An Approach using Certainty Factor Rules for Aphasia Diagnosis

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***Abstract*—Artificial Intelligence methods are frequently applied to medical domains assisting in various tasks, like diagnosis. The implementation of corresponding intelligent systems is based on available datasets and expert knowledge. In this paper, we present a rule-based approach used for aphasia diagnosis. The approach uses certainty factor rules created from a dataset of records involving persons diagnosed with aphasia. The employed certainty factor formalism is an extension to a previous certainty factor formalism. To model each case, nineteen attributes are used. Seven of them are discrete and the rest of them are integer. Experiments were performed testing the performance of the specific rule-based approach, a decision tree method and a feedforward neural network. Experimental results show that the rule-based approach performs well and requires only three of the eighteen input attributes to produce an output. To the best of our knowledge, there is no other published approach using certainty factor rules for aphasia diagnosis.**

Keywords—AI in Medicine, aphasia diagnosis, rule-based systems, certainty factor rules

I. Introduction

Rule-based methods are frequently used in the development of intelligent systems [1]. Rules represent general knowledge of the domain associating conditions and conclusions. In several domains, this type of knowledge emulates the experts' way of thinking. Rules exhibit a number of attractive features such as naturalness, modularity and ease of explanation. Naturalness involves the ease of comprehending knowledge encompassed in rules. Modularity refers to the fact that each rule is a discrete and autonomous knowledge unit that can be easily inserted in or removed from a knowledge base [2]. This feature greatly facilitates incremental development of a rule base. Various types of explanation may be provided for conclusions reached by rule-based systems and this is useful in the development and operation phases of an intelligent system [3]. Rule bases are constructed either from elicitation from experts or from available datasets [4].

The rule formalism may be augmented deriving different types of rules. Three such types of rules are certainty factor rules, fuzzy rules and neuro-symbolic rules. Certainty factors are incorporated to rules for uncertainty management [5]. Fuzzy rules enable handling of fuzzy concepts [6]. Neuro-symbolic rules seamlessly combine rules with neural networks in a rule-based context improving the efficiency of symbolic rule-based reasoning [4]. To improve knowledge representation and reasoning, distinct rule-based modules may be combined with modules based on other intelligent methods such as case-based reasoning [7].

Rule-based formalisms are used quite often in medical decision support systems. Characteristics of rules enable the corresponding intelligent systems to satisfy requirements of various medical domains. For instance, provision of explanations for reached conclusions is usually a prerequisite in systems assisting medical decisions. One of the most well-known rule-based systems involving medicine was MYCIN and its knowledge base consisted of certainty factor rules [5]. Several rule-based medical decision support systems were developed afterwards [8].

Other intelligent methods are frequently used in medicine besides rules [8]. Such methods, among others, are case-based reasoning [9], [10], bayesian networks [11], [12], ontologies [13], [14], data mining [15], [16], agents [17], [18], neural networks [19] and genetic algorithms [20], [21].

This paper discusses an approach that has been applied to aphasia diagnosis. Not many intelligent approaches have been developed in this domain although diagnosis is not an easy task. Previous intelligent approaches mainly involve application of neural networks and fuzzy methods. The presented approach is based on a rule-based formalism using certainty factors to incorporate uncertainty in reasoning. The certainty factor rules are constructed from a dataset using a method presented in [22]. The certainty factor formalism is an extension to the corresponding formalism usually applied to other rule-based approaches. To the best of our knowledge, no other rule-based approach using certainty factors has been applied to aphasia diagnosis.

The remaining part of the paper is organized as following. Section II presents main aspects involving aphasia and AI approaches that have been applied to aphasia diagnosis. Section III discusses aspects concerning the available dataset and domain variables involved. Section IV outlines the process producing certainty factor rules from available datasets. Section V presents experimental results comparing the performance of the certainty factor rules with decision trees and feed forward neural networks. Finally, Section VI concludes.

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II. Aphasia Diagnosis: Basic Aspects and AI Approaches

This section consists of two parts. The first part discusses basic aspects about aphasia, main aphasia types and diagnosis methods. The second part outlines published AI approaches that have dealt with aphasia diagnosis.

A. Main Aspects about Aphasia and its Diagnosis

Aphasia is a disorder involving language and speech and is caused by various types of damages to the brain and pathology [23], [24], [25]. Aphasia involves problems regarding syntactic structure, phonological and semantic language processing, and the use of gestures and other nonverbal methods of communication [24]. Therefore, persons with aphasia have difficulties in speech production, auditory comprehension, reading, writing and (verbal and nonverbal) communication.

