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Research Article

Cloud-based Hybrid Method for Prediction of Long Term Survival after Liver Transplantation

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Abstract

Prediction of long-term survival after Liver Transplantation (LT) is one of the most difficult area in the field of medicine. The final treatment for the last stage of liver disease is liver transplantation. Going to any transplant, everyone will think about survival. This paper summarizes the prognosis of survival of patients who have undergone liver transplantation, both in computing and in clinical terms. The system proposed a cloudbased hybrid classifier with Artificial neural network (ANN) model to address the problem of organ allocation as well as survival prediction using a United Nations for Organ Sharing (UNOS) dataset. The (UNOS) dataset contains 389 attributes, and of these 389, 256 attributes are related to liver transplantation patients, form this 256 only 70 attributes consist of donor attributes, transplant attributes, and recipient attributes, and of these 70, only 28 attributes are used in our proposed system. This model extracts the corresponding attributes using Principal component analysis (PCA) algorithm and classifies the data set into training and test sets by using hybrid classifier. The relationship between attributes has been recognized and proven by various methods of Association rule analysis, such as Apriori algorithms. The corresponding donor-recipient pairs were selected using ten-fold cross-validation (CV) in the training of medical data. The proposed efficient and accurate artificial neural network (ANN) model predicts the long-term survival of liver patients who undergo Liver transplantation (LT), and then the predicted data is uploaded to the Amazon Web Services (AWS) cloud. Finally, proposed Hybrid Classifier (MLP+LM) accuracy is compared with existing Multi-layer Perceptron (MLP), Recurrent Neural Network (RNN) algorithm.

Keywords: *Liver Transplantation (LT), Cloud based Hybrid classifier, Artificial neural network (ANN), ten-fold crossvalidation (CV), Multi-layer Perceptron (MLP), Amazon Web Services (AWS) cloud.*

1. Introduction

Liver transplantation (LT) is a life-saving procedure for patients suffering from chronic and acute liver failure and has undergone massive development over the past 50 years. Advances in the inhibition of infectious and non-infectious complications, the stability of immunosuppressive therapy, and the distribution of organs are central features that have developed since the first series of LTs. Long-term survival and quality of life are the main goals of LT. Predicting survival is an important factor used to determine the success of liver transplant surgery. Despite the fact that liver transplantation is the most favorable treatment method for those who suffer from liver diseases, the short age of donor liver sharply limits this option [1] [2]. The number of patients waiting for a liver transplant is high, but the number of people trying to donate a liver is much lower, so the mortality rate is increasing every year. Currently, candidates on the deceased donor liver transplant waiting list are preferred by medical need. Medical experts, based on the Model of End-stage Liver Disease (MELD) score, have made judgments about the liver transplantation and the prediction of the outcome of the transplant. Of the three parameters in the MELD score of bilirubin, creatinine and the International normalized ratio (INR), creatinine levels vary depending on the weight of the liver recipient. According to the principle of the MELD score, patients at the top of the waiting list are given the highest priority in organ allocation for liver transplantation. But in this case, some patients can get the donor organ early, while others have to wait longer for the donor organ, which leads to a lower survival rate [3]. Instead of using the MELD score, continuous research into more accurate models to predict the long-term survival of liver transplant patients has led to the introduction of more accurate models, such as

Artificial neural networks (ANNs). ANN uses computer technology to model systems that structurally and functionally recall biological neural networks: they consist of a set of highly interconnected processing units (neurons) linked to weighted connections and include an input layer, an output layer and one or more hidden layers. The input layer consists of the different data available for analysis and the output layer consists of the different results. In medical field, several commonly accepted statistical models are used to predict LT, without taking into account the donor-recipient comparison, donor organs are allocated to the first patient in the queue because of the shortage of donor organs in the classical method of allocation. But ANNs play a more important role by avoiding the local optimum of traditional statistical methods and logistic regression models. ANN models are successfully used in traditional statistical methods for predicting survival, taking into account the characteristics of the donor-recipient and transplanted organs. The purpose of this study was to develop a Prediction of Long Term Survival after Liver Transplantation system based on matching donor and recipient. There are many reasons for developing this system: (1) existing selection / distribution systems are based on the risk of patient death in the waiting list and do not recognize differences in the quality of donor organs; (2) efforts to increase the number of donor organs are likely to result in a relatively high proportion of donors with expanded criteria; (3) comparison of donors and recipients may provide an opportunity to predict results at the time when a particular donor liver will be allocated to a specific recipient; (4) differences in local acceptance rates and policies may be reduced; and (5) Overall outcome and effectiveness may improve [4][5].

