

Computers and Biomedical Research

AN INTERNATIONAL JOURNAL

*Official Publication of the American Medical
Association's Association
College of Medical Informatics*

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Computers and Biomedical Research
Volume 25, Number 6, December 1992

CONTENTS

A. VERDAGUER, A. PATAK, J. J. SANCHO, C. SIERRA, AND F. SANZ. Validation of the Medical Expert System PNEUMON-IA	511
CHRISTOPHER J. WILLIAMS AND JOE C. CHRISTIAN. Plots for Examination of Univariate Twin Data	527
L. EDENBRANDT, Z. R. ZENG, A. EDENBRANDT, C. MÅNSSON, L. SÖRNMO, AND S. B. OLSSON. Reconstruction of the Electrocardiogram during Heart Surgery	538
DEAN F. SITTING AND JOSEPH A. ORR. A Parallel Implementation of the Backward Error Propagation Neural Network Training Algorithm: Experiments in Event Identification	547
DAVID L. HORN, JAI RADHAKRISHNAN, SURINDER SAINI, GARY M. PEPER, AND STEPHEN J. PETERSON. Evaluation of a Computer Program for Teaching Laboratory Diagnosis of Acid-Base Disorders	562
G. COPPINI, R. POULI, M. RUCCI, AND G. VALLI. A Neural Network Architecture for Understanding Discrete Three-Dimensional Scenes in Medical Imaging	569
JAMES F. FRIEBS. The Chronic Disease Data Bank Model: A Conceptual Framework for the Computer-Based Medical Record	586
AUTHOR INDEX FOR VOLUME 25	602



0010-4879(199212)25:6-P

Vol. 25, No. 6, December 1992

COMPUTERS AND BIOMEDICAL RESEARCH

Pages 511-603

ACADEMIC PRESS, INC.

Validation of the Medical Expert System PNEUMON-IA¹

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Received June 12, 1990

The present study validates the expert system PNEUMON-IA. The aim of PNEUMON-IA is assessing the etiology of community-acquired pneumonias from clinical, radiological, and laboratory data obtained at the onset of the disease. Validation was performed using data from medical records of 76 patients with proven clinical diagnosis of pneumonia. The etiological diagnoses provided by PNEUMON-IA were compared to those established by five specialists unrelated to the development of the expert system. For each etiological possibility, both PNEUMON-IA and the experts provided a causal possibility, expressed as a linguistic label (i.e., "almost impossible"). Linguistic labels were then converted to numeric values. In the majority of cases, an etiological diagnosis was unavailable to be used as a gold standard. To overcome this limitation, distances between arrays of etiological possibilities given by specialists and by PNEUMON-IA were considered as an agreement measure between diagnoses. Cluster analysis based on those distances was used to classify PNEUMON-IA among experts. Results showed the same differences between specialists and PNEUMON-IA as among the specialists themselves. The method used to validate PNEUMON-IA could prove useful to assess the performance of expert systems in fields where no gold standard is available. © 1992 Academic Press, Inc.

INTRODUCTION

The validation of any expert system is a fundamental step in its development (1, 2). To use a diagnostic expert system such as PNEUMON-IA in clinical practice the validity of its diagnoses should be verified. We present a validation of PNEUMON-IA through the etiological diagnoses it provided, without taking into account other characteristics of the system such as its usefulness, user interface, or reasoning explanation. The originality of the validation methodology used lies in the fact that it evaluates an expert system in a field where no absolute gold standard exists as a reference.

¹ This study was supported in part by Grants FIS 87/1387 and 88/1362.

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- R02013 IF** 1) Community-acquired Pneumonia
 2) Frequent contacts with animals
 3) Bacterial Disease
- THEN** [QUITE POSSIBLE]
- Pneumococcus
-
- R02014 IF** 1) Community-acquired Pneumonia
 2) Frequent contacts with birds
 3) Bacterial Disease
- THEN** [VERY POSSIBLE]
- Pneumococcus

FIG. 1. Examples of two rules of PNEUMON-IA. R02014 is more specific than R02013 thanks to the relation *bird is a kind of animal*.

