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# On The Use of Decision Tree for Treatment Options in Medical Decision

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***Abstract— Decision making is becoming more complex and stressful for individuals and groups especially for medical professionals as a result of huge quantity of data. This paper is on the use of decision tree for treatment options in medical decision support systems. Decision tree was developed and an algorithm to identify optimal choice among complicated options in Surgery (Medical Operation) and Medical management (Drug Prescription) by calculating probabilities of events and incorporating patient evaluations of possible outcomes based on Average Life Year (ALY). This can help the medical professionals in taking decision among the available choices.***

***Keywords— Machine learning, Decision Tree, Decision making, Surgery, Medical Management, Average Life Year.***

## I. INTRODUCTION

As a result of huge quantity of data, decision making is becoming more complex for individuals and group that are making them. This is where the need for a good decision support technique arises. The decision support system should be able to process those huge data and to help the medical professionals in making their decisions stress-free and more reliably so as to eliminate mismanagement and erroneous diagnosis of patient [11].
Machine Learning (ML) is a branch of Computer Science that is concerned with designing systems that can learn from the provided inputs. Usually the systems are designed to use this learned knowledge to better process of similar inputs in the future.
ML is an area of artificial intelligence that uses algorithms to improve performance over time and to automatically learn programs from data [5]. ML is being used for the analysis of the clinical factor significance and their combinations for the prediction of progression in disease, extraction for outcomes research in medical knowledge, therapy planning and support and general management of patient [14].
The use of ML methods can offer useful aids to assist the physician in many cases, eliminate issues related to human fatigue, provide rapid identification of abnormalities and allow diagnosis in real time. ML is also being used for data analysis, such as clarification of constant data used in the Intensive Care Unit, exposure of consistencies in the data by properly dealing with imperfect data, and for intelligent alarm resulting in effective and efficient monitoring. It is argued that the successful implementation of ML methods can help the integration of computer-based systems in the healthcare environment providing opportunities to facilitate and enhance the work of medical experts and ultimately to improve the efficiency and quality of medical care. In the last decade the use of machine learning has increased rapidly throughout computer science and beyond. ML is used in spam filters, Web search, fraud detection, credit scoring, stock trading, drug design, recommender systems and other applications.
Machine learning methods can be classified as supervised and unsupervised [4]. Supervised methods are trained with labeled data; that is, cases that have known outcomes. Unsupervised methods learn from unlabeled data, and data are grouped based on similarity. Medical errors are both expensive and risky [9]. The death caused by medical errors in U.S hospital each year has increased drastically more than even from cancer, Aids and road accidents combined [19]. The result of the research carried out by the National Patient Safety Foundation founds that about 42 percent of over 100 million Americans believed that they had personally experienced a medical mistake [15].
This paper is organized as follows. Section 2 discusses Decision tree, Section 3 discusses machine learning and its problems. Section 4 discusses related works. Section 5 presents the method used, describes and discusses the validity of the obtained results. And finally, Section 6 concludes the research results.

## II. DECISION TREE

Machine learning (ML) to medical decision making can be describe as tools for solving diagnostic problems in medical fields. Decision tree is one of the most common, consistent, effective, powerful and popular classification and prediction techniques that is used in machine learning process and decision making analysis. It is a clear, measurable, and efficient method to decision making under conditions of uncertainty with a simple illustration of gathered information.
A decision tree is a method that can help in making good choices, especially decisions that involve high costs and risks. Decision trees use a graphic approach to compare competing alternatives and assign values to those alternatives by combining uncertainties, costs, and payoffs into specific numerical values [17]. The automatic learning of decision trees

 

and their use usually show very good results in various "theoretical" environments. Inability to measure quality values, high cost and complexity of such measurements and unavailability of all attributes at the same time are the typical representatives. In medical decision making, there are many conditions where decision must be made efficiently and unfailingly. Conceptual simple decision making models with the possibility of automatic learning are the most appropriate for performing such tasks. Decision tree is one of the most common, consistent, effective, powerful and popular classification and prediction techniques that is used in machine learning process and decision making analysis. It provides high classification precision with a simple illustration of gathered information [17].