This paper proposes a cloud-based hybrid classifier for prediction of long-term survival of liver transplant patients. Our system uses 28 attributes from UNOS dataset and performs the feature extraction on dataset by using Principal component analysis (PCA) [6] algorithm, and classifies the data set into training and test sets by using proposed hybrid classifier. The corresponding donor-recipient pairs were selected using tenfold cross-validation in the training of medical data. The proposed efficient and accurate artificial neural network (ANN) model predicts the long-term survival of liver patients who undergo Liver transplantation (LT), and then the predicted data is uploaded to the Amazon Web Services (AWS) cloud. Cloud computing plays an important role in reducing the combined cost of healthcare, optimizing resources, and sharing a new era of innovation, because of this information is accessed anytime, anywhere, which can be achieved when moving healthcare information to the cloud [7].

Objectives:

- To implement cloud-based Hybrid classifier with Artificial neural network (ANN) model for prediction of long term survival after liver transplantation.
- To use Principal component analysis (PCA) for ranking the attributes.
- To implement attribute selection technique with data preprocessing.
- To rank the attributes by using Weka ranker.
- To upload the predicted data on Amazon Web Services (AWS) cloud.

3. Literature Survey

The various researchers conduct study on ANNs model to predict patient survival after liver transplantation. C. G. Raji and S. S. Vinod Chandra [1], effective and accurate model of an artificial neural network (ANN) for predicting the longterm survival of liver patients undergoing liver transplantation (LT) has been proposed. A tenfold cross-validation (CV) was applied in a medical input dataset that was obtained from the United Network Organ Sharing database. They performed a

13-year survival analysis in predicting liver patients after LT. The author trained liver observation data for 13 years separately using the multi-layer perceptron model with ANN with the correct selection of data attributes. In paper [8] J. Nair, P. Bhujbal, K. Nalawade and S. Akhade, proposes a model for predicting life expectancy after liver transplantation and model is deployed using the automatic learning process. They use Moderate 200 attributes from UNOS dataset. The author performs clustering for efficient clustering between Donor data and Recipient data by using K-means algorithm. The model predicts the correct life span.

The authors L. Bertocco de Paiva Haddad,L. Ducatti, L. R. B. Carelli Mendes and W. Andraus, and L. A. C. D'Albuquerque, describes the fact that the liver transplant procedure are common and very expensive, their cost structure is still poorly understood. The liver transplantation procedures in patients with micro-costs model of development while the individual clinical predictive roles are compared using tree regression models. The authors M. P-Ortiz, P. Gutierrez,

C. HMartınez, J. Bricenoy and M. de la Mata [10], propose a new algorithm for ordinal classification based on a combination of ensemble and discriminant analysis methods. This proposal relates to the actual application of liver transplantation, where the goal is to predict the survival of the transplant. This proposal was tested using an important Biomedicine problem: predicting graft survival in a real-world data set for liver transplantation. The author [11] C. G. Raji and S. S. Vinod Chandra, introduces the several machine learning methods to predict increased survival after LT. Methods based on artificial neural networks are widely used to study medical data and predict survival outcomes. The role of machine learning tools in the medical field is growing day by day as medical data grows exponentially, where doctors cannot easily identify hidden patterns and useful information occurring in large volumes of data. One of the key areas is to predict the suitability and survival of organs during transplantation. ANN is the dominant improvement in computers and medicine. For performing machine learning operations in engineering, medicine, mathematics, Economics, science, Geology, and many other fields, the role of ANNs is remarkable.

