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Overcoming Barriers to Development of Cooperative Medical Decision Support Models

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Abstract –Attempts to automate the medical decision making process have been underway for the at least fifty years, beginning with data-based approaches that relied chiefly on statistically-based methods. Approaches expanded to include knowledge-based systems, both linear and non-linear neural networks, agent-based systems, and hybrid methods. While some of these models produced excellent results none have been used extensively in medical practice. In order to move these methods forward into practical use, a number of obstacles must be overcome, including validation of existing systems on large data sets, development of methods for including new knowledge as it becomes available, construction of a broad range of decision models, and development of non-intrusive methods that allow the physician to use these decision aids in conjunction with, not instead of, his or her own medical knowledge. None of these four requirements will come easily. A cooperative effort among researchers, including practicing MDs, is vital, particularly as more information on diseases and their contributing factors continues to expand resulting in more parameters than the human decision maker can process effectively. In this article some of the basic structures that are necessary to facilitate the use of an automated decision support system are discussed, along with potential methods for overcoming existing barriers.

I. Introduction

The concept of computer-assisted medical decision making was first envisioned in the 1960's and 1970's [1,2]. Since that time numerous systems have been explored based on a variety of approaches. Also during this timeframe many aspects of medical care have come to rely on computers, including sophisticated advances in medical signal analysis, medical imaging, and electronic health records. Electronic medical records are quickly becoming the norm, although standardization of these records has not yet occurred [3]. In spite of these advances, the potential for using automated methods to assist in medical decision making has not become a reality. In this article, automated methods are outlined that can assist the physician in the decision making process. However, many barriers remain. Possible solutions for removing these barriers are analyzed, along with discussion of areas that require further development. Practical use of automated models is not only tied to the accuracy of the models and their effectiveness, but also to acceptance by the medical practitioner.

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The optimal use of information technology to assist in medical decision making has not yet been realized. Numerous obstacles must be overcome, including the universal use of electronic medical records, development of sophisticated disease models for a broad range of conditions, and the ability to include complex data types in the automated analysis, specifically signal analysis [4] and imaging [5]. The continuing development of signal analysis methods, including electrocardiograms, electroencephalograms, electromyograms, and others have enhanced diagnostic capabilities, becoming increasingly more sophisticated since the first the electrocardiogram a century ago [6]. Beginning in the 1970's imaging technology expanded from the simple radiograph [7] to computed tomography, followed shortly by magnetic resonance imaging and fMRI imaging. While these developments have drastically changed diagnostic methods, they remain the most difficult to include in an automated system. Thus two major obstacles must be overcome to facilitate the use of automated decision making. The first obstacle is the lack of standard formats for the medical record [8]. The second is the handling of special data types, in particular signal analysis and imaging [9]. These barriers are discussed in the following section along with potential solutions.

II. Methodology

A. Barriers

Barrier 1: Comprehensive Personal Health Record

The ultimate goal of electronic health records is the collection of data for a person's entire lifetime. This personal health record (PHR) would permit diagnosis and treatment based on the individual rather than on population statistics. Statistics show that the average person moves five times in his or her life. Thus the health record must be portable. This portability can be achieved by either a standardized record format or through the use of HL7 or some similar coding standards so that the data items can be properly identified [10].

Barrier 2: Definition of Disease Models

Automated analysis requires the definition of a broad range of disease models. Development of these models requires teams that include physicians and other health care professionals with deep knowledge of the specific domain working with bioengineers and other IT professionals. The use of large de-identified databases of patients for specific diseases has been shown to be useful in model development [11].

Barrier 3: Model updating

The definition of disease models is not a static process. When more evidence becomes available a seamless method must be established for updating existing models and creating new models when necessary.

Barrier 4: Acceptance

Both healthcare professionals and patients must have confidence in the automated analysis process and be willing to use it as one input in the diagnostic process.

Figure 1 illustrates the components of a comprehensive automated decision making model [12]. Most components currently exist in some form, while others require further development before becoming effective diagnostic tools.

B. Solution Components

1. Health Records

A number of hospital-based electronic health records (EHRs) have been adopted for widespread use, including EPIC [13]. However, there is no current agreement on formats of EHRs. The methods and examples given in this section assume that a standardized medical record does not exist but that HL7 standards are used for transfer of data among institutions. While the adoption of EHRs is becoming widespread, the existence of the personal health record that contains all information from birth is not yet readily available. To make the PHR a reality, health records must be interoperable among institutions and methods must be implemented to combine a patient's information that is currently contained in separate records [14]. Personalized medicine will rely on the existence of the lifetime PHR for each patient.

2. Disease Models

The development of comprehensive disease models relies on many components that vary by disease. However, common elements can be defined:

- *a vector* $\boldsymbol{d}_j$ *that contains the position number of all relevant parameters for disease j*
- *disease algorithm that determines one or more of the following:*
    - *Presence of disease j*
    - *Absence of disease j*
    - *If disease j was previously present:*
        - *Evidence of improvement*
        - *Evidence of worsening*
        - *No change*

Sources of information for developing disease models include expert input, clinical studies, literature searches, and analysis of large data bases. Genetic components will become increasingly important as analysis of the human genome advances.

