

# Predicting the Success Rate before Liver Transplant using ANN



#### Aditi Gupta

Abstract: The counterfeit learning models, for example, the artificial neural system, radial basis function and art map have demonstrated a promising application in the medicinal industry. The present work is a comparative examination of the previously mentioned. The consequences of our examination have demonstrated that among Artificial neural system, radial basis function and art map the numeric qualities acquired from ANN were relatively better. Further, the investigation of the exactness among the three chose calculations was found 98.9708%, 97.2556%, and 58.1475% separately. As per writing overview performed, it is clear that most examinations right now got lesser consideration, particularly in India. In view of our discoveries it appears that the ANN could be the best mode to predict the joint stabilities during liver transplantation.

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

#### I. INTRODUCTION

Liver is among the most inward organs of human body, accepting a crucial activity in assimilation and serving a couple of limits, for instance the crumbling of RBC, etc. It weighs around 3 pounds3. The liver plays out various critical limits related to assimilation, absorption, immunity, and the limit of enhancements inside the body3. These limits make the liver a principal organ, without which body cells would quickly kick the pail as a result of nonattendance of nutrients3. While, reliably various human fails miserably of liver infections, it is the most unique organ of the body that plays out various fundamental limits in the body8. Our liver is exposed to different illnesses; like, decompensate cirrhosis, dynamic hepatitis 'B' or 'C' liquor harm, greasy liver malady, variation from the norm of billiard framework and so on and so forth. In ceaseless cases, an LT is administered by numerous substantial factors; for example, weight Indies, blood gathering, creatinine, egg whites, and other biochemical tests. Also, different elements that entangle the procedure are the accessibility of a giver, medicinal earnestness of the patient and land nearness of contributor, age, sex etc3. Keeping the above situations in consideration the PC innovation proves to be useful to give exactness speed, foreseeing endurance rate post-medical procedure complexity, potential cures, and organize patients9. Pill cameras alongside little mechanical segments perform novel designing assignments inside body and automated informational indexes help specialists to make progressively exact and fast analyses. Specialists counsel different specialists for exact solid analyses and digitizing the procedure regarding rate,

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exactness and other fundamental co-appointment. Organ transplant has picked up significance and force to spare lives. In any case, organ transplantation is a field that requires an enormous number of benefactors and some legitimate beneficiary information. Organ transplant is a quick developing therapeutic field that requires a strong administration track benefactors to beneficiaries of organs, the similarity among the checking process, the need for the beneficiaries dependent on the wellbeing, status numerous Biochemical test, age factor of contributor, the endurance rate and post-transplant issues that may emerge and so on. The principle intention here is advancement of mechanized models that would help unravel all the previously mentioned factors and help the patients to benefit better administrations immediately and stress.

In the light of writing, we arranged this investigation entitled "A Comparative Analysis of Various Algorithms to Predict the Survival of Liver Graft Transplant".

The greater part of the work in ANN, RBF, and ART map is being done over the globel. Be that as it may, the information from an Indian therapeutic field is yet to be tried for these algorithms2. Specialists of social insurance areas face all the more testing task in anticipating the infections from the voluminous medicinal databases3 as information mining has gotten increasingly fundamental for the same4. Information mining strategies incorporate characterization, bunching, and affiliation rule digging for finding continuous examples medicinal information for illness prediction2.

In information mining, characterization strategies assume an imperative job in therapeutic finding and foreseeing ailments. Right now, Naïve Bayes and SVM classifier calculations are utilized for liver malady prediction5.

For example, a few examinations introduced certain methods by using the stepwise strategic relapse investigation to discover the likelihood of joint disappointment in the patient6. Considerers their outcomes with the assistance of Operating Characteristics (ROC) in bend examination utilizing Labroc 1 programming. However, the creators didn't prevail to give exactness in the forecast of endurance after LT with absence of huge datasets. Consequently, ANN, Radial basis function, and ARTMAP used for Data Mining.

#### II. **METHODS & MATERIALS**

The recent experiment was carried out at the laboratory of CG-1 POST GRAD LAB, The Department of computer sciences, D.A.V. Institute of engineering and technology, Jalandhar (144001), Punjab, India.



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#### 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. <a href="https://archive.ics.uci.edu/ml/machine-learning-databases/00225/">https://archive.ics.uci.edu/ml/machine-learning-databases/00225/</a>
- 2. <u>https://archive.ics.uci.edu/ml/datasets/ILPD+(Indian+Liver+Patient+Dataset).</u>

#### 2.2 Tools for comparative analysis

The present examination was actualized in WEKA 3.8 TOOL. The outcomes were assessed utilizing Multilayer Perceptron Artificial Neural Networks with 10-overlap cross-approval. The preparing information and test information, in which the entire information was divided, gave an exactness of 100% by Multilayer Perceptron ANN model. Such methodology is accepted to lessen the post-transplantation death rate by utilizing a keen framework that can discover right giver beneficiary sets from a pool of benefactor beneficiary information.