The Expert System

The aim of PNEUMON-IA is to assess the etiology of community-acquired pneumonias from clinical, radiological, and laboratory data obtained at the onset of the disease (3-5). It uses an inference engine named MILORD (1, 4, 5) which uses fuzzy logic and linguistic labels to express uncertainty. PNEUMON-IA's knowledge is implemented through production rules (Fig. 1). Rules are grouped in modules and strategies and controlled by metarules in a multilevel architecture represented in Fig. 2. PNEUMON-IA considers the 22 possible etiological agents listed in Table 1. For each case, it provides an output which

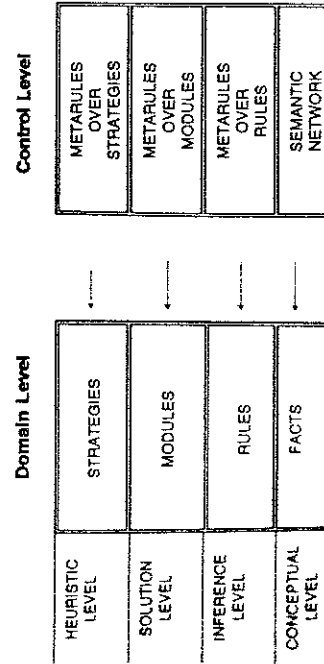


FIG. 2. Multilevel architecture of PNEUMON-IA.

TABLE 1
 ETIOLOGIES CONSIDERED BY THE EXPERT SYSTEM PNEUMON-IA

Bacterial pneumonias	Viral pneumonias
<i>Streptococcus pneumoniae</i>	<i>Respiratory viruses</i>
<i>Legionella pneumophila</i>	<i>Chicken pox</i>
<i>Enterobacteriaceae</i>	<i>Bacterial superinfection of viral</i>
<i>Haemophilus influenzae</i>	<i>Cytomegalovirus</i>
<i>Pseudomona aeruginosa</i>	
<i>Anaerobic bacteria</i>	Fungal pneumonias
<i>Staphylococcus aureus</i>	<i>Aspergillus spp.</i>
<i>Branhamella catarrhalis</i>	<i>Cryptococcus neoformans</i>
<i>Streptococcus pyogenes</i>	
<i>Mycobacterium tuberculosis</i>	Pneumonias caused by parasites
<i>Nocardia asteroides</i>	<i>Pneumocystis carinii</i>
<i>Mycoplasma pneumoniae</i>	
<i>Chlamydiae spp.</i>	
<i>Q fever pneumonia</i>	
<i>Neisseria meningitidis</i>	

includes a list of the most likely etiologies, each one qualified by a linguistic label to express its associated possibility (see Appendix).

In its present form, PNEUMON-IA knowledge base comprises 487 facts, 659 rules, 92 metarules, and 25 modules. As a programming language we used VAXLISP, a superset of CommonLISP, running on VAX computers under VMS operating system. In addition, there is a CommonLISP version of PNEUMON-IA for SUN workstations running under UNIX operating system.

The Problem

Although of obvious importance for its treatment, etiological diagnoses of pneumonia imply great uncertainty, since etiology is seldom confirmed (Table 2) and therefore it is difficult to establish a gold standard to compare this expert system with. One of the possible methods is based in the selection of a sample including only confirmed cases, as in the validation of MYCIN (6). The confirmed cases, however, are often the most severe and are caused by a limited subset of etiological agents. These facts would introduce an unwanted bias in the study.

The Proposed Solution

In the absence of a gold standard, the aim of this validation is to compare, in a sample of patients with community-acquired pneumonia, the etiological approximations proposed by PNEUMON-IA and those proposed by medical specialists. We took the consensus of several medical specialists as a reference, although in a different way to that of other expert systems validation projects

TABLE 2
ETIOLOGIES OF COMMUNITY-ACQUIRED PNEUMONIAS

Reference	n	Pneum.	Legion.	Mycopl.	Virus	Other	UK/UC ^a
(1)	210	11.5	1.5	14.0	15.0	12.5	52.0
(2)	127	76.0	15.0	2.3	8.6	12.5	3.0
(3)	314	22.0	2.5	24.0	21.0	14.0	33.0
(4)	127	54.0	0.7	14.0	7.0	3.3	21.0
(5)	301	18.6	3.9	3.3	16.1	31.6	36.5
(6)	198	39.1	6.2	16.9	4.1	13.5	20.2

Note. Figures in table reflect the percentage of each agent over the total number of agents isolated.

