Journal of
Translational Medicine

RESEARCH

Open Access

Advanced prognostic modeling with deep learning: assessing long-term outcomes in liver transplant recipients from deceased and living donors

C. G. Raji[1,2], S. S. Vinod Chandra[2], Noble Gracious[3,4*], Yamuna R. Pillai[5] and Abhishek Sasidharan[6]

Abstract

Background Predicting long-term outcomes in liver transplantation remain a challenging endeavor. This research aims to harness the power of deep learning to develop an advanced prognostic model for assessing long-term outcomes, with a specific focus on distinguishing between deceased and living donor transplantation.

Methods A comprehensive dataset from UNOS encompassing clinical, demographic, and transplant-related variables of liver transplant recipients from deceased and living donors was utilized. The main dataset has been transformed into Deceased Donor-Recipient and Living Donor-Recipient dataset. After manual extraction, the dimensionality reduction was performed with Principal component analysis in both datasets and top ranked 23 attributes were collected. A Deeplearning4j Multilayer Perceptron classifier has been employed and long-term survival analysis has been conducted with the help of liver follow-up data. The performance evaluation is done separately in datasets and evaluated the survival probabilities of 23 years.

Results UNOS database comprises 410 attributes and 353,589 records from 1998 to 2023. The outcome from the deep learning model was compared with actual graft survival to ensure the accuracy. The model trained 23 attributes and obtained Sensitivity, Specificity and accuracy values were 99.9, 99.9 and 99.91% using R-Living donor dataset. The Sensitivity, Specificity and Accuracy value obtained using R-Deceased donor dataset were 99.7, 99.7 and 99.86%. The short term and long-term survival prediction after liver transplantation has been done successfully with Dl4jMLP classifier with appropriate selection of attributes irrespective of donor type. This study's finding suggesting that the distinction between deceased and living donor transplantation does not significantly affect survival prediction after liver transplantation is noteworthy.

Conclusions The utility of the Deeplearning4j model in survival prediction after liver transplantation has been validated in this study. Based on the findings, deceased donor transplantation could be promoted over living donor transplantation.

Keywords Liver transplantation, Survival, Deceased donor, Living donor, Deep learning, Prediction

*Correspondence:
Noble Gracious
noblegracious2024@gmail.com
Full list of author information is available at the end of the article

Introduction

Liver transplantation (LT) stands as a pivotal intervention in the management of end-stage liver disease, offering a lifeline to patients facing dire health prospects [1]. As a complex and multifaceted procedure, the success of liver transplantation is influenced by numerous factors, ranging from donor type (deceased or living) to recipient health and postoperative care. The success of liver transplantation is contingent on various factors, including the type of donor (deceased or living) and the recipient's overall health [2]. Traditional prognostic models have relied on a limited set of clinical variables, often falling short in capturing the intricate interplay of factors that contribute to transplant success or failure [3]. This study focuses upon developing advanced prognostic deep learning model for assessing long-term survival after liver transplantation comparing deceased and living donor scenarios. Researchers continue to explore ways to enhance the predictive accuracy of models and refine transplantation criteria. The survival rate of liver transplantation depends on the appropriate selection of attributes and model used for survival prediction [4]. The dataset was collected from United Network for Organ Sharing (UNOS) database [3] split into Deceased donor or Living donor according to the donor type.

After manual extraction, Principal Component Analysis (PCA) method was used to reduce the dimensionality of dataset with relevant attributes [3]. The resultant 23 top ranked attributes were given separately to train the deep learning model, Deeplearning4jMultilayer Perceptron (Dl4jMLP) classifier for survival prediction using k-fold cross validation [5]. The results obtained showed that this classifier is suitable for short term survival prediction with high accuracy. Then using the follow-up dataset, we made 24 separate sets of datasets which included 23 years beyond initial six-month data for long term survival prediction. The same data attributes and model were used for 23 years beyond initial six-month survival prediction and the results were evaluated using various performance measures and performance error measures [6]. The results obtained with R-Living donor and R-Deceased donor dataset were almost similar. The comparison of Model Performance based on actual data using two datasets was done and found the results obtained from the model was little lower than the actual data available in the dataset. For a successful survival prediction, donor attributes, recipient attributes and transplantation attributes are necessary has proved by comparing the results with existing literature works.

Experimental procedures

Recruitment and endpoints

The retrospective database for this research was collected from UNOS through official procedures after providing ethical statement and agreement for the confidentiality of data.

The database consists of 410 attributes and 353,589 records from 1998 to 2023. Since MELD score was introduced in the year 2001, records of liver patients before that date were removed from the dataset. We focused on survival prediction of adult patients and therefore records with Pediatric End Stage Liver Disease (PELD) score were excluded. Based on the donor type, the dataset was divided into R-Deceased donor and R-Living donor dataset. The two sets of top ranked attributes (Table 1) were given separately to train the deep learning model [7], Deeplearning4jMultilayer Perceptron (Dl4jMLP) classifier for survival prediction [8]. The description of attributes in the R-Living Donor dataset and R-deceased donor dataset is given in Fig. 1.

In the process of k-fold cross validation, the whole dataset is divided into k folds, in which k minus one-fold is for the training dataset, and the remaining folds are taken for the validation test [9]. For better results, a ten-fold cross validation method is used to evaluate the Dl4jMLP classifier for both datasets. The results obtained showed that this classifier is suitable for survival prediction with high accuracy. The output binary class attribute is GSTATUS; this represents the status of graft after liver transplantation whose value is 'Yes' or 'No'. The survival analysis based on Dl4jMLP classifier was done on the basis of survival probability for each liver recipient was calculated.

Feature extraction, sequencing, classification

There were 410 attributes in the dataset. Not all attributes are needed for survival prediction [10]. After manual extraction, the demographic features, empty columns and missing values were removed from the dataset. PCA was applied to select most relevant attributes for survival prediction in the resultant dataset [3]. Thus 23 top ranked attributes were extracted from both datasets. By changing the number of dense layers and number of nodes, Dl4J models are evaluated. The mismatch between the donors and recipients is reduced by increasing the number of epochs in the model [3, 5]. In the Dl4jMLP model, we used a large dataset and calculated the training time taken to build the model. The R-Deceased donor dataset consists of 135,709 records and Living donor-R dataset consists of 6180 records. The records are more in the R-Deceased dataset than R-Living donor dataset consists of parameters is same for both datasets. The model

Table 1 Input parameters with its description and type of R-Living donor dataset and R-deceased donor dataset