## III. MACHINE LEARNING AND ITS PROBLEMS

Machine Learning is the study of techniques for programming computers to learn. Computer applications are wide to range of tasks, and for most of these it is quite easy for programmers to design and implement the necessary software. Machine learning is concern primarily with the accuracy and effectiveness of the resulting computer system. Though, there are many tasks for which this is difficult or impossible [18]. Prediction rules can be learnt from the data recorded by the machine learning system and consequent failure arising from the machine [3]. Secondly, where the human experts are available but are unable to explain their expertise, this is also a problem that makes machine learning difficult or impossible. In tasks such as natural language understanding, hand writing identification and speech recognition, no human being can tell or give details of steps they follow in performing them because of their expert level abilities on these tasks. Coincidentally, humans can provide machines with examples of the inputs and correct outputs for these tasks, so machine learning algorithms can learn to map the inputs to the outputs [18].

Thirdly, there are problems where events changes promptly. Taking finance for instance where the future behavior of the stock market would be predicted and the consumer purchases alongside with the exchange rate. These behaviors often change and if a programmer tries to build a good predictive computer program, such program would constantly be rewritten and frequently modified the learned prediction rule which will definitely become a burden [3].

Finally, since it is not feasible to provide each computer user with a software engineer in order to keep the rule updated, it is not also reasonable to program each user computer to his/her own rules. Considering a program to filter unwanted mail messages, this will be impossible because different users will need different filters. This is to say that there will be customization of each computer users independently which also constitute a problem to machine learning [15].

## IV. RELATED WORKS

We summarized some notable works in Machine Learning application areas in medical decision making.

Lantovics, [13] evaluates the interest of using agents to extend the medical expert systems. According to him several conditions will be checked and resolved by the agent which may be ignored by human and as a result eliminate some mistakes from the physicians' decisions. More specifically, Lantovics proposed a new system for cooperative medical diagnosis called "Contract Net Based Medical Diagnosis System". This latter owns two specific features namely the autonomy and the flexibility during the treatment of medical diagnosis problems. The problem with this proposed system is that, it does do not support the collaboration either with the Computerized Prescriber Order Entry (CPOE) or with the medical Workflow Management System (WfMS).

Laleci et al, [12] proposesd a Clinical Decision Support System (CDSS) called "SAPHIRE". The main objective of this system is to perform clinical guidelines to a patient and support the definition. It is made up of a set of collaborating agents running in a heterogeneous distributed environment. The system has two main benefits. Firstly, there is a specific agent called Electronic Health Record ("EHR agent") that is responsible in accessing and extracting clinical data from electronic healthcare. The second benefit is that the interaction with several modules in the clinical workflow is supported. The main disadvantage of this system is the non-possibility to couple with the CPOE and the use of agent only for the design of CDSS.

Wilk et al, [20] framework is on the various medical conditions that is based on multi-agent system so as to build a comprehensive clinical decision applications. The coupling issue such as CPOE, clinical workflow system, etc. has not been addressed.

Czibula et al, [2] proposesd an intelligent multi-agent system called IMASC designed to assist physicians and other health professionals with decision making tasks. Despite the powerful nature of the system, it does not support the earlier challenges, such as the coupling with CPOE and the active integration in the medical workflow management system.

According to Janecek et al. [10], the scope of his work is limited to the classification problem for progno learning the impact of feature selection on the classification accuracy using a drug discovery dataset and email. In Opitz and Maclin [16], bagging and boosting techniques empirical study was carried out where 23 dataset were presented using neural networks and decision trees. The outcome of their study show that the result obtained by bagging gives better accuracy when compared with each classifiers whereby boosting produces unreliable results.

In Hayward et al. [8], data mining scheme performance with the regression and logical techniques of a cancer patients' clinical dataset were compared. The outcome increases the performance of a classifier as a result of pre- processing the data by attribute selection whereas Meta learning is of little value. The any-time algorithm proposed by Esmeir and Markovitch [6] that mainly performs a brute force enumeration of trees in as much as the algorithm is not interrupted by the users in an attempt to enumerate more promising regions earlier, and prunes unpromising regions of the search space. Conversely, the algorithm does not exploit dynamic programming strategies [6].

Blanchard proposed [1] an algorithm for mining optimal dyadic decision trees. This algorithm functions on numerical data. It creates specific choices with respect to the discretization of the data and the optimization criterion used. It revealed that the generalization error of an optimal tree is bounded by this parameter, while also in practice the resulting trees are sometimes better than trees found by traditional tree learners. A dynamic programming algorithm is used to induce the tree. They show that this algorithm can be seen as one instance of decision tree algorithms, but that the specific choice of constraints makes it impossible to apply certain optimizations, the most important one being that closed item-sets cannot be used when inducing dyadic trees.

