Neural Network as a tool to utilize MMPI-2 results in the classification of psychiatric syndromes: Comparison with Linear Discriminant Analysis, Principal Component Analysis and Agglomerative Hierarchical Clustering.

Dr. Ginanneschi, S.

ABSTRACT Refering to a general picture of present day Neural Network studies, in the automatic diagnosis field, we have conducted a pilot study consisting of the implementation of two kinds of Neural Networks; both trained to categorize four psychiatric syndromes: Major Depression, Bipolar Depression, Obsessive Compulsive Disorder (OCD) and Borderline Personality Disorder (BPD).

During training we used the backpropagation algorithm.

The MMPI-2 had previously been administered to 68 mental patients affected by one of the four syndromes in question; most clinicians usually administer MMPI-2 after a patient's anamnesis and proceed with more sensitive tests to characterize the identified pathology; often it is used only to deny the presence of other concomitant pathologies that can mislead the diagnosis. These 4 syndromes were chosen for their similarity.

In order to judge the potential of neural computing in the chosen setting, the same data were analyzed by other additional statistical techniques: Linear Discriminant Analysis, Principal Component Analysis and Agglomerative Hierarchical Clustering.

Our study was based on the hypothesis that NN trained using MMPI-2 clinical, content and supplementary scales, will better discriminate output syndromes, than NN trained using only MMPI-2 clinical scales, or than linear techniques. The hypothesis was based on the analysis of the literature (1-12). We also expected that the reason for the potential better performance of the NN trained using MMPI-2 clinical, content and supplementary scales would be due to its similarity to human decision making using MMPI-2 data. This would introduce the possibility to develop in the future a Data Mining System for MMPI-2, to support expert human clinical decisions in the field of Psychology.

The first NN studied trained using MMPI-2 clinical scales is able to attain classifications that are statistically different from chance for 11 patients out of 34, an average 33% of right responses. The NN trained using clinical, validity, content and a supplementary MMPI-2 scale, on the contrary is able to make the right classification of 20 patients out of 33, an average 67% of correct responses.

This pilot study has verified the NN ability in a non trivial classification task.

A.I. techniques are nowadays applied to the medical field for the realization of Intelligent Systems capable of giving support to specialized clinic staff decisions in all routine activities, which demand more and more exact qualitative standards. These techniques are usually labeled under the name of Data Mining (13, 14) and Neural Networks are spreading quickly among these approaches to help build applications of data clustering, pattern recognition, and expert system rule generation, tasks that, currently, are wide-spread in laboratory data analysis (15-20). Neural networks are special computing elements that can be trained to make decisions based on historical data. They work by discovering patterns and by inducing rules that define empirical relationships. To use NNs means to assert the capability of the system to develop an implicit representation of the problem, rather than to have the most suitable model supplied by the experimenter. Refering to a general picture of present day Neural Network studies, in the automatic diagnosis field, we have conducted a pilot study consisting of the implementation of two kinds of Neural Networks; both trained to categorize four psychiatric syndromes. The staff of the "IPSICO Institute", in Florence and of the private nursing home, "Villa Margherita" in Vicenza, supplied us, in anonymous form and respecting APA norms for clinical data diffusion, real MMPI-2 data. To study the behavior of the neural networks we used a neural network simulation program: T-learn (21); for the LDA, the PCA, and the AHC we used statistical software: X-STAT (25).

Our study was based on the hypothesis that the second NN trained using MMPI-2 clinical, content and supplementary scales, will better discriminate output syndromes, than the first NN trained using only MMPI-2 clinical scales, or than linear techniques. We also expected that the reason for the potential better performance of the NN trained using MMPI-2 clinical, content and supplementary scales would be due to its similarity to human decision making using MMPI-2 data. This would introduce the possibility to develop in the future a Data Mining System for MMPI-2, to support expert human clinical decisions in the field of Psychology.

METHODS

Data. In supervised learning, the correct results (target values, desired outputs) are known and are given to the NN during training so that the NN can adjust its weights to try matching its outputs to the target values.

Individual units do not represent particular concepts, but collectively, groups of units can. This produces a rather robust architecture, which does not depend on the success of particular units, but spreads responsibility. There is evidence that our brain adopts such a robust approach.

After training, the NN is tested by giving it only input values and seeing how close it comes to outputting the correct target values. Generally a “classifier” must be tested on a data set different from the training one used. In the absence of a different data set, however, it is possible to use half of all data for the learning phase and the other half for the test one and to use different combinations of data, conducting several learning and test sets. During this study we randomly conducted 10 learning and test sets using MMPI-2 clinical scales and 15 using MMPI-2 clinical, validity, content and supplementary scales.

Every MMPI-2 profile refers to one of the four syndromes thanks to specialized clinical staff evaluation.

In the first study, using the NN trained using MMPI-2 clinical scales, we used 18 Major Depression patients, 12 Bipolar Depressive patients, 20 Obsessive Compulsive disorder patients and 18 Borderline Personality Disorder patients. To train and test the second NN, using MMPI-2 clinical, validity, content and supplementary scales, we used 18 Major Depression patients, 12 Bipolar Depressive patients, 18 Obsessive Compulsive disorder patients and 18 Borderline Personality Disorder patients.

Every MMPI-2 profile is presented to both NNs in the form of its scale values, previously converted to decimal scale. All data are in matrix format.

The choice of pathologies in this setting: Major Depression, Bipolar Depression, Obsessive Compulsive Disease and Borderline Personality Disorder, instead of others, reflects the desire to propose a non trivial NNs study. In fact, the specialized staff too, find it difficult to tell these syndromes apart only reaching their decision on the analysis of T-scores derived from MMPI-2 scales. Most clinicians usually administer MMPI-2 after a patient’s anamnesis and proceed with more sensitive tests to characterize the identified pathology; often it is used only to deny the presence of other concomitant pathologies that can mislead the diagnosis.

These 4 syndromes were chosen for their similarity. It is often necessary to make a careful differential analysis between major depression and obsessive compulsive disease or between the first and bipolar depression and various effects of comorbility are famous.

Some researches on automatic diagnosis are concentrated on analyzing different results obtainable by linear statistical techniques and parallel ones (26). Linear Discriminant Analysis allows a researcher to study the

difference between two or more groups of objects with respect to several variables simultaneously, determining whether meaningful differences exist between the groups and identifying the discriminating power of each variable; Principal Component Analysis is based on the statistical representation of a random variable; by ordering the eigenvectors in the order of descending eigenvalues (largest first), one can create an ordered orthogonal basis with the first eigenvector having the direction of largest variance of the data. Agglomerative Hierarchical Clustering proceeds by a series of binary mergers (agglomerations), initially of individual compounds, later of clusters formed at previous stages, and the different methods are distinguished by the way in which the distance between clusters is measured, in order to choose the pair to be merged next.