The most usual symptoms connected with aphasia are the following [24]:

- Difficulty in initiating speech.
- Agrammatism, that is, absence of grammatical elements (i.e., verbs, nouns, pronouns and prepositions). Structure of sentences consists of two to three words that are semantically and not syntactically connected.
- Use of grammatically incorrect phrases.
- Difficulty in producing the required words.
- Periphrasis, that is, production of phrases related to required words that may not be produced.
- Echolalia, that is, unsolicited repetition of another person's phrases.
- Use of language that makes (or seems to make) no sense.
- Personal neologisms, that is, replacement of common words with others not widely adopted by others.
- Phonemic paraphasia involving replacement of correct phonemes with incorrect ones.
- Semantic paraphasia, that is, replacement of a word with another word belonging to the same semantic category.
- Telegraphic speech involving production of brief phrases mainly consisting of nouns and verbs with the absence of function words.
- Difficulties in comprehension.
- Difficulties in reading and writing.

Different classifications have been proposed to define and discern aphasia types but most researchers and clinicians use the Boston classification system for this purpose. Eight types of aphasia are defined and discerned according to existence or absence of certain major linguistic aspects. A main categorization aspect is fluency. Four fluent (i.e., Wernicke's aphasia, Transcortical sensory aphasia, Conduction aphasia and Anomic aphasia) and four non-fluent (i.e., Global aphasia, Mixed transcortical aphasia, Broca's aphasia and Transcortical motor aphasia) types of aphasia are discerned [23]. Further categorization aspects involve comprehension and repetition abilities [23]. Repetition concerns the ability of a person to repeat another person's spoken vocalizations. Basic characteristics of these eight types of aphasia are outlined as follows [23], [24], [25]:

- *Wernicke's aphasia*. A fluent type of aphasia involving severe difficulties in comprehension, repetition and naming. Speech content makes no sense as it involves several semantic and phonemic paraphasias and neologisms.
- *Transcortical sensory aphasia*. A fluent type of aphasia involving speech with paraphasias. Repetition ability is available but abilities of comprehension and naming may be impaired.
- *Conduction aphasia*. A fluent type of aphasia involving phonemic paraphasias and severe difficulties in repetition and naming. Ability of comprehension is better.
- *Anomic aphasia*. A fluent type of aphasia with difficulties in producing required words. Speech may involve pauses and periphrases. Abilities of comprehension and repetition are available.
- *Global aphasia*. A non fluent type of aphasia with all linguistic skills impaired. Speech production is severely weak and there are severe difficulties in comprehension, repetition and naming.
- *Mixed transcortical aphasia*. A non fluent type of aphasia in which persons usually speak only when spoken to. Ability of comprehension is impaired, ability of repetition is retained to a certain degree and there are severe difficulties in naming.
- *Broca's aphasia*. A non fluent type of aphasia concerning speech with hesitation, frequent pauses, impaired prosody and agrammatism. Ability of comprehension is retained to a certain degree but abilities of repetition and naming are impaired.
- *Transcortical motor aphasia*. A non fluent type of aphasia in which abilities of comprehension and repetition are retained and ability of naming is impaired. Difficulties in initiating speech and echolalia may be observed.

For various reasons, it may be difficult to diagnose the exact type of aphasia. Different types of aphasia share symptoms and there is an overlap among aphasia types. Furthermore, persons diagnosed with the same type of aphasia may exhibit variations in observed symptoms. Consequences of brain damages may be complex leading to multiple symptoms. Certain types of aphasia are not very frequent and there may be difficulties in studying them thoroughly.

Diagnosis is performed by clinicians. Detailed examination of language functions is required to reach a diagnosis. Different clinicians may provide different evaluations for the same persons [26]. For these reasons, standardized tests such as the Boston Diagnostic Aphasia Examination, the Western Aphasia Battery (WAB) and the Aachen Aphasia Test (AAT) are used to assess language functions.

B. *AI Approaches in Aphasia Diagnosis*

Certain AI approaches have been developed for aphasia diagnosis. Seminal work is presented in [26], [27]. In [26] characteristics of an aphasia database are mentioned with the argument that it could serve as a model for testing different AI methods. This database consists of 265 AAT profiles of persons collected since 1986. Each profile involves 30 features. 146 of these profiles corresponding to persons diagnosed with Anomic, Broca's, Global or Wernicke's aphasia were used in subsequent approaches. The AAT involves a number of subtests. In [27] results are mentioned involving classification accuracy of two neural networks. Classification of the one neural network is based on subtests of AAT involving spontaneous speech assessment as less than an hour is required by clinicians to acquire the results of corresponding subtests. The involved features are six and classification accuracy is 87.55%. The other network may use all subtests of AAT (called comprehensive model hereafter). As 30 features are involved in each profile, four features were chosen using an analysis tool. Classification accuracy is 92.23% but acquisition of corresponding inputs requires more time from clinicians. The specific results showed that selection of an appropriate subset of features affects accuracy. Subsequent approaches compared the classification accuracies of these two multilayer neural networks with corresponding accuracies of other methods. Certain of these methods are presented in the following.