Raji C. G, A, and Vinod Chandra [12], proposes a Multilayer Perceptron model (MLP) model for long term survival of patients after Liver transplantation. They use 256 attributes, out of 389 attributes from United Nations Organ Sharing (UNOS) dataset. The PCA is used for feature extraction. The system performance was compared with Radial Basis Function (RBF). M. D. Ayllon, and R. Ciria [13], a donor-recipient (D-R) matching model for liver transplantation (LT) based on artificial neural networks (ANNs) from a Spanish multicenter study (donor-recipient distribution model in Espana [MADRE]) is reported. The goal is to test the ANN-based methodology in another European health system to confirm it. The ANN model was developed using a cohort of patients from king's College hospital (KCH; n=5822). ANN was trained and tested using KCH pairs for both 3-and 12-month survival models. The endpoints were the probability of graft survival and nonsurvival. The final model is a rule-based system to facilitate the decision on the most appropriate D-R comparison.

3. Proposed Methodology

A. Problem Statement

Implement an effective and accurate cloud based hybrid classifier for the prediction of long-term survival of liver patients who undergo liver transplantation (LT).

B. Proposed System Architecture

Liver transplantation is the main method of treatment for people suffering from end-stage liver disease. With various achievements in the field of liver transplantation, the survival rate is increasing day by day, and the patients are largely dependent on surgical procedure. In liver transplantation, it is very difficult to get an appropriate agreement between the donor and the recipient. The patient's survival after liver transplantation depends on the correct selection of the recipient donor for prediction. Features of receiving a donor, etc., and these characteristics are the same. The manual method of matching donor-recipient functionality is tedious. In many areas of research, the size of the input data is too large. This can lead to a relatively slow mining process. To solve these problems, we have proposed to implement an effective and accurate cloud-based hybrid classifier for the prediction of long-term survival after Liver Transplantation (LT). Figure 1 shows the cloud based hybrid classifier for the prediction of long-term survival of liver patients.

- **UNOS (United Nations Organ Sharing) Dataset:**

To collects the data from the United Nations Organ Sharing (UNOS) dataset. The dataset contains 389 attributes, and of these 389, only 70 attributes consist of donor attributes, transplant attributes, and recipient attributes, and of these 70, only 28 attributes are used. The table I, shows the 28 attributes and variables of donor and receiver.

Table I. Attribute name, variable type, and donor/receiver

Attributes Name	Variable Type	Donor/Receiver
GENDER_DON	Nominal	Donor
NON_HRT_DON	Nominal	
SGOT_DON	Numeric	
SGPT_DON	Numeric	
TBILI_DON	Numeric	
AGE_DON	Numeric	
CLIN_INFECT_DON	Nominal	
CREAT_DON	Numeric	
DIABETES_DON	Nominal	
DON_TY	Nominal	
GENDER	Numeric	Receiver
INIT_AGE	Numeric	
MALIG_TCR	Nominal	
GSTATUS	Nominal	
FINAL_BILIRUBIN	Numeric	
FINAL_INR	Numeric	
FINAL_MELD_OR_PELD	Nominal	
FINAL_MELD_PELD_LAB_SCORE	Numeric	
FINAL_SERUM_CREAT	Numeric	
FINAL_SERUM_SODIUM	Numeric	
BMI_TCR	Numeric	
ENCEPH_TCR	Nominal	
EXC_HCC	Nominal	
FINAL_ALBUMIN	Numeric	
ALKPHOS	Numeric	
FINAL_ASCITES	Numeric	
NUM_PREV_TX	Numeric	Transplantation
TX_LIV	Nominal	

