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Design Machine Learning Algorithms To Predict Liver Transplantation Survival

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Abstract—Liver transplantation (LT) is an important therapy option for people with liver disease, which has recently been improved by computerized medical field technology. Patients with LT have a bad prognosis in some cases, which is the main concern in many settings. A variety of predictive models have been developed by academics to address these difficulties. As a result, the current focus of research is on developing more precise and accurate prediction methods for use with advanced MLP techniques. Predictions are made in multiple stages using the method described below. The United Nations Organ Sharing database is used to gather medical data in the early stages of the transplant process (UNOS). Specifically, we drew on the UNOS for information on liver disease. For simplicity, the data are fed into the principal component analysis (PCA) to reduce the dimensions of the attributes. Using the Advance MLP categorization, patients will have a better chance of surviving LT if they fall into one of two distinct categories: "best survival" or "worst survival." The suggested framework was subjected to a stimulation study in order to determine its performance. There are many variables that are estimated for this proposed framework such as the following: precision/accuracy/specificity/error/f1 score/fpr/kappa/MCC. The proposed framework has an accuracy rating of 98%, which proves that the proposed design is accurate.

Keywords— Artificial Neural Networks, Liver Transplantation, Machine Learning, Multilayer Perceptron, Post-Liver Transplantation Survival Prediction.

I. INTRODUCTION

For individuals with end-stage liver failure, human liver transplantation (LT) is presently the only effective treatment option. Recent advances in liver transplantation have illuminated persons who require survival. Although the LT process has progressed much since its start in the early years, it still has a number of difficulties. Immunosuppressive medication therapy is used to keep liver transplant recipients alive. This will prevent their immune system from detecting and destroying your replacement liver. In recent years, LT has become widely used all across the world. The survival rates of liver transplanted patients may aid clinicians in making the best decision in a neutral environment before and after surgery. There are a variety of techniques to investigating the accuracy of LT prediction. Traditional research models must take into account certain common data structure concepts. For example, Cox Proportional Hazard regression implies that predictors have a similar impact on survival throughout time and does not rely on predictors.

The ability to anticipate survival is a key aspect in determining the success of LT surgery. The survival approaches for liver transplantation need various criteria, including survival forecast, immunosuppression, donor organ availability, and disease severity . In LT, there are two major distresses: long-term survival and life quality. The MELD score is obtained for various medical analyses and is used to determine optimal organ allocation. Cretonne can be “adjusted depending on the body weight of the liver recipient using three parameters”: INR (international normalised ratio), Cretonne, and bilirubin in the MELD score. In the lack of enlargement of these scoring techniques, the clinician usually decides on LT result based on MELD score. Despite this, patients with liver disease who undergo LT using the MELD score system still have dismal outcomes. Many academics are working to forecast effective value using various clustering and optimization methodologies, but there are still a few flaws in liver transplantation prediction.

The physician's ability to make more precise and accurate decisions is greatly aided by machine learning technologies. In addition, artificial neural network-based algorithms are commonly used to forecast the survival of medical datasets. In a world where medical data is being generated at an exponential rate and clinicians are finding it increasingly difficult to detect hidden patterns and useful information in massive amounts of data, machine learning in the medical business is becoming increasingly crucial. An improved Multilayer Perceptron (MLP) is used to forecast the likelihood of a patient's survival in LT. Patients with liver illness will have a better prognosis if the MLP model is implemented. UNOS database provided the datasets for training and testing, which included data from both before and after liver transplants and data from patients of both sexes separately. Because of the current study, more precise models and advanced Multilayer Perceptron models are being used to forecast the survival of liver transplant patients (MLP). As a result, the focus of this study is on precisely estimating the high and low survival rates of patients undergoing LT. Last but not least, experimental analysis forecasts the optimum ranges of precision and accuracy when compared to conventional methods.

