# Predicting Graft Failure Within Year After Transplantation Using Data Mining Techniques

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***Abstract*—The complex factors of liver transplant survival and the potential for post-transplant complications are significant challenges for healthcare professionals. This paper aims to identify the ability to use data mining techniques to develop a predictive model for liver transplant failure by identifying the relationship between abnormalities in periodic patients' laboratory results and graft failure. The researchers obtained data from King Faisal Specialist Hospital and Research Centre to address the research problems. First, the classification technique was used to predict cases with a high risk of liver transplant failure. Second, Association Rules were applied to identify associations between abnormalities in patients' laboratory results and transplant failure. Before using data mining algorithms, the patient dataset underwent a cleaning process, which involved removing duplicate entries and uncertain results. The algorithms were applied separately to the data of patients who completed the first year without complications and those who experienced transplant failure. The obtained results were then compared and we observed that abnormal levels in Aspartate Transferase (AST), Red Blood Cell (RBC), Hemoglobin (Hgb), 'Bilirubin Total', and 'Platelet' occurred exclusively in cases that faced liver transplant failure within the first year. Similarly, abnormal levels in 'AST', 'RBC', Alanine Aminotransferase (ALT), and 'Bilirubin Total' were also associated with transplant failure.**

***Keywords*—Graft failure; liver transplant; data mining; predictive model; classification; association rules**

## I. Introduction

The growth of technology use in the last decade has led to large amounts of data entering data repositories worldwide. It is unrealistic to extract valuable knowledge manually from this vast, massive data. Therefore, many technologies have been created to assist the user with tools to find useful knowledge and information from this distributed data. Data mining refers to the extraction of valuable knowledge and meaningful information from large databases; it depends on machine learning, statistical methods, and artificial intelligence. The efficacy of data mining has been extensively studied across various domains, including commercial sectors, telecommunications, and healthcare [1].

In the medical industry, sensitive data is produced daily from medical records, patient monitoring, laboratory reports, radiology images, and more. Therefore, data mining applications have shown effectiveness in the healthcare industry. Physicians can use data mining techniques to enhance patients' quality of life by using data to design the best treatment plan, diagnose potential diseases, or predict drug side effects [2].

One medical field recently used in data mining is organ transplantation. Organ transplant refers to replacing a failed organ from a patient with an organ from a Brain deceased donor or living donor. This operation gives the patient with end-stage organ failure the chance to have a normal life [3]. Liver transplantation (LT) is the ultimate medical intervention for patients with advanced liver disease. However, there are main challenges that reduce the benefits of liver transplants, the shortage of grafts available for transplant, the increase in the patients on the waiting list, and the probability of graft failure after the surgery. Patients are subjected to strict monitoring of their vital functions and extensive analysis during past and post-transplant to predict any signs of liver failure. In addition, transplant patients undergo high doses of immunosuppressants, especially within the first year post-transplant, to reduce the possibility of liver failure. However, many factors affect graft survival, making the early prediction process complex [4].

According to these challenges, physicians find it difficult to predict patients with a high risk of graft failure and improve the chance of saving the graft and the patient's life [5]. Therefore, several scores and models have been evaluated to predict contributing factors to achieve a successful post-LT outcome. It is important to note that most of these models were introduced several years ago, applied to different populations, and focused on different kinds of organ transplants; Kidney, Lung, or Heart. In this research, the focus is to study a model to predict patients with a high risk of liver failure post-liver transplant (LT).

## II. Literature Review

### A. *Data Mining in Predicted Failure Transplant Organ*

Many prior studies built different models based on data mining methodologies to predict graft survival. These studies covered kidneys, lungs, liver, and Stem Cell transplantation. Some researchers have developed a new predictive model, and others compared different data mining algorithms to improve the accuracy of predictions.

Atallah et al. [5] used hyper-classifiers to predict kidney transplant outcomes. They proposed a method to predict kidneys before transplants dependent on three stages, the preparation stage, feature selection stage, and then prediction stages. In the first stage, they proposed preparing the data which consisted of data cleaning and removal of all instances that have missing data. In the feature selection stage, only relevant features are extracted to improve the accuracy of the model. The last stage is conducting the predicting phase using the KNN algorithm. They found the highest accuracy by using this method, they achieved 81.5% accuracy.