Instead of executing complex statistical procedures, the neural network learning model iteratively converges to a pattern recognition function that is optimal in a least-mean-square sense. The iterative process implicitly estimates the statistics of the historical training data. This parallels human pattern recognition: people learn patterns over time.

Network Formulation and Calculation. As the basic network, we used a three-layered feed-forward network consisting of ten input units (the units are henceforth called “nodes” for simplicity) receiving the input signals (appropriately transformed MMPI-2 clinical scales values), five hidden nodes (responsible for internal representations), and four output nodes delivering the output signals (corresponding to the four diagnostic classes of mental syndromes), as shown in Fig. 1. The ten input nodes are responsible for receiving as input signals a single MMPI-2 clinical scale value; the test had previously been administered to 68 mental patients affected by one of the four syndromes in question. In order to explore the ability of the neural network to extract hidden information from data, we studied a second network made different from the one shown in Fig.1 by the introduction of other MMPI-2 scale values, as input nodes: two validity scales, supplementary scales, like MAC-r, PK, O-H, MDS, APS and AAS and 15 content scales; consequently the hidden units were increased to 18, Fig. 2. Each NN unit has an activation level, which can collectively describe how strongly a particular concept is held to be true. These activation levels change as the system runs. Each unit can be connected to any other unit, via a link that has a weighting or "strength". This weighting usually determines how important the output from a unit will be at the receiving unit. The

activation of units change as the network runs, and this describes the changing belief in the particular concept represented by the units.

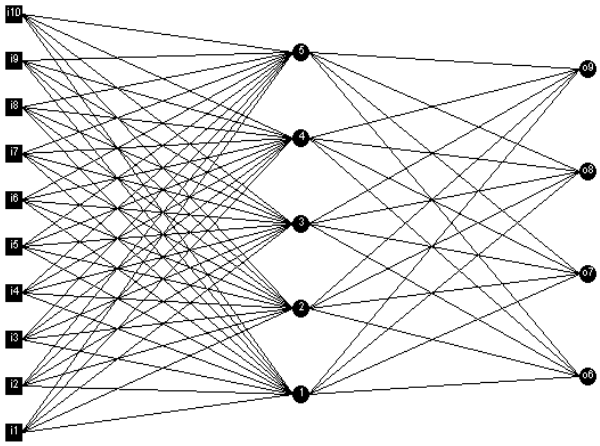

Fig. 1: Network Architecture. Representation of a three-layered feed-forward network with the first layer taking in 10 inputs, one hidden layer and the last layer producing 4 outputs.

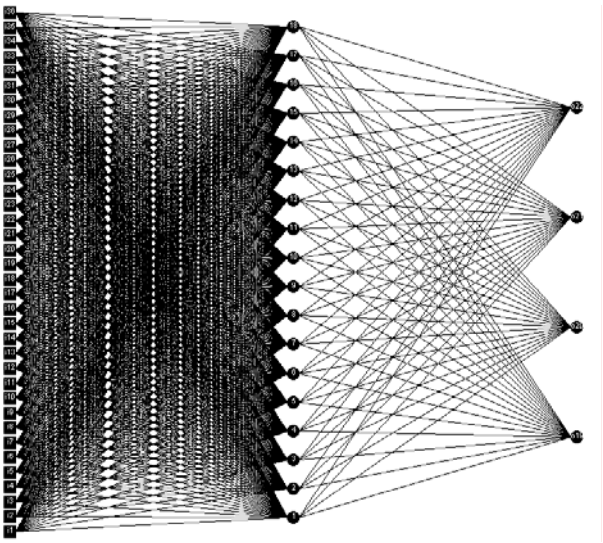

Fig. 2: Network Architecture. Representation of a three-layered feed-forward network with the first layer taking in 36 inputs, one hidden layer and the last layer producing 4 outputs.

We have already mentioned that one of the most interesting aspects of Parallel Distributed Processing systems is that programming them often consists of training them. Usually during this phase, the weights attached to the connections change. The trained network is then ready to receive new inputs, and to respond to them as hoped.

During training we used the backpropagation algorithm that includes two passes through the network: forward pass and backward pass. During the backward pass, the weights are adjusted in accordance with the error correction rule so as to make the network output closer to the desired one.

The backpropagation algorithm does gradient descent as it moves in the direction opposite to the gradient of the error, which is in the direction of the steepest decrease of the error. By varying all the weights simultaneously in proportion of how much good is done by the individual changes one obtains the direction of most rapid error decrease; the gradient search technique allow us to minimize a cost function equal to the mean square difference between the desired and actual net outputs. The networks are trained by initially selected small random weights and then presenting all training data incrementally. Weights are adjusted after every trial using side information specifying the correct class until weights converge and the cost function is reduced to an acceptable value.

The main advantage of backpropagation over traditional methods of error minimization is that it reduces the cost of computing derivatives by a factor of *N*, where *N* is the number of derivatives to be calculated (22-24). Furthermore, it allows higher degrees of nonlinearity and precision to be applied to problems. The details of computations have been described by others in recent papers and monographs; we have specifically used the formulation given in ref. 25. The convergence of a network depends on parameters like learning rate, momentum factor, slope of the activation function etc. during both networks computations here reported, these parameters were set time after time.

Evaluation of Results

In order to judge the potential of neural computing in the chosen setting, the same data were analyzed by other additional statistical techniques: Linear Discriminant Analysis, Principal Component Analysis and Agglomerative Hierarchical Clustering.

Using linear techniques it was impossible to classify the available data, in the respective four classes of syndromes. Linear methods are highly dependent on data classes given. A wrong classification can depend on: a prior wrong division into different classes, missing training data, or on data homogeneity; it is possible to demonstrate in Fig.3, Fig.4 and Fig.5 that the obtained outcomes are due to data homogeneity; because of this LDA can’t produce any kind of data pattern representation.

We also analyzed the MMPI-2 profiles that both NNs didn’t recognize during the test sets, demonstrating that human experts have the same difficulties in doing this task well. Training a NN with several examples could improve its ability in this classification task, like human expert.