3. Methods/Algorithms

Multiple algorithmic approaches are needed to develop comprehensive disease models. In many cases hybrid approaches are required. Model types include knowledge-based approaches, machine learning from disease-specific data sets, data mining methods, and special approaches for complex data types. Each of these methods requires data from databases, data repositories, research studies or clinical input. In order to achieve the goal of automated decision making a wide-based collaboration is necessary. Specific methods are listed below.

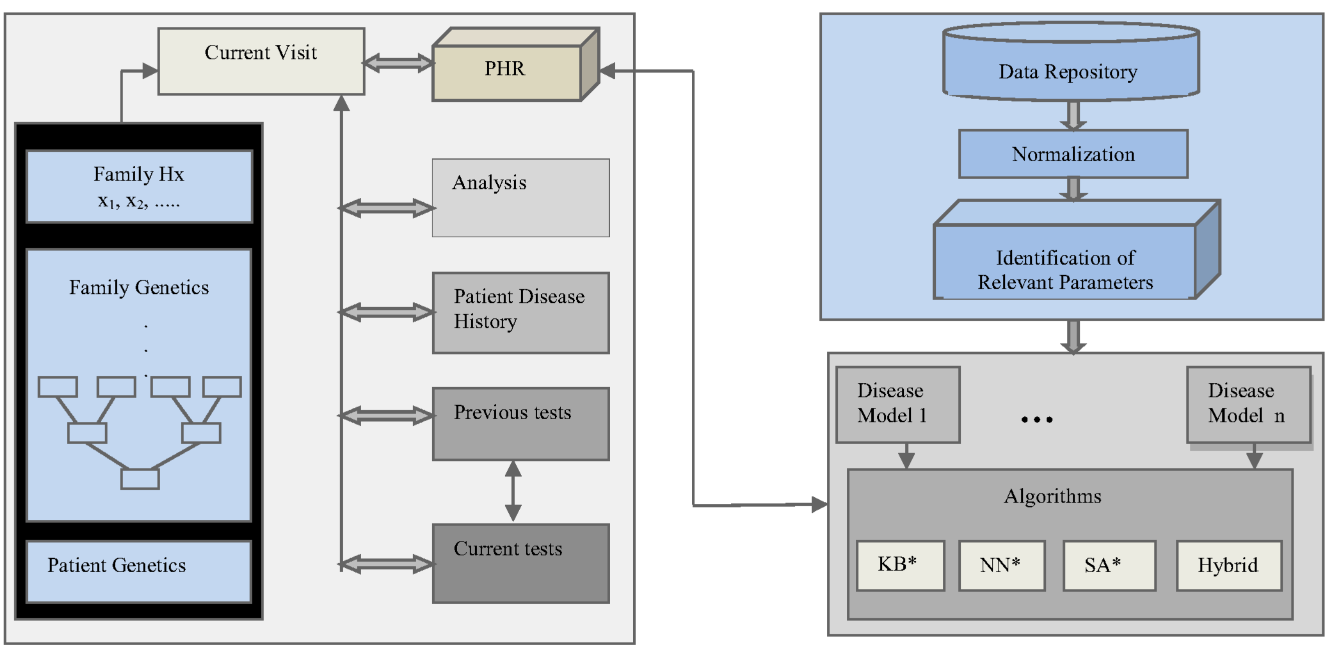

Figure 1: Required Components for Automated Diagnosis
*KB: Knowledge Based Analysis, NN: Neural Network Analysis, SA: Signal Analysis [12]

Knowledge-Based Approaches

The knowledge-based approach is based on the approximate reasoning version of EMERGE [15] to include nuances that were not possible in rules defined by AND/OR statements. An approximate reasoning approach uses the combination of weighted antecedents along with the partial substantiation of each antecedent. Values for each the w_i must be determined by either expert input or by learning methods using appropriate databases. The values for the a_i's are obtained through automated processing of symptoms and test results. A threshold is established that reflects the level of evidence required for substantiation.

Antecedent	Weighting Factor	Degree of Substantiation
1	w_1	a_1
2	w_2	a_2
.		
.		
.		
n	w_n	a_n

Condition confirmed if S > threshold T where

$$S = \sum_{i=1,n} w_i a_i \tag{1}$$

Machine Learning

A number of machine learning methods exist based on different theoretical approaches. A neural network method developed by the authors, Hypernet, is based on a potential function approach defined by the equation:

$$P(x,x_k) = \sum_{i=1}^{\infty} \lambda_i \Phi_i(x) \Phi_i(x_k) \tag{2}$$

for k = 1,2,3..., where $\Phi_i(\mathbf{x})$ are orthonormal functions and the λ_i s are non-zero real numbers. The orthogonal functions of mathematical physics may be used as potential functions. P_1 is computed by substituting the values from the first feature vector for case 1, $\mathbf{x}_1$. Subsequent values for P_k are then computed by

$$P_k = P_{k-1} + r_k P(\mathbf{x},\mathbf{x}_k) \qquad \text{where} \tag{3}$$

$$r_k = \begin{cases} 1 & \text{If } P_i < 0 \text{ and class 1} \\ -1 & \text{If } P_i > 0 \text{ and class 2} \\ 0 & \text{If } P_i > 0 \text{ and class 1 or } P_i < 0 \text{ and class 2} \end{cases}$$

The functions used in Hypernet are chosen from the set of multidimensional orthogonal functions developed by the authors [16].