Also, Oztekin et al. [11] proposed a feature selection methodology based on a genetic algorithm (GA) to achieve a high classification accuracy to predict the quality of life after a lung transplant. The GA-selection algorithm was applied along with kNN, ANN, and SVM as classification models. The result shows that SVM had the highest accuracy in predicting quality of life following lung transplantation.

In other studies, the predictor of the risk of Kidney transplant failure has been investigated in different cohorts. Naqvi et al. [16] conducted machine classification algorithms to develop prediction models for the risk of graft failure using support vector machines (SVM), AdaBoost, RF, ANN, and logistic regression over patients' data in three cohorts. The result of accuracy shows that SVM and AdaBoost have the highest rate over the cohorts.

To compare the accuracy of a different model, [10] compared nine algorithms using 10-fold stratified cross-validation, which were: logistic regression, linear discriminant analysis, quadratic discriminant analysis, support vector machines (using linear, radial basis function, and polynomial kernels), decision tree, random forest and stochastic. In the same idea, [10] [9] compared six algorithms: Naïve Bayes (NB), alternating decision trees (ADT), and logistic regression (LR) which produce models with interpretable structures, whereas multilayer perceptron (MLP), random forest (RF) and AdaBoost attempt to detect for the one which will give the highest accuracy.

On the other hand, [13] compared between three data mining (DM) methods to predict Kidney Transplant Survival. The models are the C&R Tree Model, Neural Network Model, and C5.0 Model. The accuracy of the C5.0 Model was the highest. It was 91.5% within the first year of transplant.

Also, [15] studied the cases of failure and success of LT by studying factors related to the patient and the donor and comparing the accuracy of the classification before and after the feature Selection. By comparing the accuracy results when applied Neural Network and Random Forests before FS: 0.734 and 0.787 and after FS: 0.835 and 0.818.

All previous studies have highlighted the use of classification in predicted transplantation outcomes; on the other hand, [14] used the association rules to predict important factors for who did and did not have kidney failure five years post-kidney transplant for live and deceased donor recipients. He identified factors common in both patients (live and deceased donor recipients) and factors important only in deceased donors. Also, he identified the factors associated with graft Failure. These factors match with what is usually observed in patients in the clinic. Table I summarizes the Application and Techniques Used in Organ Translation Studies.

### *B. Liver Transplant in the Kingdom of Saudi Arabia*

Organ transplant has been one of the medical revolutions in the last two decades [6]. It gave patients with end-stage organ failure a chance to live a normal life by removing the organ from one person "the donor" and transplanting it to the recipient who has organ failure. The most common organs that are transplanted include the heart, kidneys, lungs, and liver. As a result of the high burden of liver disease in the country, there is a high demand for liver transplantation. The estimated LT is around 75 patients per million.

TABLE I. APPLICATION AND TECHNIQUES USED IN ORGAN TRANSLATION STUDIES

| Title | Year | Application | Algorithms And Methods |
|---|---|---|---|
| Predicting kidney transplantation outcome based on hybrid feature selection and KNN classifier | 2019 | Predict delayed graft function after kidney transplantation | K-Nearest Neighbors (KNN) algorithm |
| A decision analytic approach to predicting quality of life for lung transplant recipients: A hybrid genetic algorithm-based methodology | 2018 | Predict the quality of life after a lung transplant | The GA-selection algorithm, kNN, Artificial Neural Networks (ANN), and support vector machines(SVM) |
| Predicting kidney graft survival using machine learning methods: prediction model development and feature significance analysis study. | 2021 | Predict the risk of kidney transplant failure | SVM, AdaBoost, random forest (RF), ANN, and logistic regression |
| ). Prediction of delayed graft function after kidney transplantation: comparison between logistic regression and machine learning methods. | 2015 | Compare the accuracy of a different model to detect which one will give the highest accuracy in Predict delayed graft function after kidney transplantation | Logistic regression, linear discriminant analysis, quadratic discriminant analysis, support vector machines, decision tree, random forest, and stochastic. algorithms: Naïve Bayes (NB), alternating decision trees (ADT), and logistic regression (LR) which produce models with interpretable structures, whereas multilayer perceptron (MLP), RF and AdaBoost |
| Comparing three data mining methods to predict kidney transplant survival | 2016 | Compared between three data mining methods to predict Kidney Transplant Survival | C&R Tree Model, Neural Network Model, and C5.0 Model |
| Machine-learning algorithms predict graft failure after liver transplantation | 2017 | Predict graft failure after liver transplantation | Neural Network and Random Forests |
| Analyzing Association Rules for Graft Failure Following Deceased and Live Donor Kidney Transplantation. | 2021 | Predicted kidneys' transplantation outcomes | Association Rules |