## V. METHODOLOGY

The most widely used tool for inductive inference and practical methods is decision tree learning. This is the method that approximate discrete valued functions in which the learned function is derives from a tree.
Every node in the decision tree ascertains a test of some quality of the query instance, and all branches descending from that node matches to one of the possible values for this quality. An instance is classified by starting at the root node of the tree, testing the attribute identified by this node, then moving down the tree branch corresponding to the value of the attribute. This process is repeated for the sub-tree rooted at the new node as long as it takes to reach the appropriate leaf node, then returning the classification associated with this leaf.

### *A. Decision-Making Using Decision Tree*

There are three key symbols in a decision tree: Decision Node is a square box like-shape. The line which runs from the box represents decision alternatives, (a line for each decision alternative). The name of the decision alternative goes on top of the line. Chance Node is represented by an oval shape while the lines from the circle represent the events that might occur at the chance node. The name of the chance driven event goes on top of the line. The third key symbol is the Terminal Node. This is a rectangular shape that represents the outcome state. After this stage, there is no other event that occurs to this node while the result or value of the outcome appears in the rectangle as presented in Fig 1.

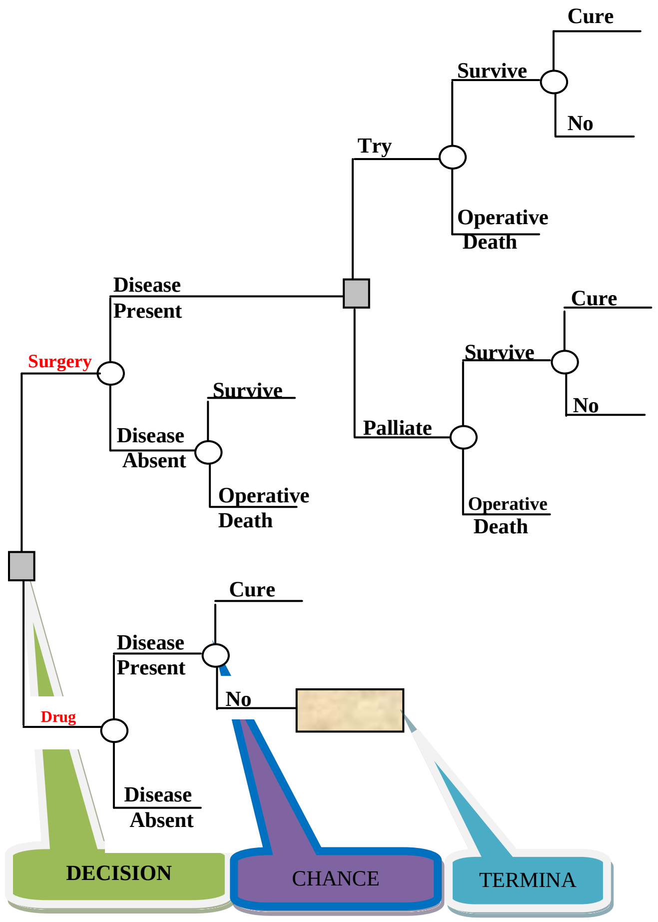


Fig. 1.Decisiontree for medical management versus surgical treatment

### *THE PROPOSED ALGORITHM*

The proposed algorithm for the decision tree for medical management versus surgical treatment is as follows;

*START*
  *ENTER CHOICE "1. DRUG OR 2. SURGERY"*
  *IF CHOICE = 1 THEN*
    *IS DISEASE PRESENT "YES OR NO"?*
    *IF YES THEN*