Contribution of the Work

- To develop an enhanced MLP technique for predicting survival after LT with high accuracy and efficiency.
- The goal is to reduce the number of attributes by applying PCA to choose the most relevant ones for the liver.
- “Weka-knowledge flow analysis discovers strong attributes from PCA filtered attributes for ranking the attributes in the prediction of survival”.
- Association rule mining was used to determine the LT characteristics of both the donor and recipient.
- The poor or best survival rate is used to evaluate the time to anticipate survival after LT among the living and dead.

The residual part of the paper is organized as follows: section2 will includes the review of several articles related to multiple approaches in prediction of survival after LT. Section 3 will contain the background of proposed methodology. And section 4 will involves the procedure involved in the proposed framework. Section 5 will be based on the result gathered through implementation. Finally, section 6 will conclude the entire research work.

II. LITERATURE SURVEY

Recently, numerous researchers were tasked with improving multiple machine learning approaches for predicting the best long-term survival after lung transplantation. A number of articles related to various machine learning approaches are discussed in the following section.

Mauro Bernardi et al**.**, the implementation of the “Model for End Stage Liver Disease” (MELD), which would help identify and priorities individuals for liver transplantation, had been evaluated by a team of researchers. The "sickest first" premise has replaced the waiting list as the method of prioritizing transplant recipients. According to their severity, patients are assigned a MELD score that is based on the results of three simple laboratory tests (serum keratinize, bilirubin, and prothrombin injection times). According to their short-term mortality risk, concordance data in laminating patients have demonstrated their great accuracy (three months). Patients with various chronic liver illnesses were able to use MELD to predict their survival in independent patient cohorts at different dates. Due to the MELD-based allocation policy for liver grafts, wait times and mortality have been shortened, and transplant rates have increased without affecting the overall survival rates of the graft and the patients who received it.

Lee et al**.**, “Acute Kidney Injury after liver transplantation was predicted using a Logistic Regression Model and Machine Learning. Logistic regression analysis can accurately predict AKI after liver transplantation using machine learning methods”. The study examined 1211 patients and obtained information on surgery, anesthesia, and other aspects of the operation as well as data from both during and before the procedure. Acute kidney injury (AKI) determined by the network criteria was the primary outcome. Machine learning techniques such deep neural networks, naive Bayes, random forest and multilayer perceptron‟s were used to build a prediction model in this study. The logistic regression analysis has been used to evaluate these methods in the area below the receiver characteristic curve (AUROC). When we used logistic regression analysis to compare seven different machine learning methods, the gradient enhancer with the greatest AUROC score had the best performance. A web-based risk estimator has been developed using our gradient boost model. However, in order to proceed with further studies, our findings need to be substantiated.

Marc L. Weber et al**.** liver transplantation, which was the first of its kind, was introduced roughly 50 years ago. Despite these developments, renal impairment remains a major complication that increases the cost of medical care, morbidity, and mortality associated with liver transplants. Cretonne-based estimates of liver function are not adequate in the final stages of liver illness and can lead to underdiagnosed, which is dangerous. In order to properly manage hepatitis after a liver transplant, it's imperative that the cause and severity of renal impairment prior to the transplant be fully understood. This is especially true for patients undergoing a simultaneous liver and kidney transplant (SLK). Individuals who are a good match for SLK transplants must be identified because of a lack of donor cells.

Laura R. Wingfield et al , The need for liver transplants has grown to the point where the supply of deceased donor organs cannot keep up with the demand, and the goal is to maximise the value of the organ registry in making listing and allocation choices. Although emerging artificial intelligence (AI) techniques boost forecasting accuracy, most

current systems used to estimate transplant results use fundamental methods such as regression modelling. Ascertain what will happen after an AI donor dies, then compare the findings to linear regression and traditional predictive modelling standards. The DRI (Donor Risk Index), MELD concept, and liver transplantation survival outcome are all examples of these models (SOFT). A total of 52 individuals were screened for eligibility after accessible databases were analyzed. Nine of them satisfied the criteria for inclusion and had a total of 18,771 liver transplantation outcomes to show for it.