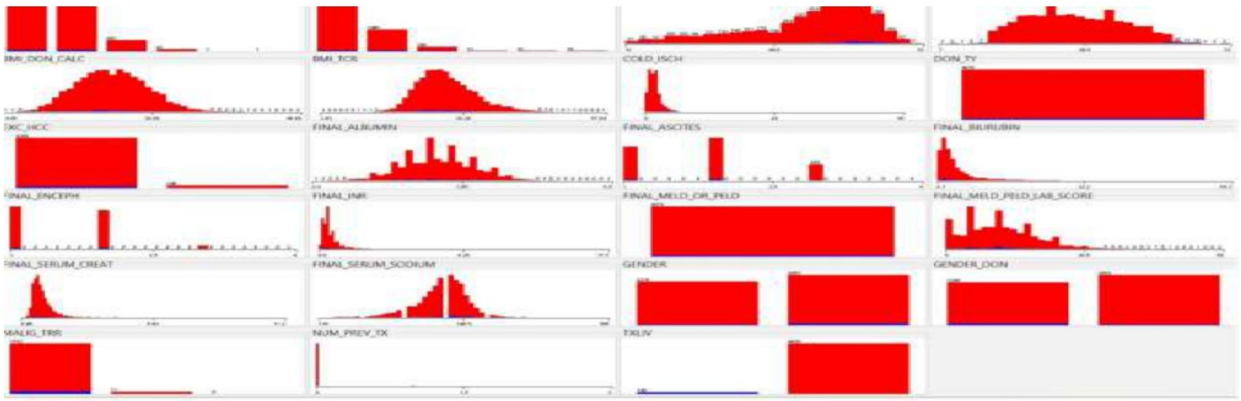
Input attributes	Description	Composite Attributes	Living donor				Deceased donor			
			Min value	Max Value	Mean & Std. deviation	Values	Min Value	Max Value	Mean & Std. deviation	Values
AGE_DON	Donor Age in Years	Donor attributes	11	78	52024±14096		2	92	40.968±16.918	
ABO_DON	Donor Blood Type					O=4028,A=1773, B=290,AB=56, A2=15,A1=18				O=67223,A=21721, B=12,205,AB= 1,132,A1=29,838, A2=2123,A1B=924, A2B=543
DON_TY	Donor Type -Deceased, Living					L=6180				C=1,35,709
GENDER_DON	Donor Gender					Female donors=3682, Male donors= 2498				Female donors= 65803, Male donors = 69,906
BMI_DON_CALC	Donor BMI		14.58	46.586	26.33±3.772		10.001	72.422	27.145±6.111	
BMI_TCR	Body Mass Index of Recipient	Recipient attributes	3.528	57.045	27.011±5.31		2.848	71.585	28.549±5.801	
FINAL_ENCEPH	Recipient Encephalopathy		1	4			1	4		
EXC_HCC	Type of Exception relative to HCC:HBL (HCC,NON-HCC: HBL=hepatoblastoma)					Missing= 423, no HCC= 5493, HCC=264				No HCC= 1,05,238, HCC=30468, HBL=3
COLD_ISCH	Total Cold Ischemic time		0	48	2.054±2.942		0	48	6.856±3.141	
FINAL_ALBUMIN	Most recent recipient Albumin		0.8	6.5	3.194±0.667		0.5	9.9	3.016±0.738	
FINAL_ASCITES	Most recent recipient Ascites		1	4	1.806±0.711		1	4	2.057±0.748	
FINAL_BILIRUBIN	Most recent recipient Bilirubin		0.8	6.5	0.1±64.3		0.1	99	9.039±11.533	
FINAL_INR	Most recent recipient INR		0.8	17.7	1.503±0.741		0.5	78	1.924±1.32	
FINAL_MELD_OR_PELD	Most recent recipient use MELD/PELD									
FINAL_MELD_PELD_LAB_SCORE	Most recent recipient MELD/PELD Lab score		6	55	15.555±6.218		6	55	15.555±6.218	
FINAL_SERUM_CREAT	Most recent recipient Serum Creatinine		9.06	11.2	0.954±0.537		9.06	11.2	0.954±0.537	
FINAL_SERUM_SODIUM	Most recent Serum Sodium		116	165	136.883±4.253		116	165	136.883±4.253	
GENDER	Recipient Gender					Female recipients =3147, Male recipients=3033				Female recipients =53428, Male recipients= 82281
AGE	Recipient Age in Years		11	78	52024±14096		12	88	53513±11.34	
MALIG_TRR	Recipient any known malignancies since listing at transplant					Y=71,N=2934,U=8, Missing=3167				Y=1171,N=133405, U=56, Missing=1077
ABO	Recipient Blood Group					O=3250,A=2340, B=495,AB=93, A2=1, A1=1				O=70243,A=37381 B=15141,AB=12459, A2=26,A1=425, A1B= 14, A2B=20
NUM_PREV_TX	The number of previous transplants	Transplantation attributes	0	3	0.015±0.129		0	9	0.078±0.313	
TX_LIV	Type of liver (W, S)					W=170, S=6010				W=1,18,241, S=17,468

processed rich datasets and the architecture of both datasets are represented in Figs. 2 and 3.

Statistical analysis

UNOS dataset consists of 410 attributes includes 242 recipient pre transplantation and post transplantation attributes, 122 Deceased donor, 46 Living Donor and remaining were transplantation and post transplantation attributes. The R-Living donor dataset consists of 293 liver patient attributes. 71 attribute columns had no value and 51 attributes including income, demographic data were filtered manually. PCA was applied to the resultant 159 attributes and extracted 24 top ranked attributes for the survival prediction after liver transplantation. The R-Deceased donor dataset consists of 374 liver patient attributes. 72 attribute columns had no value and 72 attributes including income, demographic data were filtered manually. Then PCA was applied to the resultant 230 attributes and extracted 23 top ranked attributes for the survival prediction. The top ranked attributes consist of five donor, sixteen recipient and three transplantation attributes. The follow-up dataset consists of 61 attributes. We have found 23 attributes extracted from liver transplantation dataset are present in the liver follow-up dataset. Using follow-up information, we have created 24 datasets for long term survival prediction. All the 24 datasets are trained with 23 input attributes and given to the deep learning model for survival prediction. The

R-Living Donor dataset



R-Deceased Donor dataset

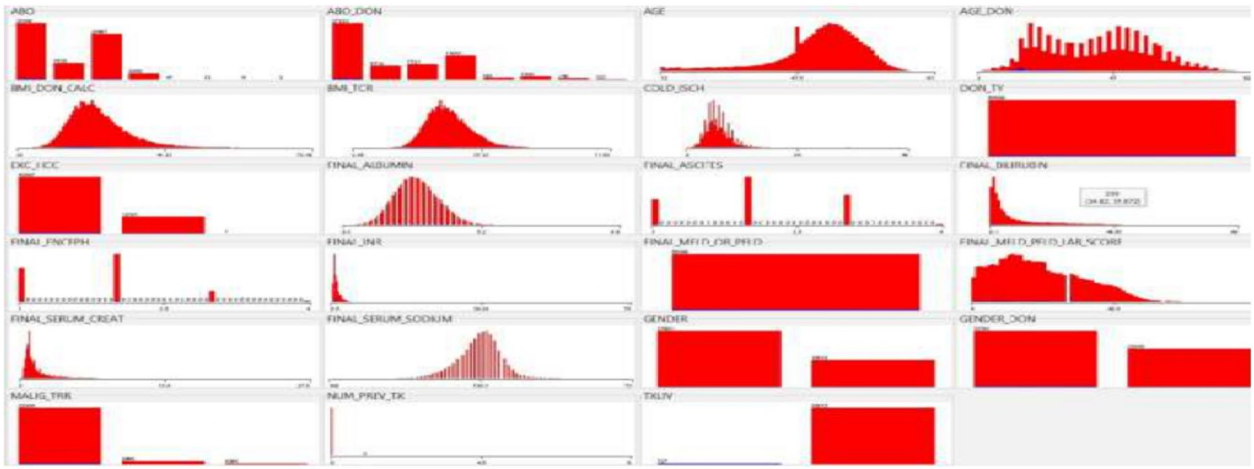


Fig. 1 Description of attributes in the R-Living Donor dataset and R-deceased donor dataset

