# A Hybrid Prediction System Using Rough Sets and Artificial Neural Networks

M. Durairaj [#1], K. Meena [*2]

[#] *Assistant Professor, Department of Computer Science and Engineering, Bharathidasan University, Tamilnadu, India*

[1] durairaj_m@csbdu.in

[*] *Vice-chancellor, Bharathidasan University, Tamilnadu, India*

***Abstract*— This paper illustrates a hybrid prediction system consists of Rough Set Theory (RST) and Artificial Neural Network (ANN) for processing medical data. In the process of developing a new data mining technique and software to aid efficient solutions for medical data analysis, we propose a hybrid tool that incorporates RST and ANN to make efficient data analysis and suggestive predictions. In the experiments, we used spermatological data set for predicting quality of animal semen. The data set used in the experiments is subjected to quantize and normalize, and use this as a reflection of the internal system state. The RST is used as a tool for reducing and choosing the most relevant sets of internal states for predicting the semen fertilization potential. Chosen optimal data set is input to constructed neural network with supervised learning algorithm for the prediction of semen quality. This paper demonstrates that the RST is an effective pre-processing tool for reducing the number of input vector to ANN without reducing the basic knowledge of the information system in order to increase prediction accuracy of the proposed system. The resulting system is a hybrid prediction system for medical database called an Intelligent Rough Neural Network System (IRNNS).**

Keywords: Artificial Neural Network, Machine learning technique, In-vitro fertilization, Rough sets theory (RST), Fertility rate prediction, IRNNS, Hybrid prediction system.

## VII. INTRODUCTION

Several machine learning techniques or data mining tools like Artificial Neural Networks (ANN), Fuzzy logic and Rough Sets Theory (RST) are used for data classification. There have been number of research works and surging interests in ANN and developing hybrid system by combining other applications with ANN. The neural network and rough sets methodologies have their place among intelligent classification and decision support systems. Knowledge of the system can be seen as organized data sets with the ability to perform classification. Hence a formal framework capable of reasoning about classifications and delivering implicit facts from explicit knowledge would be helpful. The ANN and RST can be combined to obtain such a framework. This approach is based on the rough sets feature selection mechanism and neural networks efficient classification property. Traditional model construction and simulation data mining techniques perform poorly due to the highly non linear dynamics and overwhelming complexity of data being generated.

The knowledge acquired by ANN through training process is represented by the weights of the connections between the neurons, the threshold values and the activation function. Identifying the problem description at the neural level is not possible because of the implicit knowledge representation of the neuron; therefore, neural network often called as 'black boxes'. To improve the quality of the learning, the Rough Sets Theory (RST) is used to select key parameters before training the predictor (ANN).

Rough Sets Theory, developed by Z. Pawlak and his co-workers in the early 1980s [1], has become a widely recognized data analysis method to deal with vagueness and uncertainty of data [2]. The concept of RST is founded on the assumption that every object of the universe of discourse is associated with some information [3]. The RST finds the description of sets of objects in terms of attribute values, checks dependency between attributes, finds significance of attributes, reduces attributes and derives decision rules [4]. The rough sets based reduction of the attributes space not only improves the efficiency of the predictor itself, but also provides some additional information about the mechanisms governing decision-making. One of the reasons for developing hybrid system is to build more powerful systems that can reduce drawbacks of implementing a single machine learning techniques. Some of other researchers proposed similar integrated method in other applications for classification and prediction purpose [5]-[8].

In this paper, a quick reduct algorithm based on attribute frequency in discernibility matrix is proposed for pre-processing. We also propose an intelligent rough neural network algorithm for efficient data classification and prediction. The medical data used in this work are in the format of multi-attribute information table and suit the rough set model. The paper is organized as follows. In Section II, the rough set and neural network approach is briefly reviewed. The hybrid strategy of proposed model in the data mining setting is presented. The RST based data analysis is reviewed in Section II-A, and ANNs are discussed in Section II-B. Then the overall structure of the hybrid system is presented in Section II-C. In Section III, illustrative experimental results are presented. Then this paper is concluded with brief discussion of the study and future research directions.