Cruz et al., had designed the prediction model using evolutionary multi-object artificial neural network for prediction of liver patient survival after liver transplantation. This research is constructed on a multi-objective evolutionary approach, used to form radial function neural networks, where accuracy and minimal sensitivity measurement have been employed to evaluate model performance. A rule-based system was developed using neural network models derived from the Pareto fronts. This technology will support the assignment of organs by medical specialists. The MPENSGA2 models generally produce competitive results for all the performance measurements taken into account in this research. It does not include medical specialists (the choice of an expert might be based on numerous aspects, such his/her mind status or his or her patient knowledge). The suggested rule-based approach is objective. This technique is a great tool that helps medical specialists to assign organs; nonetheless, an expert must make the ultimate assignment decision

According to the aforementioned studies, liver translation has the most impact on predicting liver patients' accurate and effective survival. Organ allocation in LT can be a difficult task in many situations. Despite the fact that these methods have evolved through time from different patient populations, they may no longer be applicable to other facilities due to changes in patient, donor, or process characteristics and practices that have occurred since the methods were first used in these facilities. Although the MELD score can be used to predict the prognosis of patients having LT, they may still be at risk. There are low survival and significant recurrence rates with these operations. It is mostly due to incorrect parameter and model selection that the survival rate is low. As a result, the focus of current research is on developing realistic survival predictions following LT. In the suggested framework, the detained explanation is provided in the next section.

III. PROPOSED METHODOLOGY

Hepatic transplantation, commonly known as liver transplantation, is performed when the liver is affected by some disease. When the liver is affected by any disease, liver transplantation is performed to assist save the patient's life. In recent years, major advancements in medical technology have resulted in an increase in the number of individuals undergoing liver transplantation. Finding a suitable donor and receiver, on the other hand, might be quite challenging. Patients with liver infection who are in the terminal stages of their illness are more likely to receive a liver transplant. The majority of the researchers devised a variety of prediction techniques for determining the rate of survival after liver transplantation in diverse situations. However, developing a suitable model that can predict the success of a liver transplantation is an extremely difficult undertaking. A large number of studies make use of machine learning techniques in order to develop prediction models. This study work is concerned with the development of a neural network-based prediction model of survival following LT in order to accomplish successful prediction. The following diagram depicts the overall structure of the suggested methodology.

