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Original Research Article

Prediction of post-operative survival expectancy in thoracic lung cancer surgery with soft computing

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ABSTRACT

Prediction of survival expectancy after surgery is so important. Soft computing approaches using training data are good approximations to model the different systems.

We present many solutions to predict 1-year the post-operative survival expectancy in thoracic lung cancer surgery base on artificial intelligence. We implement multi-layer architecture of SUB- Adaptive neuro fuzzy inference system (MLA-ANFIS) approach with various combinations of multiple input features, neural networks, regression and ELM (extreme learning machine) based on the used thoracic surgery data set with sixteen input features. Our results contribute to the ELM (wave kernel) based on 16 features is more accurate than different proposed methods for predict the post-operative survival expectancy in thoracic lung cancer surgery purpose.

Introduction

It's very important for a person to know how long he survives. People encounter different diseases throughout life and they may survive from the death of vital organ disease, by surgery or organ transplants, in some cases. Medical decision making is a serious challenge, about the risks of survival after the surgery.

Analytical data are the basis for modelling systems and computational formulae. In fact, by modelling a system and designing it, we gain a relationship between its inputs and outputs. The black box is connected between the input-output system, it can be a regression, neural network, fuzzy system, or a different equation using empirical data.

Past researches prove that artificial intelligence techniques such as an artificial neural network (ANN) (Abraham, 2005; Altan et al., 2016; Bajpai et al., 2011; Markou and Singh, 2003; Mazurowski et al., 2008; Vyas et al., 2016; Zhang et al., 2016), support vector machine (SVM) (Vyas et al., 2016), decision support (Lisboa and Taktak, 2006) and regression has good performance in predicting from experimental data.

Zięba et al. (2014) extracted 9 decision rules from the boosted SVM for medical usage of expecting postoperative survival expectancy in the lung cancer patients. They used thoracic surgery data set containing 470 instances and 17 attributes, they applied boosted SVM classifier to classify the patients into two categories: class 1 – death within one year after surgery, class 2–survival.

Matsopoulos et al. (2005) have presented an automatic three-dimensional inflexible registration layout using self-organizing maps and radial basis functions. They modeled, approximations of lung tumor masses during radiotherapy by the feature points from thoracic computed tomography (CT) data.

Delen et al. (2010) suggested a machine learning method to select the prognosticator variables which, is more powerful in the risk category of thoracic patients. They applied multilayer perceptron (MLP), M5 algorithm-based regression tree and the support vector machine with a radial basis kernel function, making the best result R^2, in the prediction of survival time after lung transplantations and prognosis analysis.

Clark (1996) tries to calculate medical risk by using different methods such as uni-variate analysis, additive method, logistic regression, Bayes' theorem and neural network via the society of thoracic surgeons database.

Bhuvaneswari et al. (2014) offered one solution to classify lung CT images based on the extracted features using gabor filter and Walsh Hadamard transform. They implemented genetic algorithm

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to select best features and they used K nearest neighbour (KNN), decision tree and multilayer perceptron to perform the classification of the lung diseases, the accuracy of neural network was higher.

In Kuruvilla and Gunavathi (2014) tomography (CT) images of the lungs are as the inputs and an approach is proposed to use feed forward back propagation neural networks method with the statistical features such as mean, standard deviation, skewness, kurtosis, fifth central moment and sixth central moment for the classification.

In the article of Paulpandi and Prasath (2014) the ANFIS method is used to categorize lung tissue on CT scan images. Mahersia et al. (2015) have reviewed the article to determine lung cancer by using different methods in three steps: pre-processing, segmentation of the lung and classification of the tumour patients.

Hashemi et al. (2013) have expressed the region, growing segmentation for feature extraction as input, they have applied Fuzzy Inference System (FIS) and artificial neural networks (ANNs) methods for mass detection in lung CT images, and the sensitivity of their results was 95%.

Polat and Güneş (2008) declared an approach for lung cancer detection by fuzzy weighting pre-processing and the artificial immune recognition system (AIRS) classifier. They selected four features from among 54 features using principles component analysis (PCA) and the classification accuracy of their proposed system was obtained 100%.

Esteva et al. (2007) developed neural networks and artificial intelligence to predict the thoracic surgery after lung resections. Their results had reported that naive bayes method achieved good results in terms of surgical risk classifying for lung separation candidates.

The up survey discussed the use of different existing methods for lung and thoracic surgery using artificial intelligence.

The number of patients who survive after surgery in comparison to patients who die is higher, in a one year period. The proper patient choice for surgery, taking risk and advantages.

So this need of system seems essential, which helps doctors to correct the classification of survival expectancy for treating patients after surgery accurately.

The motivation of undertaken study is design an intelligent system with different artificial intelligence methods to assist clinicians in predicting postoperative thoracic survival with high accuracy.

In this paper, a new intelligent method in the clinical diagnosis of thoracic lung cancer surgery is proposed, that helps doctors in patient selection and identifies the risk of death in patients after surgery.

Material and methods

Neural network

Neural networks are like the human brain's ability to predict and category. The structure of the neural network is made of activation functions and cells called neurons (Abraham, 2005). The neural network training aim is, projected output training in order to make it so close to the actual output and have a low error (Mazurowski et al., 2008). Types of education, are supervised and unsupervised training. Input data and output are applied to the system in the training supervisor, but only the input data are applied to an education system without an observer and target categories. The purpose of learning is changing the parameters of the neural network in a way that they will be appropriate for the data network performance. A variety of activation functions and different learning rules are used for this purpose (Bajpai et al., 2011).The multi layer perceptron (MLP) (Altan et al., 2016), support vector machine (SVM) (Vyas et al., 2016), radial base function (RBF) (Zhang et al., 2016), self organize map (SOM), hopfid (Markou and Singh, 2003) are some types of neural networks.