As the growth of organ transplant activities all over the world, the Kingdom of Saudi Arabia (KSA) picked up the pace in this field. In 1985, the Saudi Center for Organ Transplantation (SCOT) was established as a government center to monitor organ transplantation activities in KSA. Indeed, the first organ transplant in KSA was a kidney transplant from a living donor in 1979 [12], while the first LT was in 1991 [7]. Nowadays, there are over 20 organ transplant programs throughout the KSA, and four of them are LT centers. In Riyadh, there are three centers and the last one is in Dammam. Over 2000 LTs have been performed over the four centers, 50% of these surgeries performed at King Faisal Specialist Hospital and Research Center (KFSH&RC) in Riyadh. For each LT center, there is a waiting list based on the Model for End-Stage Liver Disease (MELD) scores.

## III. Methodology

To answer the research questions, we applied two Data Mining methodologies. First, we applied several common classification algorithms to predict failure cases. Second, we conducted Association rules to identify the relationships among patients' data.

The main steps were followed:

- Data collection.
- Data preprocessing.
- Predicting Liver Failure: a. Classification. b. Association Rules, As shown in Fig. 1:

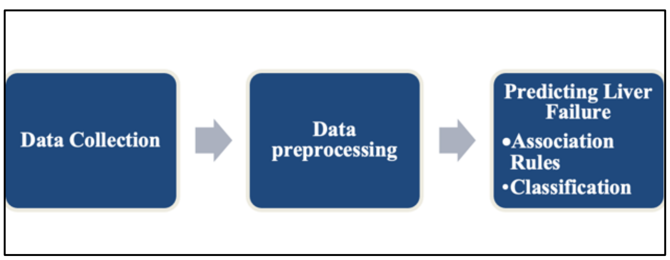


Fig. 1. Main steps of the data mining process.

### A. Data Collection

The data used in this study was obtained from KFSH&RC and presented in a CSV format. The dataset included lab results of 1118 patients who underwent LT between 2002 and 2018, totaling 772339 rows and fourteen columns. Each row represented a specific lab result for one patient on a particular date. Eighty-one different labs were taken; it is important to note that the frequency of lab repetition varied depending on the patients at other times, and not all labs were taken for every patient. Moreover, there were duplicate data, missing data, and laboratories without any results, Table II summarizes the dataset:

TABLE II. Summary of Patients' Dataset

| Data Set Size | Number of Attributes | Unique Establishment IDs |
|---|---|---|
| 772339 | 14 | 1118 |

The dataset contains six columns with different dates for each lab:

- ORIG_ORDER_DT_TM
- DRAWN_DT_TM
- RECEIVED_DT_TM
- CURRENT_START_DT_T
- LAST_UPADTE
- RESULT_PERFORM_DT_TM

By referring to the specialist doctor about the importance of these columns, it was found that the most critical column among them is: RECEIVED_DT_TM

All unimportant columns were excluded from the table, and retained only the following ones**:**

- RESULT_PERFORM_DT_TM
- MRN
- BIRTH_DT_TM
- CATALOG
- LAB_TEXT_NAME
- RESULT

Descriptions of the attributes are presented in Tables III:

Table II: Dataset attributes description

TABLE III. Dataset Attributes Description

| # | *Attribute name* | *Type* | *Description* |
|---|---|---|---|
| 1 | RESULT_PERFORM_DT_TM | Datetime | Date of receipt of the patient's analysis request |
| 2 | MRN | int64 | Unique ID for each patient |
| 3 | BIRTH_DT_TM | Datetime | The birth date of each patient |
| 4 | CATALOG | object | The categories for each laboratory test |
| 5 | LAB_TEXT_NAME | object | The name of laboratory test |
| 6 | RESULT | int64 | Represent the result of the laboratory test |

Another CSV file was obtained reviewing cases completed a year without complications and unsuccessful cases from 2001 to 2019. The number of patients in this file is 1140 cases: 1031 success cases, 121 failure cases, and 26 cases without information. Fig. 2 shows the increase in liver transplant cases during the previous years at the KFSH&RC:

### B. Data Preparation

Usually, the raw data contains noise, missing, or duplicated data that can affect the quality of data mining results, so the data preparation phase is a crucial step. The researchers follow steps that are suitable for their methodologies according to the type and size of the data and the data mining technique used [18]. This phase is also important for better understanding and realizing data. It consists of data cleaning, data labeling, and addressing class imbalances.