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        IS THERE CURE "YES OR NO"?
        IF YES THEN
           CURE
        ELSE
           NO CURE – TERMINAL
        ENDIF
   ELSE
        NO DISEASE
   ENDIF
   IF CHOICE = 2 THEN
     IS DISEASE PRESENT "YES OR NO"?
     IF YES THEN
        TRY SURGERY "SURVIVE OR DEATH"?
        IF SURVIVE THEN
             CURE
        ELSE
             NO CURE
        ENDIF
      ENDIF
  TRY PALLIATE "SURVIVE OR DEATH"?
  IF SURVIVE THEN
        CURE
   ELSE
        NO CURE
   ENDIF
 ENDIF
STOP
```

### *B. Evaluating the Decision Tree*

The option that has the greatest worth is worked out in evaluating a decision tree starting by allocating score or cash value to every likely result or outcome. Then assess how much it would cost if that outcome came about, after looking at every circle that is representing an uncertainty opinion and estimate the possibility of each outcome. When a percentage is used, the sum total must add up to 100% at each circle as shown in Fig. 2 while a fraction should add up to 1.

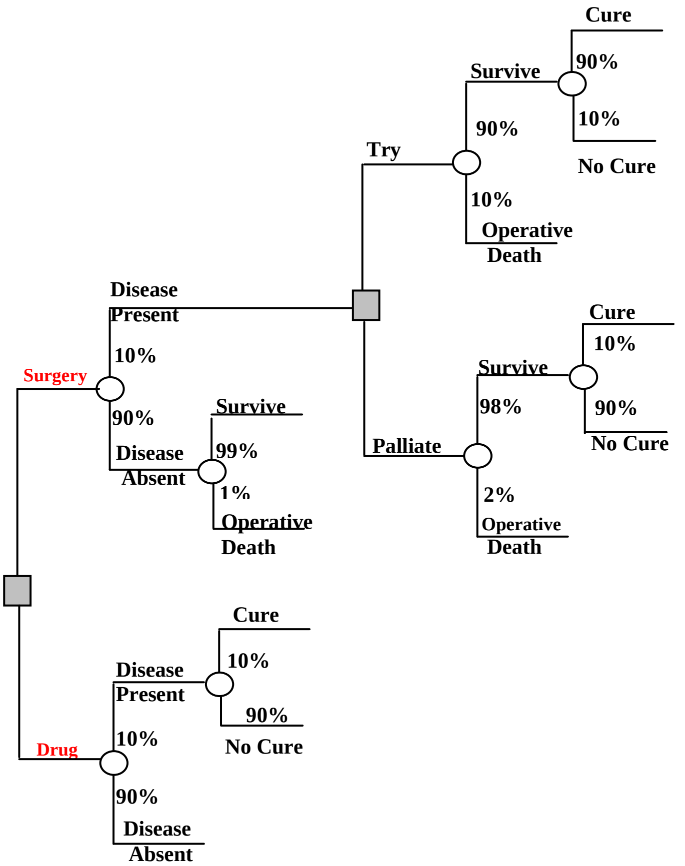


Fig. 2. Evaluated decision tree for medical management against surgical treatment

### *C. Calculating Tree Values*

After the value of the outcomes are worked out, and have been evaluated the probability of the results of uncertainty, then start calculating values that will assist in decision making. Also assign a value at each end point to the outcome presented in Fig. 3. Start on the right hand side of the decision tree, and continue to calculate back to the left. When a set of calculation has been completed on the node, record the result then ignore other calculations which lead to the outcome from then on.

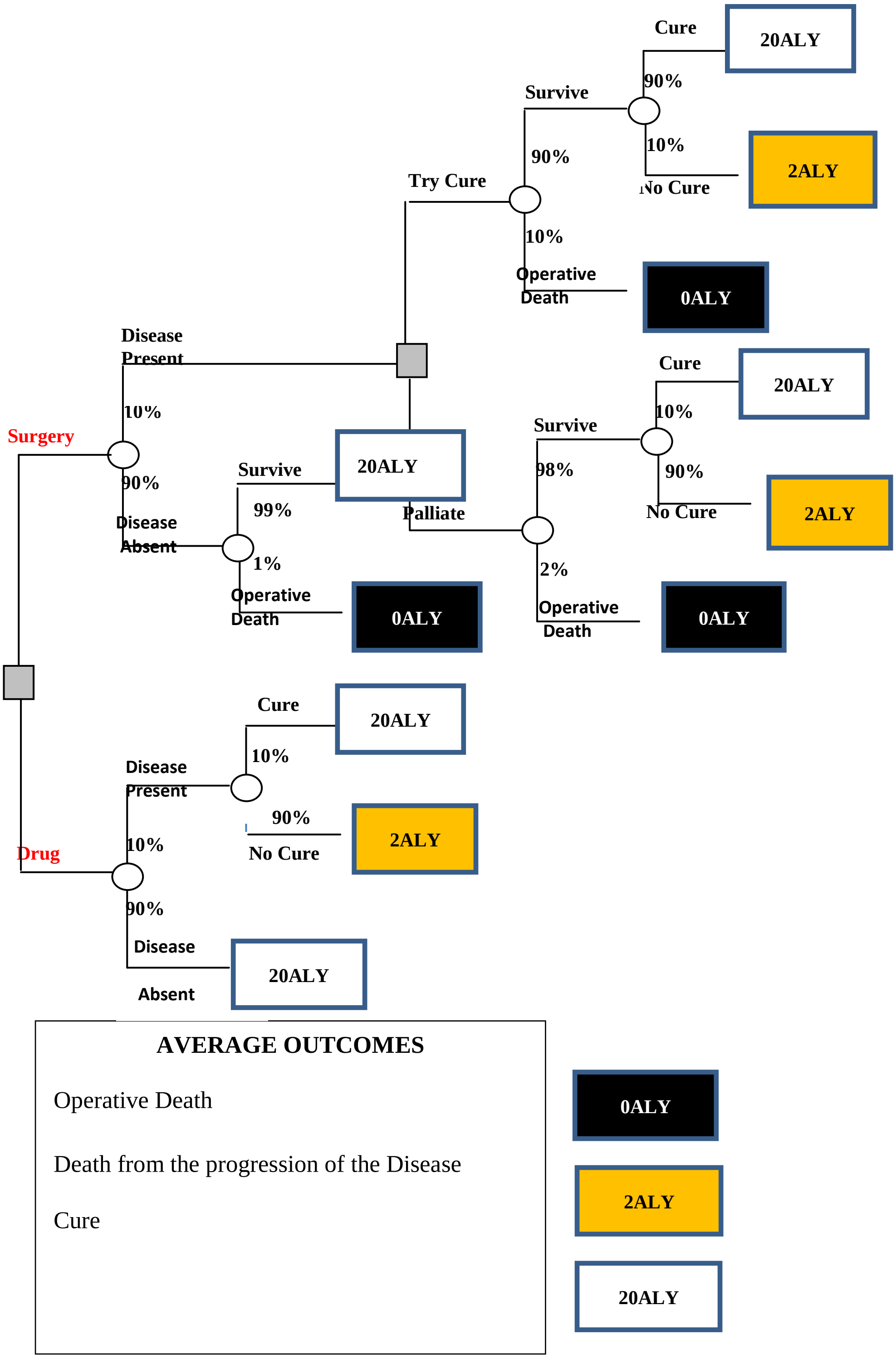


Fig. 3. Decision tree for medical management against surgical treatment with their average life year (ALY) values