The sum of percentages greater than 100 corresponds to polymicrobial etiologies.

^a UK/UC, unknown/unclear.

^b Part of the study performed before the identification of *L. pneumophila*.

(7-10). Distances between possibility arrays of etiologies given by specialists and PNEUMON-IA were taken as a measure of agreement between them. Cluster analysis of these distances allows us to classify PNEUMON-IA among clinical experts, obtaining a relative assessment of its diagnostic ability.

Although this approach provides results slightly more difficult to interpret, the bias of using only cases with confirmed etiologies does not occur. The agreement with the confirmed diagnosis in the cases that it was known was considered a secondary way of validation.

MATERIALS AND METHODS

1. Sample

It was initially decided to collect a sample of 80 medical records of pneumonia patients from four general hospitals located in the Barcelona area. Four cases were rejected because of incomplete data, leaving 76 cases for analysis. Criteria for inclusion were: clinical and radiological evidence of pneumonia; age equal to or over 14 years; community-acquired pneumonia; and a fully documented medical record. A randomized selection of cases from each hospital's files was performed, stratifying them according to the WHO's ICD code of diagnosis, to ensure that the ratio of different types of pneumonia was preserved.

2. Collection of Data

Collection of data was carried out using a form in which data of possible diagnostic interest and the etiology when confirmed were recorded. Most of the information was related to events occurring during the first 48 hr of the clinical course. Data unavailable in the medical record was classified as unknown. Radiological data were recorded in the form of B&W 35-mm slides for submission to the specialists. The interpretation of the chest X-rays for input to

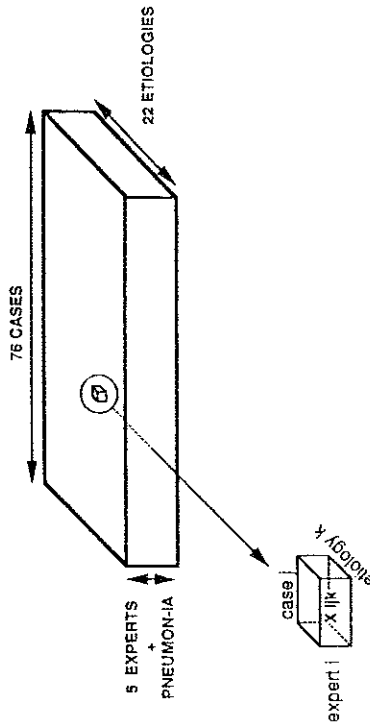


FIG. 3. Cubic matrix, the dimensions of which are the five specialists and PNEUMON-IA, the 76 cases considered, and the 22 etiologies taken into account. x_{ijk} represents one of the eight possible certainty values for a particular etiology attributed to one case by one expert.

the expert system was carried out by the system designer physician because PNEUMON-IA by itself cannot interpret X-rays. Using the intelligent data acquisition module of PNEUMON-IA, data were entered into the computer by one of the authors (A.P.), a physician familiar with PNEUMON-IA operation but unrelated to the development of PNEUMON-IA rules or database. He did not know the treating physician's diagnosis. Data were entered as required by the system if available. The system supplied a set of diagnostics at the end of the process.

3. Assessment of the Cases

PNEUMON-IA gave a diagnosis for each case. Each diagnosis took the form of an array in which the 22 possible etiologies were qualified with one of eight possible labels of possibility. The expert system generated also a validation report for each case which included all data except radiological features and system diagnoses. It was not mandatory for the experts to rate every single possible diagnosis, but it was required for them to give labels of possibility to those considered in the differential diagnosis of each case. PNEUMON-IA provided possibility labels for the diagnostics considered in its search path. These reports together with chest X-ray slides were assessed independently by five specialists from five hospitals. These specialists had not intervened in the development of the expert system. No limit was established on the number of etiologies cited to assess the cases, nor was a limit imposed on the time taken to reach them. A diagram of the data matrix of six experts (PNEUMON-IA + 5 clinical experts), 76 cases, and 22 possible etiologies is shown in Fig. 3.