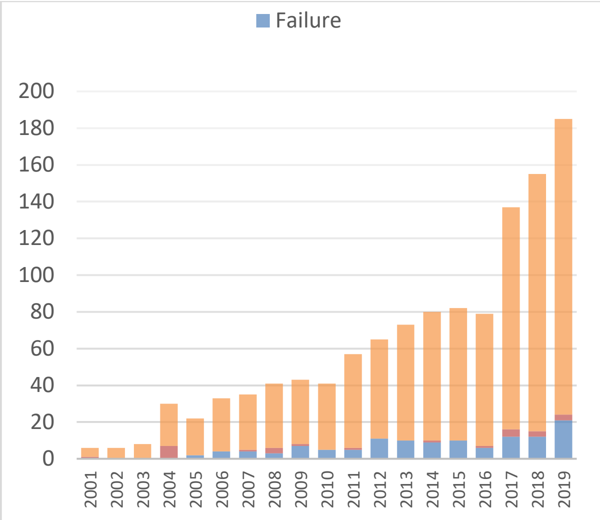


Fig. 2. The liver transplant cases during the previous years at the KFSH&RC.

*1) Data Cleaning:* The data obtained is vast, and complex, with many Null cells and duplicate data. Also, all rows were excluded for pediatric patients who were younger than 15.

Data cleaning involved removing:

- All rows with missing values.
- All rows if the “Result” column contains “Indeterminate”, “Hemolyzed”, “See the comment” or “Equivocal”.
- All rows if received date more than one year before the transplant.
- All duplicated rows.

*2) Data labeling:* The laboratory results vary in distributed values; any difference from the normal range is considered abnormal, so a "Class" column has been added, which shows the status of the laboratory results if the result is within the normal range or abnormal.

Data Labeling involved modified:

- “Result” value if “Result” = “positive” to 1 , and Negative to 0,
- Determined the normal range for each laboratory test, if the result is within the normal range the class will be = 0, otherwise if the result is above or below the class will be Abnormal = 1.

Table IV represents the normal ranges of each laboratory.

TABLE IV. LABORATORY RESULTS IN NORMAL RANGES

| LAB_TEXT_NAME | Normal Range |
|---|---|
| AFP | 0 -10 |
| Albumin | 34 - 54 |
| Alk Phos | 44 - 54 |
| ALT | 19 - 25 |
| ANA Screen | Negative |
| AST | 8 -33 |
| Bilirubin Total | 0 -21 |
| CA 125 | 0 - 35 |
| CA 19-9 | 0- 37 |
| Ca Level | 8.6 – 10.3 |
| Ceruloplasmin | 14 – 40 |
| Cl | 96- 106 |
| CMV IgG | 1 - 21 |
| CMV IgM | Negative |
| CO2 | 20 - 29 |
| Creat | 61.9 – 114.9 |
| e-GFR | 60 - 90 |
| Ferritin | 11 - 336 |
| Globulin | 20 - 39 |
| Hct | 0.3 - 0.5 |
| Hgb | 138 - 172 |
| Hgb g per dL | 14 - 18 |
| IgA | 0.8 - 3 |
| Iron | 10 - 30 |
| Iron Saturation | 0.15 – 0.55 |
| K | 3.5 – 5.3 |
| MCH | 27 - 33 |
| MCHC | 33.4 - 35.5 |
| MCV | 80 - 95 |
| Mg | 0.85 – 1.1 |
| MPV | 8.9 - 11.8 |
| Na | 135 - 145 |
| NRBC Auto | 0 - 0.3 |
| Platelet | 150 - 450 |
| PO4 | 2.3 – 4.7 |
| Pro-Brain Natriuretic Peptide | 100 - 400 |
| Protein Total | 60 - 83 |
| Quantiferon-TB | Negative |
| RBC | 4.2 - 5.4 |
| RDW | 12.2 - 16.1 |
| Sm Muscle Ab | Negative |
| TIBC | 42.96 – 80.55 |
| Total Cell Count (NRBC) | 0 - 100 |
| Toxoplas IgG | 0 - 44 |
| Toxoplas IgM | Negative |
| UIBC | 21 - 84 |
| Urea | 5 - 20 |
| WBC | 4.5 - 11 |

*3) Addressing class imbalance:* The data set has two categories, failure transplant cases and success transplant cases. There was a significant class imbalance whereby the failure transplant had a significantly lower number of instances compared with the success transplant. To solve this issue, the Minority Oversampling Technique (SMOTE) was used.