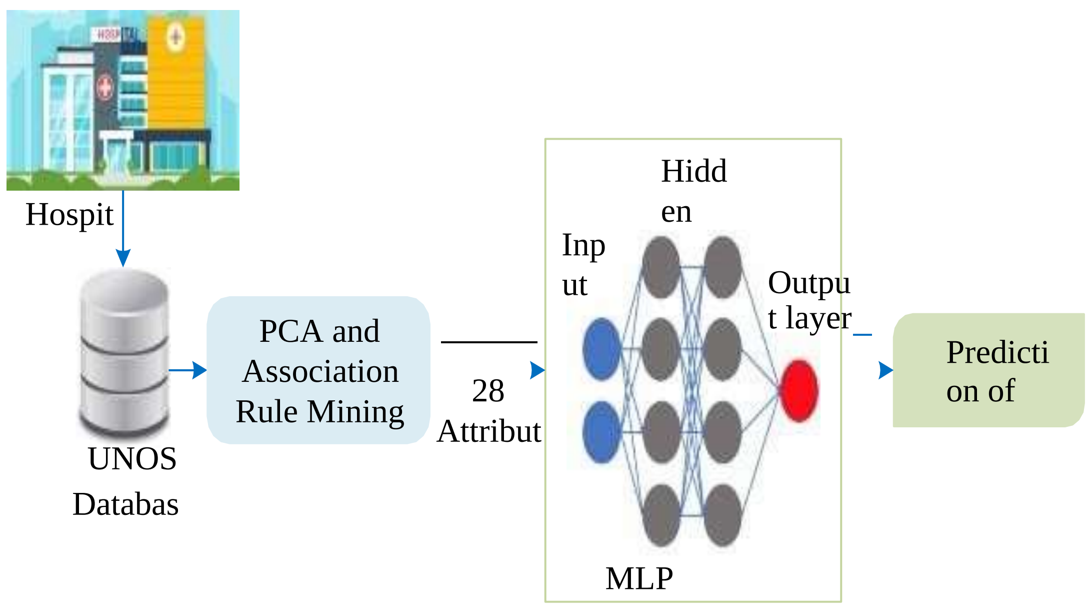

Figure 1: Proposed Architecture

Figure 1 depicts the proposed design. In the beginning, the UNOS database was used to collect medical data from hospitals. “The United Network for Organ Sharing (UNOS) database contains information about organ transplantation before and after the procedure”. The liver-related datasets are gathered from this point on. By using PCA to reduce the large attribute dimensions to smaller ones, the data from the UNOS database can be more efficiently processed. This PCA then identifies 28 qualities that are directly related to the liver. Using the PCA output, an artificial deep neural network (MLP) classifier is trained. In general, MLPs work well for problems involving the categorization and prediction of inputs that have been given a class or label. Additionally, they can be used for predicting a real-valued quantity from a series of inputs. Liver transplantation survival rates can be predicted with the aid of the MLP classifier. If the MELD score is less than 40, the patient is considered to have the best chance of survival, while if it is larger than 40, the patient is considered to have the worst chance of survival. In the following section, we'll go over the proposed design's step- by-step approach.

It is possible to discover one or more hidden layers between the input and output layers of the neurons in a Multilayer Perceptron. No coupling occurs between neurons within the same layer, and instead, each layer is connected directly from the bottom layer to the top layer. In order to calculate the pattern issue's measurement amount, the total number of neurons in the input layer is multiplied by two. The number of neurons in the output layers is the same as the number of neurons in the class. The architecture challenge is determined by the several layer options available, as well as the connections and neurons present in each layer. One of MLP's key goals is to generalize good classification by optimizing an optimal network with acceptable parameters. This is one of the company's primary aims.

IV. RESULT AND DISCUSSIONS

The proposed machine learning approach for healthcare application is tested on Mat Lab software with some configurations as follows.

- Processor: Intel (R) Core ™ i5-3330s CPU @ 2.70 GHz
- Memory (RAM): 8.00 Gb (7.88 Gb usable)
- System type: 64-bit operating system, x64 based processor.

4.1. Dataset Description

With the use of data from the UNOS database, the experimental analysis is carried out. Massive amounts of patient data are housed in the UNOS database, including information on patients before and after multiple organ transplantation. We're working with a total of 65,535 entries and 389 different attributes from several liver-related datasets. Only 256 of the 389 traits apply to liver patients. These databases contain information about transplants, recipients, and donors. There are entries of adults and men and women who have undergone liver transplants in the database. There are two phases to this dataset: the first phase is for training, and the second phase is for testing. Also displayed in Table 1 are some of the simulation steps used in the analysis.

Table 1: Simulation Parameters Taken For Analysis

Simulation parameter	**Values**
Hidden Layer Size	10
trainFcn	„trainscg‟
n_batch	204

lambda'	0.1
max. iteration	500
no. of epoch	100

This investigation's major purpose is to predict post-LT data. After gathering medical data, PCA can be used to reduce the dimensions of high qualities to low. 59 of the 256 characteristics can be manually omitted from the database. Ranking based on prediction following LT yields 28 major features, all of which are connected to liver-related information. Association rule mining is also used to match LT properties. A MLP classifier uses the preprocessing output to predict the long-term viability of LT. Assuming that the predicted rate is less than 40%, it will tell you if the survival rate is below 40 %. When it comes to how long someone might expect to live following LT, we finally have a correct model to work with. Experimentation on the suggested framework is completed with the testing of a few performance metrics. Various experiment performance metrics are discussed in detail in the next section.