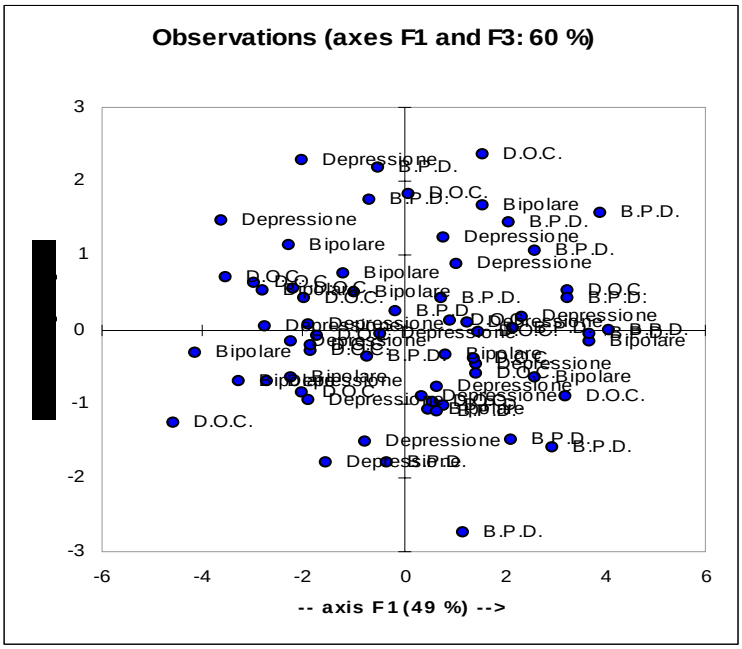

Fig. 3: PCA1. It represents many eigenvalues distribution on all data set.

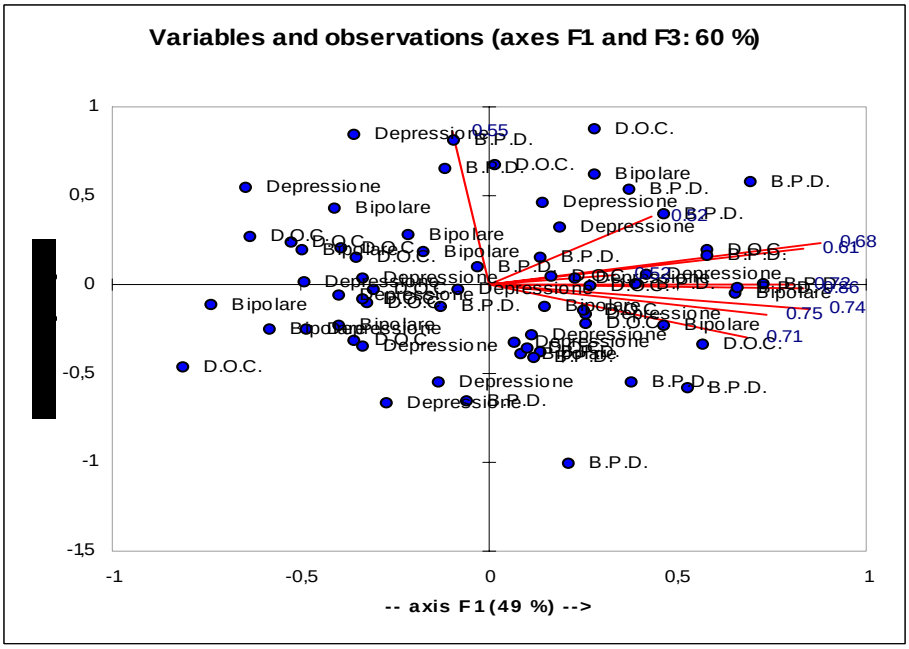

Fig. 4: PCA2. It represents many eigenvectors having the direction of largest variance of data set.

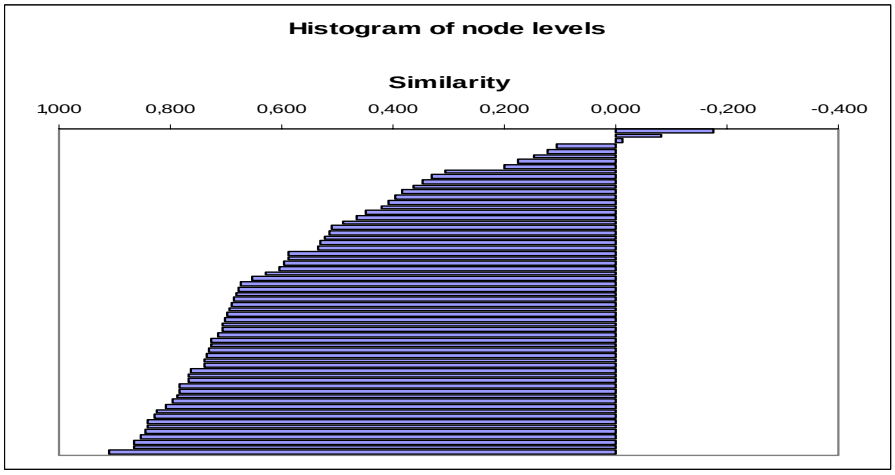

Fig. 5: AHC similarity histogram. It represents data set homogeneity.

RESULTS

We analyzed NNs learning and test sets; in Fig.6, one of the 10 error curves, obtained by training the NN using MMPI-2 clinical scales is represented. The mean cost value is 0.400; the function has a standard deviation of +- 0.1. Moreover, the cost function appears fuzzy. Fig.7 represents one of the 15 error curves obtained training the second NN, which was composed of MMPI-2 clinical, validity, content and supplementary scales. The mean value error is 0.380 but the function has a standard deviation of +-0.3; even if the cost function appearance presents a good deal of interference, it gradually decreases.

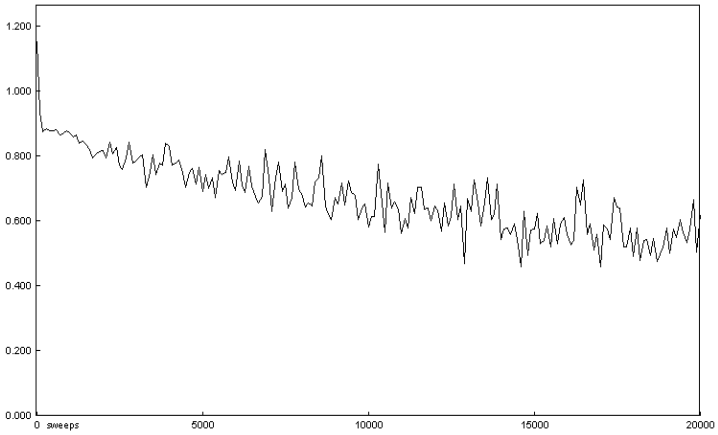

Fig.6: Error curve; this error graph shows 20000 epochs of training (for 33 patterns); function cost is between 0.0 a 0.8 and it is minimized at 0.4; the cost function appears fuzzy.