- **Data Preprocessing:**

In preprocessing stage irrelevant data is removed. The UNOS dataset contain 389 attributes, form this only 256 attributes are related to liver transplantation patients. It includes clinical and non-clinical signs of adult and pediatric liver patients. As with any data set, we can remove some attributes without using any data mining methods. To predict survival, we look at the signs of liver patients during transplantation. Registration information, information about waiting lists, information about transplantation, malignancies registered after LT, information about subsequent actions after LT and suppression of the recipient's immunity at discharge are stored in separate files. So we can remove 59 attributes from 256 attributes during preprocessing step. Among the 197 attributes, we performed a PCA to reduce the dimension. According to the standard deviation ranking, we obtained 70 relevant attributes and only 28 attributes are used that are very useful for predicting survival after LT. The ranking of the attributes in the survival prediction is performed by Weka-knowledge flow analysis. The Ranker detects strong attributes from PCA filtered attributes and ranks them according to the strength and standard deviation. The PCA filters the attributes which contains donor, recipient, and transplantation attributes in the liver transplantation dataset. While ranking 28 attributes, it is clear that all recipient attributes, donor attributes and transplant attributes have equal importance to survival prediction after liver transplantation.

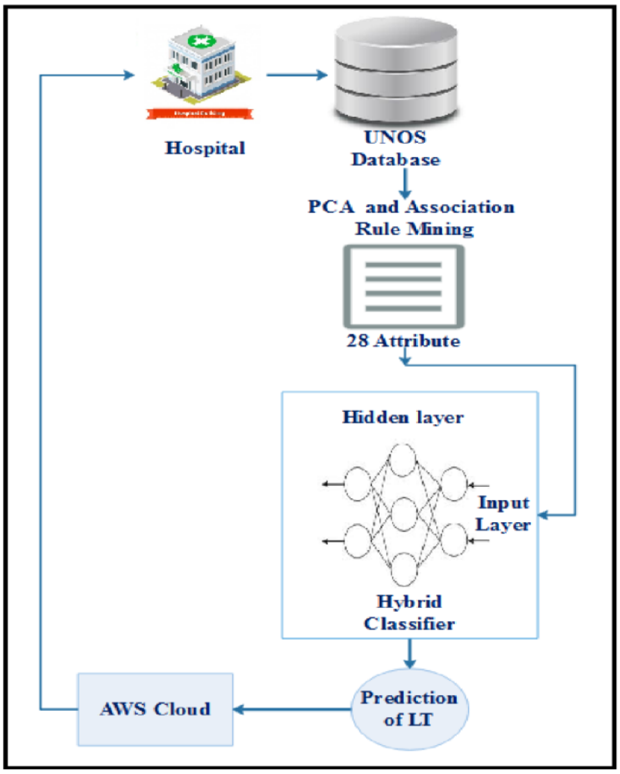

Fig. 1. Proposed System Architecture

- **Association Rule Mining Algorithm:**

The digital world pumps millions of data every day. A strong data mining algorithm is needed to draw reliable conclusions from millions of data. The analytical process designed for data mining is becoming increasingly complex with a rapid information explosion. This becomes more complex when the data is fully distributed and not indexed. Thus, evaluating and searching for relationships between variables from a large database becomes a tedious task. For this process, Associative rule mining is used. Associative rules are "if-THEN" rules that help uncover the vast relationship between seemingly unrelated data. It uses a combination of statistical analysis, machine learning, and database management to exhaustively examine data to identify complex relationships that exist. Support and Confidence are the two dimensions of quality in each Association rule. Association rule mining is used to match the donor and receiver LT attributes. Association rule mining algorithm finds out the co-occurrence of attributes by creating rules in between the attributes.

- **Hybrid Classifier (MLP+Levenburg Marquardt (LM)):**

The system prefers to run either an MLP or a hybrid classifier (MLP + LM). The standard 28 input attributes of the data set are selected and it given to the hybrid model shown in the figure 1. The model trained patient-related clinical attributes of liver transplantation (LT) using a back-propagation algorithm. The input data contains donor, recipient, and transplant attributes. The model contains many hidden layers. The activation function used in Hidden Layers is the sigmoid function, while training clinical data. Appropriate donorrecipient matching is necessary for the best survival of patients undergoing LT.