Neural networks are made of neurons and they are used for predicting the relationship between inputs and output. The relationship between input and output neurons is done by middle (hidden) layer. Neural network output is measured from the Eq. (1).

$$y_j^h = f_j^h\left(\sum_i^n w_{ij}^h p_i + b_j^h\right) \tag{1}$$

y_j^h = output of neuron j of hidden neuron
p_i = input i to hidden neuron
w_{ij}^h = weight connection among input and hidden neuron from input i to neuron j
b_j^h = bias of hidden neuron j
f_j^h = transfer function for hidden neuron j

The transfer function is computed by following equation:

$$tansig(n) = \frac{2}{1+\exp(-2n)} - 1 \tag{2}$$

We utilized feed forward neural network and back propagation (BP) learning method in this research (Fig. 1). More information about neural networks is available in (Houška et al., 2014).

Neural networks deploy a model of the system by using such a data that 70% of it is randomly selected for training data and 15% for validation and 15% for testing.

ANFIS topology

Fuzzy system

Fuzzy logic is versus binary logic, which a member belongs to all categories, but with a different membership function. Fuzzy system is composed of a set of rules and membership functions. Rules created by the system designer are responsible for the inference system. The type of membership functions are influenced by the behaviour of input variables. Minimum and maximum fuzzy operators apply the rules (Zadeh, 1965).

The fuzzy system design process is as follows:

1. Converting numeric values to linguistic variables (fuzzifying of inputs).
2. Designing rules.
3. De-fuzzification of output.

Fuzzy systems are divided to two categories: type1-Mamdani and type2-takagi-sugeno model (Sugeno, 1985). Learnability of the neural network, using training input data and making calibration membership functions and accurate the fuzzy rules (Buckley and Hayashi, 1994). Ann and fuzzy system can be used together, the so-called "fuzzy neural networks". Sugeno unlike mamdani system, is used in the final part of a function in terms of the input variables, so

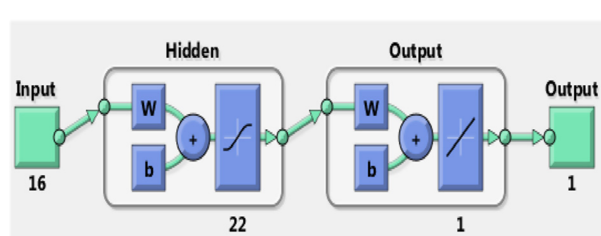


Fig. 1. Neural network structure.

that it can be a zero-order sugeno (fixed), one or more order (Jang, 1993; Kayacan and Khanesar, 2015).

Many applications of the neuro fuzzy systems are student modelling, medical systems, economic systems, traffic control, image processing, prediction, manufacturing, electrical systems and social sciences expressed in (Kar et al., 2014; Melin and Castillo, 2013; Precup and Hellendoorn, 2011).

Melin and Castillo (2013) states that the neuro fuzzy system type-2 is applied to classify matters, mostly because of the ability of adapting more uncertainty.

Data are as the rules in neural systems. Adaptive fuzzy neural networks used rules, membership functions and training data. (Zięba et al., 2014) extracted 9 decision rules and 16 pre-operative features for prediction problem of 1-year survival period by boosted SVM method from data set that we apply these features for prediction the post-operative survival expectancy in the lung cancer in this study. Among the neural networks; reasons for the select ANFIS methodology is that ANFIS have calibrated the membership functions by using training data and offers better performance in forecasting and optimization.

Adaptive neuro fuzzy influence system

The neuro-fuzzy system creates multiple rules from the multiple input-output data. The basic rules of the fuzzy system are as follows in Fig. 2:

$$\begin{aligned}
&1.\text{if}(\text{d is}M_{11})\text{and}(\text{e is}M_{21})\text{then}Z_1 = r_1(\text{d},\text{e})\\
&2.\text{if}(\text{d is}M_{11})\text{and}(\text{e is}M_{22})\text{then}Z_2 = r_2(\text{d},\text{e})\\
&3.\text{if}(\text{d is}M_{11})\text{and}(\text{e is}M_{23})\text{then}Z_3 = r_3(\text{d},\text{e})\\
&\vdots\\
&9.\text{if}(\text{d is}M_{13})\text{and}(\text{e is}M_{23})\text{then}Z_9 = r_9(\text{d},\text{e})
\end{aligned} \tag{3}$$

With $Z_K = r_K(\text{d,e})$ K = 1,..,9 and Where M_{ij}, Z_K and r_K demonstrate the jth MF of the ith input, the output of kth rule, and the kth output MF, in order.

Layer 1. The Numerical values become to linguistic values using the membership function.

Generalized bell MFs for (i = 1 or i = 2), (j = 1, 2, 3), (x = d or x = e):

$$M_{ij}(x) = Gbell(x; aij, bij, cij) = 1/(1 + |\frac{(x-c_{ij})}{a_{ij}}|^{2b_{ij}}) \tag{4}$$

Where aij, bij, cij are premised parameters that define the shape of the membership function. Gaussian, bell and trapezoidal MFs are defined by two, three and four parameters.