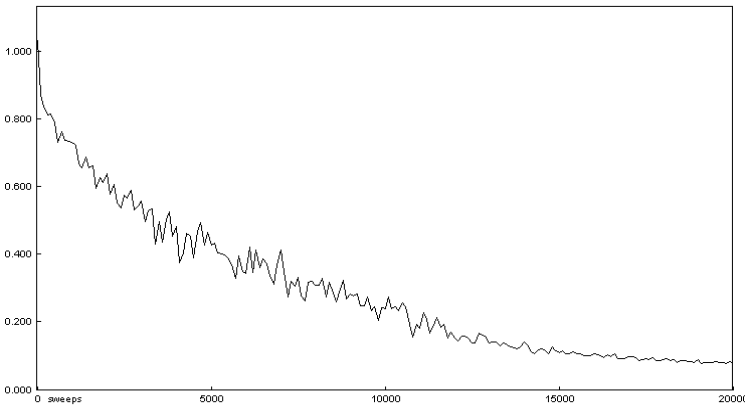

Fig.7: Error curve; this error graph shows 20000 epochs of training (for 34 patterns); function cost is between 0.0 a 1.0 and it is minimized at 0.1, the cost function appearance presents interferences that gradually decrease .

These initial outcomes, demonstrate that during the learning set, the second NN obtains a right internal representation of the problem and can associate every input data pattern to its relative syndrome output.

Tab.1 and Tab.2 summarize NNs results during all training sets conducted.

Output activations using clinical 7-20000.wts and clinical7.data (Training Set)			
0.818	0.029	0.031	0.050
0.795	0.034	0.198	0.029
0.935	0.036	0.065	0.009
0.847	0.056	0.313	0.008
0.938	0.027	0.069	0.009
0.943	0.015	0.009	0.028
0.977	0.026	0.059	0.017
0.991	0.010	0.027	0.018
0.849	0.075	0.185	0.027
0.000	0.645	0.001	0.638*
0.098	0.876	0.001	0.000
0.009	0.783	0.001	0.009
0.022	0.808	0.030	0.000
0.000	0.621	0.000	0.601
0.001	0.729	0.006	0.020
0.204	0.053	0.552	0.001
0.963*	0.031	0.038	0.024
0.006	0.001	0.987	0.012
0.183	0.008	0.855	0.009
0.239	0.012	0.743	0.006
0.001	0.000	1.000	0.000
0.000	0.138	0.941	0.000
0.016	0.003	0.989	0.000
0.031	0.001	0.997	0.000
0.070	0.003	0.989	0.000
0.246	0.002	0.041	0.922
0.002	0.207	0.003	0.803
0.039	0.017	0.009	0.883
0.015	0.014	0.025	0.954
0.007	0.103	0.010	0.841
0.001	0.286	0.004	0.577
0.182	0.002	0.025	0.987
0.000	0.468*	0.000	0.553
0.001	0.240	0.002	0.867

Tab.1: Output data generated after training NN using MMPI-2 clinical scales. NN doesn't classify 3 patients, signed with *.

Output activations using complete 1-10000.wts and complete 1.data (Training Set)			
0.953	0.014	0.109	0.000
0.943	0.007	0.000	0.032
0.931	0.004	0.017	0.001
0.945	0.031	0.011	0.000
0.933	0.000	0.010	0.019
0.950	0.002	0.000	0.087
1.000	0.002	0.010	0.000
0.999	0.028	0.000	0.000
0.935	0.049	0.033	0.000
0.000	0.903	0.061	0.004
0.017	0.986	0.002	0.001
0.000	0.964	0.000	0.097
0.023	0.985	0.025	0.000
0.017	0.952	0.034	0.000
0.063	0.878	0.000	0.011
0.002	0.000	0.994	0.004
0.030	0.000	0.986	0.001
0.011	0.000	0.947	0.024
0.000	0.001	0.997	0.038
0.087	0.001	0.974	0.000
0.036	0.000	0.990	0.013
0.003	0.000	0.996	0.004
0.053	0.018	0.937	0.000
0.002	0.057	0.976	0.000
0.000	0.000	0.092	0.915
0.004	0.013	0.000	0.971
0.000	0.057	0.004	0.934
0.001	0.057	0.000	0.960
0.116	0.001	0.000	0.945
0.000	0.032	0.000	0.923
0.004	0.046	0.000	0.912
0.019	0.019	0.000	0.914
0.001	0.001	0.000	0.998

Tab.2: Output data generated after training NN using MMPI-2 validity, clinical, content and supplementary scales. NN exactly classifies all patients.

NN Cluster Analyses of training set data (Fig.8; Fig.9) clearly display these outcomes: the first NN studied isn't able to discriminate between OCD patients and BPD ones; the second NN learns to correctly classify every class of syndromes.

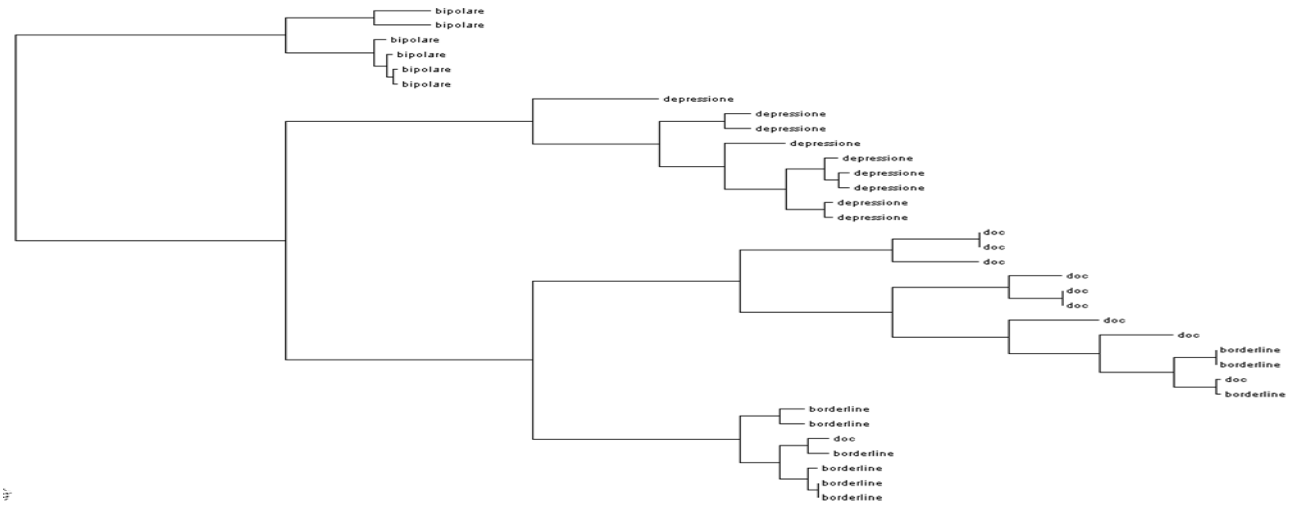

Fig.8: Cluster Analysis of training set. Every group of syndromes is separately categorized. NN trained using clinical scales wrongly classify some OCD and BPD patients.