### *D. Calculating the Value of Uncertain Outcome Nodes*

When the value of the uncertain outcome is calculated is the same as calculating the value of uncertain outcomes (circles on the diagram), do this by multiplying the value of the outcomes by of these values. Working from right to left of Fig. 4.

 

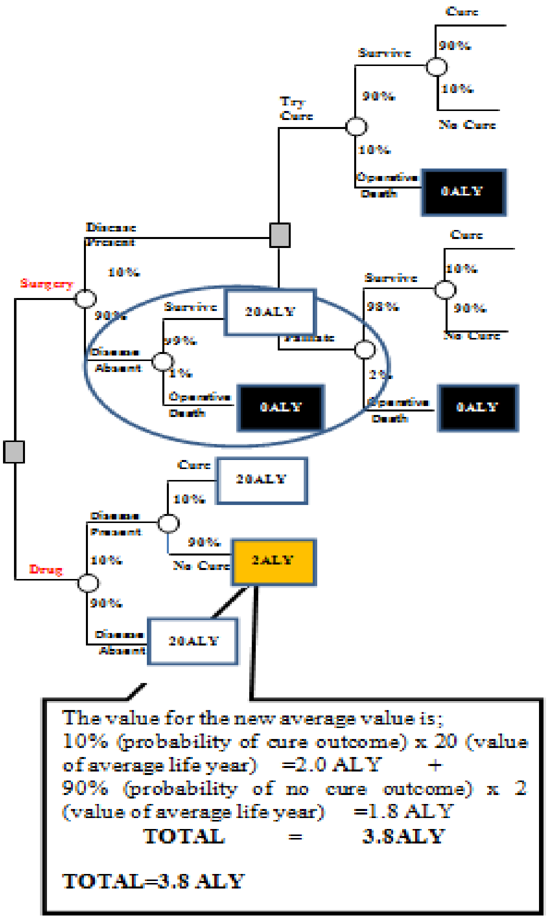


Fig. 4: showsthecalculationofuncertainoutcomenode

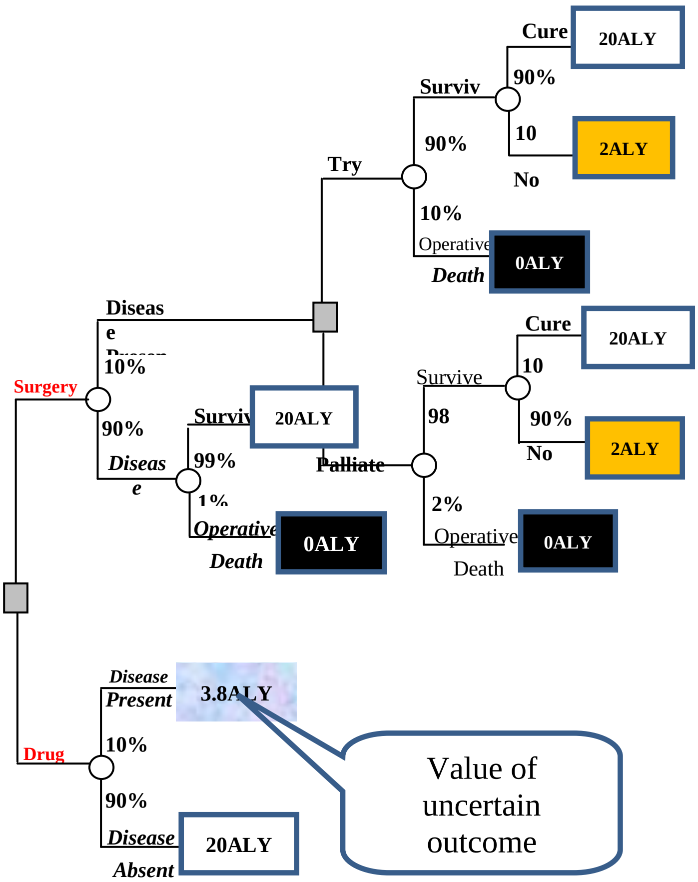


Fig. 5 shows the value of uncertain outcome by replacing the chance nodes with the average.

Continue to calculate and replacing the next chance node with the average until final decision node of the two choices is reached as seen in Fig. 6.

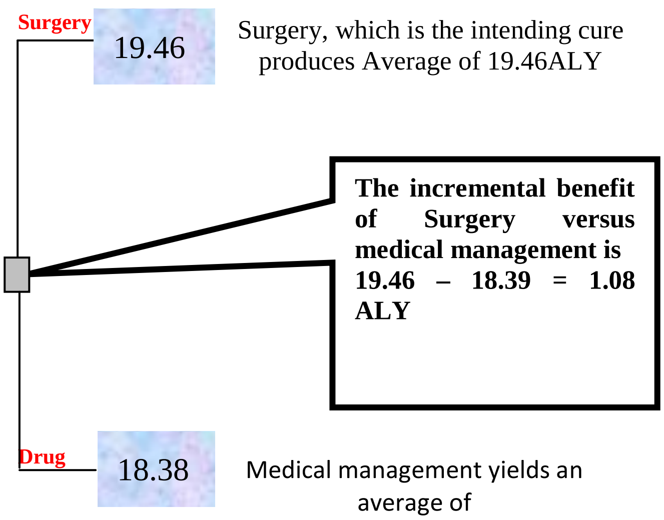


Fig. 6: Decision Tree result of Surgery against Medical Management

The outcome of each decision is more apparent now. The final decision node of the two choices shows the incremental benefit of Surgery against Medical Management as 19.46 – 18.39 = 1.08 ALY. The benefit of using decision tree makes the decision very clear, measurable and efficient.

This decision analysis can be repeated using other outcome measures instead of just using average life years. Expected value (EV) can also be used since it measures the relative advantage of decision alternatives.

EVChance Node =EVBranch1 + EVBranch2 + … + EVBranchN.

It is a mathematical combination of Payoffs and probabilities. One of the significance of the decision tree model is the transparent nature it possessed. Comparing it to other models, it makes explicit of all possible alternatives and traces every alternative to the final conclusion in a single view which allow for simple judgment among several alternatives.

## VI. CONCLUSION

Many choices that are made by people are usually made without considering the decision making process thoroughly. Decisions can be made under time constraint that will affect careful attention of the choices and the consequences. Decisions could possibly be swayed by the emotional state of a person at the