The output is binary, and the linear function is used in hidden layers for the output layers. When the data is passed through the hidden layers, the donor and recipient were correctly matched. Errors can be reduced by adjusting the weights to achieve the best result. As the model inputs and outputs are related to the task inputs and data, one must specify the total number of nodes in the hidden layer. Training time increases with the number of hidden layers and leads to a decrease in the number of errors that occurs in the training process. In each training donor-recipient mapping is performed with the help of hidden layers using a back propagation algorithm and produces a binary survival result as 0 or 1. The formula for calculating the hidden layers are: sample model and the validation sets, the k-fold cross validation method is used to compare the accuracy of two or more classification models. The formula for calculating the kFold Cross Validation is:

$$CV = \frac{1}{k}\sum_{i=1}^{k} Ai \tag{2}$$

Where Ai is the individual fold accuracy and k is the number of folds. This means that the entire data set is trained and tested k times. We used a ten-fold cross-validation procedure with ten equal numbers of folds to train and test the entire data set.

Prediction of Liver Transplantation:

The survival rate of LT is the time between the occurrence of life and death. The survival analysis of each liver patient has been carried out for several years so far. Survival probability of each patient is calculated from this equation:

$$S_p = \frac{(Patients\ living\ at\ the\ start) - Patients\ died)}{Patients\ living\ at\ the\ start} \quad (3)$$

The probability of survival of liver patients can be calculated based on the number of liver patients living at the beginning of the disease. Of the total number of liver patients who lived at the start, we found a difference between the number of liver patients who lived at the start and the number of liver patients who died.

Algorithms

- **Algorithm 1:** Hybrid classifier (MLP + LM) with Back-

Propagation Algorithm (Proposed Algorithm)
1. Take input dataset
2. Take each entry of dataset and convert it into matrix form
3. Assign randomly weight and bias matrix
4. Do multiplication of weight, bias and input matrix for each hidden layer Where,

$T= I + O$, so a becomes (I+ O)/2

Here, I indicate the number of attributes and O indicates the number of classes. Since the output attributes are in the form 0 and 1, the linear function was applied from the hidden layer to the output layer. In this model the classification accuracy was computed and produced the best survival output.

- **k-Fold Cross Validation:**

Cross-validation is a recalculation procedure used to evaluate machine learning models on a limited sample of data. The procedure has a single parameter called k, which indicates the number of groups into which this sample of data should be divided.
The entire data set can be divided randomly into k mutually exclusive folds of the same size, (DS1, DS2, ..., DSn) in kfold cross validation. To reduce the bias between the random

5. Generate result matrix
6. Repeat step 1 and 5 for each entry in the dataset.

Algorithm 2: PCA Algorithm

Store the data in matrix form;
Let the matrix be S;
Calculate the mean value of each column;
M= Mean (S);
Subtract row mean C = S-M
Calculate the co-variance matrix
V = Cov(P)
Calculate eigan value and eigan vectors
Val,vectors = Eig(V1)
Sort the eigan vectors in descending order of eigan values

D. Mathematical Model:

Let 'S' be the system that predicts survival of patient after LT using machine learning.
S = {I, O, F}
I = {Input to train the system};
O = {Output of the system};
F = {Functions of the system};

1) I = {I1};
I1 = {LT patients dataset with relevant attributes after applying PCA from UNOS};
F = {Apply PCA (), MLP (), RNN (), Hybrid Classifier () Predict ()};

- Apply PCA() = {Performs PCA Analysis};

$$V^{-1}CV = D \quad (4)$$

where,
V = Matrix V of eigenvectors
C = Covariance matrix
D = Diagonal matrix of eigenvalues of C.