*4) Reorganized dataset:* In the dataset, each row represented a specific laboratory result for one patient at a particular date. To prepare the dataset, the dataset was reorganized. Each row represents all laboratory results for one patient at a specific date.

*5) Feature selection:* The feature selection stage is predicated upon the principle of diminishing the pool of features to only encompass the most valuable features, thereby augmenting the model result. Researchers employ various techniques to eliminate irrelevant features, to enhance the efficiency and accuracy of the model.

In studies [5], [19], and [16] removed all unnecessary features, and all patient identifications (such as transplant ID, donor ID, and patient ID). Moreover, the study in [20] removed all unnecessary attributes, and kept only 27 relevant attributes from the dataset containing 389 attributes. Also, they removed the data of pediatric patients [21]. Identify the critical features used in statistical tests of the association between each feature and output variable. They exclude only three variables from the model. The study in [11] used Genetic Algorithms to minimize the number of features. They also excluded the feature with a large number of missing values. The dataset encompasses a total of 81 laboratory tests, with the exclusion of laboratories that conducted tests for only 10% of the patients or laboratories that showed normal results in the majority of patients. Consequently, 33 laboratory tests remained in the dataset.

## C. Predicting Liver Failure Use DM Algorithm

We have followed two DM approaches to answer the research questions, using classification to predict the failure cases, and to investigate the labs that have highly impacted on liver failure we used the Association rules method.

*1) Classification:* Classification is a predictive supervised learning technique that classifies the data into predefined classes. It is one of the most widely used DM techniques in medical research [9]. It aims to predict target classes; it could be a binary or multilevel approach. In binary classification, there are two classes to predict, such as patients with "positive "or "negative" diagnoses. On the other hand, in multilevel classification, there are more than two predicted classes.

In this research, we have applied five algorithms: Random Forest – KNN – GaussianNB – SVC – ANN.

*2) Association rules:* Association Rules Mining (ARM) also known as "Market basket analysis" is an unsupervised learning method used with transactional databases [8]. [17] introduce Association Rules as generating associations or/and correlations among frequent items in large transactional databases.

Let transactional database $\mathcal{T}$ contain a set of items, $\mathcal{I} = i_1, i_2 \dots, i_m$ as binary attributes, each transaction $t$ represented as set of items $i_k \subset \mathcal{I}$ where $i_k$=1 ,the advance of ASM is to seek for the term: $\mathcal{X} \rightarrow \mathcal{Y}$ where $X, Y \subset \mathcal{I}$ and $X \cap Y = \emptyset$. Apriori algorithm is a well-researched ARM algorithm. The concept of the Apriori Algorithm is using a breath-first strategy to eliminate unnecessary rules that are unsatisfied with minimum support (mins up) and minimum confidence. To implement Apriori Algorithm, 2 steps are performed:

First step: Find all possible candidates $C$ from each itemset in the database, where a large k-itemset is generated from k-1-itemset with satisfied minsup.

Second step: generate all rules from these candidates' itemsets.

Minimum support formula is:

$$Support = \frac{feq(X, Y)}{number\ of\ t}$$

The formula for association rules algorithm set of features,

$$confidence(X|Y) = \frac{feq(XY)}{feq(X)}$$

## D. Model Evaluation

The evaluation stage of the algorithms employed holds paramount significance in the data mining process, as it demonstrates the viability of the technique utilized. Various mechanisms are employed to conduct evaluation techniques based on their respective types.

*1) Classification evaluation:* In the evaluation of classifications, researchers employ a variety of techniques. In our current study, we have utilized the Confusion Matrix method to assess the effectiveness and accuracy of these classifications. The confusion matrix is widely recognized as the most commonly used tool for measuring classification effectiveness [22]. This method proves particularly valuable in quantifying important measurements such as Recall, Precision, and Accuracy.