Four approaches presented in [28], [29], [30] and [31] discuss approaches whose classification accuracies are not better than the corresponding ones exhibited by the aforementioned neural networks. However, they may produce more comprehensible knowledge bases compared to neural networks. In [28] the previously built neural network model is compared with a fuzzy clustering approach. Accuracy result for the comprehensive model is 91% and the same subset of features is used. It is argued that the fuzzy approach requires setting of fewer parameters compared to the neural network. In [29] a clustering approach discovering fuzzy rules from data is presented and compared with the previously built neural networks. The same subsets of features are used. Accuracy results for spontaneous speech assessment and comprehensive model are comparable to the ones of neural networks (i.e., 86% and 91%, respectively) but the discovered fuzzy rules are more comprehensible compared to the neural networks. In [30] genetic programming methodologies are used to construct crisp and fuzzy rule-based systems for aphasia diagnosis and classification of Pap test examinations. Results for four different genetic programming methodologies are mentioned. Accuracy results range from 79.1% to 90.8%. Once again it is argued that the accuracy of previously built neural networks is better but the constructed rule-based systems are more comprehensible. In [31] three different fuzzy clustering approaches for creation of fuzzy rule-based systems were compared using the aforementioned dataset. The purpose of this research work was to experimentally study these clustering approaches. The neural networks seem to perform better in terms of accuracy.

Three approaches were presented which exhibit better accuracy compared to the aforementioned neural networks and also use fewer features [32], [33], [34]. In [32] a two-layer fuzzy rule-based approach is implemented. In this approach, the output produced by the first layer fuzzy rules is used as input to the second layer fuzzy rules. The classification accuracies are better compared to the corresponding accuracies of aforementioned neural networks. More specifically, the best accuracy results acquired for spontaneous speech assessment and the comprehensive model are 91.30% and 93.61%, respectively. Furthermore, the fuzzy systems use fewer features (i.e., two and three features, respectively) to produce the output. Note that the best accuracy result of this approach for the comprehensive model is reported to be higher (i.e., 95.55%) in [33], [34]. In [33] a fuzzy rule-based approach is presented using fuzzy probability estimators in reasoning. The same number of features is used as in [32]. Compared to [32], the best accuracy results acquired are improved for spontaneous speech classification (i.e., 96.74%) and are slightly worse for comprehensive data (i.e., 94.46%). In [34] a self-organized multi-agent system based on fuzzy probabilities is presented. Six features are used. The best accuracy results acquired for comprehensive data are slightly better (i.e., 94.49%) compared to [33] and slightly worse compared to [32]. However, on average the results are better compared to [33], [32] and [27].

Finally, an approach based on a new generalization of the Dempster–Shafer Theory is used in [35]. This approach is compared to neural networks, [32] and [33]. On average it performs better compared to these other approaches.

III. The Available Dataset and Involved Attributes

For the construction of the system's rule base, we used a dataset consisting of records of persons with aphasia. Each record contains the clinical and linguistic characteristics of the corresponding person and the diagnosed type of aphasia. The dataset was created based on data taken from the AphasiaBank, a database created for the study of language and communication in persons with aphasia [36], [37]. It should be mentioned that each record in the database, contains the diagnosis made by clinicians as well as the one derived through the WAB test.

An initial dataset was created based on database data. This dataset was processed in order to derive the final dataset from which the rule base was constructed. Processing involved exclusion of certain records to ensure validity. More specifically, the involved processing steps were the following:

1) Exclusion of records with contradicting diagnoses. In certain records contained in the database, the type of aphasia diagnosed through clinical interaction differed from the one diagnosed with the typical WAB test. For validity reasons, we excluded such records. Therefore, the final dataset contained only records in which the clinicians and the WAB test diagnosed the same type of aphasia.

2) Exclusion of records with missing data. Records with missing data were also excluded.

3) Checking the number of records corresponding to specific types of aphasia. The set of records resulting after applying the two previous processing steps did not involve every type of aphasia as there were no records involving Transcortical sensory aphasia and Mixed transcortical aphasia. Furthermore, there were few records in the dataset involving specific types of aphasia. More specifically, only three records corresponded to persons with Global aphasia and only two records corresponded to persons with Transcortical motor aphasia. These five records corresponding to these two types of aphasia were very few to be taken into consideration in the construction of the rule base. Therefore, they were excluded.