- Initiate classifiers
  - MLP() = {Initiate MLP classifiers on data, Learning rate 0.3 };
  - RNN () = {Initiate RNN classifiers on data, Learning rate 0.02};
  - Hybrid Classifier()= {Initiate hybrid classifier on data, Learning rate 0.01};
- Predict() = { Predict survival of the patients}

2) O = {O1};
O1 = {Prediction: predicts survival of patient after LT 0-
Survived, 1-Not survived};

4. Result and discussions

A. Experimental Setup

Hardware and software of proposed system given below: Software Technology:
1. Technology: Core Java
2. Tools: JDK 1.8, Netbeans 8.0.2
3. Operating System: Windows 7

- Hardware Technology
  1. Processor: 1.0 GHz
  2. RAM: 1 GB
  3. Hard Disk: 730 GB
- Amazon Web Services (AWS) cloud

B. Experimental Results and Discussion

The medical prognosis is the evaluation of the cure, the functional level of the organ, the recurrence of the affected disease, complications, period for which the patient is hospitalized, the duration of life of the patient or patient group. Medical expectations help clinical researchers and physicians to discover certain patterns of disease. It also supports medical researchers to allocate resources according to requirements. The prognosis helps to make a decision about the state of the disease. LT has been widely accepted as a therapeutic treatment over the past 50 years. The number of people with liver diseases is preserved by this important medical activity. Medical researchers estimated that the overall result of LT is 88%. Clinically, the prediction of patient survival after LT is based on the End-stage Liver Disease (MELD) score. There are many positive results in the prediction by the MELD score, but there are some disadvantages. The MELD score will not accurately predict short-term mortality in 15%–18% of the patients with chronic liver disease listed for liver transplantation.

The paper uses the LT dataset from UNOS, a promising dataset that has been certified. The formatting of the data set is very important before the operation. The extraction of related attributes from a large data set requires data mining techniques. Extracting related attributes from a medical dataset requires careful attention. The UNOS dataset contain 389 attributes, form this only 256 attributes are related to liver transplantation patients. So we can remove 59 attributes from 256 attributes during preprocessing step. Among the 197 attributes, we performed a PCA to reduce the dimension. According to the standard deviation ranking, we obtained 70 relevant attributes and only 28 attributes are used that are very useful for predicting survival after LT. By generating rules using Association rule mining algorithms, we could prove that our extracted 28 attributes are more suitable for predicting survival in LT. We ranked all the input attributes used to train the model using the WEKA library. Using weight coefficients, we found that all the attributes of the donor, recipient, and transplant have the same significance in ranking. Table II shows the ranking of input attributes after PCA.

Table II Ranking of input attributes after pca

Rank	Score	Attributes
1	89.9	AGE_DON
2	88.6	BMI_TCR
3	87.1	GENDER_DON
4	85.3	FINAL_ALBUMIN
5	83.5	CREAT_DON
6	81	SGOT_DON
7	78.2	SGPT_DON
8	76.9	CLIN_INFECT_DON
9	75.3	FINAL_BILIRUBIN
10	72.1	FINAL_ASCITES
11	70	FINAL_INR
12	69.4	GENDER
13	67.8	DON_TY
14	67.5	DIABETES_DON
15	66.6	INIT_AGE
16	64.2	TBILI_DON
17	63.8	EXC_HCC
18	61.9	FINAL_MELD_PELD_LAB_SCORE
19	60	FINAL_MELD_OR_PELD
20	58.4	FINAL_SERUM_CREAT
21	58.1	FINAL_SERUM_SODIUM
22	57.2	NON_HRT_DON
23	55.9	ENCEPH_TCR
24	54.7	MALIG_TRR
25	53.5	MALIG_TCR
26	51.6	NUM_PREV_TX
27	50.5	TX_LIV
28	66.6	ALKPHOS

In this way, the most relevant top-rank attributes are successfully extracted from the dataset using PCA mining algorithms, ranking, and Association rules. The associated attributes from the Association rules were selected to build the prediction model. For any analysis and experiments, the choice of the appropriate model and data set affects the outcome of the event. Although a rich set of data is collected and preserved, only a small subset was used to predict patient survival.