To find these measurements, the Confusion Matrix technology depends on comparing the prediction results and the real values as shown in Table V:

TABLE V. CONFUSION MATRIX

| | | **Actual Value** | |
|---|---|---|---|
| | | ***Positive ( 1)*** | ***Negative (0)*** |
| **Predictive Value** | **Positive ( 1)** | **True Positive** | **False Positive** |
| | **Negative (0)** | **False Negative** | **True Negative** |

To elucidate the concept of four fields; "True Positive, False Negative, False Positive, and True Negative" in the context of our research, it is important to note that we are dealing with two classes for which we aim to construct a predictive model:

True Positive (TP): The prediction of the state is positive, and the actual outcome is positive.

True Negative (TN): The prediction of the state is Negative, and the actual outcome is Negative.

False Positive (FP): The prediction of the state is positive, and the actual outcome is Negative.

False Negative (FN): The prediction of the state is Negative, and the actual outcome is positive.

To find the values of Recall, Precision, and Accuracy from Confusion Matrix:

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{Precision}= \frac{TP}{TP+FP}$$

Accuracy = how many correct predictions from both classes; Positive and Negative.

*2) Association rules evaluation:* Association Rules Evaluation is a crucial aspect of data analysis that aims to uncover meaningful relationships and patterns within datasets. This research delves into the intricacies of association rule mining, a popular technique employed in one key aspect of our research that involves measuring the strength of association rules through metrics such as support, confidence, and lift. These metrics allow us to quantify the level of dependency between items or variables in a rule. Additionally, we explore various evaluation measures like conviction and leverage to gain a comprehensive understanding of the associations discovered.

The minimum support formula is:

$$Support = \frac{feq(\,X,Y)}{number\ of\ t}$$

The formula for association rules algorithm set of features,

$$confidence(\,X|Y) = \frac{feq(XY)}{feq(X)}$$

### E. Tools and Software

The research is based on classification techniques and the hardware used is a MacBook Pro (14-inch, 2021) with M1 pro 3.22 GHz processor 8 Cores, and the memory is 16 GB 2133 MHz LPDDR5. The research used Python software, specifically on a Jupyter Notebook. Python was chosen because it has a large support community and various libraries that provide extensive functionality. One such library used in this research is scikit-learn, which supports different classification methods and is widely accessible. Also, panda’s library ‹was used extensively by taking advantage of the functions that supported the preparation phase of the data.

## IV. Results

The complexity of the data is quite intricate, as no patient has undergone more than 13 tests in a single day. After eliminating the laboratories that were only utilized for 10% of patients, we were left with 31 labs, which is a huge amount to handle. To address our research inquiries, we employed two data mining approaches. These techniques will examine the outcomes achieved through the classification technique, followed by an assessment of the results obtained using association rules.

### A. Association Rules

The dataset provided encompasses all laboratory tests conducted for each patient on specific dates. The data within the table lacks a systematic arrangement. To address this, we have employed the association rule mining technique to uncover relationships between abnormal results. By comparing the outcomes generated from a dataset comprising both failure cases and alive cases, we aim to identify significant associations. Association rule mining holds great significance in transactional datasets as it enables the discovery of intricate relationships among different data elements. Consequently, its application in analyzing patient laboratory results proves highly convenient.

In order to implement Association Rules, the initial phase entailed categorizing each laboratory result with a corresponding class. The class denoted as "Normal" was encoded as 0, which will be traversed by the algorithm. Conversely, the class labeled as "Abnormal" was encoded as 1, which will be interpreted by the algorithm.

Moving on to step two, the dataset consisted of 2366 rows. Out of these, 372 rows were dedicated to failure cases (FC) and 1994 rows to success cases (SC). However, there was an imbalance in the final dataset. To address this issue, the SMOTE algorithm was applied. This resulted in an expanded dataset with a total of 3988 rows. This expansion ensured that both FC and SC had an equal representation of 1994 rows each. For step three, the association rule technique was employed on both the FC and SC datasets using identical parameters. The minimum support was set at 0.4, while the minimum confidence threshold was set at 1. The researcher applied the Apriori algorithm to analyze the data and obtained interesting results. Specifically, the researcher discovered that a total of 1848 rules were generated in instances of success, while 1968 rules were generated in cases of failure. To further investigate these findings, the researcher compared the results and found that most of the rules appeared in both cases of failure and success. Additionally, the support and confidence values for these rules were very close. The analysis revealed that certain rolls, namely AST, RBC, Hgb, 'Bilirubin Total', and 'Platelet', were higher in cases that experienced liver transplant failure within the first year. Furthermore, height was also found to be associated with AST, RBC, ALT, and 'Bilirubin Total', as indicated in Table VI.