## VIII. ROUGH SETS THEORY

The method of rough set data analysis has the following advantages over traditional methods [9], [10]. Rough set method is unlike probability in statistics or membership grade in the fuzzy set theory, based on the original data sets not any external information [11]. It is suitable for both quantitative, qualitative attributes and discovers hidden facts in data in the form of decision rules. The derived decision rules describe the knowledge contained in the information tables and eliminate the redundancy of original data. The results obtained by rough set method are simple and explainable. Finding minimal subsets (reducts) of attributes that are efficient for rule making is a central part of its process [12]. RST is a combinatorial tool for reducing quantized data sets by discarding attributes that have no or limited discriminatory power [2], [4] and [13].

### A. Basic notions

The basic notions of RST are: *information system, approximations, reduction of attributes* and *others*.

*1) Information system:* An information system is defined as I=(U,A), where U is a non-empty set of finite objects called universe, the finite attribute set A={$a_1$,.. $a_n$}, where each attribute $a \in A$ is a total function $a : U \rightarrow V_a$, where $V_a$ is called the domain or value set of attribute $a_i$.

An approximation space is an ordered pair A = (U, R), where U is a finite and non-empty set of elements called attributes, R is an equivalence relation about U. Any set $B \subseteq A$ there is an associated equivalence relation called B-indiscerbility relation defined as:

$$IND_A(B) = \{(x, y) \in U^2 \mid \forall a \in B, a(x) = a(y)\} \quad \ldots \ldots (1)$$

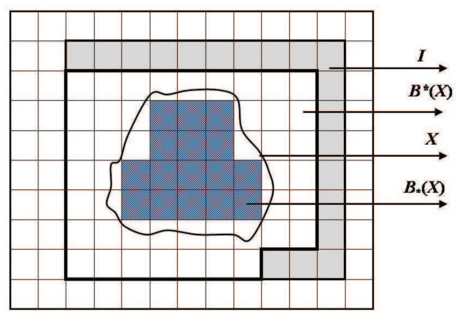
If $(x, y) \in IND_A(B)$, then x and y are indiscernible from each other by attributes from B. The indiscernibility is an equivalence relation.

*2) Approximations:* In this way, RST provide a simple form to treat with the uncertainty. Given information system I, let $X \subseteq U$ be a set of objects and $B \subseteq A$ is a selected set of attributes. The lower and upper approximations of X with respect to B are defined as:

$$B_*(X) = \cup\{Y \in U \mid IND(P) : Y \subseteq X\}, \quad \ldots. \ldots. (2)$$

$$B^*(X) = \cup\{Y \in U \mid IND(P) : Y \cap X \neq \varphi\}. \ldots. \ldots. (3)$$

The *B*-lower approximation $B_*(X)$, is the complete set of objects in U which can be *certainly* classified as elements in X using the set of attributes B and the B-upper approximation $B^*(X)$, is the set of elements in U that can be *possibly* classified as elements in X. The B-boundary of X in the information system I*,* is defined as: $BND(X)= B^*(X) - B_*(X)$. The rough set approximations are illustrated in Fig. 1.




I – Information System,

B*(X)- Upper approximation,

Fig. 1. Rough set approximations

*3) Reduction of Attributes:* Reduct is a minimum attributes subset that retains the decision attributes dependence degree to conditional attributes. The subset $R \subseteq B \subseteq A$ such that $Y_B(Y)=Y_R(Y)$ is called Y-reduct of B and denoted as $Red_Y(B)$. The *core* is possessed by every legitimate *reduct* and cannot be removed from the information system without deteriorating basic knowledge of the system. The set of all indispensable attributes of B is called *Y*-core. Formally,

$$Core_Y(B) = \cap Red_Y(B) \quad \ldots \ldots. \ldots. \ldots. (4)$$

The *Y-core* is intersection of all *Y-reducts* of *B*, included in every *Y-reducts* of *B*.

*3) Accuracy:* Accuracy measures how much a set is rough. If a set has $B_*(X) = B^*(X) = X$, the set is precise called *crisp* and for every element $x \in X \in U$. This is expressed by the formula:

$$\alpha_B(X) = \frac{|B_*(X)|}{|B^*(X)|} \quad \ldots \ldots \ldots \ldots \ldots (5)$$

When $0 \leq \alpha_B(X) \leq 1$, and if $\alpha_B(X) = 1$ $X$ is crisp with respect to B.