The final dataset consisted of 164 records involving four types of aphasia. These four types of aphasia were Broca's, Wernicke's, Anomic and Conduction aphasia. The number of records in the final dataset corresponding to each one of these four types of aphasia was fifty-seven, thirteen, sixty-nine and twenty-five, respectively.

Each record in the dataset consisted of nineteen attributes, that is, eighteen input attributes and one output attribute. The output attribute corresponds to the diagnosed type of aphasia. The eighteen input attributes correspond to characteristics of involved persons. Seven of the nineteen variables are discrete and the rest are integer. More specifically, the attributes involved in each dataset record are the following:

- *Age.* This attribute corresponds to the person's age and is an integer.
- *Gender.* This is a discrete attribute whose value corresponds to either 'man' or 'woman'.
- *Years of education.*
- *Lesion topography.* This is a discrete attribute denoting the topography of brain damage. It takes four values corresponding to 'right hemisphere', 'left hemisphere', 'left and right hemisphere' or 'not specified'.
- *Speech apraxia.* This is a discrete variable indicating the existence of speech apraxia. It takes three values corresponding to 'yes', 'no' or 'not specified'.
- *Dysarthria.* This is a discrete variable indicating the existence of dysarthria (i.e., problems in articulation). It takes three values corresponding to 'yes', 'no' or 'not specified'.
- *Movement disorders.* This is a discrete variable indicating movement disorders. It takes six values corresponding to 'right hemiparesis', 'right hemiplegia', 'left hemiparesis', 'left hemiplegia', 'no movement disorders' or 'not specified'.
- *SS1.* This is an integer variable involving spontaneous speech parameters regarding clarity, communication and responses to questions.
- *SS2.* This is an integer variable involving spontaneous speech parameters regarding speech flow, syntax, paraphasias and prosody.
- *Avc1.* This is an integer variable involving auditory comprehension parameters regarding comprehension of oral sentences and responding to questions with yes/no.
- *Avc2.* This is an integer variable involving auditory comprehension of words through images.
- *Avc3.* This is an integer variable involving auditory comprehension of instructions.
- *Repetition.* This is an integer variable involving repetition of words, phrases and sentences.
- *Naming_1.* This is an integer variable involving naming of objects.
- *Naming_2.* This is an integer variable involving naming of category/group of words-objects.
- *Naming_3.* This is an integer variable involving completion of sentences.
- *Naming_4.* This is an integer variable involving open-ended questions and speech of responses.
- *Speech flow.* This is a discrete variable indicating speech flow and takes three values corresponding to 'speech with flow', 'speech without flow' or 'not specified'.
- *Class.* This is a discrete variable indicating the diagnosed type of aphasia. It takes four values corresponding to Broca's, Wernicke's, Anomic and Conduction aphasia.

IV. CERTAINTY FACTOR RULE BASES FROM DATASETS

A method producing certainty factor rule bases from datasets is presented in [22]. Compared to [5], the specific method introduced a more generalized formula for combining the certainty factors of rules having the same conclusion. The formula includes weights that are computed using a genetic algorithm. To produce rules from data, dataset instances are clustered into groups. A rule is created for each group and certainty factors are assigned. The specific approach has been previously used to predict the success (or failure) of technical high school students to the National exams in Greece. Results were better for the generalized formula combining certainty factors compared to the typical formula used in MYCIN.

A corresponding tool called ACRES (i.e., Automatic CReator of Expert Systems) implementing the method is freely available [22]. The tool may be used to automatically create CLIPS-based expert systems. Various settings are available to the user. The certainty factors of rules having the same conclusion may be combined either with the formula used in MYCIN or with the more generalized formula.

Given a variable for which we want predictions made and a subset of variables (with discrete values) to be used for the prediction, ACRES generates a set of rules from a training set with the following steps:

1. Cluster instances in groups, so that each group contains instances that have identical values in the variables of the subset
2. From each such group produce one rule that has as conditions the common attribute-value pairs of the instances and as conclusion the possible classes of the output variable
3. Associate each possible class *i* with a Certainty Factor.

The system has been extended to offer two alternative methods for estimating Certainty Factors. Consider an output variable C associated with n possible classes $C_{i..n}$ and a dataset N containing |N| instances. Evidence *E* is a certain pattern of values for a set of variables of the dataset and *D* is the set of instances in the dataset that this pattern occurs. We represent the absolute frequency of class C_i in D as $f(C_i,D)$ and the absolute frequency of class C_i in N as $f(C_i,N)$.

