EasyChair Preprint

№ 4923

Donor-Recipient for Liver Transplantation Using CNN and LSTM Deep Learning Techniques

Usha M Devi and A Marimuthu

January 22, 2021

DONOR-RECIPIENT FOR LIVER TRANSPLANTATION USING CNN AND LSTM DEEP LEARNING TECHNIQUES

[1]Usha Devi M,
Ph.D. Research Scholar, PG and Research Department of Computer Science,
Government Arts College, Coimbatore-18.
usha.devi145@gmail.com

[2]Dr.A.Marimuthu,
Associate professor,
PG and Research Department of Computer Science,Government Arts College,
Coimbatore-18.
mmuthu2005@gmail.com

***Abstract*- Objective:** Prediction of the survival of liver transplantation has been an potential role in understanding and improving the matching procedure between the recipient and graft. The allocation of organs in liver transplantation is a problem that can be resolved using deep learning techniques. The methods of allocation which included the assignment of an organ to the first patient on the waiting list without taking the characteristics of the donor and characteristics of the recipient and transplant organ were used to determine graft survival. UCI Repository data set has been used which consists of male and female liver patient records.

Methods and Materials: In order to address the problem of organ allocation, the CNN method and comparison of LSTM which is used to evaluate model performanance for accuracy.

Conclusion: To achieve the high rate of survival of liver transplantation and selecting the attributes of donor, recipient sand transplantation.

***Keywords*– Liver transplant, CNN, LSTM and Deep learning.**

I. INTRODUCTION

Liver diseases are complex and heterogeneous in nature developing under the influence of various factors that affect susceptibility to disease[1]. These include sex, ethnicity, genetics, environmental exposures such as viruses, alcohol, diet and chemical, body mass index and comorbid conditions such as diabetes. Various types of complex data are generated in hepatology practice and research that could benefit from AI-based approaches: EHR data, transient elastography other imaging technologies, histology, biobank data, data from clinical trials, clinical sensors, wearables and a variety of molecular data such as genomics, transcriptomics, proteomics, metabolomics, immunomics, and microbiomics.

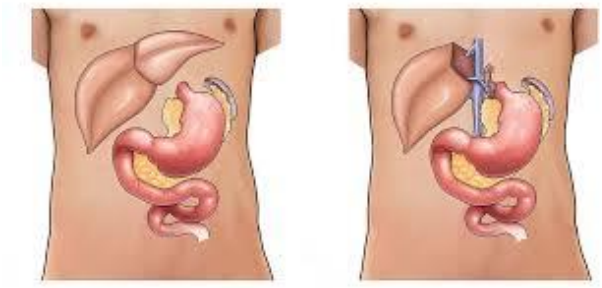

Figure 1: Liver Transplant Surgery

The deep neural networks have been a tremendous breakthrough in machine learning which enabling machines to learn patterns of data by modeling them through a combination of simple nonlinear elementary operations which Neural networks have been applied to predict 3-month graft survival and assist with donor-recipient matching for patients with end-stage liver disease as well as predicting the presence of liver disease from imaging[2]. This can be further extended into convolutional neural networks and recurrent neural networks which handle localstructures and sequential data. Local structure can be important in data and it is important to incorporate this existing structure. CNNs use multiple convolution filters learned by the network at different layers to aggregate information from neighboring pixels whereas RNNs allow temporal dependability across different time points by modifying the architecture to receive input from its past state. The power of neural networks can be further applied into survival analysis and time-to-event predictions where NNs can be used to predict risk function or even the parameters of the distribution modeling likelihood of the event[3]. Deep neural networks generalize some of these approaches by learning the data-set distribution whether explicitly or implicitly and

generating samples from those learned distribution. For example, the variational autoencoder parameterizes the distribution of the data set and trains the neural network to learn the distribution that fits the training data set best by maximizing its likelihood. The generative adversarial model uses two separate networks, one to generate fake samples which is considered as generatand another to discriminate whether the given input is fake or real which is considered as discriminator[4]. The goal of one is to generate samples that are closer to the true distribution whereas the other wants to better differentiate the generated and true training samples. This method of training results in a model able to generate samples that are very similar to the training distribution. This method can also be further extended to impute missing data. CNN is usually used for images RNN for sequential data and survival analysis for time to death. For other types of general classification all different methods will generally be evaluated to see what works best.

