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Data Mining Algorithms for Pharmacovigilance

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Abstract: In this paper, various data mining algorithms for pharmacovigilance is analyzed and a decision support system for hospital is proposed.. Overall analysis of adverse events of a specific drug helps in finding the potential danger of using the specific drug. Decision support system with good classification accuracy to improve its use in hospital for computer aided diagnosis by doctors is also analyzed,

Index Terms: Pharmacovigilance, Adverse event, classification accuracy, computer aided diagnosis.

I. INTRODUCTION

Data mining deals with extracting meaningful patterns from huge datasets using hybridized method involving computational intelligence, artificial intelligence and statistics[1]. Medical data mining deals with classification techniques using medical datasets [2] that improves the quality of computer aided of health services. Figure 1 shows the decision support system used in hospitals.

Pharmacovigilance(PhV) aims at the best use of medicine to cure the disease[3] with no adverse effects and World Health Organization (WHO) defines it as "the science and activities relating to the detection, assessment, understanding and prevention of adverse effects or any other possible drug-related problems" [4]. PhV must "promote and protect public health by reducing burden of ADRs and optimizing the use of medicines".

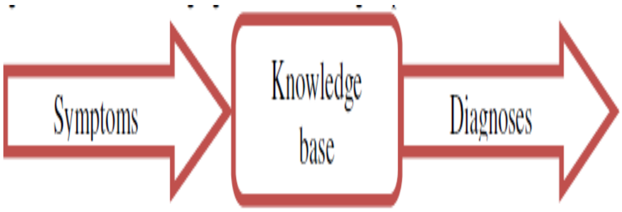

Fig. 1a Decision support system

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systems

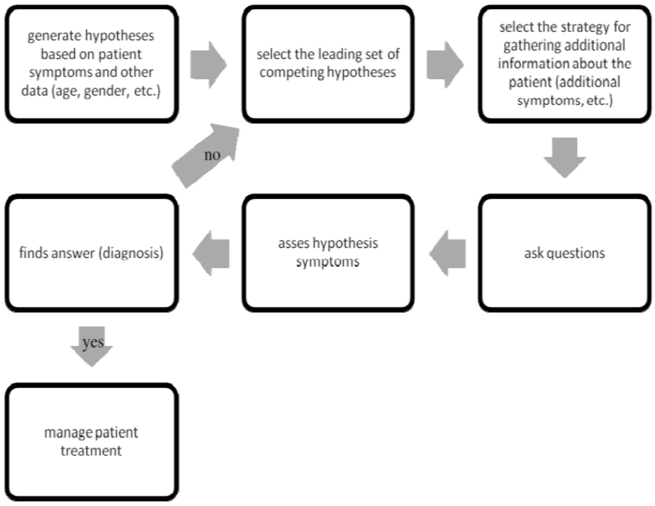

Figure 1(b) Hypothesis based decision support system

II. PREVIOUS WORK

Clinical Decision Support System is an approach where we give the application the required features about any specific disease in which we train the algorithm to predict whether the patient has that disease or not[5-10]. This Clinical Decision Support System plays a major role in today's busy life where time has become a major issue and also seriousness of the disease can be found immediately and necessary actions can be taken to cure the disease[11-14]. Also, in some of the cases we can avoid the unnecessary tests which are performed to find whether the disease is present or not[15-23].

A classification technique based Artificial Neural Network[24] is designed with Back Propagation Network and Cascaded Correlation Neural Network and got accuracy of 79.45%. A feature selection based on Convolutional Neural Network and classification is designed based on Deep Belief Network [25-26] and got accuracy of 90%. A feature selection based on Entropy Ensemble of Neural Networks[27] is designed with Recursive Feature Elimination and better results are achieved . Classification was based on Support Vector Machine with Recursive Feature Elimination and got an accuracy of 85.66%[28].In [29] classification based on Deep Belief Network was designed and got accuracy of 83.9%. Table 1 shows some important class of drugs and its adverse effects.