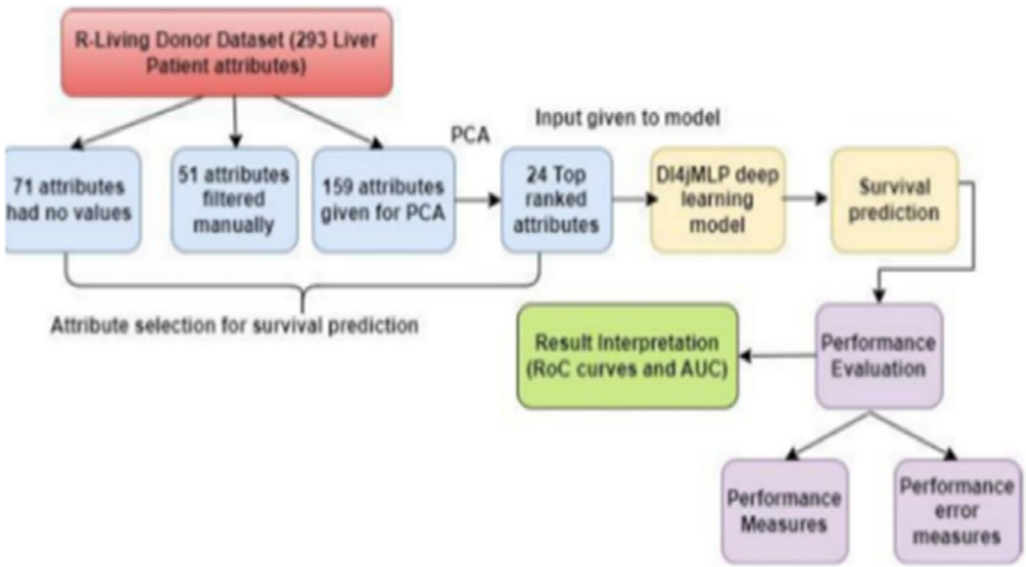


Fig. 2 Architecture of survival prediction using R-Living donor dataset

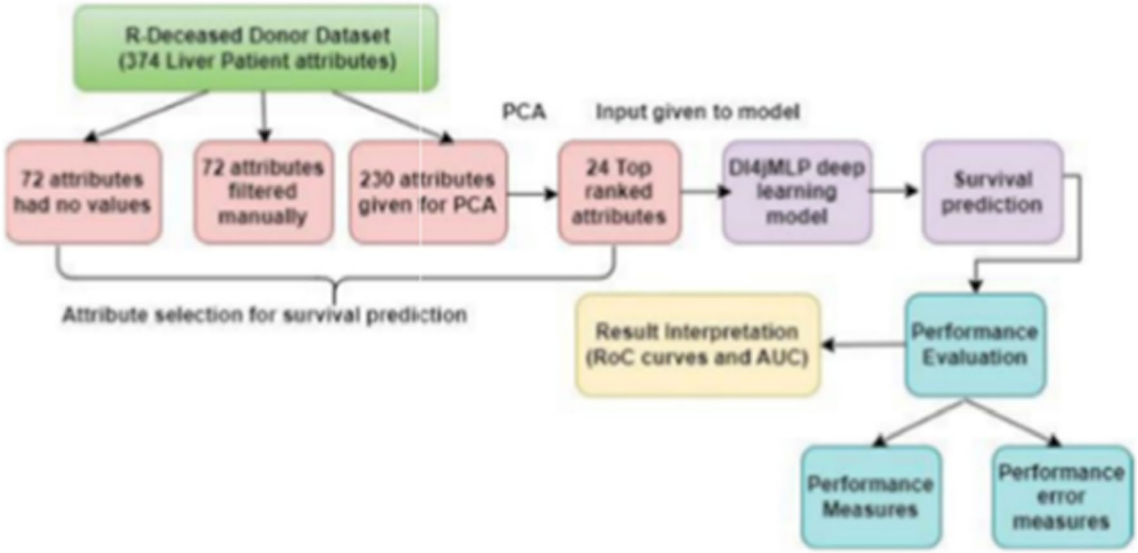


Fig. 3 Architecture of survival prediction using R-Deceased donor dataset

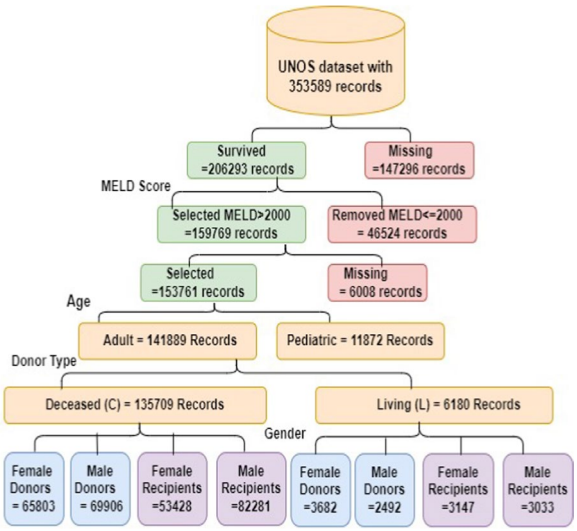


Fig. 4 Description of input attributes and analysis

datasets contain the output attribute as GSTATUS in the liver transplantation dataset and GRF_STAT in the follow-up dataset. According to the relevant features and characteristics, the attributes are ranked using Ranker algorithm.

Results

Description of study population

In total, 353,589 liver patient records were present in the UNOS dataset is given in Fig. 4. We found 147,296 records were missing and included 206,293 patients who survived. The study was focused on the survival prediction after 2001 when MELD score was introduced. Among the data from 1998 to 2023, we removed 46,524 records before 2001. From the resultant 159,769 records, 6008 records were missing, and 153,761 records remained following with the introduction of MELD score in 2001. According to age, there were 141,889 adult records and 11,872 pediatric records. We conducted the study among adult patients and PELD records were removed. A total of 135,709 deceased donors and 6180 living donors presented in the dataset. Thus, the adult records were split into recipient (R)-deceased donor records and R-Living donor records. Both deceased and living donor datasets contain male and female donors, male and female recipients. After manual extraction and PCA, 24 attributes were selected with 23 input attributes (Table 1) and one output attribute. The short term and long-term survival prediction has been done successfully using both datasets with Dl4jMLP classifier due to the appropriate selection of attributes in the UNOS liver transplantation dataset.