Layer 2. The second layer is calculated as the weight of the rule (ωk), after the first layer using the membership function of the fuzzy values and the operator "and",

$$\begin{aligned}
w_1 &= M_{11}(\text{d})M_{21}(\text{e})\\
w_2 &= M_{11}(\text{d})M_{22}(\text{e})\\
&\vdots\\
w_9 &= M_{13}(\text{d})M_{23}(\text{e})
\end{aligned} \tag{5}$$

Layer 3. In the third layer, the normal weight is calculated using the following equation.

$$\overline{w}_k = w_k / \sum_{i=1}^{9} w_i, k = 1, \ldots 9 \tag{6}$$

Layer 4. The weighted rules de-fuzzy Output, the fourth layer as follows.

$$\overline{w}_k z_k = \overline{w}_k r_k(d,e) = \overline{w}_k(p_{k,1}d + p_{k,2}e + p_{k,3})k = 1, \ldots, 9 \tag{7}$$

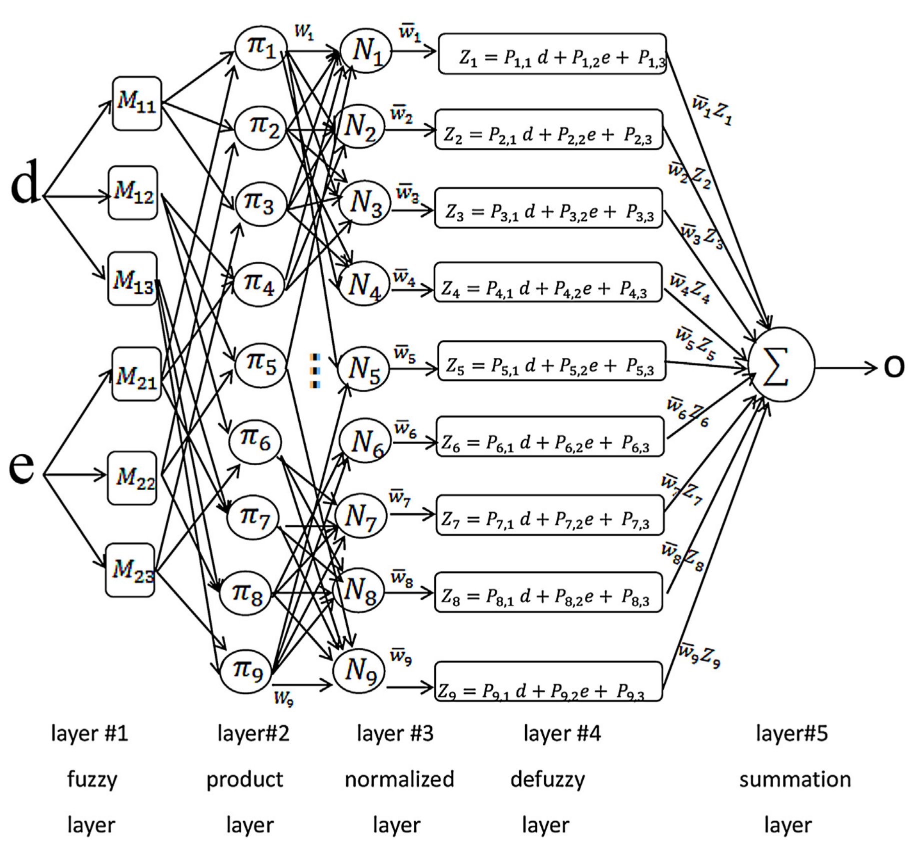


Fig. 2. Adaptive neural network fuzzy structure (Sugeno).

Pk are conclusion parameters that state output in the de-fuzzy value, lineal input form.

Layer 5. Fuzzy weighted sum of the output of all rules is calculated as follows in the fifth layer.

$$O = \sum_{i=1}^{9} \overline{w}_k z_k = \sum_{i=1}^{9} w_k z_k / \sum_{i=1}^{9} w_k \tag{8}$$

One of the restrictions of adaptive fuzzy neural network based on takagi-sugeno model is increasing the number of ANFIS inputs more than six, out of memory message which occurs when it depends on the hardware (Khoshnevisan et al., 2014).

Because of hardware limitations, we are able to run ANFIS up to six inputs and since the number of input variables is greater than six then we can use various topologies of ANFIS (Iraji, 2017).

Multi-layer ANFIS topology

Counts of premise parameters and rules were determined by the fuzzy subtractive clustering technique and then the conclusion parameters were distinguished by using linear least squares technique and hybrid learning algorithm were handled for training the sugeno (Angiulli and Versaci, 2003).

When the number of rules and parameters of ANFIS increase, the number of inputs and linguistic variables increase too, so ANFIS shows little efficiency. Our proposed solution is using several layers, which can be from a few ANFIS numbers of input variables of a maximum of six.

ANFIS topology which can be considered for the sixteen inputs (Fig. 3) from various topologies, is different combinations of features calculated manually for four ANFIS with 5,5,5,1 inputs named ANFIS 5-3-1 models.

We can model our design with a multi-layer model of ANFIS depending on the number of input features and topology issues given above. The important point in this multi-tier model is, the combination of variables as inputs to the small ANFIS which will result in a better indicator, for example it has fewer errors than the actual output. We choose a name for our proposed model as "multi-layered ordered ANFIS model" (Iraji, 2017).

Extreme learning machine

Huang et al. (2006) have presented extreme learning machine (ELM) as a learning rule for single layer feed-forward neural network that determines the weights of the input randomly and the output weights analytically. ELM is an efficient algorithm to speed up learning, it has a greater ability than non-linear activation functions and kernels that ascertains network parameters.