4.2. Experimental Analysis

The experimental evaluation of this proposed framework machine learning approach took into account a number of variables. Considered parameters include, but are not limited to: accuracy (sensitivity), specificity (specificity), error (precision), F1 Score, FPR, Kappa, and MCC. In order to demonstrate the effectiveness and accuracy of the post-LT prediction, these parameters are assessed in the proposed work. ANN, k-nearest neighbours (KNN), and Support Vector Machines (SVM) are among the existing machine learning algorithms compared in this study (SVM). The MLP algorithm is compared to the standard techniques. Accurate predictions can be made utilizing the MLP technique in the proposed framework. Metrics values for the proposed and existing machine learning algorithms are shown in Table 2. **Table 2:** Metrics Evaluated for the Proposed and Existing technique

Performance metric	ANN	KNN	SVM	Proposed
Accuracy (%)	0.87	0.8	0.71	0.95
Sensitivity(%)	0.82	0.79	0.71	0.99
Specificity(%)	0.82	0.75	0.68	0.82

The comparison of accuracy among the proposed and existing machine learning techniques is shown in figure 2. The graph is plotted among the several techniques and the values of accuracy on both X and Y- labels respectively. The accuracy is high in proposed technique compared to existing techniques. The accuracy for the proposed method is found to be 0.95 % is more than the existing three methods. ANN has 0.87 %, KNN have 0.8% and SVM have 0.71%. Figure 3 depicts the results of the comparison analysis performed on the basis of Sensitivity for the proposed and existing approaches. On both the X and Y axes, a graph is created showing the relationship between various approaches and sensitivity in %. The sensitivity for the proposed method is found to be 0.99% is more than existing methods. The existing methods such as, ANN have 0.82 %, KNN have 0.79 % and SVM have 0.71%.