Table 1 Drugs and its effects

Class of Drugs	Effects
Tetracycline	Poor absorbtion of tetracyclines
Amino glycoside	Hearing problem, kidney problem
Anti diabetic	Lower blood sugar
Warfarin	Increased risk of bleeding
Phenytoin	CNS and Respiratory depression
Barbiturates	Muscle weakness,Reduced consciousness, coma
Lithium	Hypothermia
Alprazalon, Diazepam	CNS depression, sedation
Warfarin	Haemorrhage
Methotrexate	Bone marrow suppression
Benzodiazepines	Sedation and Respiratory suppression
Ethanol	Additive CNS effect, Death
Predmisone	Edema
Theophyllines	Insomnia, seizures, restlessness
Miconazole	Severe hypoglycaemia

III. KNOWLEDGE BASED DECISION SUPPORT SYSTEM

Figure 2 shows the knowledge based decision support system where problem specific knowledge is used for decision making. The flowchart of choice based implementation of DSS is shown in figure 3. The usage of medical DSS in hospitals is shown in figure 4.

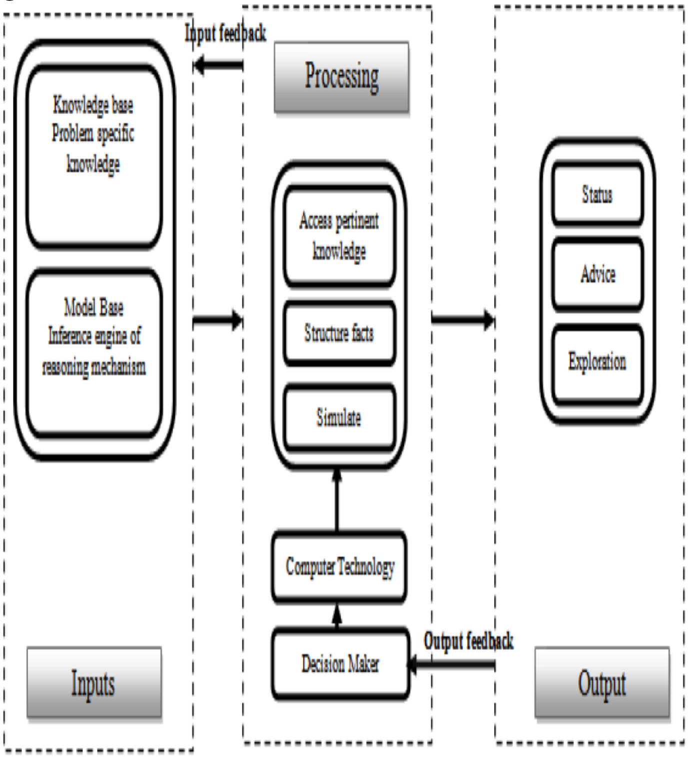

Fig 2 Knowledge based DSS

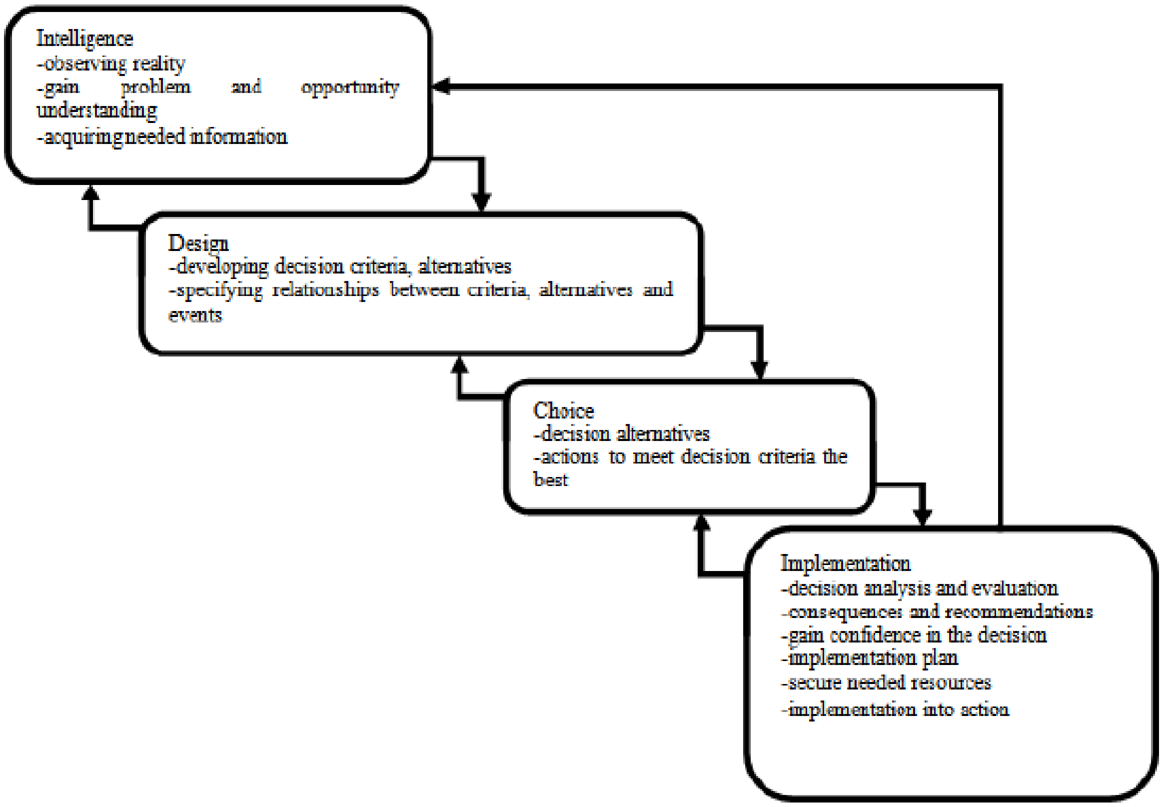

Fig 3 Implementation of DSS

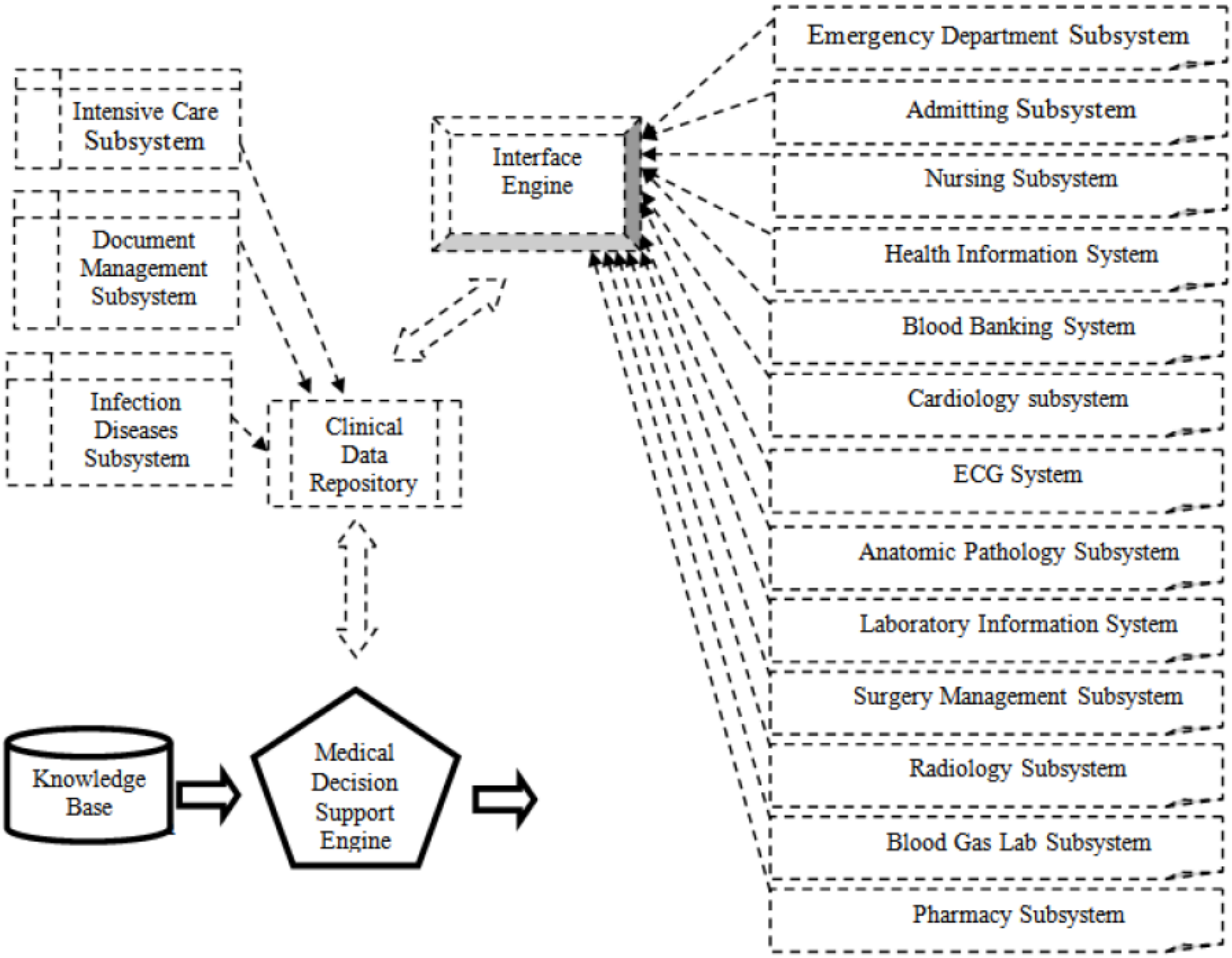

Fig 4 DSS for hospitals

IV DATA MINING ALGORITHMS

Many data mining algorithms are used for Pharmacovigilance purpose and two important algorithms are analyzed in this work

Given: $Sampl$ – the set of training examples ($Sampl \subseteq T$, T is decision table), d_k- the attribute which value is to be predicted by the tree, $S = \{s_1, ..., s_I\}$ the set of symptoms