Our proposed system uses different classification algorithms to train more diverse classifiers in order to create better classification. The basic idea is to use a combination of classifiers to naturally reduce variance and use a stronger algorithm to explicitly increase classification performance. The MLP and LM are two fundamentally different classification algorithms, and therefore it is interesting to see that hybrid classification created with them together can achieve better classification performance compared to non-hybrid classifier created with them individually. The hybrid classifier (MLP+LM) performs better not in a deterministic but a probabilistic manner. In a hybrid classifier where two classification algorithms are used, if one is different and unstable while the other is more accurate, then there is a higher probability that we can have a higher value of accuracy gain; the gain is measured against, where only one of the two classification algorithms MLP and RNN is used. The hybrid classifier calculation is done by following formula:

$$w_{k+1} = w_k - (J_k^T J_k + \lambda^I)^{-1} J_k e_k \tag{5}$$

Where, w = weight J= Jacobian matrix
J_e= Error gradient
$J^T J$ =cross-product Jacobian

This paper proved that Hybrid model is a powerful for forecasting purposes. We used this model to predict

the best outcome of patients after LT. We also experimented our model with existing work and proved that the highest accuracy has been obtained in the hybrid model with the data set. In experiment, accuracy parameter used to evaluate the effectiveness of the Hybrid model. The Hybrid classifier, MLP, and RNN are used to prove the accuracy of proposed cloud based hybrid model. Here True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN) terms are used for calculating the accuracy of model. In which, if LT is a failure in the patient, but it implies success, and the result is truly negative (TN). Both a true positive and a true negative proved condition (also called the truth standard). If the diagnostic result shows that the LT is successful, who actually has it fail, and the test result is false Positive (FP). Similarly, if the result of a diagnostic test suggests that the LT is unsuccessful, but it was successfully performed, the test result is false negative (FN). Both false-positive and false-negative test results indicate that they are the opposite of the actual state.
Hence, accuracy is calculated using this formula:

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)}\ \% \quad (6)$$

Table III shows that accuracy comparison between hybrid classifier, RNN and MLP algorithm. The figure 2, shows that the Hybrid classifier is more accurate than the MLP and RNN. It shows higher 95.22 % accuracy.

Table III. Accuracy comparison between hybrid classifier, mlp and Rnn

Algorithm	Accuracy in %
Hybrid Classifier	95.22
MLP	88.90
RNN	92.26

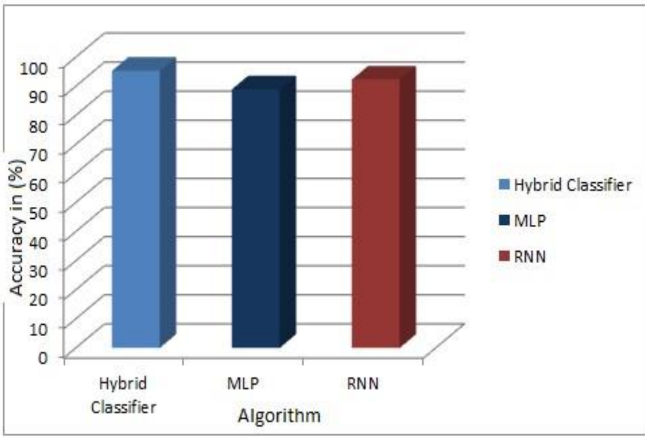

Fig. 2. Accuracy Graph

Conclusions

Liver transplantation is the best and most accurate solution for the final stage of liver disease. The most important aspects of liver transplantation are organ collection and sharing. Now a day, liver transplantation is one of the challenging areas in the field of organ transplantation. Medical experts predict the survival of patients after liver transplantation based on the MELD score. As creatinine varies depending on the body weight of a liver patient and is lower in women than in men, the research team presented ANN models to predict patient survival after liver transplantation. The system uses UNOS dataset for prediction of Long Term Survival after Liver Transplantation. The predicted data is uploaded onto the AWS cloud. Cloud computing plays an important role in reducing the combined cost of healthcare, optimizing resources, and sharing a new era of innovation, because of this information is accesses anytime, anywhere, which can be achieved when moving healthcare information to the cloud. The system records 95.22 % accuracy for survival prediction. We compared the proposed hybrid model with existing MLP and RNN classifiers. Given all this data, we could estimate that cloud based hybrid model is the most appropriate ANN model for predicting long term survival of patients after liver transplantation.

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