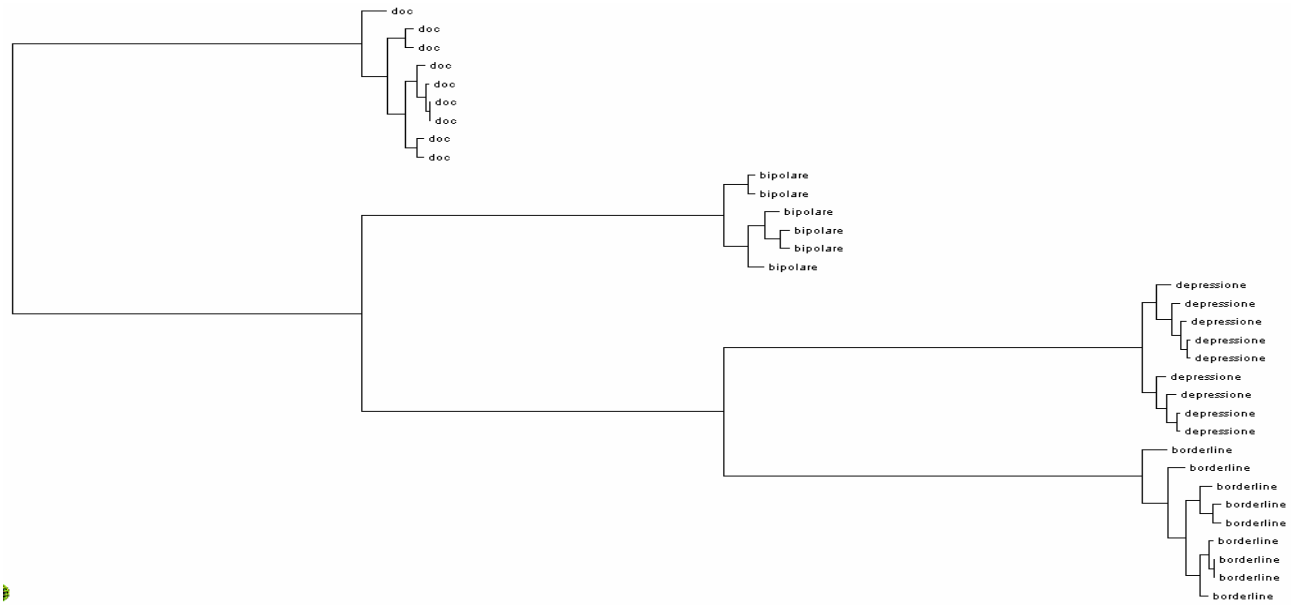

Fig.9: Cluster Analysis of training set. Syndromes are separately categorized. NN trained using MMPI-2 validity, clinical, content and supplementary scales correctly classify all patients.

During the test set, we used a random combination of data patterns not used for NNs training; our results are summarized in Tab.3 and Tab.4. The first NN studied is able to attain classifications that are statistically different from chance for 11 patients out of 34, an average 33% of right responses. The NN trained using clinical, validity, content and a supplementary MMPI-2 scale, on the contrary is able to make the right classification of 20 patients out of 33, an average 67% of correct responses.

Moreover, during the 4th validation proof, the second NN exactly classified all 33 patients.

Cluster analysis during the test set of NN trained using MMPI-2 clinical scales, shows the ambiguous resulting patterns, Fig.10.

In the case of NN trained using MMPI-2 clinical, validity, content and supplementary scales, cluster analysis during the test sets highlights a compact and distinct new patterns classification, even if some psychiatric patients are badly diagnosed, Fig.11.

In Fig.12 we present cluster analysis of the 4th validation proof, in which the NN exactly classify all 33 patients, in their respective classes of syndromes.

Set	Right classifications
1	12/34*
2	9/34
3	12/34*
4	10/34
5	14/34**
6	11/34
7	16/34**
8	11/34
9	10/34
10	10/34

Tab.3: Table presents surfacing outcomes by random selected test sets, released on the first NN trained. We define every outcome different from chance using the Binomial Test, * = $p<0.05$; ** = $p<0.01$.

Set	Right classifications
1	18/33**
2	14/33*
3	15/33**
4	33/33**
5	17/33**
6	20/33**
7	14/33*
8	18/33**
9	17/33**
10	17/33**
11	17/33**
12	24/33**
13	26/33**
14	26/33**
15	26/33**

Tab.4: Table presents surfacing outcomes by random selected test sets, released on the second NN trained. We define every outcome different from chance using the Binomial Test, * = $p<0.05$; ** = $p<0.01$.