## IX. ARTIFICIAL NEURAL NETWORK

ANN is an interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. As computers become faster, the ANN methodology is replacing many traditional tools in the field of knowledge discovery and some related fields. ANN is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. The learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

The main neural networks types based on their structures are Single layer perceptron, Multi-layer perceptron, Backpropagation net, Hopfield net and Kohonen feature map. Multi-layer perceptron (MLP) is recognized as the best ANN used in classification from examples [14]. In this work, the *multi-layer perceptron* with *back-propagation* supervised learning algorithm is used for experimentation. Due to its extended structure, MLP is able to solve every logical operation, including XOR problem. The back-propagation algorithm in MLP is the solution of choice for many machine learning tasks [15],[16]. An advantage of supervised learning is the minimization of error between the desired and computed unit values. The predictive performance of ANN is measured by computing the mean squared error (MSE), defined as:

$$MSE = \frac{1}{NP} \sum_{j=0}^{P} \sum_{i=0}^{N} (d_{ij} - y_{ij})^2 \quad \ldots \ldots (6)$$

where P is number of output processing elements, N is number of exemplars in the data set, $y_{ij}$ is network output for exemplar i at processing element j and $d_{ij}$ is target output for exemplar i at processing element j.

## IV. INTELLIGENT ROUGH NEURAL NETWORK SYSTEM (IRNNS)

1) The framework of hybridizing RST and ANN-based Set all weights of units to random values ranging from -1.0 to +1.0.
2) Set an input pattern to the neurons of the net's input layer.
3) Activate each neuron of the following layer.

learning system is shown in Fig. 2 and 3. These two techniques can be used for both classification and regression tasks without any converting mechanism. Incorporating these two technologies in one as an Intelligent Rough Neural Network System for efficient processing of medical data base is described in this section. The proposed hybrid system uses RST for pre-processing of data and ANN for classification or prediction. Some researchers have proposed and used similar integrated method in other applications [5], [6]. An algorithm developed for proposed hybrid system is given below and illustrated in Fig. 2.

### *A. Algorithm for Intelligent Rough Neural Network System*

**Algorithm:** IRNNS

**Given:** Medical data set.

**Objective:** Obtain crisp set of influential parameters and construct suitable ANN architecture for prediction.

// Pre-processing phase using RST.//

Step 1. Discretize the data.

Step 2. Construct the information system.

Step 3. Select influential parameters in the form of reduct set by applying Reduct algorithm.

Step 4. Check the selected parameters by considering biological importance. If satisfied go to Step 5 for training ANN *else* go to Step 1.

// ANN construction and training phase.//

Step 5. Data set ($i_n$, $t_n$) $n$ = 1,2, … $k$, where input $i_n$ and target $t_n$. Split the data into three subsets as training, cross-validation and test sets.

Step 6. Construct suitable ANN architecture. Structuring ANN with supervised back propagation learning algorithm includes following steps:

*1)* Set all weights of units to random values ranging from -1.0 to +1.0.
*2)* Set an input pattern to the neurons of the net's input layer.
*3)* Activate each neuron of the following layer.

