Artificial Neural Network for Predictingthe Success Rate beforeGraft Transplant

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Abstract: -The artificial learning models such as artificial neural network, radial basis function and art map have shown a promising application in the medical industry.The present work is acomparative analysis of the above mentioned.

The results of the investigation have indicated that among artificial neural network, radial basis function and art map the numeric values obtained fromartificial neural network werecomparativelybetter. Further, the analysis of the accuracy among the three selected algorithms was found98.9708%, 97.2556%, and 58.1475% respectively. According to literature survey performed, it is evident that most studies in this regard have received lesser attention, especially in India. Based on the findings it seems that artificial neural network could be the best mode topredict the graft survivals during liver transplantation.

***Keywords**: artificial neural network(ANN), radial basis function and adaptive resonance theory MAP, liver transplant(LT).*

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1. Introduction

Liver is one of the biggest inner organ in our body, assuming a fundamental job in digestion and serving a few capacities, for example disintegration of RBC, and so forth. It weighs around 3 pounds[3]. The liver performs numerous significant capacities identified with absorption, digestion, insusceptibility, and the capacity of supplements inside the body[3]. These capacities make the liver a fundamental organ, without which body cells would rapidly kick the bucket because of absence of nutrients[3]. While, consistently numerous human bites the dust of liver sicknesses, it is the most dynamic organ of the body that plays out different basic capacities in the body[8].Our liver is subjected to various ailments such as decompensate cirrhosis, progressive hepatitis 'B' or 'C' alcohol damage, fatty liver disease, abnormality of billiard system etc. etc. In chronic cases, a LT is suggested however, a LT is governed by many bodily factors such as body mass Indies, blood group, creatinine, albumin, and other biochemical tests. In addition to this, the other factors that complicate the process are the availability of a donor, medical urgency of the patient and geographical proximity of donor, age, sex etc[3]. Keeping the above scenarios in view the computer technology comes in handy to provide accuracy speed, predicting survival rate post-surgery complication, possible remedies, and prioritize patients[9]. Pill cameras along with miniature robotic components perform novel engineering tasks inside body and computerized data sets help doctors to make more accurate and quick diagnoses. Doctors consult other doctors for accurate reliable diagnoses and digitizing the process in terms of speed, accuracy and other necessary co-ordination. Organ transplant has gained importance and momentum to save lives. But organ transplantation is field that requires a large number of donors and a proper recipient data. Organ transplant is a fast emerging medical field that requires a solid networking to keep a record of donors and recipients of organs, the compatibility checking process, the priority of the recipients based on the health status many Biochemical test, age factor of donor, the survival rate and post-transplant problems that may arise etc. The main motive here is development of computerized models that would help solve all the above mentioned and help the patients to avail better services without undue delay and stress.

In the light of literature, I planned this study entitled "A Comparative Analysis of Various Algorithms to Predict the Survival of Liver Graft Transplant".

Most of the work in Artificial Neural Networks, radial basis function, and art mapis being carried out across the globe[1]. However, the data from Indian medical field is yet to be tested for these algorithms[2]. Researchers ofhealthcare sectors face more challenging task in predicting the diseases from the voluminous medical databases[3] as data mining has become more essential for the same[4]. Dataminingtechniques include classification, clustering, and association rule mining for finding frequentpatternsmedicaldatafordisease prediction[2].

Indatamining, classificationtechniquesplay a vital role inmedicaldiagnosisandpredictingdiseases. In this research work, Naïve Bayes and SVMclassifieralgorithmsareusedforliver diseaseprediction[5].

For instance, several studieshave derived the expressions using stepwise logistic regression analysis to find out the probability of graft failure in the patient[6].Such studies evaluated their results with the help of Receiver Operating Characteristics(ROC) curve analysis using Labroc 1 software. But the authors did not succeed to provide accuracy in the prediction of survival after LT with lack of large datasets. Hence, in this study ROC for prediction was used but a comparative study of ANN, Radial basis function, and ARTMAP for Data Miningwas also done[7].