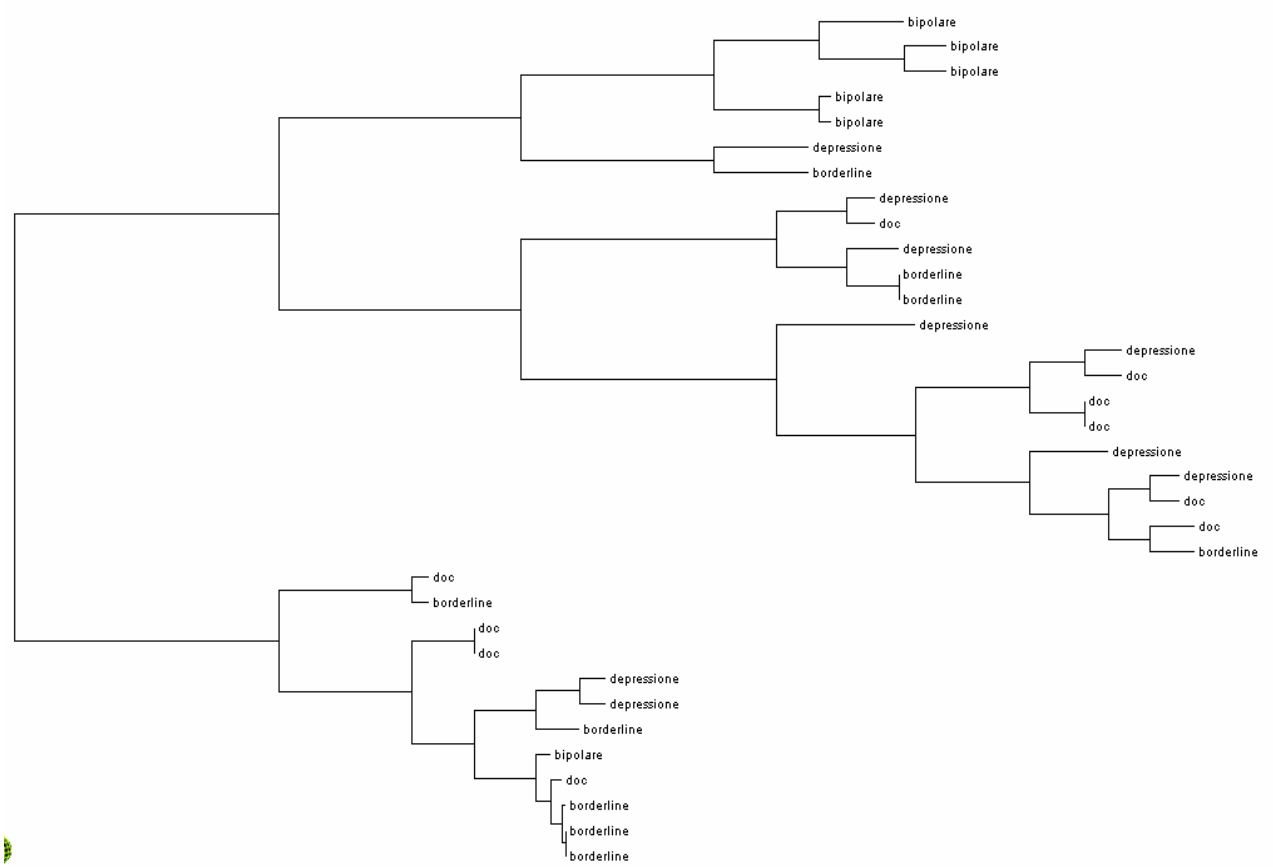

Fig.10: Cluster Analysis of test set. Syndromes aren't separately categorized. NN trained using clinical MMPI-2 scales wrongly classify all patients.

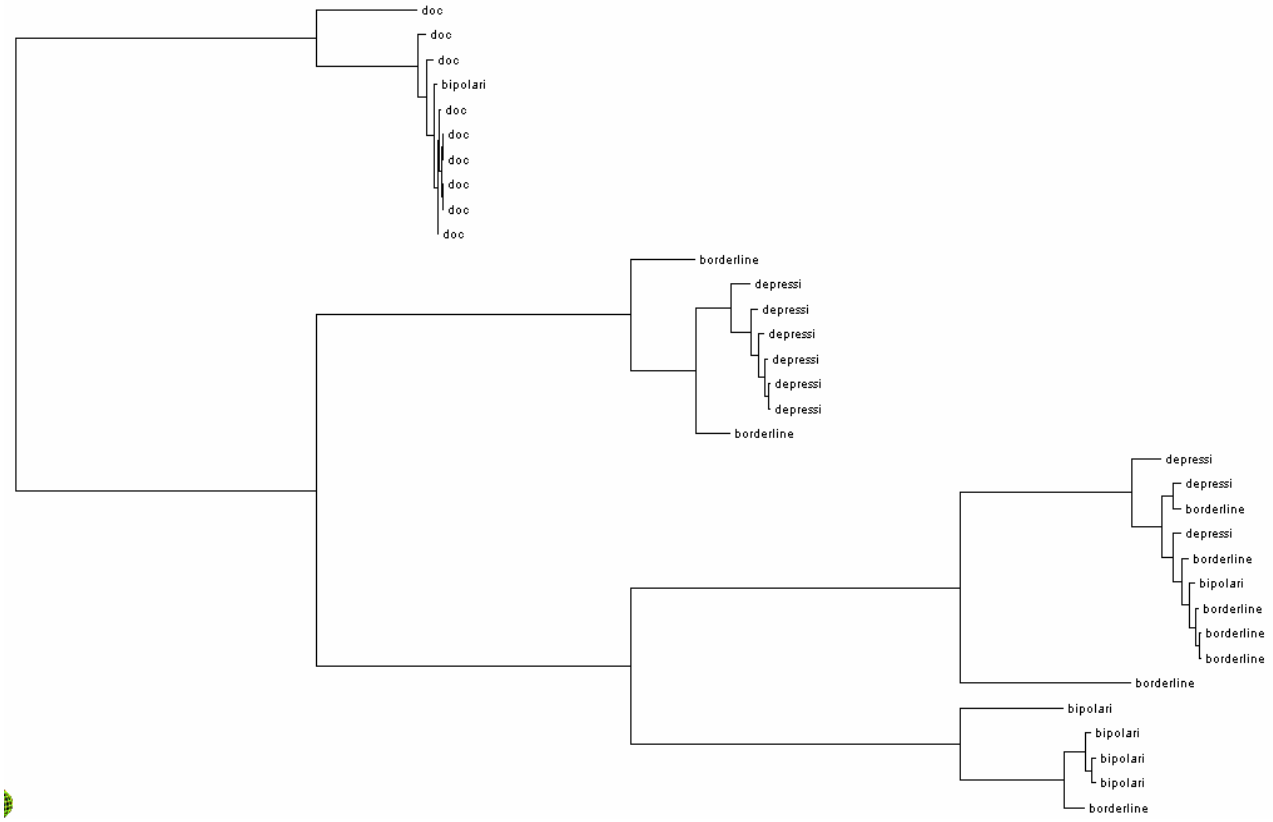

Fig.11: Cluster Analysis of test set. Syndromes are separately categorized. NN trained using validity, clinical, content and supplementary MMPI-2 scales correctly classify nearly all patients.