Survival analysis based on Deep learning model

The Dl4jMLP classifier is an important constituent in the Deeplearning4j (DL4J) library works in a Java centric ecosystem which enables us to create and train neural networks for classification tasks [11]. Both the datasets include 23 input attributes is given to the Dl4jMLP classifier which consists of dense layers and output layer with SoftMax activation function [12]. During training, the loss function mentioned is LOSSMCXENT and weight initialization function is XAVIER. For updating weights in the Dl4jMLP classifier during training, we used the optimization algorithm as Stochastic gradient descent

and learning rate set to 0.001. The input attributes are trained using the SoftMax activation function and weight initialization given as 0.0. The survival analysis (Table 5A) could be done in terms of number of years by calculating the survival probability of liver transplantation patients (Table 5B) [13]. The survival analysis based on Dl4jMLP classifier was done on the basis of survival probability for each liver recipient [14]. In the follow-up dataset, there are 1,622,648 liver patient records and 61 attributes. The follow up information was available from the year 1988 to 2023. Since the UNOS dataset was collected during the month of July 2023, there were only 1087 records available in the dataset. The records in the Liver dataset and liver follow up dataset are linked using the attribute, TRR_ID_CODE which is common in both datasets. According to the date of follow-up, 7815 single liver patient records are extracted for the survival year 2001 to 2023. The number of epochs used with R-Deceased donor and R-Living donor datasets is 10 [15]. In each epoch, the output is calculated and the best survival output is obtained with ten epochs. The architecture of long term survival prediction is given in Fig. 5.

Key study outcomes

The results of the deep learning model are evaluated on the basis of performance measures [3, 11, 16]. As it is a lifesaving model, the results need to be evaluated with performance error measures also given in Table 2B and 3C [11, 17]. The performance measures such as Accuracy, Sensitivity and Specificity are evaluated for the R-Deceased donor and R-Living donor datasets in the short-term survival prediction were given in Table 2A and 3B. For the long-term survival prediction represented in Fig. 5, the performance error measures are calculated using follow-up data available in the dataset [14, 18] (Tables 2D and 3E). The model has obtained the Sensitivity result as 99.9, Specificity value as 99.9 and accuracy as 99.91% using R-Living donor dataset. We have taken the performance error measures as MAE, RMSE, RAE and RRSE from the deep learning model [3, 5, 11, 19]. Using the R-Living donor dataset, the value obtained for MAE is 0.0009, RMSE is 0.0213, RAE is 0.259% and RRSE is 4.9925%. The total time taken to train the model using the using R-Living Donor dataset is also included in Tables 2C. The differentiation of survival prediction with R-Living and R-Deceased datasets is given in Fig. 6A and B. The ROC curve for the representation of Accuracy with both datasets is given in Fig. 6C and the area under curve is noted. This shows that clinical significance of similar survival predictions between deceased and living donor datasets has obtained and represented.

The Sensitivity, Specificity and Accuracy value obtained using R-Deceased donor dataset are 99.7, 99.7 and 99.86%. The time taken to train the model for short term survival prediction using R-Deceased donor dataset is 105.02 s and R-Living donor dataset is 48.33 s.

From the dataset, we could see that the number of patients were decreasing year by year. The transplantation date, re-transplantation date and lab date were included in the follow-up dataset. Among these, the number of patients who came for review in the hospitals each year were obtained according to the lab date. Our analysis revealed that the number of records decreased each year due to patient deaths and other factors (Table 3). For a good survival, thorough review is needed year after year as per the advice of doctors. The survival analysis in percentage is calculated (Table 3) and the survival analysis in sixth month was taken as 100%. During the first-year follow-up, the survival analysis was 98% (see Table 4).

The three literature works included long-term survival prediction were taken for the comparison include Guijo-Rubio et al. [7], Haseli et al. [20] and Raji et al. [3] were comprised in Table 5. The accuracy of our model was compared using two datasets with existing research works is given in Fig. 6D.

In 2021, David Guijo-Rubio et al. conducted the study for the survival prediction at three months, one-year, two-year and five-years [7]. They used statistical methods and machine learning methods for donor-recipient matching in liver transplantation [7]. But they could

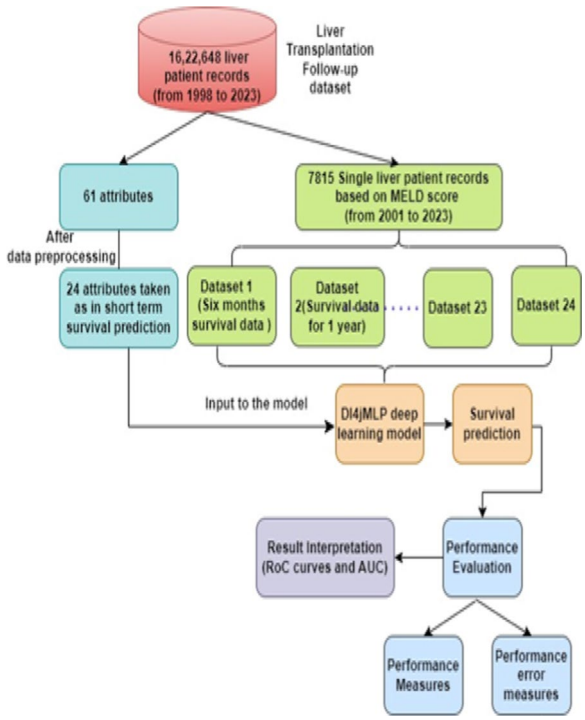


Fig. 5 Architecture of long-term survival prediction

Table 2 R-Living donor dataset survival prediction

A

Performance measures	Sensitivity	Specificity	Accuracy	Time taken in seconds
R-Living donor dataset	99.9	99.9	99.91%	48.33

B

Performance error measures	MAE	RMSE	R A E	R R S E
R-Living donor dataset	0.0009	0.0213	0.259%	4,9925%

C

Evaluation measures	Output Prediction Based on	Number of years/Values Obtained											
		0.5	1	2	3	4	5	6	7	8	9	10	11
Performance Measures	Sensitivity (%)	88.7	89.9	89.7	97.7	99.4	99.8	99.9	99.7	99.8	99.7	99.7	99.8
	Specificity (%)	100	100	100	100	68.4	62.5	38.9	50.12	45.0	31.6	47.4	64.3
	Accuracy (%)	90.9	90.9	90.0	97.79	98.54	99.11	98.9	98.79	98.92	98.77	99.3	99.19
Time taken		0 . 8	1 . 1	1.84	2.95	5 . 1	8.35	9.03	8.18	9.16	9.66	9.79	11.16
Performance Measures	Output Prediction Based on	12	13	14	15	16	17	18	19	20	21	22	23
	Sensitivity (%)	99.9	99.8	99.6	99.9	99.9	99.9	99.9	99.9	1 . 0	99.9	1 . 0	99.4
	Specificity (%)	41.7	50.0	40.0	34.6	42.3	66.7	47.1	60.0	36.8	77.8	58.3	66.0
	Accuracy (%)	99.51	99.11	98.79	99.04	99.33	99.75	99.58	99.66	99.6	99.83	99.69	99.16
Time taken		11.22	12.34	15.89	17.44	15.22	18.63	18.12	23.98	20.89	25.93	24.98	7.72