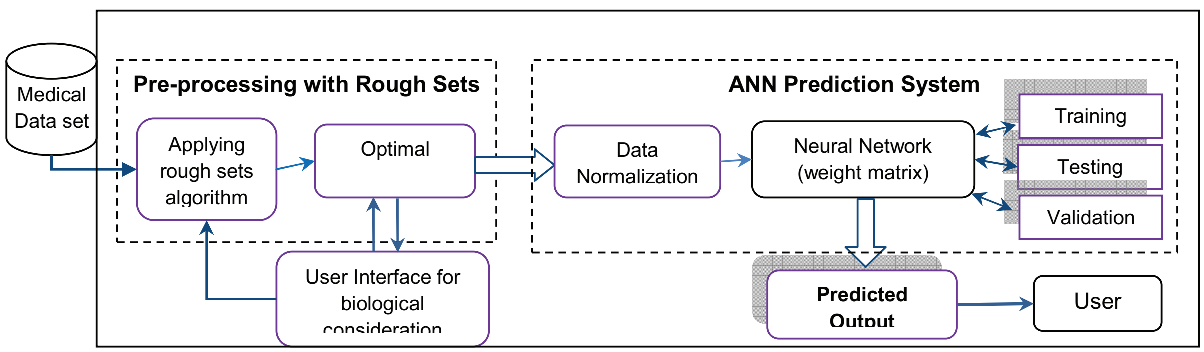



Fig. 2. Overview of Hybrid IRNNS Model

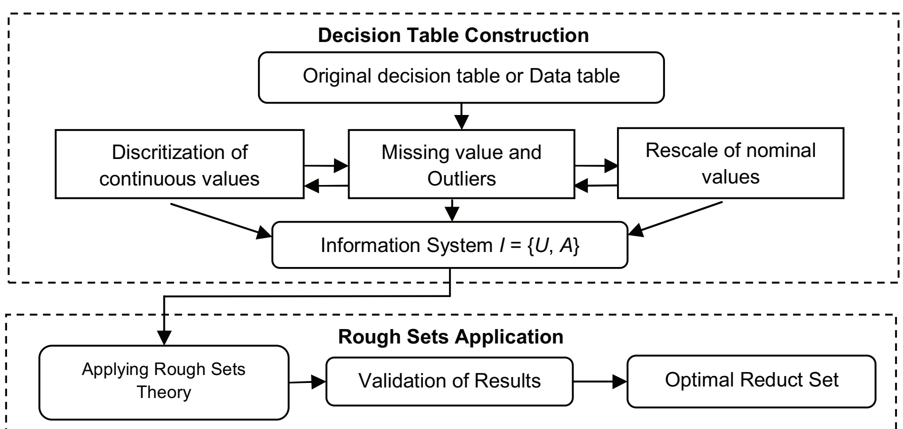



Fig. 3. Different stages of Pre-processing with Rough Sets

(Multiply the weight values of the connections leading to the neuron with the output values of the proceeding neurons and add up these values. Pass the result to an activation function, which computing the output value of this neuron.)

4) Repeat this until the output layer is reached.
5) Compare the calculated output pattern to the desired target pattern and compute an error value.
6) Change all weights of each weight matrix using the formula
*Weight (old) + learning rate * output error * output (neurons i) * output (neurons i+1) * (1 - output (neurons i+1))*

7) Go to Step 2.

8) The algorithm ends, if all output patterns match their target patterns.

Step 7. Now, the constructed ANN is ready for prediction or classification.

(The performance of this network was subsequently optimized by varying the number of nodes in the hidden layer and remove redundant nodes.)

*B. Pre-processing with Rough sets theory*

The rough sets based reduction of attribute space improves the efficiency of the predictor itself [13], [17]. The RST pre-processing model consists of two stage approaches, the first stage involves decision table reconstruction and the second stage involves the application of optimal reduct algorithm for data analysis. The different stages of data analysis using rough sets model is illustrated in Fig. 3. The algorithm used in IRNNS is described below.

*1) Quick Reduct Algorithm:* The basic concept is that intersection of every items of discernibility matrix and reduct cannot be empty. The object of matrix i and j would be indiscernible to the reduct, if there are any empty intersections between items $c_{ij}$ with reduct, this contradicts the definition that reduct is the minimal attribute set discerning all objects.

Let reduct set $OptRed = \phi$. Sort the discernibility matrix $|c_{ij}|$ and examine every items of discernibility matrix $c_{ij}$. If their intersection is empty, a shorter and frequent attribute $|c_{ij}|$ is picked and inserted in *OptRed* and skip the entry otherwise. Attributes in shorter and frequent contribute more classification power to the reduct. If there is only one element in $c_{ij}$, it must be a member of reduct. Repeat the procedure until all entries of discernibility matrix are examined. Finally, we get the optimal reduct in *OptRed*.