II. LIVER TRANSPLANT

Donor Age

The donor age has been steadily increasing over the past decade. In the year 1991, 13 percentage of cadaveric liver donors were over the age of 50, 10 years later it is close to 30 percentage. Initially donor age _50 years was thought to be associated with poor graft outcomes, but the studies 4, 8-12 have shown that aged donors (_50 years) without additional risk factors have similar outcomes to younger donors and age itself should not be a contraindication to liver donation[6]. Donor age of more than 70 years, However was found to be associated with lower patient and graft survival. In contrast to other organs, the liver may be more immune to senescence particularly in the otherwise healthy person[7]. This is possibly because of the liver's large functional reserve, regenerative capacity and dual blood supply which exceeds its metabolic needs. On the other hand the older donor livers tend to be smaller and darker-colored and may have developed fibrous thickening of the capsule. Whether these morphologic changes impact on organ function after transplantation should be elucidated. It has been shown that older donor livers are more susceptible to endothelial cell injury from cold ischemia and show decreased adenosine triphosphate synthesis after reperfusion which may influence the decreased regenerative capacity and decreased synthetic function seen in these organs[5]. In older age when controlling for other factors may not adversely impact patient and graft survival, recipients of older donor livers seem to experience a greater degree of delayed function with a notable cholestatic pattern after transplantation. However over 75 percentage of the recipients in this study did regain normal liver function by maintaining cold ischemia time to 8 hours or less, long-term graft function was shown to be equivalent in donors greater and less than 50 years of age. Older donors also have an increased incidence of steatosis which may potentiate cold preservation injury. Therefore older donors need to be carefully selected and each organ requires an assessment based on other risk factors especially steatosis and CIT[8].

Table 1. Potential Risk Factors Associated With Liver Graft Dysfunction

Donor	Perioperative	Recipient
Age	Warm ischemia	Age
Gender	Blood product use	Renal insufficiency
Cause of brain death	Technical complications	Medical status
Race		Use of vasopressors
Partial liver grafts		Retransplantation
Weight		
Cold preservation		
Intensive care unit length of stay		
Use of vasopressors		
High serum sodium		
Steatosis		

Matching of tissue

The role of human leukocyte antigen matching in liver transplantation is not as clearly defined as with kidney transplantation[9]. In a few studies, the human leukocyte antigen (HLA) matching did not impact graft survival but did decrease acute rejection. Conflicting results have also been published in which better matching decreased graft survival[10]. The results of lymphocytotoxic crossmatches

have been more reliable positive cross-matches are associated with decreased graft survival and increased acute rejection. Dvorchik et al have recently have shown that two mismatches at the DR loci are associated with an increased rate of acute rejection compared with 0 or 1 mismatches[11]. The length of time in the intensive care unit further augmented acute rejection in those patients with two DR mismatches. HLA matching at the DR loci may be useful in marginal liver grafts with which the likelihood of a prolonged ICU stay is increased. However, the practicality of this approach particularly when ischemia time may be prolonged is questionable[12].

III. CONVOLUTIONAL NEURAL NETWORKS

This work which presents a methodology for the classification of multiple hepatic structures from biopsy images based on convolutional neural networks. Particularly in medical image analysis, CNN architectures can overcome the problemswhich is caused by the hand-crafted features used in traditional techniques due to their fully automated feature extraction, the proposed method could be integrated into a complete prognostic tool for differentiating the healthy from the diseased tissue structures and measuring the severity of the diseases in clinical trials.