D

Evaluation measures	Output Prediction Based on	Number of years/Values Obtained											
		0.5	1	2	3	4	5	6	7	8	9	10	11
Performance Error Measures	MAE	0.1471	0.1847	0.2806	0.1393	0.7712	0.0521	0.0512	0.0447	0.0431	0.0443	0.0367	0.0322
	RMSE	0.114	0.254	0.3299	0.1748	0.1208	0.0998	0.095	0.1006	0.0951	0.1001	0.0891	0.0785
	RAE (%)	112.23	138.5	385.88	253.76	139.63	144.46	153.15	117.68	138.29	158.17	138.04	92.44
	RRSE (%)	105.21	94.25	182.49	107.86	73.59	75.52	74.54	73.88	77.18	85.79	78.36	59.98
Performance Error Measures	Output Prediction Based on	12	13	14	15	16	17	18	19	20	21	22	23
	MAE	0.0304	0.0308	0.0355	0.0314	0.0264	0.0167	0.0194	0.015	0.0187	0.0089	0.0139	0.0438
	RMSE	0.0701	0.0784	0.1027	0.092	0.0751	0.0497	0.0637	0.059	0.0624	0.0396	0.0543	0.0901
	RAE (%)	200.19	168.49	133.29	124.98	112.25	110.34	146.73	143.75	147.94	89.33	101.94	250.23
	RRSE (%)	82.24	83.40	90.01	82.96	70.02	58.04	79.53	83.09	79.57	57.10	66.38	99.19

A performance evaluation of R-living donor dataset in terms of performance measures for short term survival prediction, B performance evaluation of R-living donor dataset in terms of performance error measures for short term survival prediction, C performance evaluation of R-living donor dataset in terms of performance measures for long term survival prediction, D performance evaluation of R-living donor dataset in terms of performance error measures for long term survival prediction

attain accuracy of 63.3%, 63.1%, 62.9% and 65.4% only [7]. In 2012, Najmeh Haseli et al. conducted research on pediatric patients for one-year, three-year, five-year and 10 years [20]. They attained the accuracy of 73%, 67%, 66% and 66% from their model [20]. In 2017, Raji et al. conducted research on survival prediction for 13 years using machine learning model [3]. Due to the difficulty in holding large dataset in the model, the authors used a subset of data to train the model [3]. With that, good result was achieved. In comparison, our proposed model trained a large amount of data.

Discussion

Liver transplantation is a life-saving medical procedure that involves the surgical replacement of a diseased or damaged liver with a healthy one from either a living or deceased donor. This complex intervention is typically reserved for individuals facing end-stage liver disease, acute liver failure, or thorough evaluation of the patient's overall health and specific liver cancers. The process begins with a compatibility with potential donors. Survival prediction in liver transplantation is integral in optimizing patient care, resource allocation, and overall success of transplantation programs. It empowers both healthcare providers and patients with valuable information, fostering a more efficient and personalized approach to liver transplantation. Matching the liver organ from donors to the recipients is a big task. However, to achieve the outcome, survival following liver transplantation is critical. There is a lack of precise models to predict survival following liver transplantation [10]. Due to the lack of precise models in the survival prediction, doctors started using computer-based prediction models for survival prediction. Deep learning models can perform good in the survival prediction area with rich and large datasets. A rich dataset is essential for the research problem in the survival prediction. Thus, we collected UNOS dataset which includes the detail of donors, recipients and transplantation.

We conducted research for this socially relevant problem using a unique deep learning model. Since the dataset for the research was collected from UNOS database, it contained details of donors, recipients and transplantation. For a successful survival prediction, all these

Table 3 A R-deceased donor dataset survival prediction, B results of performance measures for short term survival prediction, C results of performance error measures for short term survival prediction, D results of performance measures for long term survival prediction, E results of performance error measures for long term survival prediction

B

Performance measures	Sensitivity	Specificity	Accuracy	Time taken in seconds
R-Deceased donor dataset	99.7	99.7	99.86%	105.02

C

Performance Error measures	MAE	RMSE	R A E	R R S E
R-Deceased donor dataset	0.0018	0.0362	0.3684%	7.2616%

D

Evaluation measures	Output Prediction Based on	Number of years/Values Obtained											
		0.5	1	2	3	4	5	6	7	8	9	10	11
Performance Measures	Sensitivity (%)	92.5	88.9	89.6	94.6	96.8	98.7	99.5	99.7	99.5	99.8	99.9	1.0
	Specificity (%)	74.2	88.9	89.6	59.4	64.9	52.1	50.4	44.6	48.5	52.2	51.9	45.4
	Accuracy (%)	89.04	89.14	89.61	90.7	93.83	95.00	96.8	97.64	98.27	98.65	98.08	98.98
Time taken		0.91	1.54	2.9	13.75	23.06	38.21	36.25	59.03	81.93	68.31	37.24	43.9
Performance Measures	Output Prediction Based on	12	13	14	15	16	17	18	19	20	21	22	23
	Sensitivity (%)	99.8	99.6	99.9	99.9	99.9	99.9	99.9	99.9	99.9	99.9	99.9	99.9
	Specificity (%)	36.3	32.3	40.2	39.7	48.1	41.1	35.4	40.0	50.7	44.3	53.4	45.0
	Accuracy (%)	99.65	98.66	98.94	99.27	99.26	99.47	99.43	99.52	99.45	99.55	99.51	99.54
Time taken		4055	43.65	48.17	43.34	47.43	49.27	49.31	76.84	65.38	68.02	65.97	31.93