**Algorithm:** Quick reduct algorithm
**Input:** an information system $(U, A \cup \{d\})$,
where $A = \cup\, a_i$, $i = 1,\ldots,n$.
**Output:** an optimal attribute set *OptRed.*
Step 1. $OptRed = \phi$, $freq(a_i) = 0$, for $i = 1,\ldots,n$.
Step 2. Generate discernibility matrix *DisMat.*
Step 3. Count frequency of every attribute $a_i$ in *DisMat;*
$freq(a_i) = freq(a_i) + n / |c|$ *for every* $a_i \in |c|$
Step 4. Merge and sort discernibility matrix *DisMat.*
Step 5. For every object $c_{ij}$ in *DisMat* Do
{
Step 6. if ($c_{ij} \cap OptRed == \phi$) then
{
Step 7. Select attribute $a_i$ with maximal $freq(a_i)$ in *OptRed.*
*Step 8.* $OptRed = OptRed \cup \{a\}$.
}
}
*Step 9.* Return *OptRed*

The quick reduct algorithm can be very useful for classifying unseen objects [18]. The idea of the algorithm is, taking frequency of attribute as heuristic. The technique is also applicable to optimal/approximate rule generation for they are also based on discernibility matrix. The middle- sized noisy dataset can be reduct by this algorithm, and can be used as input for ANN for further optimal classification / prediction.

## V. ILLUSTRATIVE EXPERIMENTS

To illustrate the use of proposed hybrid method of data classification, let us consider an example of spermatalogical data set from the in-vitro fertilization (IVF) test outcomes for predicting bulls' semen fertility rate. The outcomes of the experiments are consulted with experts while selecting significant parameters using RST.

*A. Data Set*

The spermatological data used in the experiments are collected from Reproductive physiology laboratory in National Institute of Animal Nutriton and Physiology, Bangalore. The sperm functional parameters such as progressive forward motility, plasmalemma integrity, acrosomal integrity, sperm nuclear morphology and mitochondrial membrane potential were collected. The percentage of observed cleavage rate was calculated by dividing the number of oocytes cleaved out of the total number of oocytes inseminated.

### *B. Application of rough sets theory in semen evaluation*

Rough set theory is used for finding most effective minimal sperm functional attributes known as *reduct* set; those are effective in predicting cleavage rate or fertilization potential. When evaluating semen, the ultimate goal is to accurately predict its fertilizing potential [19].

The decision table, representing the spermatological data set, is constructed using eight condition attributes and one decision attribute of observed cleavage rate. In order to get better results, the data set is normalized by selecting maximum value and dividing all other values by the maximum value, the method generally used for normalizing input to neural network [20]. Since the new decision table contains discrete set of values, it does not require further discretization when considering indiscernibility relation. The next step is creating reducts, which are subset vectors of attributes that facilitate rule generation with minimal subsets. The proposed quick reduct algorithm is applied for creating minimal attribute set called *reduct*. The idea of the algorithm is taking frequency of attribute as heuristic, and it is worth to mention that applying reduction algorithm to get minimal subset of attributes is an NP-hard problem [21]. To calculate frequency of attributes, discernibility matrix is constructed and sorted. Every items of discernibility matrix $C_{ij}$ is examined and shorter and more frequent attribute $\{a_6\}$ is picked and assigned in *OptRed*. As known, attributes in shorter and frequent contribute more classification power to the reduct. The attribute $\{a_6\}$ is only one element, so it is a member of reduct as per algorithm. By repeating the procedure until all entries of discernibility matrix are examined, we get optimal reduct in *OptRed* (e.g. Table 2). The obtained optimal reduct set contains all the classification power of original decision table. All other possible reduct sets based on indiscernibility matrix are shown in Table 1.