#### 2.3 Artificial Neural Networks Algorithm

Firstly we initialized the weight, bias, and learning rate and then analyzed the stopping condition if it was false We performed bipolar or binary training vector pairs: t.

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

$$x_i = s_i$$

then the output response of each output unit was calculated j=1 to m: 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 to calculate the output response:

$$y_{j} = \int (y_{inj}) = \begin{cases} iif y_{inj} > \theta \\ 0 if - \theta \le y_{inj} \le \theta \\ -1 if y_{inj} < \theta \end{cases}$$

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

If  $t_i = y_i$  then

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

 $b_i$  (new) =  $b_i$ (old) +  $\propto t_i$ 

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

Test for the stopping condition, i.e. When the weights remained unchanged, we stop the training process else it will be started again from the activation.

## 2.4 RADIAL BASIS FUNCTION Algorithm

We initialized the weight, bias, and learning rate. Then we checked the stopping condition if it was false, we performed the input unit ( $x_i$  for all i=1 to n) to receive input signals and transmit it to the next hidden layer. We then selected the centers for the radial basis function. The centers were selected from the set of input vectors. It may be made notable that a satisfactory count of hubs of centers were selected to ensure an adequate sampling of the input vector space.

We calculated the output from the invisible layer unit:

$$V_i(x)_{i} = \frac{\exp[-\sum_{j=1}^{r}(xji-xji)2]}{\sigma_i^2}$$
....

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Retrieval Number: E2837039520/2020©BEIESP DOI: 10.35940/iiitee.E2837.039520 There  $x_{ji}$  was the hub of the RADIAL BASIS FUNCTION unit for the input variable:  $\sigma_i$  the broadness of ith RADIAL BASIS FUNCTION unit:  $x_{ij}$  the jth variable of the input taking in arrangement.

We calculated the output of the neural network:

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

We calculated the mistakes and test for the ceasing state. The ceasing state was the number of epochs.

#### 2.5 ARTMAP Algorithm

Learning rate was initialized (vigilance parameter and error) and then the ceasing condition was checked if it was false. We set activations of all  $F_1(a)$  and  $F_1$  units as follows

#### $F_2 = 0$ and $F_1(a) = input vectors$

The input alarm through  $F_1$  (a) to  $F_1$  (b) layer was sent like si=xisi=xi .....

For every inhibited F<sub>2</sub> node

 $y_j = \sum_{i=1}^{n} ibijxiy_j = \sum_{i=1}^{n} ibijxi$  the condition is  $y_j \neq -1$ ....

We then performed step 8-10 when the reset was accurate Find **J** for  $y_J \ge y_j$  for all nodes **j** 

We once more calculated the activation on  $F_1$  (b) as follows xi=sitJixi=sitJi...

Now, after figuring out the norm of vector  $\mathbf{x}$  and vector  $\mathbf{s}$ , we checked the reset condition as follows –

If  $||\mathbf{x}|| / ||\mathbf{s}|| < \text{vigilance parameter } \boldsymbol{\rho}$ , then inhibit node  $\mathbf{J}$  and go to step 7

Else If  $||x||/||s|| \ge \text{vigilance parameter } \rho$ , then proceeded further.

Weight revision for node **J** was performed as follows – bij(new)= $\alpha$ xi $\alpha$ -1+||x||bij(new)= $\alpha$ xi $\alpha$ -1+||x||

tij(new)=xitij(new)=xi.....

The stopping condition for algorithm was checked as follows –

- No weight variation.
- Reorganization of the unit.
- 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 comparing the performance and accuracy with RADIAL BASIS FUNCTION and ARTMAP in the study<sup>10</sup>. This was due to the balanced nature and high training pace, ARTIFICIAL NEURAL NETWORK is far better than other models and the exactness is superior than ARTMAP. ARTIFICIAL NEURAL NETWORK is comparatively sensory towards the data noise and to the order of demonstration of taking in arrangements of input patterns.

#### 2.7 Parameters

 KAPPA Statistic: - Inter-related compliance for qualitative components is measured using Cohen's kappa coefficient (κ). It is believed to be a more vigorous measure than simple percent agreement computation,





as  $\kappa$  considers the possibility of the compliance occurring accidently  $^{11}$ .

- **MEAN ABSOLUTE ERROR**(MAE) is a calculation 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<sup>12</sup>.
- ROOT-MEAN-SQUARE deviation (RMSD) or rootmean-square error (RMSE) (also called root-meansquared error) is used to calculate the variation betwixt values (sample and population values) anticipated by a model or an estimator and the values actually observed<sup>13</sup>.
- The **absolute error** is the degree of the contrast between the literal and the near value. The **relative error** is the **absolute error** divided by the degree of the literal value. The percent **error** is the **relative error** expressed in terms of per 100<sup>12</sup>.
- 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 choose the most constant value)<sup>12</sup>.
- 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)<sup>14</sup>.
- FP Rate: where **FP** is the statistic of untrue positives, TN is the statistic of correct negatives and N=**FP**+TN is the entire statistic of negatives. The **untrue positive rate** (or "false alarm **rate**") usually refers to the anticipation of the **untrue positive** ratio<sup>14</sup>.
- Precision = TP / (TP+FP)<sup>15</sup>.
- Recall =  $TP / (TP+FN)^{15}$ .
- The **F measure** (**F1 score** or **F score**) is a **measure** of a test's accuracy and can be defined as the weighted harmonic mean of the exactness and recollection of the test<sup>15</sup>.
- MCCC: Matthews Correlation Coefficient Interpretation 16.
- ROC: In statistics, recipient managing characteristic curve, i.e. *ROC curve*, is a graphical plot that portrays the analyzing power of a dual classifier system<sup>15</sup>.