E

Evaluation measures	Output Prediction Based on	Number of years/Values Obtained											
		0.5	1	2	3	4	5	6	7	8	9	10	11
Performance error measures	MAE	0.025	0.124	0.1733	0.1067	0.0791	0.0629	0.0448	0.0334	0.024	0.0217	0.194	0.0212
	RMSE	0.211	0.254	0.261	0.2248	0.195	0.176	0.1484	0.127	0.1074	0.0987	0.0876	0.0903
	RAE(%)	47.1	51.3	56.50	49.30	46.18	43.38	43.89	46.94	51.51	47.09	50.40	60.05
	RRSE(%)	61.2	63.5	66.76	68.39	66.69	65.26	65.73	67.39	70.47	65.18	63.24	68.16
Performance error measures	Output Prediction Based on	12	13	14	15	16	17	18	19	20	21	22	23
	MAE	0.0228	0.0243	0.0209	0.0169	0.0148	0.0124	0.0134	0.0141	0.0147	0.0104	0.0113	0.0178
	RMSE	0.0964	0.0983	0.0917	0.0806	0.076	0.0707	0.0711	0.0647	0.07	0.0645	0.0676	0.0653
	RAE(%)	63.60	70.75	67.07	75.23	62.82	79.70	101.15	99.95	80.18	74.83	61.94	133.03
	RRSE(%)	72.26	75.22	73.68	77.40	70.18	80.58	87.67	77.40	73.34	77.70	70.99	80.87

features are necessary [15]. Initially we split the dataset into R-Living donor dataset and R-Deceased donor dataset according to the donor type, DON_TY (Table 1). Both the datasets include sufficient parameters for a successful survival prediction after liver transplantation. We performed short term survival prediction for three months and long-term survival prediction for 23 years beyond initial six months with both the datasets. Empty columns in both datasets were removed as described [15]. Then we removed the irrelevant attributes such as demographic features of donor and recipients etc. manually from the dataset. Then Principal Component Analysis (PCA) was applied to both datasets and extracting 23 top ranked attributes with one output attribute. The 23 attributes were used to train the deep learning model, Dl4jMLP classifier [16]. Applying tenfold cross validation, the model trained the input attributes and kept a class attribute as output attribute [17]. The assigned class attribute for short-term survival prediction is GSTATUS.

With the help of follow-up data, we performed 23 years of survival after liver transplantation. The liver transplantation dataset and follow-up dataset were linked using the attribute, TRR_ID_CODE. The output attribute present in the follow-up dataset is GRF_STAT. We performed survival analysis and calculated survival probabilities for each dataset. The output of the model is evaluated using various performance and performance error measures [18]. The final result is represented using ROC curves and the Area Under Curve from ROC curves is noted [19]. Predicting the survival in liver transplantation has been based on the MELD score. It does not take into account non-hepatic factors that can impact post-transplant survival, such as age and the presence of other chronic illnesses. The performance of our model was compared with actual survival data available in the dataset. This has proved that the output of the model is close to the actual survival data. Other methods have been carried out for survival prediction after liver transplantation. To ensure the accuracy and efficiency of our proposed model we compared the model with existing models. We compared the output of the model with existing studies on terms of accuracy. One key challenge for the successful survival prediction is the unavailability of reliable, accurate and robust datasets. Traditional statistical models and methods cannot create adequate and effectively powered data sets for survival prediction in

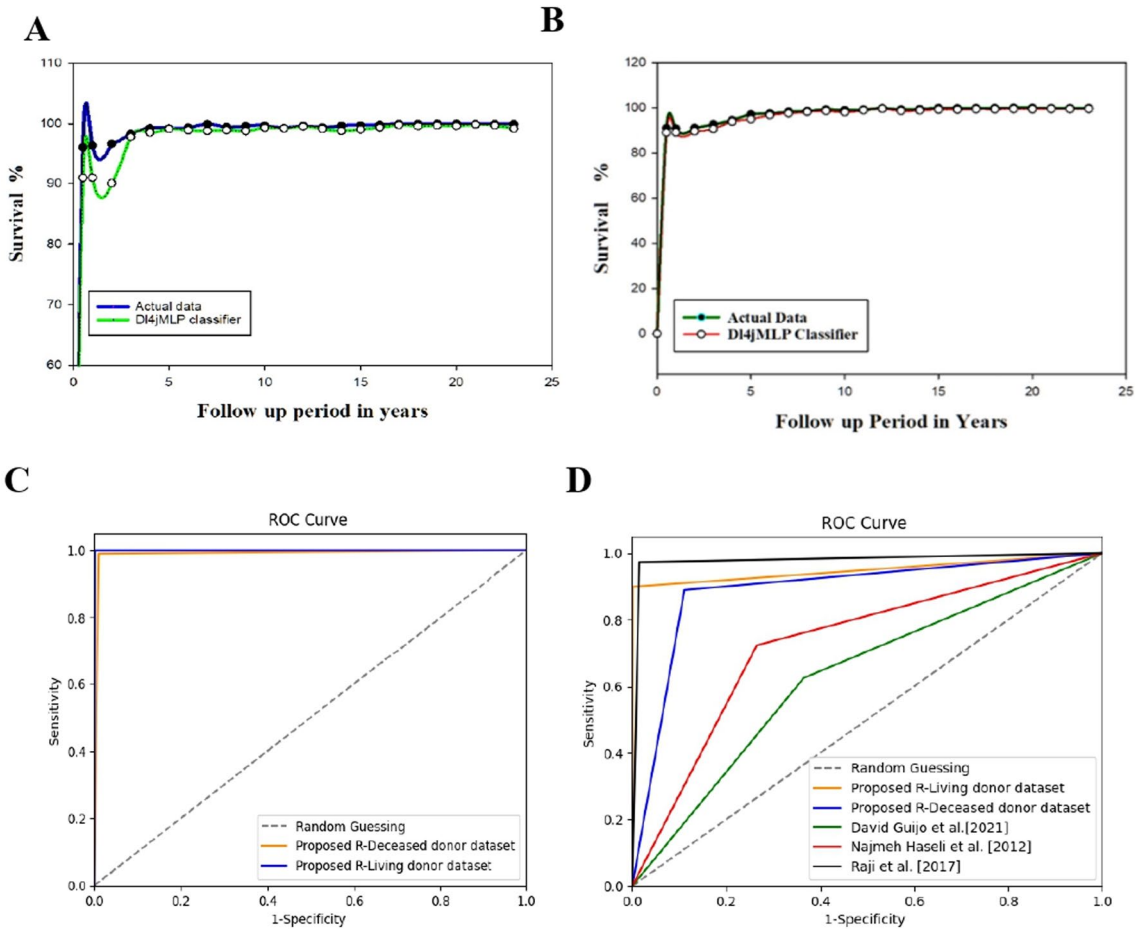


Fig. 6 **A** Comparison of actual survival with the prediction by the model using R-Living donor dataset. **B** Comparison of actual survival with the prediction by the model using R-Deceased donor dataset. **C** Performance Evaluation of R-Living Donor and R-Deceased Donor datasets for short term survival prediction. **D** Comparison of Survival Analysis with Existing Approaches in terms of Accuracy

all time [20]. Huge, high-quality data sets are required in order to produce precise models. Comparing to the existing research works, our proposed and top ranked attributes are significant in the successful survival prediction after liver transplantation. To facilitate studying large dataset, we split the data into two datasets based on the type of donors. With this, we reached good accuracy for 23 years of data. This was validated for six months survival prediction also. The AUC values obtained were represented using ROC curves. The study shows that for the long-term survival prediction after liver transplantation, Dl4jMLP classifier is good.