TABLE VI. Unique Results Shown with FC

| ***Rules*** | ***support*** | ***confidence*** |
|---|---|---|
| ‘AST’ ^ 'RBC' ^ 'Hgb'^ 'Bilirubin Total'^ 'Platelet' | 0.46 | 0.95 |
| ‘AST’ ^ 'RBC' ^ ’ ALT’^ 'Bilirubin Total' | 0.40 | 0.91 |

It was deemed necessary to seek the expertise of a specialist doctor at KFSH&RC for their evaluation. The esteemed specialist doctor duly reviewed the findings and concurred that this discovery holds a significant interest.

### B. Classification

The study aimed to investigate the efficacy of using DM in identifying the most vulnerable cases of LTF based on periodic laboratory results. To achieve this objective, a comprehensive analysis was conducted using a commonly employed algorithm. The primary focus was to assess the potential of DM in accurately pinpointing individuals at high risk for LTF, solely relying on their lab test outcomes.

After preprocessing and organizing the data, we proceeded to apply various algorithms including Random Forest, K-Nearest Neighbors (KNN), Gaussian Naive Bayes (NB), Support Vector Classifier (SVC), and MLPClassifier on the dataset. The outcomes revealed that Random Forest exhibited the highest accuracy among all algorithms. It achieved an accuracy rate of 85 percent. Following closely behind, KNN demonstrated a respectable accuracy of 81 percent, while MLP Classifier achieved an accuracy of 78 percent. On the other hand, SVC and Genesis NB yielded lower accuracies with rates of 60 percent and 54 percent respectively. Table VII shows the Performance Evaluation for all five algorithms.

TABLE VII. PERFORMANCE EVALUATION FOR CLASSIFICATIONS

| Classifier | Precision | Recall | Precision | Recall | Accuracy |
|---|---|---|---|---|---|
| | Success Case | | Failure Case | | |
| Random Forest | 86 | 84 | 84 | 86 | 85 |
| KNN | 83 | 80 | 79 | 82 | 81 |
| GaussianNB | 80 | 73 | 77 | 83 | 78 |
| SVC | 62 | 53 | 58 | 66 | 60 |
| ANN | 60 | 35 | 52 | 75 | 54 |

The results were presented to a specialist doctor who agreed with the reality of some of the results.

## V. CONCLUSION

Data mining technologies hold significant promise in healthcare, especially in predicting medical outcomes and identifying risks. This study, in collaboration with the Organ Transplant Center of Excellence and the Center of Genomic Medicine at KFSH&RC, demonstrates the predictive power of data mining in liver transplant outcomes. Using patient data from 2002 to 2018, two data mining techniques, classification, and association rules, were applied. Among five algorithms tested, Random Forest proved most effective, achieving an 85% accuracy rate in predicting liver transplant failure. The association rules technique, using a support value of 0.4 and a confidence value of 1, identified elevated levels of 'AST', 'RBC', 'Hgb', 'Bilirubin Total', and 'Platelet' as significant indicators of transplant failure. These findings were validated by the hospital's Adult Transplant Hepatology consultants, who stressed the need for further research incorporating larger sample sizes and additional variables such as age, gender, body mass, and liver failure causes. Expanding this study to other organs and hospitals across Saudi Arabia could enhance predictive accuracy and clinical utility.

The influence of data mining technologies is particularly evident in contemporary technological revolutions within the realms of marketing, industry, finance, and education. However, in the domain of health research, investigations are still centered on exploring the potential benefits of data technologies to aid physicians in predicting diverse diseases and detecting potential hazards to patients' lives at an early stage, thereby presenting a significant challenge to medical practitioners. According to the results obtained, depending on patients' laboratory data only to predict the failure of liver transplant is not enough, so further research is recommended to add a larger sample size of patients including age, gender, body mass, and the cause of liver failure to increase the accuracy of the system and obtain high credible results. The study can also be applied to study failure in transplanting other organs and expand research to all hospitals and centers within Saudi Arabia.

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