time such decision is being made. When adequate information is lacking, less than best decisions is likely to be made. Even in situations where time and information is available they often do a poor job of understanding the probabilities of consequences. The ultimate concerns of decision making are merging information about probability with information about needs and benefits. The use of Machine learning (ML) to medical decision making offers techniques, and tools that can help to solve diagnostic problems in a variety of medical fields. The use of ML methods can offer useful aids to assist the physician in many cases, eliminate issues related to human fatigue, provide rapid identification of abnormalities and allow diagnosis in real time.

## REFERENCES

[1] G. Blanchard, C. Schafer, Y. Rozenholc, and K. R. Müller, “Optimal dyadic decision trees”, Mach Learn 66(2–3):209–241, 2007

[2] I. G. Czibula, G. S. Cojocar, and A. M. Guran, “IMASC – An Intelligent MultiAgent System for Clinical Decision Support”, Proceedings of the First International Conference on Complexity and Intelligence of the Artificial and Natural Complex Systems, pp.185-190, 2009.

[3] T. G. Dietterich, Pedro Domingos, Lise Getoor, Stephen Muggleton and Prasad Tadepalli, “Structured machine learning: the next ten years”, Springer Science Business Media, LLC, DOI 10.1007/s10994- 008-5079-1, 2008.

[4] R. O. Duda, P. E. Hart, and D. G. Stork, “Pattern Classification”, Second Edition. Wiley- Interscience, 2001

[5] M. H. Dunham, “Data Mining: Introductory and Advanced Topics”, Prentice Hall, 2003.

[6] S. Esmeir, and S. Markovitch, “Anytime learning of decision trees”. Jounal of Machine Learning Research 8:891–933, 2007.

[7] J. Hall, “First, make no mistakes”. The New York Times. New York, 2009.

[8] J. Hayward, S. Alvarez, C. Ruiz, M. Sullivan, J. Tseng, and G. Whalen, “knowledge discovery in clinical performance of cancer patients”. In IEEE international conference on Bioinformatics and Biomedicine, USA, pp 51-58, 2008.