SLFN function with L hidden nodes includes both additive and RBF hidden nodes that are formulated by the following equation:

$$y_l(x_i) = \sum_{k=1}^{l} \beta_k G(a_k, b_k, x_i), i = 1 \ldots N \tag{9}$$

In this equation a_k, b_k are learning parameters of k^{th} hidden neuron and β_k is the associated weight of k^{th} hidden neuron to output neuron. Input data are (x_i, t_i) and N is the number of samples where $x_i = [x_{i1} x_{i2} \cdots x_{in}]^T \in R^n$ and $t_i = [t_{i1} t_{i2} \cdots t_{im}]^T \in R^m$. Activation functions for additive hidden neuron are defined, and functions like sigmoid (equation 10) and gaussian (equation 11) for RBF hidden node are exemplified:

$$G(a_k, b_k, x_i) = g(a_k x_i + b_k) \tag{10}$$

$$G(a_k, b_k, x_i) = g(b_k \| x_i - a_i \|) \tag{11}$$

Eq. (9) can be expressed as the following closed form formula:

$$H\beta = T \tag{12}$$

So that:

$$H\left(\tilde{a}, \tilde{b}, \tilde{x}\right) = \begin{bmatrix} G(a_1, b_1, x_1) & \cdots & G(a_L, b_L, x_1) \\ \vdots & \ddots & \vdots \\ G(a_1, b_1, x_N) & \cdots & G(a_L, b_L, x_N) \end{bmatrix}_{N*L} \tag{13}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L*m} \text{and}\ t = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N*m} \tag{14}$$

Matrix H calculates the output of the hidden layer in a neural network.

Discussion and experimental results

Zięba et al. (2014) presented Boosted SVM for discovering rules from data set of the post-operative survival expectancy in the lung cancer patients and extracted 16 features for prediction the post-operative survival expectancy.

We tries to provide a way for predicting the post-operative survival expectancy in the lung cancer patients with a thoracic surgery data set (Zięba et al., 2014), 470 sample and number of input variables is 16 features that are defined below.

f1. DGN: Diagnosis – specific combination of ICD

f2. PRE4: Forced vital capacity – FVC

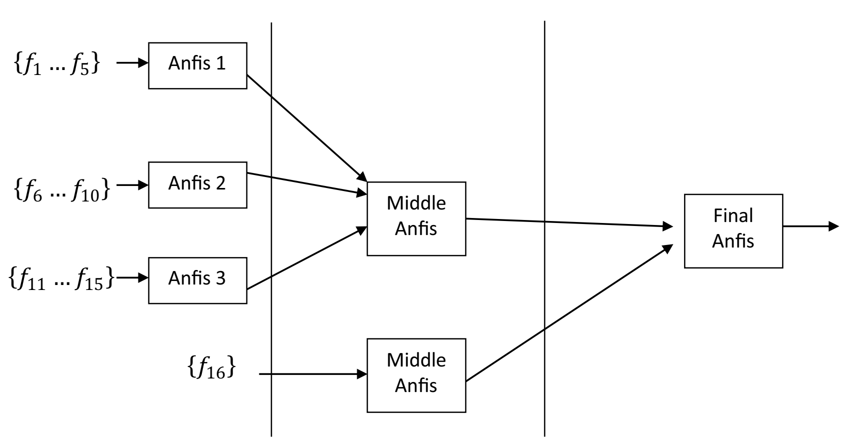


Fig. 3. ANFIS (5, 3, 1) topology model.

f3. PRE5: Volume that has been exhaled at the end of the first second of forced expiration – FEV1 (numeric)
f4. PRE6: Performance status – Zubrod scale
f5. PRE7: Pain before surgery
f6. PRE8: Haemoptysis before surgery
f7. PRE9: Dyspnoea before surgery
f8. PRE10: Cough before surgery
f9. PRE11: Weakness before surgery
f10. PRE14: T in clinical TNM – size of the original tumour
f11. PRE17: Type 2 DM – diabetes mellitus
f12. PRE19: MI up to 6 months
f13. PRE25: PAD – peripheral arterial diseases
f14. PRE30: Smoking
f15. PRE32: Asthma
f16. AGE: Age at surgery
Output: Risk1Y: True value if died in 1 year survival period

The number of patients who survive after surgery in comparison to patients who die is higher, in a one year period; from total samples, 400 patients are positive (survival) and 70 patients are negative (died).

It is important, selecting patients for thoracic lung cancer surgery with a low risk of post-operative in short-term 30-day period or long-term 1 or 5 year survival (Zięba et al., 2014). We consider 1 year survival period for prediction the post-operative survival expectancy in the lung cancer patients in this paper.

We implement our proposed system in Matlab version 7.12 on a laptop, 1.7 GHZ CPU, and we used the roots mean square error (RMSE) in order to determine the evaluation indicator to determine the best method.

$$MSE = \frac{1}{N}\sum_{1}^{N}(output_{actual} - output_{predicted})^2 \quad (15)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}(output_{actual} - output_{predicted})^2} \quad (16)$$

Fig. 4 shows RMSE between actual and predicted survival expectancy after thoracic lung cancer surgery using neural network from 1 to 35 hidden neurons. As it is seen in Fig. 4, the optimum number of hidden neurons is 22. Neural network architecture 16–22-1 was considered and it reached best performance. Fig. 5 shows the amount of MSE for the training, validation and testing the data using the best topology of neural network is epoch five. For the optimum network performance at epochs, MSE for training, validation and testing data are 0.1689, 0.1699 and 0.1718 in Fig. 5.

Table 1 shows various arrangement structures of inputs for four ANFIS with five and one inputs.

The RMSE for training, validation, testing and total data for three ANFIS with five and one features are exhibited in Table 2.