The prevailing data for kidney transplant clearly suggests a survival advantage for live donor over deceased donor [21]. The proposed study suggests that this is not the case in liver transplant, with equivalent outcomes in live and deceased donor transplants. This would be an argument in favor of the deceased donor option especially since the live donor operation in liver transplant may be associated with significant operative risk and complications [22]. The reliance on a single dataset, such as the UNOS, can constrain the model's applicability to broader populations. Deep learning models can perform well in researching rich and large datasets which is essential for survival prediction [23, 24]. We found the survival in deceased donor dataset is similar to the living donor dataset (Fig. 5C). Promoting deceased donor liver transplantation over living donor transplantation in terms of ethical considerations, reduced risk to donors, equitable access, optimal timing and avoidance of donor related complications is supported by our study. Continuous refinement of prediction models and incorporation of emerging technologies will further enhance our ability to optimize patient selection and improve outcomes in liver transplantation. Continued research and validation are essential to ensure the reliability and clinical utility of deep learning models in this critical domain.

Table 4 A survival analysis, B calculation of survival probabilities, C comparison of model performance based on actual data using R-living donor dataset, D comparison of model performance based on actual data using R-deceased donor dataset

A

Year	0.5	1	2	3	4	5	6	7	8	9	10	11
Total records	1005	984	895	889	786	674	617	539	444	381	323	290
Survival analysis (%)	100	98	89	88	78	67	61	54	44	38	32	29
Year	12	13	14	15	16	17	18	19	20	21	22	23
Total records	219	170	130	128	94	72	61	46	25	23	19	6
Survival analysis (%)	22	17	13	13	9	7	6	5	2	2	2	1

B

Year	0.5	1	2	3	4	5	6	7	8	9	10	11
Survival Probabilities	100%	98%	99%	99%	99%	98%	91%	86%	79%	83%	82%	89%
Year	12	13	14	15	16	17	18	19	20	21	22	23
Survival Probabilities	68%	71%	69%	98%	64%	69%	85%	67%	16%	91%	79%	-1.2%

C

Year	0.5	1	2	3	4	5	6	7	8	9	10	11
Actual Survival	90.95	90.81	91.12	92.68	94.55	97.14	97.62	98.32	98.62	99.25	98.94	99.21
Deep learning model	89.04	89.14	89.61	90.7	93.83	95.00	96.8	97.64	98.27	98.65	98.08	98.98
Year	12	13	14	15	16	17	18	19	20	21	22	23
Actual Survival	99.79	99.26	99.43	99.90	99.81	99.82	99.84	99.99	99.98	99.81	99.78	99.84
Deep learning model	99.65	98.66	98.94	99.27	99.26	99.47	99.43	99.52	99.45	99.55	99.51	99.54

D

Year	0.5	1	2	3	4	5	6	7	8	9	10	11
Actual Survival	96.1	96.4	96.67	98.30	99.23	99.22	99.35	99.91	99.46	99.62	99.69	99.26
Deep learning model	90.9	90.9	90.0	97.79	98.54	99.11	98.9	98.79	98.92	98.77	99.3	99.19
Year	12	13	14	15	16	17	18	19	20	21	22	23
Actual Survival	99.67	99.38	99.68	99.75	99.84	99.96	99.96	99.99	99.98	99.92	99.95	99.93
Deep learning model	99.51	99.11	98.79	99.04	99.33	99.75	99.58	99.66	99.6	99.83	99.69	99.16

Deceased donor transplantation helps expand the pool of available organs, addressing the growing demand for transplants. Policies that encourage deceased donation, such as presumed consent or opt-out systems, could enhance organ availability. Living donor transplantation carries inherent surgical risks and long-term health implications for the donor. Policies promoting deceased donors should not discourage altruistic living donation, as it plays a critical role in addressing organ shortages. Current transplantation policies, such as those of the United Network for Organ Sharing (UNOS), prioritize equity, utility, and justice in organ allocation. Promoting deceased donor transplantation aligns with these goals by expanding access while minimizing harm to living donors. However, such policies must be continually reviewed to adapt to societal and technological advancements. The deep learning model can predict individual survival probabilities, enabling clinicians to tailor post-transplant management strategies based on patient-specific factors. Integrating the model into organ allocation systems, transplantation networks can prioritize recipients who are likely to achieve the best outcomes. By predicting long-term survival, the model ensures that organs are distributed in a manner that aligns with ethical principles of utility and fairness. By leveraging this model, clinicians and policymakers can make more informed decisions, ultimately improving outcomes for transplant recipients and optimizing the use of limited healthcare resources.

Table 5 Comparison of survival analysis with existing approaches in terms of accuracy

Year	**0.5**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Model												
Proposed model using R-Living Donor dataset (%)	90.9	90.9	90.0	97.79	98.54	99.11	98.9	98.79	98.92	98.77	99.3	99.19
Proposed model using R-Deceased Donor dataset (%)	90.95	90.81	91.12	92.68	94.55	97.14	97.62	98.32	98.62	99.25	98.94	99.21
David Guijo-Rubio et al. (2021) (%)	63.3	63.1	62.9	–	–	65.4	–	–	–	–	–	–
Najmeh Haseli et al. (2012) (%)	–	73	–	67	–	66	–	–	–	–	66	–
Raji et al. (2017) (%)	96. 03	98.94	98.35	99.64	99.61	99.35	99.84	99. 51	97.22	99.52	98.92	98.89
Year	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Model												
Proposed Model using R-Living Donor dataset (%)	99.51	99.11	98.79	99.04	99.33	99.75	99.58	99.66	99.6	99.83	99.69	99.16
Proposed model using R-deceased Donor dataset t (%)	99.79	99.26	99.43	99.90	99.81	99.82	99.84	99.99	99.98	99.81	99.78	99.84
David Guijo-Rubio et al. (2021) (%)	–	–	–	–	–	–	–	–	–	–	–	–
Najmeh Haseli et al. (2012) (%)	–	–	–	–	–	–	–	–	–	–	–	–
Raji et al. (2017) (%)	98.33	97.14	–	–	–	–	–	–	–	–	–	–

Acknowledgements
We thank to UNOS for the availability of data in a speedy shipment. We would like to express my sincere gratitude to the Kerala Government and Kerala State Higher Education Council for their financial support, which has enabled the successful execution of post-doctoral research. We would like to express our sincere gratitude to the Department of Computer Science, University of Kerala for providing an enriching and supportive environment during the course of research. We are also thankful to the authorities of Medical Colleges in Kerala State for sharing the valuable information in organ transplantation with us. We thank Dr Philip G.Thomas, Multiorgan Transplant Surgery and Senior Consultant in Liver Biliary and Pancreatic Surgery, San Antonio, Texas for his insightful suggestions and help provided in manuscript preparation. We thank Ashik Sainu Kadambot Mohiyadeen, Senior Consultant Gastroenterologist & Medical Director, Department of Gastroenterology, Aster Hospital, Muscat, Oman for his clinical advice.