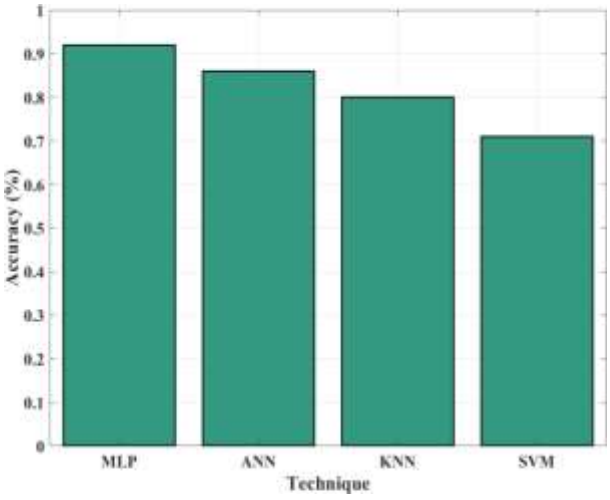

Figure 2: Comparison of accuracy

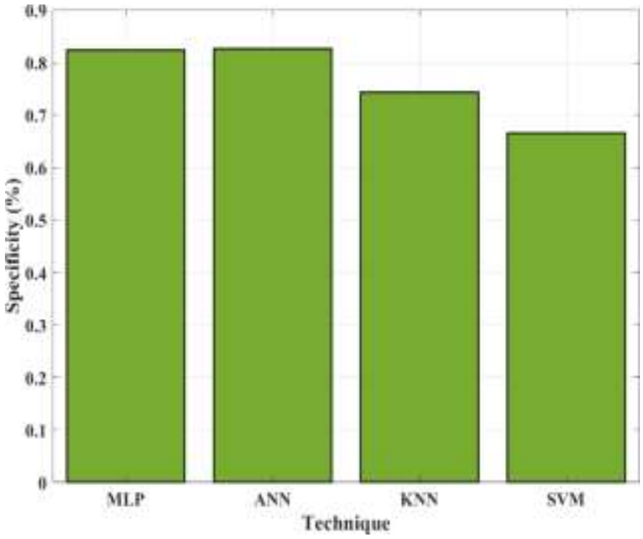

Figure 4: Comparison of Specificity

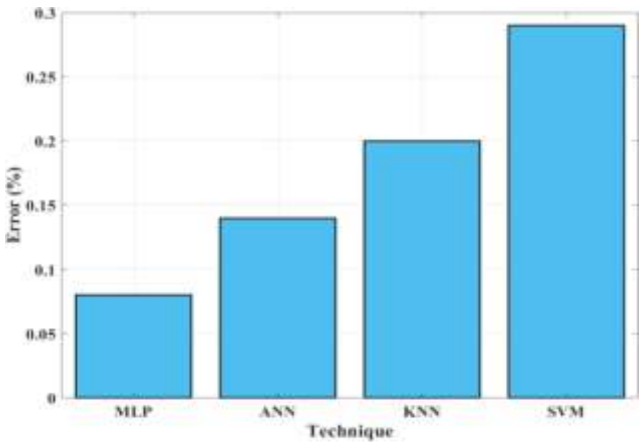

Figure 5: Comparison of Error

The comparison analysis done based on specificity for the proposed and existing approaches is given in figure 4. The graph is drawn among various techniques and specificity in percentage on both X and Y axes respectively. The specificity for the proposed method is found to be 0.82 % is almost equal to the ANN approach. The existing methods such as, ANN have 0.82 %, KNN have 0.75 % and SVM have 0.68 %. The comparison analysis done based on Error for the proposed and existing approaches are given in figure 5. The graph is drawn among various techniques and Error in percentage on both X and Y axes respectively. The Error for the proposed method is found to be 0.07 % is less than compared to existing approaches. The existing methods such as, ANN have 0.14 %, KNN have 0.2 % and SVM have 0.29 %.

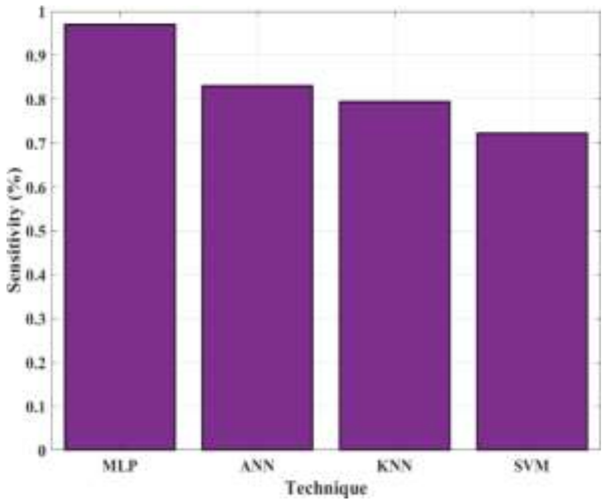

Figure 3: Comparison of Sensitivity

V. CONCLUSION

The goal of this study is to develop a cutting-edge multilayer perceptron network prediction method that is both accurate and reliable. LT therapy is now available to a wide range of individuals with liver disease thanks to advances in technology. The policy on pre- and post-transplant surgical procedures for the allocation of patients and organs has achieved significant development. Research in this area is aimed at eliminating the roadblocks that exist in the present healthcare system. This enables the PCA mining approach and the association rules mining algorithm to remove the most essential liver-based characteristics from the dataset. The proposed framework was compared against ANN, KNN, and SVM as well. Thus, the proposed Advance MLP-based trained model has been realized with great accuracy results. To put it simply, the Advance MLP approach outperforms other linear models in terms of accuracy and ease of use. The suggested approach seeks to predict the best outcomes for patients who have undergone LT.

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