TABLE 3

Linguistic label	Assigned possibility
Impossible	0.0000
Almost impossible	0.0330
Slightly possible	0.1077
Somewhat possible	0.2416
Possible	0.4500
Quite possible	0.6500
Very possible	0.8486
Sure	1.0000

4. Concordance Measures between Specialists and the Expert System

In order to establish the concordance between diagnoses made by specialists and PNEUMON-IA, distances between possibility arrays provided by each specialist and by the expert system were calculated for each case. To compute the distances, linguistic labels were substituted by a number which is a central trend parameter of the range of numeric values compatible with the linguistic labels (5) (Table 3).

The following distances were considered (17):

— Euclidean

$$d(i, j) = \sqrt{\frac{1}{N} \sum_{m=1}^N (x_{im} - x_{jm})^2}$$

where d is the distance, i and j are a pair of experts, N is the total number of etiological possibilities, m is each of the etiological possibilities, and x is the numerically expressed certainty.

— City-block

$$d(i, j) = \frac{1}{N} \sum_{m=1}^N |x_{im} - x_{jm}|$$

City-block distance penalizes the existence of many small differences. In our case city-block distance will magnify the discrepancies between a couple of experts giving slightly different possibilities to a relatively great number of etiological diagnoses.

— Chebychev

$$d(i, j) = \text{Max}_m |x_{im} - x_{jm}|$$

This distance penalizes the existence of large differences even though they may occur in a low number of etiologies. In our case, Chebychev distance will magnify discrepancies between a couple of experts giving a few disparate etiological possibilities for the same patient.

TABLE 4

MATRIX OF DISSIMILARITIES CALCULATED FROM THE CITY-BLOCK DISTANCE

	E1	E2	E3	E4	E5
E2	0.0495				
E3	0.0636	0.0663			
E4	0.0540	0.0611	0.0700		
E5	0.0581	0.0658	0.0671	0.0702	
ES	0.0566	0.0643	0.0670	0.0659	0.0692

To establish the overall distance between pairs of experts these distances were averaged over the 76 cases considered. Using the obtained 6 by 6 matrix of the averaged distances (Table 4), a hierarchical cluster analysis (17) was carried out to condense the information contained in a similarity or dissimilarity matrix by a progressive agglomeration of experts as a function of their similarity. When two experts are clustered, another matrix of dimension $(n - 1) * (n - 1)$ must be built for the process to continue. Every pair of similarity or dissimilarity coefficients of the two clustered experts to the rest of them is then substituted by a single new value. There are several methods for obtaining this new value. In the method presented in this paper, we use the average linkage criteria, which define the new values as an arithmetic mean of the previous ones. Both an advantage and disadvantage of the hierarchical cluster analysis is that the method does not provide a fixed number of clusters but rather a progressive agglomeration of the experts which more or less allows grouping of them by observing the dendrogram closer or further from its vertex. This clustering process has the particularity that all the groups are consistent because the reduction of their number is always generated by aggregating smaller groups. Cluster analysis is a descriptive analysis and does not supply information about the statistical significance of the observed differences between experts, but it is useful enough for the present study because it provides an intuitive relative classification of PNEUMON-IA among human experts. This progressive agglomeration of experts is graphically represented by a "dendrogram," a figure that presents the experts or groups of experts as connected by links placed at a position of the horizontal axis that is proportional to the similarity between experts or groups of experts.

5. Cross-Evaluation of Specialist's Proficiency

Specialists were asked to assess their colleagues' proficiency in a confidential report, recording scores for each one on a scale from 1 to 10. Results were averaged and specialists were ranked from highest to lowest proficiency. The scores were: specialist E1 obtained a 10, specialists E2 and E3 obtained scores between 8 and 8.5, and specialists E4 and E5 obtained an average score of 6.5.