Results: The decision tree $Tree$

BEGIN

1. For $1 \leq k \leq K$ compute decision frequencies $freq(d_k, Sampl)$
2. If all cases in $Sampl$ belongs to the same class d_k set the node is a leaf with associated class d_k.
3. Else set as a node the most frequent class d_k, and count the classification error a of the leaf is the weighted sum of the cases in $Sampl$, whose class is not d_k.
4. For $s_i, i \in (1, I)$ count $Gain(Sampl, s_i)$
5. Set $s_g := s_i$ the attribute with the highest $Gain(Sampl, s_i)$
6. If s_g is continuous find $Threshold$
7. For each $Sampl'$ in the splitting of $Sampl$ DO 8-9
8. If $Sampl' = \emptyset$ set as a child of s_i is a leaf
9. Else below this new branch add the subtree C4.5 for d_k and $S = \{s_1, ..., s_I\} \backslash s_g$
10. Compute errors of s_g

Given: $Sampl$ - the set of training examples ($Sampl \subseteq T$, T is decision table), d_k- the attribute which value is to be predicted by the tree, $S = \{s_1, \ldots, s_l\}$ the set of symptoms

Results: The decision tree $Tree$

BEGIN

1. If all examples are positive, Return the single-node tree $Root$, with label = + END
2. If all examples are negative, Return the single-node tree $Root$, with label = - END
3. If number of predicting attributes is empty, then Return the single node tree $Root$, with label = most common value of the target attribute in the examples END