Table 2 shows that the least of the RMSE for total data is 0.306768 in model #2, that proves the {f5-f8-f9-f10-f11} {f12-f13-f14-f15-f16} {f1-f2-f3-f4-f7} {f6} is the best proficiency between ANFIS 5-1 models. The RMSE for training, testing and validation are acquired 0.267037, 0.362269 and 0.402857 for this model.

Fig. 6 shows {f5-f8-f9-f10-f11} {f12-f13-f14-f15-f16} {f1-f2-f3-f4-f7} {f6} is the best performance from ANFIS 5-1 models.

In the proposed ANFIS system a database of 470 records was considered, In order to train and test the fuzzy neural network. After calculating sixteen features were described above for 470 records, 328 records were considered for training ANFIS and 71 record were allocated to test and 71 record for validate the system.

After setting the network parameters to generate fis = grid partition, optim.method = hybrid, linier, training fis epochs = 11, the gbell membership function with two mf RMSE for all data Obtained 0.3068.

In order to model the proposed system without multi-layer ANFIS topology and with one ANFIS, the number of promise parameters is $(2*3)^{16} = 2821109907456$ using the gbell membership function and two linguistic variables, the number of rules = 2^{16}, conclusion parameters = $17^*\left(2^{16}\right)$. This cannot be performed for practical implementation of such a system, when an out of memory error occurs. As a large number of variables

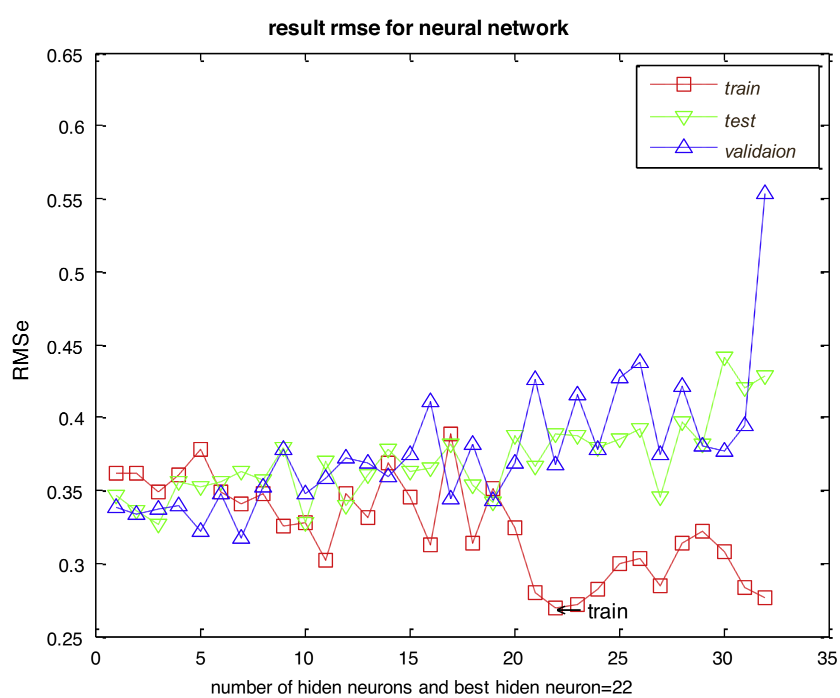
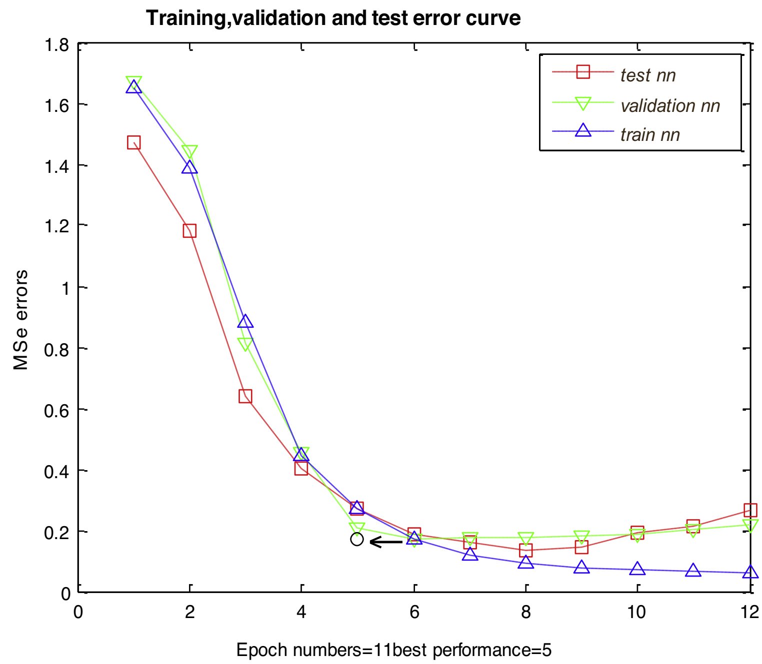


Fig. 4. RMSE between actual and predicted survival expectancy after thoracic lung cancer surgery using a neural network for determine number of hidden neurons.