Handling of Complex Data

One of the major difficulties is the development of algorithms for signal analysis and imaging data. An approach for signal analysis is based on chaos theory.

Chaotic Analysis of Time Series

The logistic equation is one of the best known of the chaotic functions:

$$a_n = A\, a_{n-1}(1 - a_{n-1}) \qquad 2 \le A \le 4 \tag{4}$$

An approximate solution obtained by the authors for continuous values show that in fact the chaotic behavior of the logistic function is not apparent when viewed as a continuous, and not as a discrete, model except in the narrow mathematical definition. The continuous solution is

$$a_n = ½ [1 - T_{2^n}(1-2a_0)] \tag{5}$$

where $T_n(x)$ is the Chebyshev function and n is assumed to be a real number (17).

One method of numerically describing the data distribution is through the use of the central tendency measure (CTM), computed by selecting a circular region around the origin of radius r, counting the number of points that fall within the radius, and dividing by the total number of points. Let t = total number of points, and r = radius of central area. Then

$$CTM = [\sum_{i=1}^{t-2} \delta(d_i)]/(t-2) \tag{6}$$

where
$$\delta(d_i) = \begin{cases} 1 & \text{if } [(a_{i+2}-a_{i+1})^2+(a_{i+1}-a_i)^2]^{.5} < r \\ 0 & \text{otherwise} \end{cases}$$

This method is useful for detecting patterns in lengthy time series, such as 24-hour Holter electrocardiogram recordings.

Hybrid Systems

In many cases a combination of methods is necessary resulting in the use of hybrid systems. As disease models increase in complexity to better represent the disease profile the need for a hybrid approach will increase.

3. Cooperative Medical Decision Making

Currently many researchers are working on the development of disease models. Although some cooperative efforts are underway, the cooperative approach must be expanded to provide larger data sets and combined methodologies that are capable of addresses complex disease models [18]. Methods must be established to facilitate the development of multi-group solutions to model development. Approach is (***put in text)

Learning from Databases

One approach is to cooperative decision making is the use of streaming data from multiple institutions. These combined data sets are first a

4. Missing Components

In addition to wide-spread development of disease models, other components are needed. These include methods for standardizing data values from different instruments, developing methods of updating models when new information becomes available, and finally gaining acceptance and confidence in the medical community.

III. Results and Examples

A patient case is presented based on automated analysis using the methods described above. Patient Scenario: Patient X reports with: chest pain, shortness of breath.

Step 1: Rule out Myocardial Infarction (MI) (Rule-Based System) [19]

Rule for Chest Pain/MI	w_i	a_i
BP < 100/60	0.5	0.6
Abnormal mental status	0.1	0.1
Cold, clammy skin	0.1	0.1
Gray, cyanotic skin	0.1	0.1
Weak peripheral pulses	0.1	0.3
Urinary output < 30 cc/hr	0.1	0.6
Then Possible MI	T 0.6	

Sum = 0.5x0.6 + 0.1x0.1 + 0.1x0.1+0.1x0.1 x 0.1x0.3 x0.1x0.6 = 0.48

Results Sum < 0.6,
MI not confirmed, investigate possible CHF

Step 2: Rule out Congestive Heart Failure (CHF) (CTM measure for Holter data) [20]
(CTM > 90, negative, 60 – 90, uncertain, < 60 CHF)

CTM = 0.75, possible CAD
Examine clinical data

Step 3: Rule out coronary artery disease (Hybrid Neural Network Model/CTM Model) [21]

x_1	Abnormal Holter ECG	0.75
x_2	Dyspnea	0.25
x_3	Orthopnea	0.10
x_4	Edema	0.40
x_5	Functional impairment	0.10
x_6	PND	0.10
x_7	BUN	0.05

(Values normalized to the interval [0,1].

Previous trained neural network is run with the above data

$$D(\boldsymbol{x}) = \sum_{i=1}^{7} w_i x_i + \sum_{i=1}^{7} \sum_{\substack{j=1 \\ i \neq j}}^{7} w_{i,j} x_i x_j \tag{7}$$

CHF not confirmed, follow-up in 6 mo. Recommended.

IV. Conclusion

The development of comprehensive medical decision support systems is both a technical challenge and an organizational challenge. Many research endeavors need to be combined to develop effective disease models. These models will rely not only on technical advances but also on the accumulation of large de-identified data sets both for model development and testing. While some of these efforts are underway, much more remains to be done. The secon vital piece is th existance of the personal health record that contains a lifetime of information for the patient. These two advances taken in tandum can change the current healthcare paradigm that relies on population statistics for diagnosis, treatment, and prognosis. The barriers enumerated in this article must be addressed to form the basis necessary for creation of a new diagnostic paradigm.

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