#### III. RESULTS

The following results have also been summarized in Table 1.

#### 3.1The comparative analysis

Comparative analysis for Kappa Statistics in an 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 (ANN, 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.

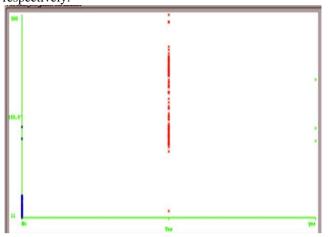


Figure 1: Showing the accuracy value for Artificial Neural Network

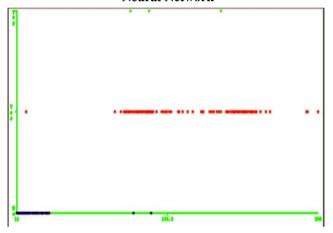


Figure 2: Showing the accuracy value for Radical Basis
Function

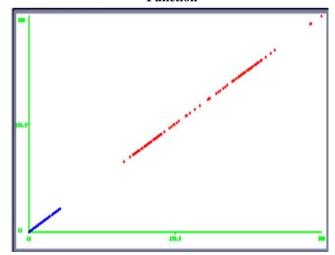


Figure 3: Showing the accuracy value for ARTMAP



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

Sr.	Parameters	Artificial Neural	Radical Basis Function	ARTMAP
No.		Network		
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

#### IV. DISCUSSIONS

The results of the present study indicated that among Artificial Neural Network, Radial Basis function, and ARTMAP, the Artificial Neural Network yielded best On comparing ANNs, **RADIAL** results FUNCTION, and ARTMAP indicated that ANNs are more superior and beneficial than other algorithms. ANNs follow the continuous and relevant order while functioning. 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<sup>10</sup>. 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<sup>17</sup>. Unlike RADIAL BASIS FUNCTION and ARTMAP, the computational complexity of ANNs does not dependent upon the input space<sup>18</sup>. On one hand, ANNs use empirical risk minimization while on the other hand, ARTMAP and RADIAL **BASIS FUNCTION** use structural management<sup>19</sup>. 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<sup>20</sup>. In nutshell, the ANN is generally treated as the best algorithm because of its highest classification accuracy<sup>10</sup> and the results of the present study are also incoherence with the same.

Our model edified many e.g. and predicted the success rate of patients after LT successfully. Out of 100 % patients, 70 percent of patients were Surviving after LT without any difficulty. The post transplantation result of every patient relies upon the pre transplantation condition of the patient the join trait and the intricacy of medical procedure. Sometimes the complexities happen in a split second after medical procedure or over the long haul.

As of now, gathering and allocation of liver organs are the most significant parts of LT<sup>22</sup>. The shortage in the number of givers is the primary issue for the patients and each organ allotment must be exact in such a scenario<sup>10</sup>. LT has progressed from a test treatment to a standard treatment

giving expanded scope of intense and constant liver diseases<sup>22</sup>.Recently per day's LT is one of the difficult regions in the field of organ transplantation<sup>22</sup>. The liver gets harmed because of liquor or liver illness as well as because of ill-advised nourishment utilization just as hereditary disorders<sup>23</sup>. Clinical investigations demonstrated that in the following decade, over 90% of individuals will be influenced by liver problems<sup>22-23</sup>. 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 according to the weight of the body of the patient<sup>24</sup>. With the equivalent dataset, the join endurance 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<sup>10</sup>. 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 successful25.

#### V. CONCLUSION

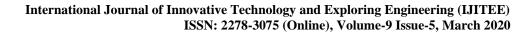
During the tenure of this study it was observed that the classification of liver diseases is more accurate in ANN data mining than Radial Basis Function and ARTMAP. ANN prediction of the liver provides a good basis for analyzing the texture of the liver, where as Radial Basis Function and ARTMAP impose 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 our study. We 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 approval system for donation. Here people sign up as donors and the family consent is required. Countries like Belgium, Spain, and Singapore have a antipathetic approach of anticipated approval which permits organ donation by default unless donor has exceptionally opposed it during his life time. Hence the said 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 in adequate coordinations 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.

#### ETHICAL STATEMENT

The research presented in the study is true and best to my knowledge. None of the data has been manipulated or tampered with in any respect.

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