICU ventilators, Hemodialysis Machines, Patient Monitors, Defibrillators, Infusion/Syringe Pumps, Anesthesia Machines, Infant Incubators, Electrosurgical Units, etc. This list was shortlisted to 735 devices, having excluded devices that share the same brand and instillation date. Additional variables were collected for the shortlisted devices to include age, price, repairing costs, the availability of alternative devices in case of failure, and the utilization of each device.

Medical Equipment Maintenance number (EM#) was also utilized as an input variable and was calculated as described by Fennigkoh and Smith and Medical Equipment Maintenance Program Overview. EM# as a numerical value is computed based on function (2-10 points, critical function such as life support has higher points), application (1-5 points, risk of potential patient death has higher points), required maintenance (1-5 points, Extensive maintenance has higher points), and history (-2 to 2 points, more frequent failure has higher points). Using those numbers, the EM# is found using the following equation [24, 25]:

EM# = Function + Application + Maintenance + History

Therefore, the data consisted of six input variables representing five maintenance strategies scored based on medical expert maintenance officer.

Each device, depending on its age, EM#, main price cost, spare parts cost, availability, and utilization, was appointed to a maintenance strategy based on expert's opinion (No maintenance attention needed, Routine preventive maintenance, Major preventive maintenance, Corrective maintenance, and Replacement).

PROPOSED METHOD

Although the traditional *k*NN classifier is very simple and has some limitations, its performance can be improved to match other sophisticated classifiers to decide which maintenance strategy best fits a specific medical device. As traditional *k*NN does not take into consideration the level of importance for each device input variable, its performance degraded especially when dealing with different scales for each input. Therefore, input variable should be weighted based on its importance to this specific problem by giving more weights to certain input. Weights should not be assigned randomly and can be obtained directly from on-hand data. For simplicity, any heuristic algorithm will help in finding the best weights assigned for each variable. GA was employed to achieve this optimization problem due its simplicity. This way, the voting scheme in *k*NN classifier can be dramatically improved by giving more weights for a specific class rather than others due to unbalanced data using this proposed modified *k*NN method (*mk*NN).

GA's parameters were selected manually to achieve acceptable results in less time. A visible solution was represented using a chromosome with eleven continuous elements as follow ($w_1,w_2,w_3,w_4,w_5,w_6,cw_1,cw_2,cw_3,cw_4,cw_5$) , where the first six variable represent the weights of each input variable in *k*NN classifier, and the last five variables represent the weights assigned to each maintenance strategy respectively. For example, a chromosome of (*0.5,0.5,0.5, 0.5,0.5,0.5, 0.5,0.5,0.5,0.5,0.5*) is a special case of traditional *k*NN classifier as all inputs have same weights and all maintenance strategy have the same weights when applying the voting scheme. The following GA parameters were used to reduce the computational time but keeping acceptable performance: Population size= 20, Elite children= 2, Iterations= 100, uniform continuous crossover, and uniform mutation.

To test the accuracy of all included methods, patterns' order was randomized at the beginning of each run, then divided into 80% for Training and 20% for Testing; Training data was used to help the classification model in recognizing the patterns within the data by finding the best weights for each input, while the Testing data was used to validate the model on unseen data. This process was repeated for twenty runs to further validate the model.

RESULTS AND DISCUSSION

Training and Testing accuracy for all methods is summarized in the boxplots shown in Figures 1 and 2. Although Traditional *k*NN outperformed all methods in training data (statistically significant difference with α=0.05), it didn't perform well using the testing data due to overfitting (80.95% mean Testing accuracy). On the other hand, *mk*NN outperformed the traditional *k*NN in addition to all other methods (85.09% mean Testing accuracy). *mk*NN was significantly better than traditional *k*NN by 3.5-4.7%. This can be explained by better generalization obtained by fine-tunned weights. Although no significant difference in testing accuracy was found between traditional *k*NN and DT, *k*NN implementation was much simpler as DT required about fifty splits to obtain the achieved results. SVM and LDA performed the worst as they couldn't detect nonlinear relation between input and output variables. After inspecting the resulting GA optimized weight, it is worth noting that price and availability had the least effect on selecting the best maintenance strategy. Similarly, major preventive maintenance was giving the least voting weight to reduce the effect of having more training examples for such maintenance strategy when using the proposed voting scheme.

CONCLUSION

Fine-tuning *k*NN classifier by giving appropriate weight to maintenance strategy and individual input variable (price, age, equipment management number, repair cost, availability, and utilization) provides more robust maintenance decision system. This enables the selection of the best maintenance method based on medical device condition without the need for expert opinion. The proposed *mk*NN classifier accuracy was significantly higher than several other classifiers when applied on relatively large data from medical devices.

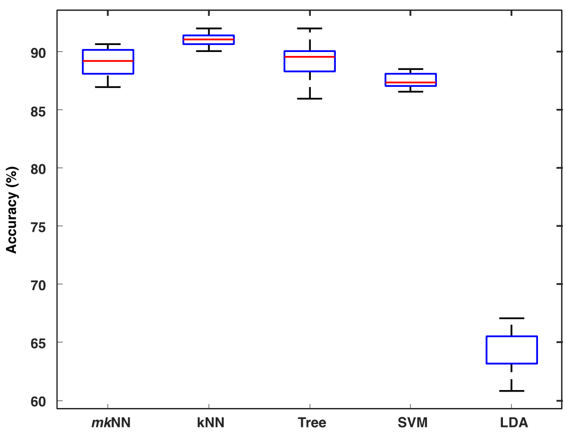

Figure 1: Training Accuracy

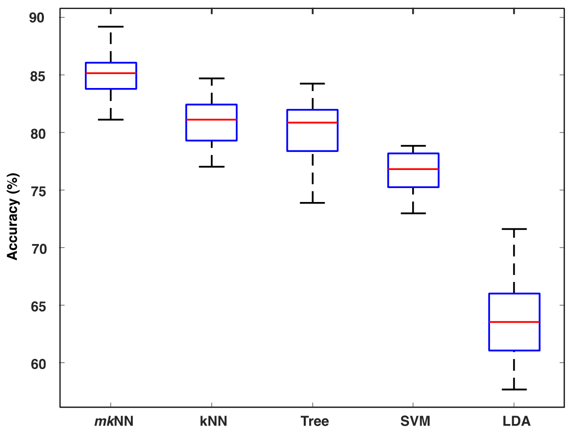

Figure 2: Testing Accuracy.

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