TABLE 5
ETIOLOGICAL POSSIBILITIES CONSIDERED IN THE SAMPLE

	E1	E2	E3	E4	E5	ES
<i>S. pneumoniae</i>	62	57	65	65	56	63
<i>L. pneumophila</i>	27	27	30	4	48	27
Enterobacteriaceae	27	27	36	11	25	39
<i>H. influenzae</i>	18	29	20	17	11	16
<i>P. aeruginosa</i>	0	2	0	0	0	0
Anaerobes	22	12	16	15	19	27
<i>S. aureus</i>	7	2	5	8	9	4
<i>B. catarrhalis</i>	0	0	1	0	0	0
<i>S. pyogenes</i>	5	2	1	0	0	0
<i>M. tuberculosis</i>	7	17	6	3	9	3
<i>N. asteroides</i>	1	0	0	1	1	0
<i>M. pneumoniae</i>	10	10	25	10	15	19
<i>Chlamydiae</i> spp.	5	6	19	2	8	29
Q fever	5	7	8	2	7	8
Meningococcus	0	0	0	0	0	0
Viral	1	3	2	1	2	24
Chicken pox	0	0	0	0	0	0
Superinfection	0	0	0	0	0	1
Cytomegalovirus	0	0	0	0	0	0
<i>Aspergillus</i> spp.	1	2	0	0	1	1
<i>C. neoformans</i>	0	0	0	0	0	0
<i>P. carinii</i>	1	1	0	0	0	0
Total	199	204	34	139	215	261
Mean etiology/case	2.62	2.76	3.08	1.83	2.83	3.43

RESULTS

1. Frequency of Diagnoses

A descriptive statistical analysis for each specialist was carried out by determining the absolute and relative frequency of the etiologies mentioned with a possibility greater than "almost impossible" (Table 5). Since each specialist usually provided more than one etiological diagnosis for each case, the total number of etiologies recorded was greater than the number of cases. The number of etiologies per case varied between 1.83 for E4 and 3.43 for PNEUMON-IA, the global average being 2.76. The etiology most often cited corresponded to *Streptococcus pneumoniae*, with an average of 61 mentions in 76 cases. The expert system considered pneumonia caused by *Chlamydiae* spp. more commonly than the clinical experts (29 vs an average of 12). However, specialist E3 cited this etiology on 19 occasions. It should be noted that the expert system cited viral pneumonias more often than the specialists did. Although no data were available on the true etiology for the majority of pneumonias, these differ-

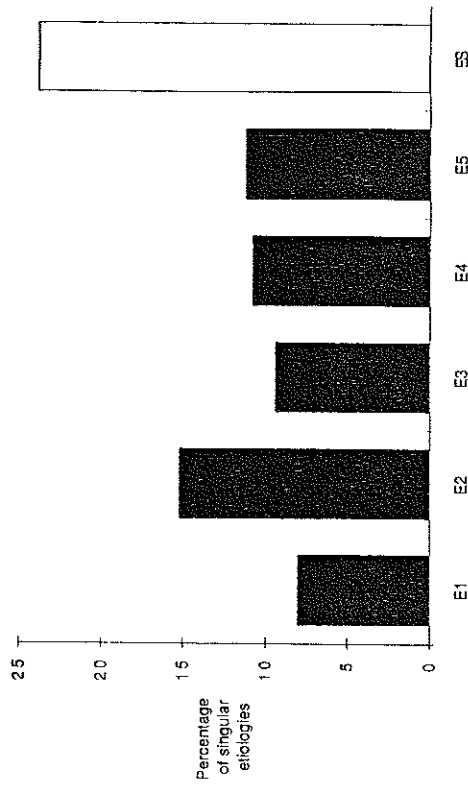


FIG. 4. Percentage of singular etiologies. E1 to E5, human specialists; ES, expert system PNEUMON-IA.

ences might be due to an underestimation of this etiology by the specialists, since the majority of patients suffering from viral pneumonia are not hospitalized and no effective specific chemotherapy is available.

2. Singular Etiologies

We considered "singular etiologies" those mentioned only by one specialist in one particular case. One way of determining the concordance of a single specialist with the consensus of the group is to note the occurrence of singular etiologies. Figure 4 shows the percentage of singular etiologies recorded by each specialist. The expert system recorded more singular etiologies (23.8%) than any clinical specialist. However, if viral etiologies are excluded, the percentage is reduced to 15.7%, close to the specialist E2. These results are attributable to the larger number of etiologies provided for each case by PNEUMON-IA, particularly with reference to viral pneumonias as has been pointed out previously.