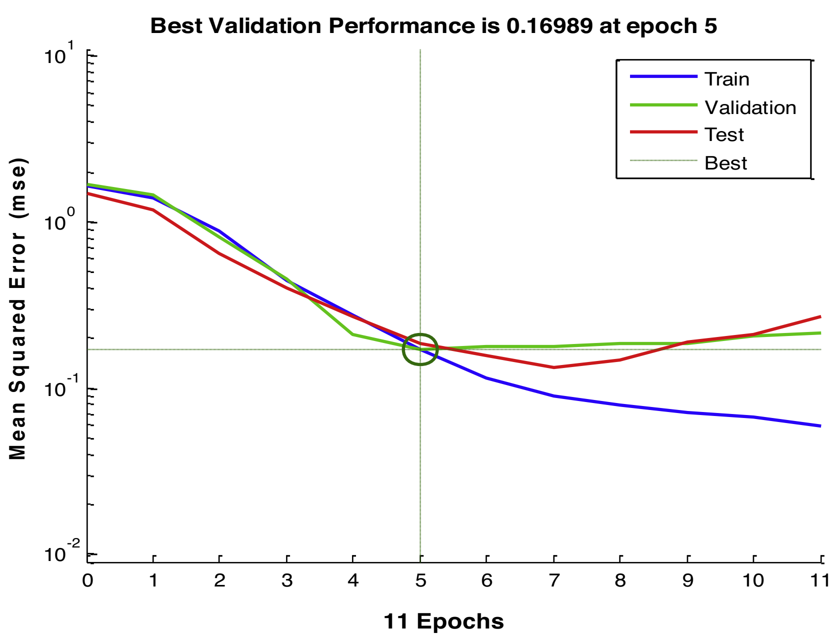


Fig. 5. (a) Training, validation and test error curve (b) best performance for neural networks with validation data.

Table 1
Different states of three ANFIS with five inputs.

#	ANFIS1 inputs					ANFIS 2 inputs					ANFIS 3 inputs					ANFIS 4 inputs
1	f1	f2	f3	f4	f7	f6	f5	f8	f9	f10	f11	f12	f13	f14	f15	f16
2	f5	f8	f9	f10	f11	f12	f13	f14	f15	f16	f1	f2	f3	f4	f7	f6
3	f15	f16	f1	f2	f15	f4	f7	f6	f5	f8	f9	f10	f11	f12	f13	f14
4	f12	f13	f14	f15	f12	f1	f2	f3	f5	f8	f9	f10	f4	f7	f6	f11
5	f4	f7	f6	f5	f4	f9	f10	f11	f12	f13	f14	f15	f16	f1	f2	f3
6	f15	f16	f1	f2	f15	f4	f5	f8	f9	f10	f11	f12	f13	f14	f7	f6
7	f9	f10	f11	f12	f9	f7	f6	f5	f8	f10	f3	f7	f6	f11	f1	f2
8	f7	f6	f5	f8	f7	f10	f11	f12	f13	f14	f15	f16	f1	f2	f3	f4
9	f8	f9	f10	f11	f8	f13	f14	f15	f16	f1	f2	f3	f4	f7	f6	f5
10	f3	f5	f8	f9	f3	f4	f7	f6	f11	f12	f13	f14	f15	f16	f1	f2

Table 2
Comparison of RMSE for training, testing, validation and all data in different states of four ANFIS with five and one features.

#	RMSE train	RMSE test	RMSE valid	RMSE all
1	0.275007	0.517481	6.80345	2.6619
2	0.267037	0.362269	0.402857	0.306768
3	0.275976	8.6047	2.93205	3.54075
4	0.274822	19.6154	3.81331	7.77004
5	0.285803	3.35755	0.57471	1.34533
6	0.271773	63.7432	0.473719	24.7767
7	0.283403	0.805178	4.10769	1.64419
8	0.275315	11.9491	6.15746	5.22969
9	0.280856	0.538154	0.598568	0.391052
10	0.284871	0.30507	3.29699	1.30873

affects the design of the system using the ANFIS method, multi-layer architecture topology of SUB-ANFIS (MLA-ANFIS) must necessarily be used.

A comparison of the promise and conclusion parameters in the first and final layers of the multi-layer architecture topology in the SUB-ANFIS (MLA-ANFIS) models is given as (Iraji, 2017); In the best 5-1 ANFIS model for the first layer, the promise parameters are; the number of rules is: $2^5 + 2^5 + 2^5 + 2^1$ and the conclusion parameters are: $6\left(2^5\right) + 6\left(2^5\right) + 6\left(2^5\right) + 2\left(2^1\right)$; the number of promise parameters in the second layer are $(2 * 3)^4$; the number of rules is 2^4 and the conclusion parameters are $5\left(2^4\right)$.

We train extreme learning machine (ELM-base) structure after infix hidden neurons=22 and activation function = sig. Also, we set the number of parameters = 100 in ELM (poly kernel) and ELM (lin kernel), the kernel matrix parameters to [0.1, 1000.1000] in the ELM (RBF kernel), ELM (wave kernel).

Because eradicate an over-learning phenomenon, we implement all methods 10 runs with randomly selected training, validation and testing data for each simulation on the same data set.

Table 3 shows the average of confusion matrix according to the predicted and actual data using neural networks, best ANFIS topology 5-3-1, regression, ELM (base), ELM(RBF kernel), ELM (wave kernel), ELM (poly kernel) and ELM (lin kernel) to prediction of survival expectancy after thoracic lung cancer surgery.

Average of correct classification index and average RMSE for 10 runs between methods are compared in Table 4 using the proposed methods. Average of correct classification index calculate 88.79, 87.62, 84.94, 86.55, 85.36, 85.21, 85.11 and 84.98 after applying ELM (wave kernel), ANFIS topology, regression, neural network, ELM (base), ELM (RBF kernel), ELM(poly kernel) and ELM (lin kernel) methods.