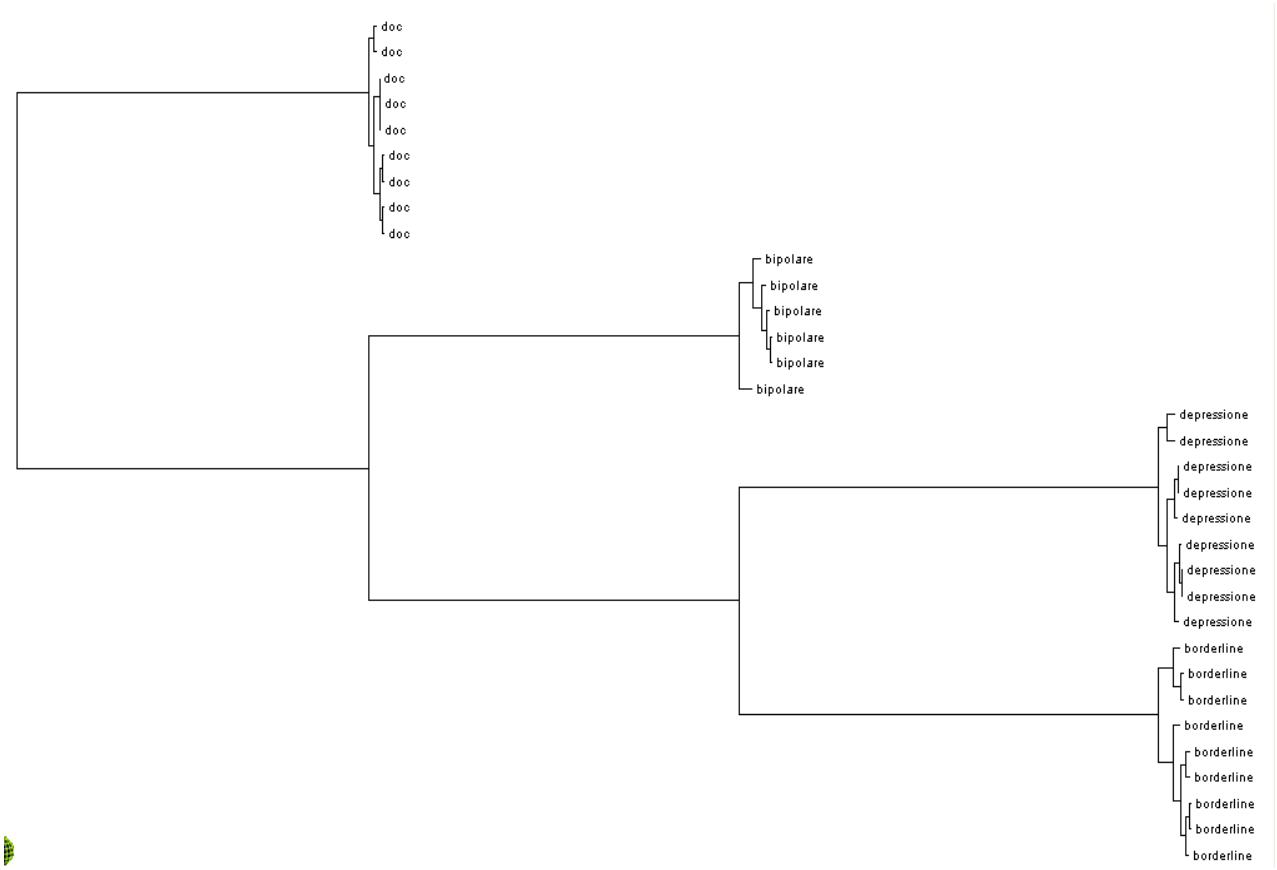

Fig.12: Cluster Analysis on test set. Syndromes are separately categorized. NN trained using validity, clinical, content and supplementary MMPI-2 scales correctly classify all patients.

Discussion

NNs and Linear Statistical Analysis outcomes confirm the hypothesis that a NN trained using clinical, validity, content and supplementary MMPI-2 scales would manifest better ability in the discrimination task between the patients' profiles, than another one, trained using only clinical scales. The hypothesis was based on the analysis of the literature (1-12) and we also suggested that the better performance of the second NN would be due to its similarity to human decision making using MMPI-2 data. This would introduce the possibility to develop in the future a Data Mining System for MMPI-2, to support expert human clinical decisions in the field of Psychology.

To understand in which cases both NNs fail to classify input patterns in its relative classes of syndromes, and if these mistakes can be assimilated to human ones, we analyzed data input. Fig. 13 and Fig.14 represent a MMPI-2 profile that the clinical staff classifies as an OCD patient, but both NNs wrongly classified as BDP.

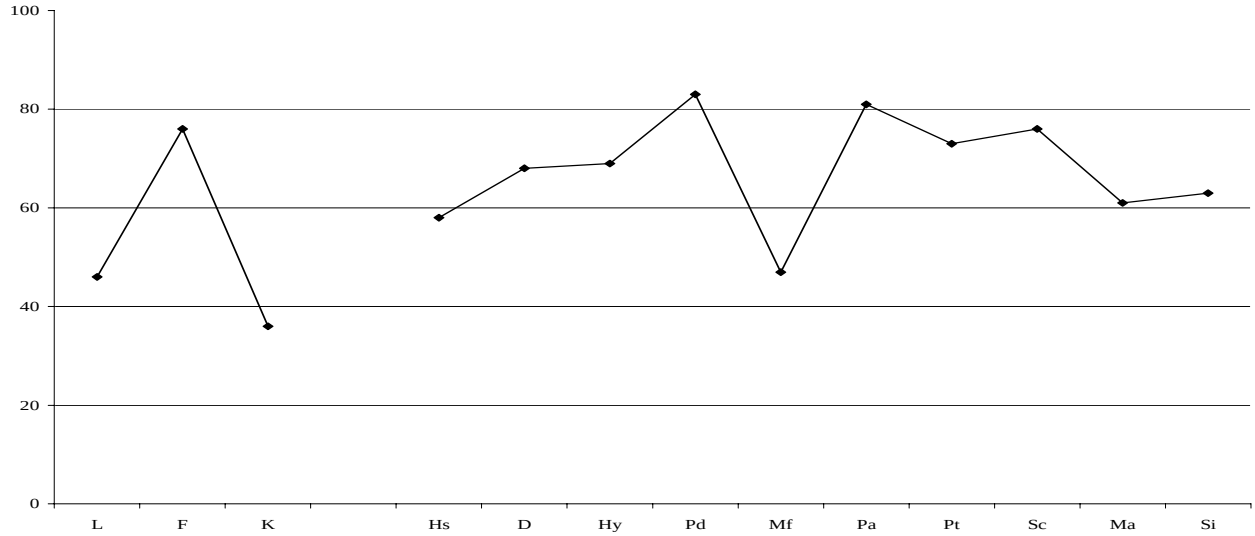

Fig.13 MMPI-2 Validity and Clinical scales.

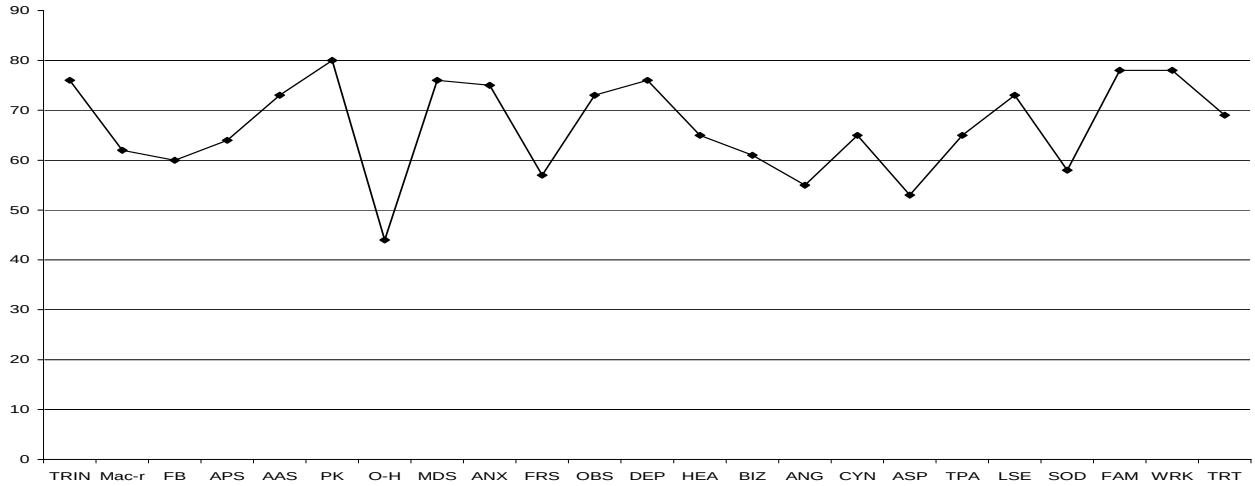

Fig.14 MMPI-2 Validity, Content and Supplementary scales.