3. Omitted Etiologies

An "omitted etiology" was considered as an etiology mentioned by every specialist (including PNEUMON-IA) but one. The number of omitted etiologies is a measure of disagreement with the consensus. Figure 5 shows the number of etiological diagnoses omitted by each specialist. The number of omitted etiologies by PNEUMON-IA (5 cases) was less than half the omissions made by the specialists such as E2 (12 cases) or E4 (19 cases). This is also an

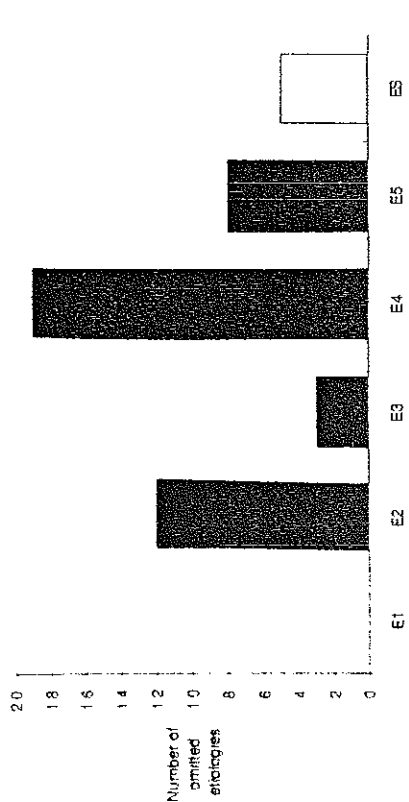


Fig. 5. Number of omitted etiologies. E1 to E5, human specialists; ES, expert system PNEUMON-IA.

indirect consequence of the larger number of etiologies per case proposed by PNEUMON-IA.

4. Confirmed Etiologies

Although only 10 of the 76 cases selected were confirmed by microbiologic examination, it is interesting to analyze the concordance between the etiologies proposed by the specialists and the expert system with this subset of real ones. Figure 6 shows that the confirmed etiology was mentioned by the expert system as the most likely etiologies in 4 occasions (the specialists moved in a range from 3 to 6), and on 7 occasions including also the second most likely diagnosis with a range of 3 to 8 among the group of specialists.

5. Distances between Specialists

5.1. City-block distance. Table 4 shows the 6 by 6 dissimilarity matrix obtained using the city-block distance once all cases were averaged. In Figure 7 we represent graphically as a dendrogram results of a cluster analysis of these distances. As it can be observed in this dendrogram, the distance between specialists E1 and E2 was the smallest. The distance among other specialists progressively increased with no groupings being apparent. PNEUMON-IA occupies a halfway position. Specialists E3 and E5 appeared outside the cluster (E1, E2, E4, PNEUMON-IA) and isolated from each other.

5.2. Euclidean distance. Figure 8 shows the dendrogram of the cluster analysis resulting from a matrix of euclidean distances. Like with city-block distance, specialists E1 and E2 are the closest. The expert system forms a cluster with E1 and E2, other specialists being excluded from this group and isolated from each other.

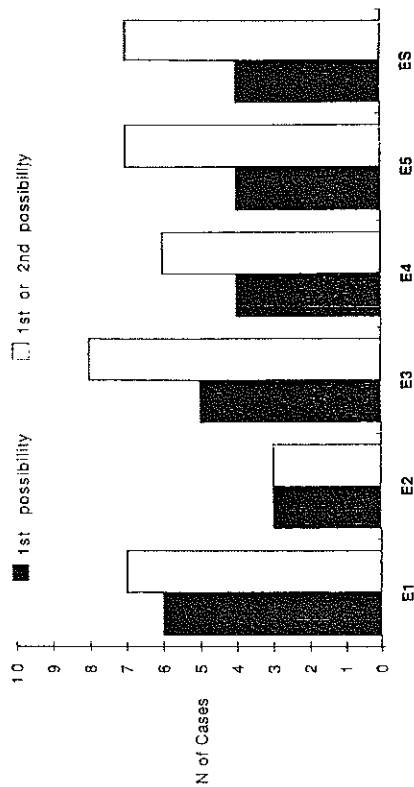


Fig. 6. Number of correct diagnoses in 10 cases with confirmed etiology. E1 to E5, human specialists; ES, expert system PNEUMON-IA.