[9] HealthGrades, (2009). Sixth Annual Patient safety in American hospitals Study.

 

[10] A. G. K.Janecek, W. N. Ganster, M. A. Demel, and G. F. Ecker, "on the relationship between feature selection and classification accuracy", Journal of machine learning and research 4" 90 -105, 2008.

[11] B. Kavishwar, Wagholikar, Vijayraghavan Sundararajan and W. Ashok Deshpande, "Modeling Paradigms for Medical Diagnostic Decision Support: A Survey and Future Directions", Journal of Medical Systems 36 (5), 2012.

[12] G. B. Laleci, A. Dogac, M. Olduz, I. Tasyurt, M. Yuksel, and A.Okcan, "SAPHIRE: A Multi-Agent System for Remote Healthcare Monitoring through Computerized Clinical Guidelines", in Agent Technology and e-Health, pp. 25-44, 2008.

[13] B. Lantovics, "Cognitive Medical Multi-agent Systems", in Broad Research in Artificial Intelligence and Neuroscience, Volume 1, Issue 1. 2010.

[14] Z. Laurence Rubenstein and R. Karen Josephson, "Falls and Their Prevention in Elderly People: What Does the Evidence Show?" Med Clin N Am 90 (2006) 807–824

[15] Louis and Harris Associates, "100 million Americans see medical mistakes directly touching them as patients, friends, relatives", National Patient Safety Foundation, 2007.

[16] D. Opitz, and R. Maclin, "popular ensemble methods: an empirical study. Journal of Artificial intelligence research 11", 169-198, 1999.

[17] R. Olivas, "Decision Trees A Primer for Decision-making Professionals", 2007.

[18] J. Ray Solomono, "Machine Learning: Past and Future", Computer Learning Research Center Royal Holloway, University of London IDSIA, Galleria, 2009.

[19] R. SoRelle, "Reducing the rate of medical errors in the United States". Circulation 101(3): E39-40, 2000.

[20] S. Wilk, W. Michalowski, and D. O'Sullivan, "Engineering of a Clinical Decision Support Framework or the Point of Care Use", in AMIA'08 Symposium Proceedings, page – 814. 2008.

 