TABLE 1
POSSIBLE REDUCT SETS BASED ON INDISCERNIBILITY MATRIX

| Reduct Sets | Support | Length |
|---|---|---|
| $\{a_3,a_4,a_6\}$ | 100 | 3 |
| $\{a_1,a_3,a_8\}$ | 100 | 3 |
| $\{a_1,a_3,a_4\}$ | 100 | 3 |
| $\{a_3,a_6,a_8\}$ | 100 | 3 |
| $\{a_4,a_6,a_8\}$ | 100 | 3 |
| $\{a_1,a_4,a_8\}$ | 100 | 3 |

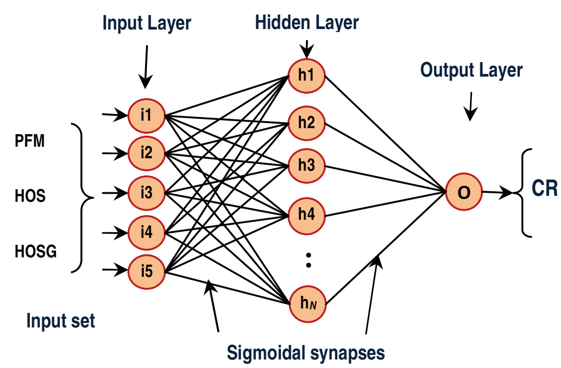
The biological importances of the parameters are considered while obtained optimal reduct set. If obtained reduct sets are not satisfied considering their biological importance, control goes to step 1 of the IRNNS algorithm. The reduced / crisp data set is effective to train ANN. The experiments to determine the prediction accuracy of ANN is described in the remaining part of this section.

TABLE 2
OPTIMAL REDUCT SET OBTAINED BY APPLYING QUICK REDUCT ALGORITHM AND CONSIDERING BIOLOGICAL IMPORTANCE

| Optimal Reduct Set | Support | Length |
|---|---|---|
| $\{a_1,a_3,a_4,a_6,a_8\}$ | 100 | 5 |

### *C. Network training and classification*

The constructed sample multi-layer perceptron (MLP) structured ANN is used for the prediction of animal semen fertility rate using obtained influential IVF parameters. The multi-layer perceptron (MLP), used to devise model of ANN, is illustrated in Fig. 4.




PFM – Progressive forward motility, HOS - Hyposomotic swelling test, SNM – Sperm nuclear morphology, MMP – Mitochondrial membrane potential, SZB – Sperm-zona binding, CR – Predicted Cleavage rate

Fig. 4. The constructed sample multi-layer perceptron (MLP) for predicting semen fertility rate.

Different processes involved in the optimization of ANN are: (1) selecting training and validation subsets, (2) analysing and transforming data, (3) selecting variables, (4) network construction and training, and (5) model verification. A properly trained ANN is capable of generalizing the information on the basis of the knowledge acquired during the training phase and correctly infers the unseen part of population even if the sample data contain noisy information. To train ANN, a suitable training, validation and test sets are selected. In this work, the training, validation, and test sets are provided by the following parameters.

- PFM - Progressive forward motility
- HOS – Hypoosmotic swelling test
- HOSG – Hypoosmotic swelling and Giemsa test
- SNM – Sperm nuclear morphology
- SZB – Sperm zonapellula bining

The target set is composed by the (CR) observed cleavage rate. The target set corresponding to the training set is directly provided by recorded field fertility rate of animals. The input set values are pre-processed in order to guarantee that all training values will be converted into the range of possible outputs of the network, and so the network can be trained. Descriptive statistics for all quantitative input variables to train ANN is illustrated in Table 3.

TABLE 3
DESCRIPTIVE STATISTICS FOR ALL QUANTITATIVE INPUT VARIABLES TO TRAIN ANN

| Selected Parameters | Mean ± S.E. | Minimum | Maximum |
|---|---|---|---|
| PFM | 43.25 ± 2.69 | 36.27 | 49.31 |
| HOS | 39.58 ± 2.32 | 31.85 | 47.68 |
| HOS-G | 30.63 ± 4.56 | 24.71 | 39.39 |
| SNM | 70.14 ± 7.5 | 65.02 | 74.66 |
| SZB | 88.27 ± 3.18 | 73.77 | 107.09 |
| CR | 38.07 | 8.63 | 48.01 |

The computer simulations of biological neuron layers of ANN are created. The MLP shown in Fig. 4., has the following characteristics:

1. *input layer:* 5 nodes as selected parameters for training are five;
2. *hidden layer:* one hidden layer with 10 nodes (fixed after analysis);