5.3. Chebychev distance. The dendrogram of the cluster analysis resulting from Chebychev distances was similar to the dendrogram obtained with euclidean distances with regard to specialists E1 and E2 and the expert system. Only the relative positions of specialists E3, E4, and E5 changed.

DISCUSSION

Diagnostic expert systems with output restricted to a single and easily auditable diagnosis are a minority. Their accuracy can be easily compared with that of clinicians (18, 19). Well accepted parameters such as sensitivity, specificity, and positive and negative predictive values are often appropriate. Medical expert systems which output a list of diagnoses with their associated possibilities are relatively common. When such systems are applied to a problem where the correct answer is known, the validation process is notably straightforward. Nonetheless, even in the above-mentioned cases, it is astonishing how seldom the computers' and doctors' diagnoses have been directly compared on the same patient on the same occasion using the same indicators (20).

Unfortunately, this scenario is unlikely to be customary in modern clinical practice where the correct answer is seldom known for a given problem. Despite this limitation, validation of an expert system requires some measure of success. This means that some approximation to the truth should be known. In the literature, different approximations have been used, such as the opinion of one or more experts, a biochemical property, a reaction to therapy, or survival. Interestingly, clinicians tend to emphasize the clinical outcome as the best variable (21). From the proposed gold standards, strictly diagnostic systems such as PNEUMON-IA can only employ the expert's opinion.

To compare expert system opinions with clinical experts judgements a "grad-

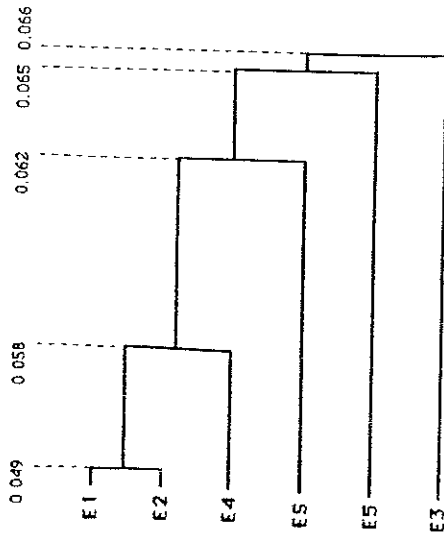


FIG. 7. Dendrogram of cluster analyses from city-block distances.

ing approach" can be used. Briefly, it offers medical records and the diagnosis given by the expert system to a panel of expert clinicians which "grades" the expert system conclusions. Typical appraisal reports of accuracy include a list of degrees and the proportion of expert system diagnosis which merit each one (i.e., unacceptable: 5%, acceptable: 70%, ideal: 25%). Limitations inherent to this approach rely on the subjectivity of the grading process and the lack of a real

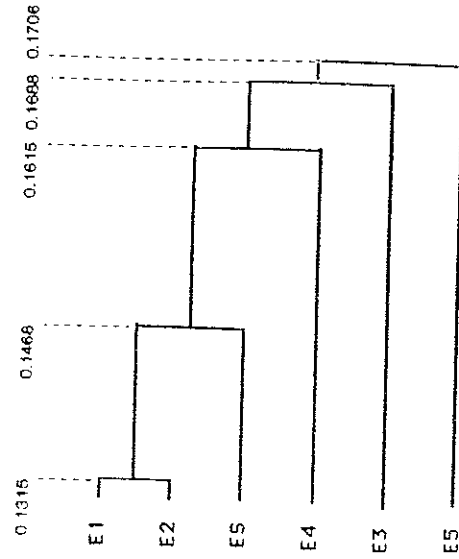


FIG. 8. Dendrogram of cluster analyses from euclidean distances.

"human vs machine" comparison. To partially overcome the latter, diagnosis emitted by clinicians on the same cases can be concurrently graded (10).