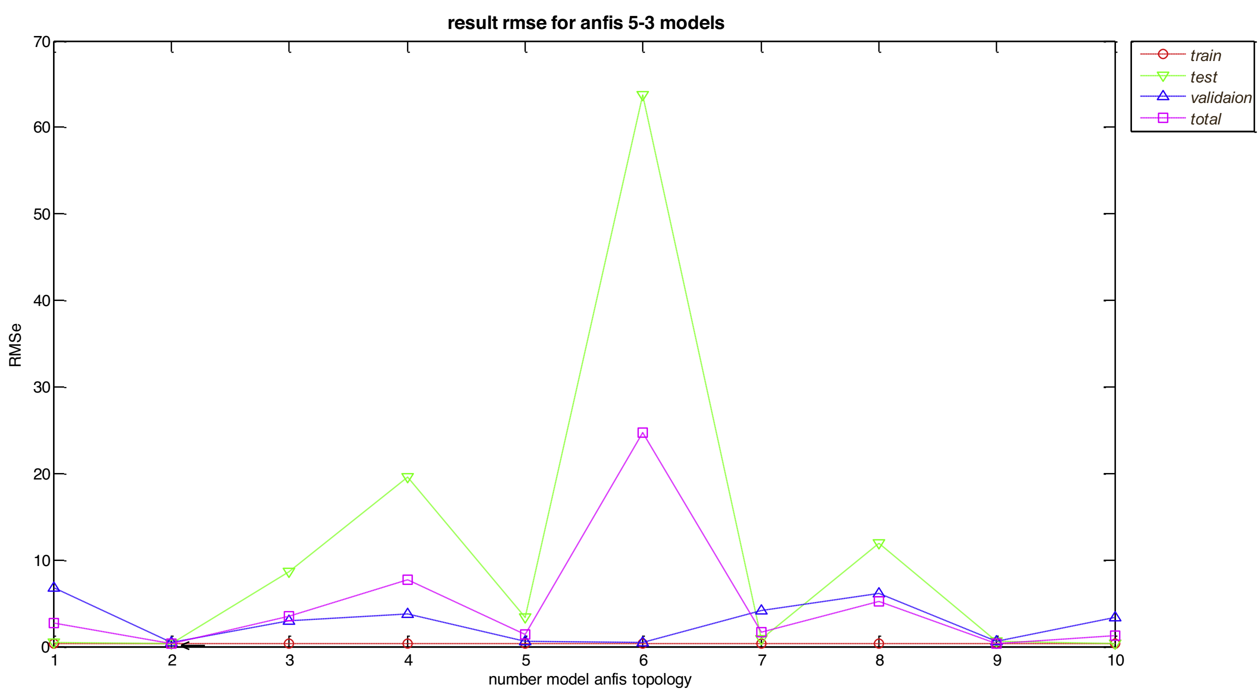


Fig. 6. Comparison between RMSE of ANFIS 5-3-1 models for training, testing, validation and all data.

Table 3
Comparison of average of confusion matrix for 10 runs between the methods.

Method	TN	FN	FP	TP
ELM(wave kernel)	57.1	39.8	12.9	360.2
Best ANFIS-5-5-5-1	28.8	17	41.2	383
Regression	0.5	1.3	69.5	398.7
Neural Network	18.2	11.4	51.8	388.6
ELM(base kernel)	3.5	2.3	66.5	397.7
ELM(RBF kernel)	1.2	0.7	68.8	399.3
ELM(poly kernel)	0	0	70	400

Table 4
Comparison of average of correct classification index and average of RMSE for 10 runs between the methods.

Method	RMSE	correct classification index
ELM(wave kernel)	0.33463	88.78724
Best ANFIS-5-5-5-1	0.3418	87.61699
Regression	0.34288	84.93619
Neural Network	0.3554	86.55318
ELM(base kernel)	0.38261	85.36169
ELM(RBF kernel)	0.38455	85.21275
ELM(poly kernel)	0.3859	85.1064
ELM(lin kernel)	0.38756	84.97873

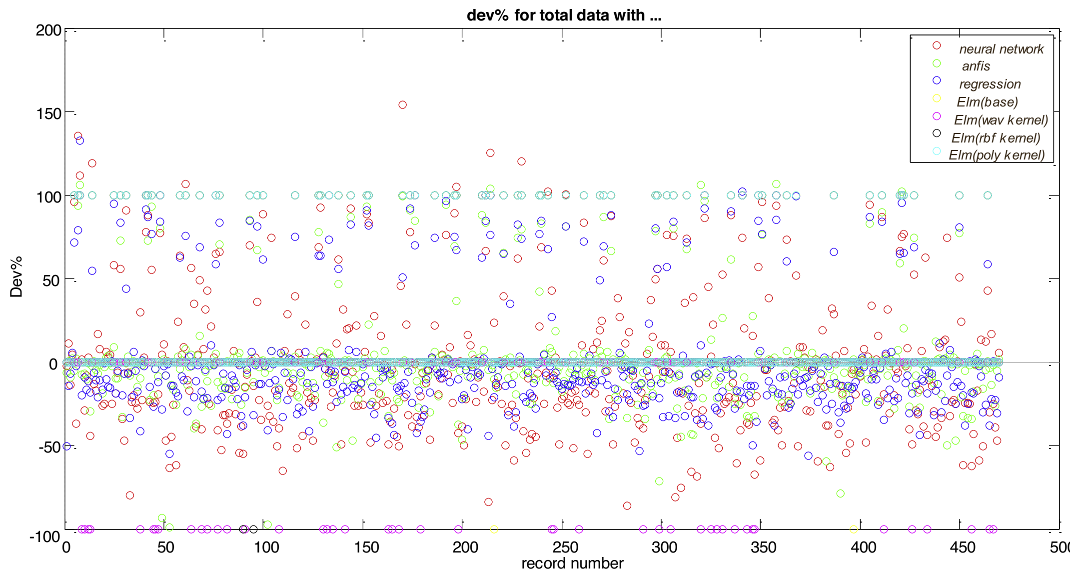


Fig. 7. Comparison of deviation of predicted survival expectancy after thoracic lung cancer surgery by the proposed methods.