2. Research Methedology

2.1 Process of data collection

The data used in this study were retrieved from the liver transplant dataset available at Indian Transplant Registry - *www.transplantindia.com* and the following archives: -

1. *https://archive.ics.uci.edu/ml/machine-learning-databases/00225/*
2. *https://archive.ics.uci.edu/ml/datasets/ILPD+(Indian+Liver+Patient+Dataset).*

2.2 Tools for comparative analysis

The current study was implemented in WEKA 3.8 TOOL. The results were evaluated using Multilayer Perceptron Artificial Neural Networks with 10-fold cross-validation. The whole data was divided into training data and test data which gives an accuracy of 100% by Multilayer Perceptron Artificial Neural Network model. Such approach is believed to reduce the post-transplantation mortality rate by using an intelligent system that can find correct donor-recipient pairs from a pool of donor-recipient data.

2.3 Artificial Neural Networks Algorithm

Firstly the weight, bias, and learning rate were initializedand then the stopping condition was checkedif it was false bipolar or binary training vector pairswere performed: t.

I then set activation of each input unit i=1 to n:

$x_i = s_i$

Then the output response of each output unit j=1 to m was calculated: First, the net input was calculated as

$y_i n_j = b_j + \sum_{i=1}^{n} x_i w_{ij}$

Then activations were applied over the net input calculate the output response:

$$y_j = \int (y_{inj}) = \begin{Bmatrix} i if y_{inj} > \theta \\ 0 \ if -\theta \leq y_{inj} \leq \theta \\ -1 \ if y_{inj} < \theta \end{Bmatrix}$$

Adjustments were made in weights and bias for j = 1 to m and i=1 to n.

If $t_j = y_j$ then

w_{ij} (new) = w_{ij} (old) + $\propto t_j x_i$

b_j (new) = b_j(old) + $\propto t_j$

Else, we had w_{ij} (new) = w_{ij} (old), b_j(new) = b_j (old)

Test for the stopping condition, i.e. if there was no change in weights then training process was stoppedelse started again from activation.

2.4 RADIAL BASIS FUNCTION Algorithm

I initialized the weight, bias, and learning rate. Thenthe stopping condition waschecked if it was false,I performed the input unit (x_i for all i=1 to n) to receive input signals and transmit to the next hidden layer. I then selected the centers for the radial basis function. The centers were selected from the set of input vectors. It may be noted that a sufficient number of centers were selected to ensure an adequate sampling of the input vector space.

the output from the hidden layer unit was calculated:

$$V_i(x)_i = \frac{\exp\left[-\sum_{j=1}^{r}(xji - xji)2\right]}{\sigma_i^2}\ldots.$$

Where x_{ji} was the center of the RADIAL BASIS FUNCTION unit for the input variable:σ_i the width of ith RADIAL BASIS FUNCTION unit: $x_{ij \text{ the jth}}$ variable of the input pattern.

Icalculated the output of the neural network:

$$y_{net} = \sum_{i=1}^{k} w_{im} v_i(x_i) + w0\ldots.$$

Icalculated the error and test for the stopping condition. The stopping condition was the number of epochs or to a certain extent of weight change.

2.5 ARTMAP Algorithm

Learning rate wasinitialized (vigilance parameter and error) and then the stopping condition was checkedif it wasfalseIset activations of all F_1(a) and F_1 units as follows

F_2 = 0 and F_1(a) = input vectors

The input signal from F_1 (a) to F_1 (b) layer was sent like

si=xisi=xi …..

For every inhibited F_2 node

yj=∑ibijxiyj=∑ibijxi the condition is $\mathbf{y_j \neq -1}$**…..**

step 8-10 were performed when the reset was true.

Find **J** for $\mathbf{y_J \geq y_j}$ for all nodes **j**

I again calculated the activation on F_1 (b) as follows

xi=sitJixi=sitJi**….**

Now, after calculating the norm of vector **x** and vector **s**, I checked the reset condition as follows −

If ||**x**||/ ||**s**|| < vigilance parameter **ρ**,then inhibitnode **J** and go to step 7

Else If ||**x**||/ ||**s**|| ≥ vigilance parameter **ρ**, then proceeded further.

Weight updating for node **J** was done as follows −

bij(new)=αxiα−1+||x||bij(new)=αxiα−1+||x||

tij(new)=xitij(new)=xi**…...**

The stopping condition for algorithm was checked as follows −

- No change in weight.
- Reset of units.
- The maximum number of epochs reached.