Most Authors (27, 28), maintain that a prototypic BPD profile is characterized by a generalized elevation of most scales and, just like these authors, the NNs have wrongly classified the data patterns. The greater quantity and quality of the data used for training and testing the second NN, makes this system capable to exactly categorize more patients than first one, according to equivalent expert human ability.

Linear statistical techniques cannot discriminate classes of syndromes by using MMPI-2 patients' results.

This pilot study has verified the NN ability in a non trivial classification task.

The world diffusion of MMPI-2 and the importance of making a precocious and accurate diagnosis in psychology suggest that it would be very useful to amplify this research using a bigger data sample in order to improve the NN capacity to support expert human decisions in psychological diagnosis.

Bibliography

1. Ben-Porath, V.S., Butcher, J.N. The Comparability of MMPI and MMPI-2 Scales and Profiles. Psychological Assessment: A Journal of Consulting and Clinical Psychology, 1991.
2. Boone, D.E. Validity of MMPI-2 Depression content scales with psychiatric inpatients. Trenton Psychiatric Hospital, New York. Psycol. Rep., 1994.
3. Butcher, J.N., Graham. J.R., Ben-Porath, Y.S., Tellegen, A., Dahlstrom, W.G., Kaemmer, B. Minnesota Multiphasic Personality Inventory-2. Manual for administration, scoring, and interpretation. Revised edition. Minneapolis, University of Minnesota Press, 2001.
4. Evans, R.W., Ruff, R.M., Braff, D.L., Ainsworth, T.L. MMPI characteristics of borderline personality inpatients. J. Nerv. Ment. Dis., 1984.
5. Evans, R.W., Ruff, R.M., Braff, D.L., Cox, D.R. On the consistency of the MMPI in borderline personality disorder. Biological Sciences Research Center, University of North Carolina, School of Medicine, Chapel Hill. Percept. Mot. Skills, 1986.
6. Fals-Stewart, W., Schafer, J. MMPI correlates of psychotherapy compliance among obsessive-compulsives. Department of Psychiatry, University of California, San Diego School of Medicine. Psychopathology, 1993.
7. Franklin, C.L., Strong, D.R., Greene, R.L. A taxometric analysis of the MMPI-2 Depression scales. Pacific Graduate School of Psychology, California, USA. J. Pers. Assess., 2002.
8. Hurt, S.W., Clarkin, J.F., Frances, A., Abrams, R., Hunt, H. Discriminant validity of the MMPI for borderline personality disorder. J. Pers. Assess., 1985.
9. Munley, P.H., Busby, R.M., Jaynes, G. MMPI-2 findings in schizophrenia and depression. Psychological Assessment, 1997.
10. Resnick, R.J., Goldberg, S.C., Schulz, S.C., Schulz, P.M., Hamer, R.M., Friedel, R.O. Borderline personality disorder: replication of MMPI profiles. Virginia Commonwealth University, Department of Psychiatry, Medical College of Virginia, Richmond. J. Clin. Psychol., 1988.
11. Streit, K., Greene, R.L., Cogan, R., Davis, H.G. Clinical correlation of MMPI depression scales. Department of Psychology, Texas Tech University, Lubbock. J. Pers. Assess., 1993.
12. Widiger, T.A., Sanderson, C., Warner, L. The MMPI, prototypal typology, and borderline personality disorder. J. Pers. Asses., 1986.
13. Lee, I.N., Liao, S.C., Embrechts, M. Data mining techniques applied to medical information. Lally School of Management and Technology, Rensselear Polytechnic Institute, New York, USA. Med. Inform. Internet Med., 2000.
14. Liao, S.C., Lee, I.N. Appropriate medical data categorization for data mining classification techniques. Department of Internal medicine, Chang Gung Memorial Hospital, Taiwan. Med. Inform. Internet Med., 2002.
15. Callan, R. The Essence Of Neural Networks. Prentice Hall, 1999.
16. Kattan, M.W., Beck, J.R. Artificial neural network for medical classification decision. Arch. Pathol. Lab. Med., 1995.
17. Eyde, L., Kowal, D., Fishburne, F., in: Gutkin, T.B., Wise, S.L. The computer and the decision making process. Lawrence Erlbaum, Hillsdale, 1991.
18. Sharpe, P.K., Caleb, P. Artificial neural networks within medical decision support system. Bristol Transputer Centre, Faculty of Computer Studies and Mathematics, University of the West of England, Frenchay. Scand. J. Clin. Lab. Invest. Suppl., 1994.
19. McClelland J.D., Rumelhart, D.E. Distributed memory and the representation of general and specific information. Journal of Experimental Psychology: General, 1985.
20. McClelland J.D., et al. Parallel Distributed Processing. Explorations in the microstructure of cognition, 2 vol., Psychological and Biological Models. Cambridge, Mass: MIT Press, 1986.
21. Young, S., Elman, J., Plunkett, K., 1996.
22. Rumelhart, D.E., Hinton G. E., Williams, R. J. Learning internal representations by error propagation, 1986.
23. McCord, N.M., Illingworth, W.T. A practical guide to Neural Nets. Addison Wesley, New York, 1991.
24. Rumelhart, D.E. Introduction to Human information processing. Chichester: Wiley, 1977.
25. X-STAT. Thierry Fahmy
26. Reibnegger, G., Weiss, G., Werner-Felmayer, G., Judmaier, G., Wachter, H. Neural networks as a tool for utilizing laboratory information: comparison with linear discriminant analysis and with classification and regrassion trees. Institute for Medical Chemistry and Biochemistry, University of Innsbruck, Austria. Proc. Natl. Acad. Sci., 1991.
27. Evans, R.W., Ruff, R.M., Braff, D.L., Ainsworth, T.L. MMPI characteristics of borderline personality inpatients. J. Nerv. Ment. Dis., 1984.
28. Evans, R.W., Ruff, R.M., Braff, D.L., Cox, D.R. On the consistency of the MMPI in borderline personality disorder. Biological Sciences Research Center, University of North Carolina, School of Medicine, Chapel Hill. Percept. Mot. Skills, 1986.