Under a methodological point of view, the system used to validate PNEUMON-IA is a new approach as it evaluates the expert system from different perspectives, using two groups of techniques: frequency analysis and distance analysis. Frequency analysis includes the contrast between the number of diagnosis given by clinicians and PNEUMON-IA and the number of omitted and singular etiologies. All these techniques are interdependent and give, among other data, information about diagnostic exhaustivity.

Distance analysis supplies also some degree of "grading" of the expert system among clinicians (as well as of clinicians among themselves). The approach used to test PNEUMON-IA combines simplicity and comprehensiveness, and can be helpful to validate any other system with similar characteristics.

An alternative and widely used tool for assessing interrater (interexpert) reliability is the Cohen kappa coefficient. Several formulations of this coefficient have been proposed: from the simplest that assesses the agreement between two raters (22), to the case where the reliability among multiple raters using nominal variables is considered (23), to the more complex case where each rater of a group chooses a subset of items from a list (i.e., a subset of possible diagnostics for a patient) (24). Our case is still more complex: several raters using an ordinal variable to qualify the possibility of each diagnostic of a set. Although it could be theoretically possible to generalize the kappa coefficient to our problem and compare the results obtained with each strategy, the exercise is beyond the scope of this paper.

The results obtained applying our approach to PNEUMON-IA validation show that differences between etiological diagnoses made by the expert system and those made by some specialists were smaller than differences between some specialists themselves. Specialists with highest proficiency scores gave the closest diagnoses. The best specialist was, moreover, the one with the least omitted etiologies and least singular etiologies. The expert system was closer to the "best" than to the "worst" specialist. PNEUMON-IA supplied the highest number of singular etiologies, largely because it takes viral etiologies into consideration more often. The success of the expert system in cases of confirmed etiologies was similar to that of clinical specialists. Etiological diagnoses emitted by the expert system PNEUMON-IA agreed with the best known specialists in our area.

In summary, in a knowledge area where a gold standard is not readily available, this method of validation gives a broad overview of the system expertise.

APPENDIX

Patient status: Pneumonia IA Knowledge Base Date: 03-01-89
Hospital: La Alianza

Patient's history: (Clinical Record) Juan H

Table with columns: FACT, INTERNAL_NAME, VALUE. Lists various medical facts like 'Community Acquired Pneumonia', 'Chest pain', 'Fever', etc., with their internal names and values.

Table with columns: FACTS SUPPORTED (NO DIAGNOSTIC), FACTS SUPPORTED (DIAGNOSTIC), RULING OUT. Lists supported and ruled out diagnoses like 'Pneumococcal pneumonia', 'Legionella', etc.

ACKNOWLEDGMENT

We thank Marta Pulido, M.D., for editorial assistance.

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Plots for Examination of Univariate Twin Data

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Received February 25, 1992

We discuss informative plots for univariate twin data that can be used in conjunction with twin data analyses. The plots are useful for spotting outliers, spotting possible single gene effects, and displaying the contribution of individual twin pairs to the fit of genetic models of the data. We illustrate the use of the plots on bone mineral data, and present programs for generating the plots in SAS. © 1992 Academic Press, Inc.

1. INTRODUCTION

The ability of researchers to conduct sophisticated statistical analyses of twin data is rapidly increasing. This is due to the introduction of flexible models for twin data analysis (1, 2), to increased availability of computer programs to perform these analyses (3, 4), and to tremendous recent advances in computer hardware. The increased emphasis of fitting more interesting models to data, however, at times appears to overshadow the role of simple exploratory data methods such as plots. The role of visual displays of data was perhaps best described by Sir. R. A. Fisher:

The preliminary examination of most data is facilitated by the use of diagrams. Diagrams prove nothing, but bring outstanding features readily to the eye; they are therefore no substitute for such critical tests as may be applied to the data, but are valuable in suggesting such tests, and in explaining the conclusions founded upon them. (5)

In this spirit we present two simple plots for examination of univariate twin data. We suggest that plots such as these be routinely examined, and further that presentation of these plots along with twin analyses greatly enhances understanding of results. We illustrate the use of the plots on bone study data, and we present a macro for producing these plots in the Statistical Analysis System computer package (SAS Institute, Cary, NC 27511).

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