2.6 Evaluation Parameters (ARTIFICIAL NEURAL NETWORK, RADIAL BASIS FUNCTION, and ARTMAP)

ARTIFICIAL NEURAL NETWORK was used for the comparison of performance and accuracy with RADIAL BASIS FUNCTION and ARTMAP in the study[10]. This was due to the stable nature and high training speed,ARTIFICIAL NEURAL NETWORK is superior to all other models and the accuracy is far better than ARTMAP. ARTIFICIAL NEURAL NETWORK is more sensitive to data noise and to the order of presentation of input patterns.

2.7 Parameters

- **KAPPA Statistic:** - Cohen's **kappa coefficient** (κ) is a **statistic** which measures inter-rater agreement for qualitative (categorical) items. It is generally thought to be a more robust measure than simple percent agreement calculation, as κ takes into account the possibility of the agreement occurring by chance[11].
- **MEAN ABSOLUTE ERROR**(MAE) is a measure of the difference between two ongoing variables. Allocation Disagreement is MAE minus Quantity Disagreement. The **Mean Error** is given by It is also possible to identify the types of difference by looking at a plot[12].
- **ROOT-MEAN-SQUARE**deviation (RMSD) or **root-mean-square error** (**RMSE**) (or sometimes **root-mean-squared error**) is used to measure of the differences between values (sample and population values) predicted by a model or an estimator and the values actually observed[13].
- The **absolute error** is the magnitude of the difference between the exact value and the approximation. The **relative error** is the **absolute error** divided by the magnitude of the exact value. The percent **error** is the **relative error** expressed in terms of per 100[12].
- The **Relative absolute error** (and analogically **Root relative squared error**) is calculated as the Mean **absolute error** divided by the **error** of the ZeroR classifier (a classifier, that ignores all predictors and simply selects the most frequent value)[12].
- TP RATE: The fundamental prevalence-independent statistics are sensitivity and specificity. Sensitivity or True Positive **Rate** (TPR), also known as recall, is the proportion of people that tested positive and are positive (True Positive, **TP**) of all the people that actually are positive (Condition Positive, CP = **TP** + FN)[14].
- FP Rate: where **FP** is the number of false positives, TN is the number of true negatives and N=**FP**+TN is the total number of negatives. The **false positive rate** (or "false alarm **rate**") usually refers to the expectancy of the **false positive** ratio[14].
- Precision = TP / (TP+FP)[15].
- Recall = TP / (TP+FN)[15].
- The **F measure** (**F1 score** or **F score**) is a **measure** of a test's accuracy and is defined as the weighted harmonic mean of the precision and recall of the test[15].
- MCCC: Matthews Correlation Coefficient Interpretation[16].
- ROC: In statistics, a receiver operating characteristic curve, i.e. *ROC curve*, is a graphical plot that illustrates the diagnostic ability of a binary classifier system[15].

3. Results

The following results have also been summarized in Table 1.

3.1The comparative analysis

Comparative analysis for Kappa Statistics in the ANN, RADIAL BASIS FUNCTION, and ARTMAP was found to be 0.979, 0.94552, and 0 respectively. The Mean Absolute Error for the above three was found to be 0.0116, 0.0184, and 0.328 respectively. The Root Mean Squared Error was found to be 0.0803,0.1353, and 0.04046 respectively. The Relative Absolute Error was noted 3.5371%, 5.6213%, and 100% respectively. The Root Relative Absolute Error was noted as 19.8605%, 33.434%, and 100% respectively.

3.2 The accuracy of algorithms (ARTIFICIAL NEURAL NETWORK, RADIAL BASIS FUNCTION, and ARTMAP)

The accuracy value for Artificial Neural Network (Figure 1), Radical Basis Function (Figure 2) and ARTMAP (Figure 3) was found to be 98.9708%, 97.2556%, and 58.1475% respectively.