Author contributions
RCG, VSS, NG, YRP, AS were elaborated the study design and data collection. NG worked as medical officer for this research work. YRP and AS were involved in the data analysis and interpretation. RCG, VSS, NG wrote the original manuscript of research work. All authors revised and approved the final version of the manuscript. All authors contributed to its review and editing. VSS and NG supervised the study and RCG acquired the funding. All authors had access to the data and reviewed, verified, and consented to the published version of the manuscript. All accept the responsibility to submit the manuscript for publication.

Funding
This study was supported in part by a direct grant for Chief Minister's Nava Kerala Post Doctoral Fellowship scheme from the Government of Kerala under Department of Higher Education and KSHEC (KSHEC-A3/344/Govt.Kerala—NKPDF/2021). The funder of the study did not have a role in study design, data collection, data analysis, data interpretation or manuscript preparation.

Availability of data and materials
The data that support the findings of this study are available from UNOS OPTN but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

Declarations

Ethics approval and consent to participate
The data were collected based on OPTN data as on 5th June 2015. This work was supported in part by Health Resources and Services Administration contract 234–2005-370011C. The content is the responsibility of the authors alone and does not necessarily reflect the views or policies of the Department of Health and Human Services, nor does the mention of trade names, commercial products, or organizations imply endorsement by the U.S. Government.

Consent for publication
All authors approved the publication of this manuscript.

Competing interests
The authors declare no competing interests.

Author details
[1]Department of Computer Science, Assumption College Autonomous, Changanassery, Kerala, India. [2]Department of Computer Science, University of Kerala, Thiruvananthapuram, Kerala, India. [3]Kerala State Organ and Tissue Transplant Organization (KSOTTO), Government Medical College, Thiruvananthapuram, Kerala, India. [4]Department of Nephrology, Govt TD Medical College, Alappuzha, Kerala, India. [5]Department of Gastroenterology, Government Medical College, Thiruvananthapuram, Kerala, India. [6]Department of Gastroenterology, Queen Elizabeth Hospital Kings Lynn NHS Trust, Norfolk, England.

Received: 29 October 2024 Accepted: 29 January 2025
Published online: 16 February 2025

References

1. Segev DL, et al. Machine learning to predict transplant outcomes: helpful or hype? A national cohort study. Transpl Int. 2020;33(11):1472–80.
2. Chien-Liang L, et al. Predicting short-term survival after liver transplantation using machine learning. Sci Rep. 2020;101:5654.
3. Raji CG, Safna AK. Computational methods for predicting the outcome of thoracic transplantation. J Big Data. 2022;9(1):58.
4. Kargar B, Gazerani VG, Pishvaee MS. Predicting liver transplantation outcomes through data analytics. In: Bohlouli M, Bigham BS, Narimani Z, Vasighi M, Ansari E, editors. Data science: from research to application. Cham: Springer International Publishing; 2020. p. 142–60.
5. Nitha VR, Vinod Chandra SS. ExtRanFS: an automated lung cancer malignancy detection system using extremely randomized feature selector. Diagnostics. 2023;13(13):2206.
6. Nitha VR, Vinod Chandra SS. Novel CEFNet framework for lung disease detection and infection region identification. Biomed Sign Process Control. 2024;96:106624.
7. Guijo-Rubio D, et al. Statistical methods versus machine learning techniques for donor-recipient matching in liver transplantation. PLoS ONE. 2021;16(5):e0252068.
8. Nitski O, et al. Long-term mortality risk stratification of liver transplant recipients: real-time application of deep learning algorithms on longitudinal data. Lancet Digital Health. 2021;3(5):e295–305.
9. Nti IK, Nyarko-Boateng O, Aning J. Performance of machine learning algorithms with different K values in K-fold cross-validation. J Inf Technol Comput Sci. 2021;6:61–71.
10. VanDerwerken DN, Wood NL, Segev DL, Gentry SE. The precise relationship between model for end-stage liver disease and survival without a liver transplant. Hepatology. 2021;74(2):950–60.
11 Saki N, Haybar H, Aghaei M. Subject: motivation can be suppressed, but scientific ability cannot and should not be ignored. J Transl Med. 2023;21(1):520.
12. Ayllón MD, Ciria R, Cruz-Ramírez M, Pérez-Ortiz M, Gómez I, Valente R, O'Grady J, de la Mata M, Hervás-Martínez C, Heaton ND, et al. Validation of artificial neural networks as a methodology for dono' recipient matching for liver transplantation. Liver Transpl. 2018;4:192–203.
13 Zhiyong Y, et al. Learning with multiclass AUC: theory and algorithms. IEEE Trans Pattern Analy Mach Intell. 2021;44(11):7747–63.
14. Kers J, Bülow RD, Klinkhammer BM, Breimer GE, Fontana F, Abiola AA, Hofstraat R, Corthals GL, Peters-Sengers H, Djudjaj S, von Stillfried S. Deep learning-based classification of kidney transplant pathology: a retrospective, multicentre, proof-of-concept study. Lancet Dig Health. 2022;4(1):e18-26.
15. Aghaei M, Khademi R, Far MAJ, Bahreiny SS, Mahdizade AH, Amirrajab N. Genetic variants of dectin-1 and their antifungal immunity impact in hematologic malignancies: a comprehensive systematic review. Curr Res Transl Med. 2024;72(4): 103460.
16 Bhat M, et al. Artificial intelligence, machine learning, and deep learning in liver transplantation. J Hepatol. 2023;78(6):1216–33.
17. Börner N, et al. A novel deep learning model as a donor-recipient matching tool to predict survival after liver transplantation. J Clin Med. 2022;11(21):422.
18. Nagai S, et al. Use of neural network models to predict liver transplantation waitlist mortality. Liver Transpl. 2022;28(7):1133–43.
19. Ivanics T, et al. Machine learning–based mortality prediction models using national liver transplantation registries are feasible but have limited utility across countries. Am J Transpl. 2023;23(1):64–71.
20. Haseli N, et al. Long-term survival and its related factors in pediatric liver transplant recipients of shiraz transplant center, Shiraz, Iran in 2012. Hepat Monthly. 2023;13(7): e10257.

21. Reddy MS, et al. National liver allocation policy—consensus document by the liver transplantation society of India for a nationally uniform system of allocation of deceased donor liver grafts. J Clin Exp Hepatol. 2023;13(2):303–18.
22. Aghapour SA, Torabizadeh M, Bahreiny SS, et al. Investigating the dynamic interplay between cellular immunity and tumor cells in the fight against cancer: an updated comprehensive review. IJBC. 2024;16(2):84–101.
23. Aghaei M, Khademi R, Bahreiny SS, Saki N. The need to establish and recognize the field of clinical laboratory science (CLS) as an essential field in advancing clinical goals. Health Sci Rep. 2024;7(8): e70008.
24. Aswathy AL, Anand HS, Vinod Chandra SS. COVID-19 severity detection using machine learning techniques from CT-images. Evol Intel. 2023;16(4):1423–31.

Publisher's Note