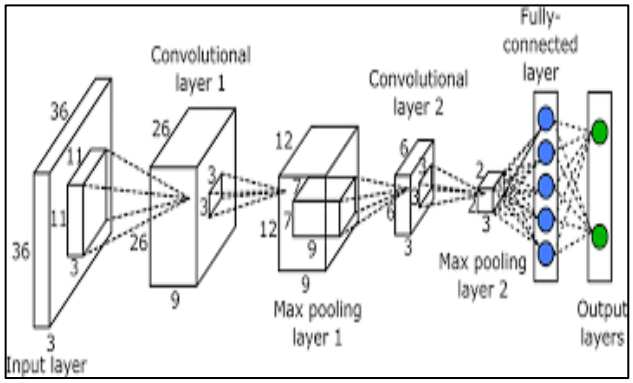

Figure 2: Working principle of CNN

Non-alcoholic fatty liver disease is a common cause of liver disorder worldwide. Many studies investigating the natural history of NAFLD have verified its progression from chronic non-alcoholic steatohepatitis to end-stage cirrhosis and hepatocellular carcinoma, because a multitude of complications impede their accurate identification and treatment, their prevalence has been evaluated with a variety of diagnostic methods. Quantitative assessment through digital histological imaging has been established as the gold standard in clinical trials with liver biopsies being the mean for the detection and staging of NASH and NAFLD[13].

IV. LSTM

Long Short-Term Memory hidden units are powerful and increasingly popular models for learning from sequence data. They effectively model varying length sequences and capture long range dependencies. We present the first study to empiricallyevaluate the ability of LSTMs to recognize patterns in multivariate time series of clinical measurements.

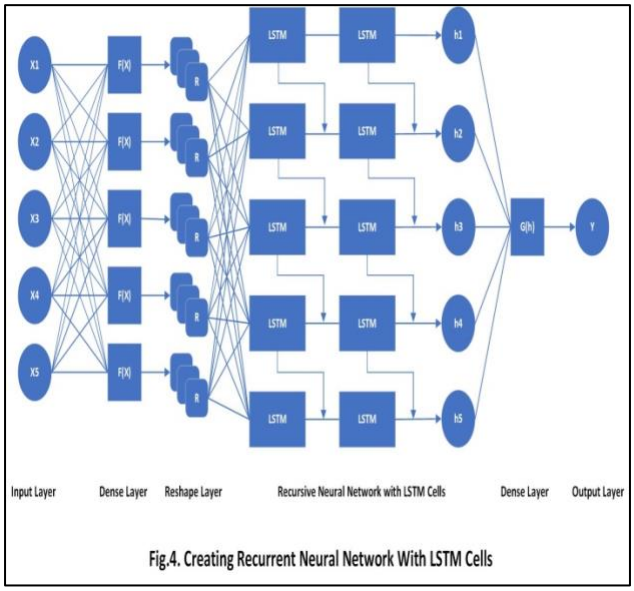

Figure 3: Working principle of LSTM

we consider multilabel classification of diagnoses, training a model to classify 128 diagnoses given 13 frequently but irregularly sampled clinical measurements. We establish the effectiveness of a simple LSTM network for modeling clinical data. Then we demonstrate a straightforward and effective training strategy in which we replicate targets at each sequence step. Trained only on raw time series and our models out perform several strong baselines including a multilayer perceptron trained on hand-engineered features.

V. RESULTS AND DISCUSSION

4.1. Dataset description

Patients undergoing partial split or living donor liver transplantation and patients undergoing combined or multi-visceral transplants were excluded from the study. We included all transplant recipients 18 years of age or older. Recipient and donor characteristics were reported at the time of transplant. A multi-centric retrospective analysis of eleven Spanish liver transplantation units was conducted that was based on all of the consecutive liver transplants performed between January 1, 2017 and December 30, 2018. All patients were followed from the date of transplant until death, graft loss or the completion of the three months after their liver transplant.

4.2 Exerimental Results

For experimentation, deep Learning techniques such as CNN and LSTM was implemented in the Google Colab platform using python programming. Root Mean Square Error is used for the performance metrics to evaluate the proposed Donor receipient mapping for Liver Transplant. Table 2 shows the Root Mean Square Error value for mapping Donor Recipient Mapping using CNN algorithm.