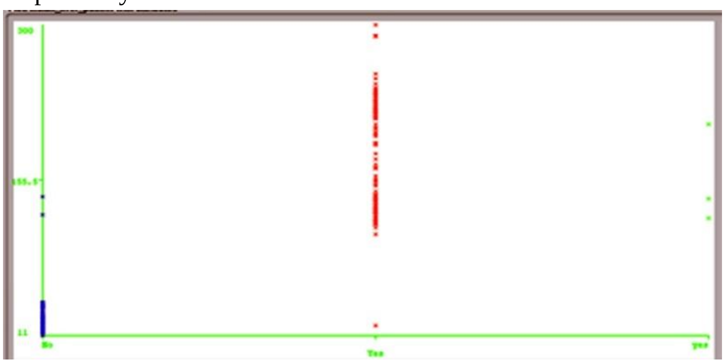

Figure 1: Showing the accuracy value for Artificial Neural Network

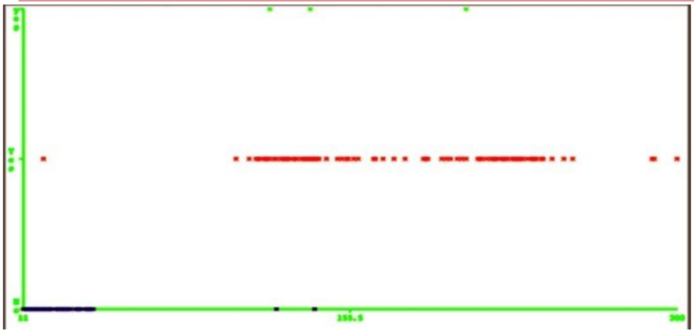

Figure 2: Showing the accuracy value for Radical Basis Function

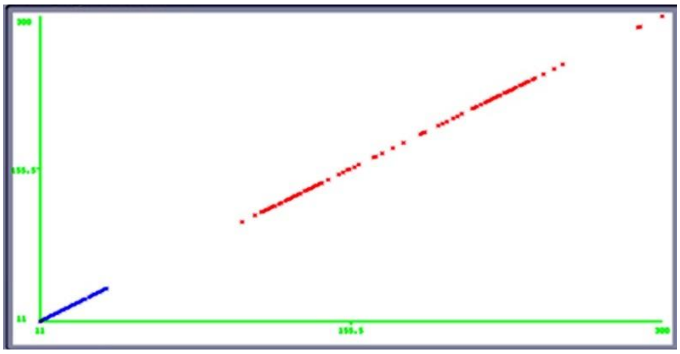

Figure 3: Showing the accuracy value for ARTMAP

Table: 1*Showing the comparative analysis of Artificial Neural Network, Radical Basis Function, and ARTMAP with respect to various parameters.*

Sr. No.	Parameters	Artificial Neural Network	Radical Basis Function	ARTMAP
1	Kappa statistics	0.979	0.9452	0
2.	Mean Absolute error	0.0116	0.0184	0.328
3.	Root mean squared error	0.0803	0.13535	0.4046
4.	Relative absolute error	3.5371%	5.6213%	100%
5.	Root-relative absolute error	19.8605%	33.434%	100%
6.	TP Rate	1.000	1.000	0.000
7.	FP Rate	0.000	0.000	0.000
8.	Precision	1.000	1.000	0.000
9.	Recall	1.000	1.000	0.000
10.	F-Measure	1.000	1.000	0.000
11.	MCCC	1.000	1.000	0.000
12.	ROC Area	1.000	1.000	0.497

4. Discussions

The results of the present study indicated that among Artificial Neural Network, Radial Basis function, and ARTMAP, the Artificial Neural Network yielded best results. On comparing ANNs, RADIAL BASIS FUNCTION, and ARTMAP indicated that ANNs are more superior and beneficial than other algorithms. ANNs function in a sequential and logical order[10]. Firstly, they adopt the sound theory and then proceed towards implementation and experimentation whereas, RADIAL BASIS FUNCTION and ARTMAP adopt "a hands-on" approach where application and experiments are given more priority and theory is involved later[10]. ANNs have several other benefits over RADIAL BASIS FUNCTION and ARTMAP such as ARTIFICIAL NEURAL NETWORKs involve simple geometric interpretation and gives a solution which is viable, while RADIAL BASIS FUNCTION and ARTMAP suffer from multiple complexities and its solutions are limited to a local level only[17]. Unlike RADIAL BASIS FUNCTION and ARTMAP, the computational complexity of ANNs does not dependent upon the input space[18]. On one hand, ANNs useempiricalrisk minimization while on the other hand, ARTMAP and RADIAL BASIS FUNCTION use structural risk management[19]. The main reason for ANNs to be more popular and preferred is their capacity to overcome the biggest problem experienced with ARTMAP and RADIAL BASIS FUNCTION, i.e. overfitting[20]. In the nutshell, the ANN classifier is generally considered as the best algorithm because of its highest classification accuracy[10]and the results of the present study are also incoherence with the same.