4. Set $s_g := s_i$ the attribute with the highest $Gain(Sampl, s_i)$
5. Set s_g as a $Root$ of the decision tree
6. For each $v \in Values(s_g)$ DO 7-10
7. Add a new tree branch below Root, corresponding to the test $s_g = v_i$.
8. Let $examples(v_i)$, be the subset of examples that have the value v_i for s_g.
9. If $examples(v_i)$ is empty Then below this new branch add a leaf node with label = most common target value in the examples END
10. Below this new branch add the subtree ID3 ($examples(v_i)$, d_k, $S = \{s_1, \ldots, s_l\} \setminus s_g$)

END

Return $Root$

V CONCLUSIONS

In this paper, decision support systems used for treatment is analyzed and an architecture used in hospital for decision making is proposed. As pharmacovigilance has become an important research area as on date, some important commonly used drugs and its effects are tabulated. Data mining algorithms used for Pharmacovigilance is also analyzed. Future work will be to enhance the algorithms for effective pharmacovigilance.

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AUTHOR PROFILE

Kamatchi Sankar profile which contains their education details, their publications, research work, membership, achievements, with photo that will be maximum 200-400 words.

Latha Parthiban profile which contains their education details, their publications, research work, membership, achievements, with photo that will be maximum 200-400 words.