Table 2: Donor Recipient Mapping using CNN

MELD	Don1	Don2	Don3	Don4	Don5
Rec11(39)	.2951±.1310	.2698±.1363	.2794±.1364	.2493±.1273	.2364±.1411
Rec12(34)	.3045±.1336	.2688±.1297	.2779±.1278	.2536±.1336	.2337±.1355
Rec13(32)	.3004±.1229	.2720±.1361	.2759±.1281	.2455±.1336	.2394±.1389
Rec14(29)	.2932±.1218	**.2553±.1314**	.2690±.1311	**.2323±.1344**	.2314±.1380
Rec15(28)	**.2493±.1421**	.2565±.1321	**.2605±.1312**	.2710±.1369	**.2304±.1366**

Table 3: Donor Recipient Mapping using LSTM

MELD	Don1	Don2	Don3	Don4	Don5
Rec6(26)	.2936±.1321	.2640±.1315	.2775±.1283	.2562±.1327	.2412±.1407
Rec7(25)	.2238±.1332	.2579±.1365	.2527±.1368	.2817±.1388	.2378±.1422
Rec8(25)	.2935±.1409	.2654±.1268	.2760±.1319	.2607±.1357	.2362±.1375
Rec9(25)	.2696±.1364	.2571±.1316	.2608±.1300	**.2554±.1306**	**.2340±.1371**
Rec10(24)	**.2162±.1286**	**.2558±.1324**	**.2480±.1298**	.2870±.1339	.2372±.1437

Table 3 shows the Root Mean Square Error value for mapping Donor Recipient Mapping using LSTM algorithm.

VI. CONCLUSIONS

The increasing waiting time for liver transplantation donor organs remain in short supply. The criteria for marginal donors vary from center to center because of the lack of organs more centers are transplanting livers that were previously considered unacceptable. There are enough donors to meet the needs of the transplant waiting list and marginal donors may be a viable option to expand the donor pool. This paper proposed a Donor Receipient Match for Liver Transplant and predict the survival rate using CNN and LSTM deep Learning techniques. Among that CNN yields better results.

REFERENCES

1. S. S. V. Chandra and C. G. Raji, “Predicting the Survival of Graft Following Liver Transplantation using a Nonlinear Model”, vol. 24, no. 5, pp. 443–452, 2016.
2. S. Pourahmad and S. Nikeghbalian, ”Five Years Survival of Patients after Liver Transplantation and its Effective Factors by Neural Network and Cox Poroportional Hazard Regression Models”, vol. 15, no. 9, 2015.
3. C. Hervás-Martínez, and M. De La Mata, “Predicting Patient Survival after Liver Transplantation Using Evolutionary Multi Objective Artificial Neural Networks”, vol. 58, no. 1, pp. 37–49, 2013.
4. LeCun, Y., Bengio, Y. and Hinton, G. E. Deep learning. Nature, 521, 436-444, 2015.
5. N. A. Terrault and J. P. Roberts, ”Gender Difference in Liver Donor Quality are Predictive of Graft Loss”, vol. 11, no. 2, pp. 296–302, 2011.
6. M. Vivareli and A. D. Pinna, “Artificial Neural Network is Superior to MELD in Predicting Mortality of Patients with End-Stage Liver Disease”, vol. 56, no. 2, pp. 253–258, 2007.
7. N. A. Terrault and J. P. Roberts, “Gender Difference in Liver Donor Quality are Predictive of Graft Loss”, vol. 11, no. 2, pp. 296–302, 2011.

8. Kamath P, Wiesner R, Malinchoc M, Kremers W, Therneau T, Kosberg C, et al. “A model to predict survival in patients with end-stage liver disease”. Hepatology ; vol:33, no:2, pp:464–470, 2001.
9. Busuttil RW, Tanaka K. “The utility of marginal donors in liver transplantation. Liver Transplant” vol:9, no:7, pp:651–663, 2003.
10. Brice˜no J, Solorzano G, Pera C. “A proposal for scoring marginal liver grafts”. Transplant International, vol:13, no:2, pp:49–52, 2000.
11. Dreiseitl S, Ohno-Machado L. “Logistic regression and artificial neural network classification models: a methodology review”. Journal of Biomedical Informatics ; vol:35, no:6, pp:352–359, 2002.
12. Obermeyer Z, Emanuel EJ.” Predicting the future big data, machine learning, and clinical medicine” , N Engl J Med ; vol:375, pp:1216-1219, 2016.
13. Berglund E, Lytsy P, Westerling R. Adherence to and beliefs in lipid-lowering medical treatments: a structural equation modeling approach including the necessity concern framework. Patient Educ Couns, vol: 91, pp:105-112, 2013.