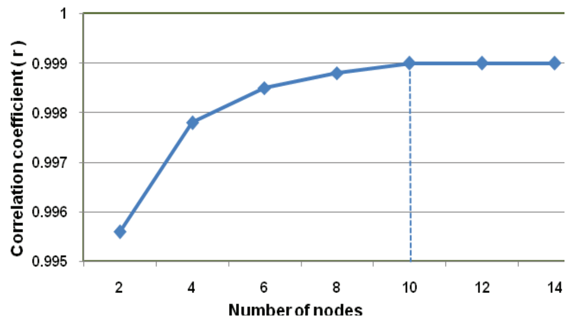



Fig. 5. Optimum number of nodes for the hidden layer

3. *output layer:* output layer has one node as constructed neural network would be used to predict a fertility rate

The performance of this network was subsequently optimized by varying the number of nodes in the hidden layer, the learning coefficient and the decrease factor of this coefficient and selecting the configuration with the highest predictive ability is illustrated in Fig. 5. Once trained, the network is ready to run validation and test set. The ANN validation phase in our experiment is shown in Fig. 6. Now, the ANN is trained well and ready for the prediction phase.

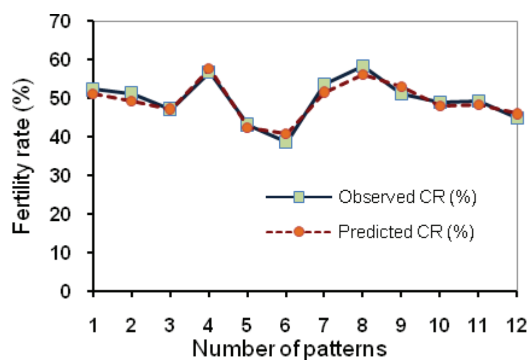



Fig. 6. Desired and actual output of ANN during validation test.

*D. Results*

The proposed hybrid prediction system is applied for pre-processing of medical database and to train ANN for making prediction. The prediction accuracy is observed by comparing observed and predicted cleavage rate (e.g. Fig. 7.).

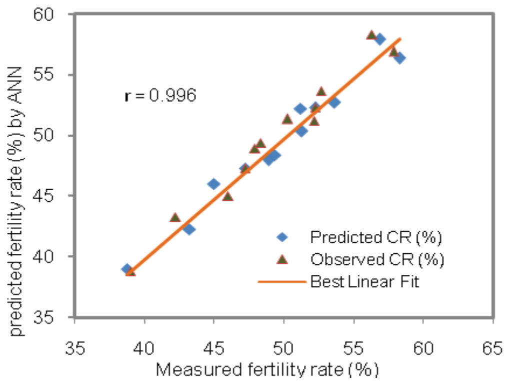



Fig. 7. Prediction accuracy: comparison between observed and predicted cleavage rate.

## VI. CONCLUSIONS AND FUTURE WORK

The experimental results show that the proposed hybrid architecture is very efficient for medical data analysis in significantly lesser processing time. Since RST is a useful tool for incomplete or noisy data processing, proposed hybrid architecture is a promising and intuitively sound methodology for large or medium size medical data base with incomplete data.

In addition, the results show that the hybridization of two machine learning techniques like ANN and RST is a promising alternative to the conventional methods of data analysis in this era of fast computers. The training time of the ANN with reduced sets of inputs is also quite naturally shorter and improves prediction accuracy.

The RST is useful pre-processing tool for the input to ANN to improve classification and prediction. It is observed from the experiments that the hybridization of RST and ANN significantly improves the overall predictive ability of ANN. The proposed hybrid method is quite effective for classifying pattern from abundant and noisy data. The hybrid strategy is accepted as a valid approach to data mining, because no single method has enough capability to deal with various data mining settings.

Future work involves incorporating biological information into the model. Another direction for the future work involves systematic comparison of different machine learning algorithms, hybridization of rough sets and neural network ensembles for building predictors to improve performance more.