The proposed model trained many instances and predicted the success rate of patients after LT successfully. Out of 100 % patients, 70 percent of patients were alive after LT without any difficulty. The post transplantation result of every patient relies on the pre transplantation condition of the patient the join quality and the intricacy of medical procedure sometimes the complexities happen in a split second after medical procedure or over the long haul When inconveniences happen remain in the emergency unit broadened and the shot of mortality increments[21].

As of now, gathering and sharing of liver organs are the most significant parts of LT[22]. The shortage of givers is the primary issue looked by patients and each organ allotment must be exact in such a scenario[10]. LT has progressed from a test treatment to a standard treatment choice for a wide scope of intense and constant liver diseases[22].Now per day's LT is one of the difficult regions in the field of organ transplantation[22]. The liver gets harmed because of liquor or liver illness as well as because of ill-advised nourishment utilization just as hereditary disorders[23]. Clinical investigations demonstrated that in the following decade, over 90% of individuals will be influenced by liver problems[22-23]. The forecast by restorative specialists depends on MELD score. Merge score is accepted to give the accurate result. The parts of MELD score incorporates Bilirubin, Creatinine, and INR, out of which the creatinine worth changes as per the body weight of the patient[24]. With the equivalent dataset, the join survival rate is 79.11% and unites disappointment rate 20.89% utilizing MELD score. Notwithstanding the MELD score, different AI strategies are presented for the anticipating of expanded survival after LT[10]. ANN is another organically enlivened figuring approach which is an extremely incredible progression in the field of PCs and prescription. So as to perform AI tasks in designing, drug, arithmetic, financial matters, science, topography and numerous others, the job of counterfeit neural systems has been very successful[25].

5. Conclusion

During the tenure of this study it was observed that classification of liver diseases is more accurate in ANN data mining than Radial Basis Function and ARTMAP. ANNprediction of the liver provides a good basis for analyzing the texture of the liver, whereasRadial Basis Function and ARTMAP impose some difficulties to analyze the structure of the liver.Further analyzing texture is a challenge but Radial Basis Function and ARTMAP are cost effective. Further, ANN techniques provided good accurate results according to thestudy. I also believe that a lot can be improved in the accuracy of diagnosing the liver diseases based on texture analysis. Additionally, the accuracy of such studies completely depends on classifiers applied.

The LT programmes took off after the use of immune suppressants like cyclosporine cyclophosphamide widely and as the survival rate surged from 28% to 50%. But the progress of lever transplants in India remained low and one of the major causes was lack of donors which even today remain far below from that of the West.

With a population of 1.2 billion plus there are only 0.08 persons per million PMP as compared to countries like the USA, UK, Germany etc that have a 20-30% PMP. The reason being that these countries have a family consent system for donation where people sign up as donors and the family consent is required. Countries like Belgium, Spain, and Singapore have an aggressive approach of presumed consent which permits organ donation by default unless donor has explicitly opposed it during his life time. Hence these countries have double the rate of donation i.e. between 20-40 PMP.

The number of cadaver donors in India remains considerably low till date because of cultural, religious and political reasons. Living donor LT is more prevalent in India and has also shown better survival rates.

Poor organ donation rate also arises due to inadequate co-ordinations and implementation of governmental policies. In India, Brain stems death patients could not be used as donors. Although there are so many accidental cases leading to Brainstem death. India has one major problem that LT is available in large private hospital and also inter net accessibility to large number of people due to high cost. Also, India needs a strong network for donor-recipient data and to ensure equitable distribution of organs. India also need to strengthen awareness programmes to improve rates of cadaver organ donation. Moreover living donor transplant is a complicated process where two operation theatres with two dedicated teams are required to co-ordinate various steps so that time of taking out part of liver from one donor coincides with the time of taking out part of the liver from the recipient. A patient is likely to remain in operation theatre for 14-20 hrs.

6. References

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