According to Table 4 the Average of RMSE compute 0.334, 0.341, 0.342, 0.355, 0.382,0.384, 0.385 and 0.387 exerting ELM (wave kernel), ANFIS topology, regression, neural network, ELM (base), ELM(RBF kernel), ELM (poly kernel) and ELM (lin kernel) methods. Comparison average of correct classification index and average of RMSE for 10 runs between methods proves that the ELM (wave kernel), ANFIS topology systems have the best performance than the other methods.

Fig. 7 shows the deviations of predicted survival expectancy after thoracic lung cancer surgery from actual (dev%) by proposed methods.

In this paper performance measures namely sensitivity, specificity, geometric mean calculated for prediction evaluation (Table 5). Survival people after thoracic lung cancer surgery are positive and dead people are negative. According bellow equations Specificity is the ratio of positives, that correctly recognized and Specificity is the ratio of negatives that correctly recognized. In mathematics, the geometric mean is a type of mean or average that it is defined as the m^{th} root of the product of m numbers (Eq. (19)).

$$\text{Sensitivity} = \text{TP}/(\text{TP}+\text{FN}) \tag{17}$$

$$\text{Specificity} = \text{TN}/(\text{FP}+\text{TN}) \tag{18}$$

Where;

True positive = count of records that correctly recognized
False positive = count of records that incorrectly recognized
True negative = count of records that correctly rejected

Table 5
Performance comparison of proposed the methods for measures (sensitivity, specificity, geometric mean).

Method	Sensitivity	Specificity	Geometric mean
ELM(wave kernel)	90.05	81.5714	85.7059
Best ANFIS-5-5-5-1	95.75	41.1429	62.7649
Regression	99.675	0.7143	8.4378
Neural Network	97.15	26	50.2583
ELM(base kernel)	99.425	5	22.2963
ELM(RBF kernel)	99.825	1.7143	13.0816
ELM(poly kernel)	100	0	0
ELM(lin kernel)	99.725	0.7143	8.4399

False negative = count of records that incorrectly rejected

$$\text{Geometric mean} = \sqrt[m]{x_1 x_2 \ldots x_m} \tag{19}$$

Referring to Table 5 it can be observed that ELM (wave kernel) is a better classifier than the other methods with g-means(85.7059), sensitivity (90.05) and specificity (81.5714) and Best Anfis-5-5-5-1 method is a secondary top method with g-means(62.7649), sensitivity (95.75) and specificity (41.1429); whereas that specificity of ELM (rbf kernel) is higher, but Specificity and g-mean gave a poor value (13.0816).

Conclusion

The aim of this research was to create a solution to use soft computing techniques namely neural network, ANFIS topology, regression, extreme learning machine (ELM base), ELM (RBF kernel), ELM (wave kernel), ELM (poly kernel), ELM (lin kernel) for problem prediction the post-operative survival expectancy in thoracic lung cancer surgery. Forasmuch as input features were more than normal capacity of ANFIS inputs due to hardware and software limitations; we have examined a multi-layer model of ANFIS topology for this purpose and have defined RMSE and correct classification indicators. The advantage of the used approach was the design of a system with all sixteen input features using the multi-layer ANFIS. Different combinations of input variables were created in this topology. We have implemented all proposed methods 10 runs on the thoracic surgery data set from UCI datasets. From the total number of data, 70% were randomly chosen to train, 15% for validation and 15% for testing.

Our results show that the amounts of the RMSE = 0.33463, correct classification indicator = 88.78724 and g-means (85.7059) with sensitivity (90.05) and specificity (81.5714) for ELM (wave kernel) to predict one-year mortality of patients undergoing lung cancer resection surgery is better than the others proposed algorithm, whereas that Zieba's et al. (2014) g-means was (65.73) with sensitivity (60.00) and specificity (72.00) using the same data set and the performed calculations in experimental results in Tables 3–5 prove this claim. We have shown that our approach can be successfully to solve problem prediction of the post-operative survival expectancy in thoracic lung cancer surgery and the quality of the proposed method by comparing with other solutions is higher.

For future work, we could change the number and type of membership function input linguistic variables in multi-layer ANFIS topology and better results would probably be achieved. It could also be considered, using genetic algorithms to determine the ELM structure weights accurately, the number of hidden neurons and ELM structure parameters could be specified more precisely. Study other than one-year survival period after lung cancer surgery could have done in future works. Factors associated with lung cancer survival after surgical resection are multiple and complex. Many of them were not included in this study, and these prognostic variables comprise: neoadjuvant therapy, biomarkers, anatomopathological findings, and genomic analysis of the tumor are limitations of this study. Since models accuracy is not 100%, these systems can only be used for a population-based decision-taking, but not to decide on an individual patient.

The temporal and possibly regional validity of a score requires constant re-evaluation of the risk adjustment system. Thus, an adequate score to evaluate a group of surgical patients at a certain moment could overestimate or underestimate the expected risk of another group in the future, when the standards of quality demand better results. That is why modelling to predict risk must be an iterative process over time to adapt the system to new requirements and quality levels. The data are very basic role in learning of intelligent systems and we can increase the accuracy of the proposed system by training new data from other health centres of different parts of the world.

Conflict of interests

No conflicts of interest are declared related to the publication of this paper.

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