*Z. Pawlak, "Rough sets," International Journal of Computer and Information Sciences, pp. 11:341-346, 1982.*

*Z. Pawlak, "Rough Sets: Theoretical Aspects of Reasoning About Data," Kluwer Academic Publishers, Boston, MA, 1991.*

*E.H. Francis Tay and Lixiang Shen, "Economic and financial prediction using rough sets model, Computing, Artificial Intelligence and Information Technology," European Journal of Operational Research, vol. 141, pp. 641-659, 2002.*

*Z. Pawlak, "Rough sets," Rough Sets and Data Mining," Kluwer Academic Publisher, Dordrecht, pp. 3-8, 1997.*

*Yu Wang, Mingyue Ding, Chengping Zhou and Tianxu Zhang, "A Hybrid Method for Relevance Feedback in Image Retrieval Using Rough Sets and Neural Networks", International Journal of Computational Cognition, vol. 3:1, 2005.*

*B.S. Ahn, S.S. Cho, and C.Y. Kim, "The integrated methodology of rough set theory and artificial neural network for business failure prediction," Expert Systems with Applications, vol. 18, pp. 65-74, 2000.*

*M. Beri, and G. Trotta, "An Approach to Develop Classification Expert Systems with Neural Network," Computational Intelligence III, Elsevier science, Netherlands, 1991.*

*Y. Hayashi, "A Neural Expert System Using Fuzzy Teaching Input", In Proceedings of 92 IEEE International Conference on Fuzzy System FUZZ-IEEE, Piscataway, NJ, pp. 485-491, 1992.*

*A.I. Dimitras, R. Slowinski, R. Susmaga, and C. Zopounidis, "Business failure prediction using rough sets," European Journal of Operational Research, vol. 114, pp. 263-280, 1999.*

*S. Greco,B. Matarazzo, and R. Slowinski, "A new rough set approach to evaluation of bankruptcy risk," Operational Tools in the Management of Financial Risks, Kluwer Academic Publishers, Dordrecht, pp. 121-136, 1998.*

*E. Krusinska, R. Slowinski, and J. Stefanowski, "Discriminant versus rough set approach to vague data analysis," Applied Stochastic Models and Data Analysis, vol. 8, pp. 43-56, 1992.*

*J. Han and M. Kamber, "Data mining: concepts and techniques," Morgan Kaufmann Publishers, San Francisco, 2001.*

*Tomasz G. Smolinski, Darrel L. Chenoweth, and Jacek M. Zurada, "Application of Rough Sets and Neural Networks to Forecasting University Facility and Administrative Cost Recovery," Artificial Intelligence and Soft Computing, vol. 3070, 2004.*

*Yaile Caballero, Rafael Bello, Yanitza Salgado and Maria M. Garcia, "A Method to Edit Training Set Based on Rough Sets," International Journal of Computational Intelligence Research, vol. 3:3, pp. 219-229, 2007.*

*M. Durairaj and K. Meena. "Application of Artificial Neural Network for Predicting Fertilization Potential of Frozen Spermatozoa of Cattle and Buffalo," International Journal of Computer Science and System Analysis, pp. 1-10, 2008.*

*B. Yegnanarayana, "Artificial Neural Network," Eastern Economy Edition, 2001.*

*M. Durairaj and K. Meena, "Intelligent Classification Using Rough Sets and Neural Networks," The ICFAI Journal of Information Technology, vol. 3, pp.75-85, 2007.*

*K. Thangavel, P. Jaganathan, A. Pethalakshmi and M. Karnan, "Effective Classification with Improved Quick Reduct For Medical Database Using Rough System," BIME Journal, vol. 5:1, 2005.*

*Leonardo F.C. Brito, Albert D. Barth, "Comparison of methods to evaluate the plasmalemma of bovine sperm and their relationship with in vitro fertilization rate," Theriogenology, Elsevier, pp. 1539-1551, 2003.*

*A. Chouchoulas, J. Halliwell, and Q. Shen, "On the Implementation of Roush Set Attribute Reduction," In Proceedings of the 2002 UK Workshop on Computational Intelligence, pp. 18-23, 2002.*

*W. Ziroko, "The Discovery, Analysis, and Representation of Data Dependencies in Databases," in G. Piatctsky-Shapiro, and W. Frawley, (cds), Knowledge Discovery in Databases, AAAI/ MIT Press, Cambridge, MA, pp. 31-54, 1990.*