The first approach relies solely on the probability found from the frequency of a class in D. For a class C_i the certainty factor is estimated using the conditional probability that an instance is classified in class C_i, given that evidence E is true.

$$P(Ci \mid E) = \frac{f(Ci, D)}{|D|}$$

Obviously the above value would be between 0 and 1, so we use the following formula to produce a value in the interval [-1 , 1].

$$CF(Ci, E) = 2 \times P(Ci \mid E) - 1$$

The alternative method combines the above probability with the a priori probability found from the general frequency of class C_i in the entire dataset ($P(C_i)$). Using the definition of certainty factors provided in MYCIN, we can combine these two probabilities to produce the measures of Belief MB (C_i, E) and Disbelief MD (C_i, E), which can be used to estimate the Certainty Factor.

V. Experimental Results

Experiments were run using the final dataset consisting of 164 records that was created as described in Section III. To run the experiments, the dataset was divided into training and test sets. Training sets consisted of two thirds of the dataset records. Test sets consisted of one third of the dataset records. Three runs were performed for each pair of training and test sets. The results involve the average performance of the three runs.

The experiments compared three intelligent approaches: (i) an expert system whose rule base consisted of certainty factor rules created as described in the previous section, (ii) a decision tree method and (iii) a multilayer feedforward neural network. We describe main aspects involving the implementation of the last two intelligent systems.

The decision tree method employed is J48, an open source implementation of the C4.5 algorithm [38] in WEKA [39]. The predefined parameter values for J48 in WEKA are used. The constructed decision trees involved four input features i.e., ss2, repetition, ss1 and avc3.

The multilayer feedforward neural network was constructed using the MATLAB Neural Network Tool. More specifically, the constructed neural network was a pattern recognition network whose parameters were defined after several testing. The network exhibiting the best performance for all three test sets consisted of eighteen input nodes, thirty-two hidden nodes and four output nodes. The training function used is resilient backpropagation (i.e., ‘trainrp’ in the corresponding tool). The transfer functions for the first and second level were the Log-sigmoid and the linear functions, respectively.

TABLE I. EXPERIMENTAL RESULTS FOR THE THREE APPLIED METHODS

Intelligent method	Precision	Recall (Sensitivity)	F-measure	Number of Required Features
Decision tree method (J48)	0.88	0.90	0.87	4
Feedforward neural network	0.93	0.84	0.86	18
Certainty factor rules	0.80	0.80	0.80	3

Table I depicts experimental results concerning the three applied methods. More specifically, for each method it depicts the precision, recall (sensitivity) and F-measure. It is considered necessary to record these three measures because the output variable takes four values. The decision tree method performs slightly better than the neural network approach. The certainty factor based approach displays worse performance than the other two methods. We address the lower performance to the way that this approach generates rules, resulting in specialized rules that underperform when the training set is small and does not cover all the possible combinations of values for the features.

The Table also depicts the number of input features required by each intelligent method in order to produce an output. We can see that despite the worse performance, the rule based approach used less features than the other methods. Again, this is an issue of the rule generation method, since adding more features, results in more specialized rules and reduced performance for small training sets. On the other hand, the decision tree method used four input features and achieved similar results to the neural network approach that utilizes all eighteen input features.

Summarizing the results, the decision tree method performs better than the other two methods in terms of recall and F-measure and requires only one additional feature. The rule based approach performs worse than the other methods but uses less features and shows a better balance among the three metrics.

It should be mentioned that the specific results regarding precision and the number of required input features are comparable to the best results of other approaches involving aphasia diagnosis that were discussed in a previous section.

VI. Conclusions

In this paper, we present an approach that employs certainty factor rules in aphasia diagnosis. Aphasia diagnosis is a domain in which various AI approaches could be tested. Experimental results show that the specific rule-based approach performs well compared to a decision tree method and feedforward neural networks. More specifically, the rule-based approach performs slightly worse than the other methods in terms of classification accuracy but uses less features to produce an output. Up till now, certainty factor rules had not been used in aphasia diagnosis. The results are promising and show that application of certainty factor rules could be considered in this domain.

Our future work in this context involves three possible main directions. One main direction concerns performing further experiments. Experiments could involve the rule-based formalism as well as other intelligent methods. We are currently working on improvements to the certainty factor approach presented here, to address the generalization issue mentioned and on an alternative certainty factor generation method, utilizing the Bayes Theorem. The other main direction could involve implementation of a rule-based approach using fuzzy certainty factors. Experiments could be performed to test the performance of the alternative certainty factor rule-based approaches. Finally, an approach integrating multiple intelligent methods could be used since integrated approaches may provide advantages in knowledge representation and reasoning [40], [41].

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