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Liver cirrhosis prediction using logistic regression, naïve bayes and KNN

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Abstract

Liver cirrhosis, often a symptomless blood-borne disease in its early stages, presents significant diagnostic and treatment challenges. As the disease advances, these difficulties only increase. This study introduces an artificial intelligence system based on machine learning to aid healthcare providers in the early detection of liver cirrhosis. With this aim, three distinct predictive models have been developed using a variety of physiological metrics and machine learning techniques including Logistic Regression (LR), Naïve Bayes and KNN Classification. Among these, LR emerges as the most effective, achieving an accuracy of approximately 85%. The models are developed using the openly accessible Liver Cirrhosis data dataset.

Keywords: Liver Cirrhosis; Machine Learning; Logistic Regression; Naïve Bayes and KNN

1. Introduction

Cirrhosis, the end-stage of liver disease characterized by significant fibrosis or scarring, presents a critical challenge in healthcare due to its complex pathogenesis and significant morbidity and mortality rates. Primarily caused by chronic hepatitis infections, alcoholic liver disease, and non-alcoholic fatty liver disease, cirrhosis results in a progressive deterioration of liver function. This leads to various complications, including portal hypertension, ascites, and liver failure, substantially diminishing patient quality of life and necessitating extensive medical interventions.

Liver cirrhosis is a disease that affects the whole human population. It is a blood-borne illness that spreads by direct contact with infected people's blood or blood-containing bodily fluids. Almost 71 million individuals worldwide are chronically unwell because of this condition, and an estimated 399,000 people died from it in 2016 [1]. According to the WHO (World Health Organization), liver cirrhosis is a worldwide illness. According to the research conducted by the WHO, 3–4 million individuals get infected with this virus each year. When compared to wealthy nations in Europe and North America, poor developing Asian and African countries have the greatest frequency of this virus. Furthermore, the number of people suffering from chronic illnesses is increasing in countries such as Pakistan, China, and Egypt [1-2]. Liver cirrhosis virus symptoms appear much later in the disease's progression. Approximately 80% of infected patients do not experience any symptoms after contracting an infection in the early stages, resulting in greater liver damage and higher fatality rates [3]. There is no effective vaccination against the liver cirrhosis virus. As a result, determining the

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extent to which the afflicted patient's liver has been damaged may benefit doctors in the diagnosis and treatment of chronic infection as well as in its effective management [4-7].

The traditional approach to managing cirrhosis involves a combination of clinical assessments, imaging studies, and invasive liver biopsies. However, these methods often come with limitations, such as the invasiveness of biopsies and the subjectivity of imaging and physical examination findings. Moreover, the asymptomatic nature of early cirrhosis often leads to delayed diagnosis until serious complications arise, underlining the need for more proactive and less invasive diagnostic techniques [8-10].

In recent years, machine learning (ML) has emerged as a transformative tool in the medical field, offering novel avenues for enhancing diagnostic accuracy and patient care. By leveraging large datasets and identifying complex patterns that may not be discernible through traditional analyses, ML algorithms can significantly improve the prediction and management of diseases like cirrhosis.

The potential of ML in cirrhosis management is multifaceted. First, predictive models can be developed to identify individuals at high risk of developing cirrhosis, enabling earlier interventions that could prevent progression to severe stages. Second, machine learning can enhance the prediction of disease complications, such as the development of hepatocellular carcinoma or acute variceal bleeding, thus optimizing the monitoring strategies and therapeutic approaches for at-risk patients.

Moreover, ML models can integrate diverse data types, including clinical variables, laboratory results, imaging data, and even genetic information, to create comprehensive risk profiles and personalized treatment plans. This holistic approach not only promises to improve patient outcomes through tailored therapies but also enhances resource allocation within healthcare systems by identifying which patients require the most immediate and intensive care [11-15].

Research in this area often involves analyzing retrospective patient data to develop and validate models. For instance, studies involving patients with primary biliary cholangitis (PBC) referred to major medical centers can provide valuable insights into the progression of liver disease. Such datasets enable the training of robust ML models that can predict survival rates, likelihood of disease progression, and responses to specific treatments like D-penicillamine.

As the field progresses, collaboration between clinicians, data scientists, and statisticians will be crucial in addressing the ethical, practical, and technical challenges of implementing ML in clinical settings. Ensuring the accuracy, transparency, and fairness of these models is paramount to their acceptance and effectiveness in real-world scenarios.

In conclusion, machine learning represents a promising frontier in the battle against cirrhosis. By harnessing the power of advanced analytics and vast datasets, healthcare providers can revolutionize the diagnosis and management of cirrhosis, potentially reducing the disease burden and improving outcomes for millions of affected individuals worldwide. [16-20, 33-42].

2. Literature Reviews

Machine learning approaches have shown promising results in identifying the stages of liver cirrhosis, with some studies focusing on the integration of clinical and imaging data to refine prediction models.

For instance, machine learning models that analyze gut microbiome data have been effective in predicting liver fibrosis and cirrhosis. These models utilize statistical methods such as the bivariate mixed-effects model to evaluate diagnostic accuracy metrics like sensitivity and specificity, alongside advanced visualizations like summary receiver operating characteristic curves (SROC) [21].

Another significant contribution comes from integrating artificial intelligence (AI) with imaging modalities like ultrasonography and MRI, which have been used to enhance the diagnostic precision of liver fibrosis and non-alcoholic fatty liver disease (NAFLD). Such studies typically employ a variety of AI techniques, including deep learning, to analyze image data, providing insights into the disease's progression and aiding in early diagnosis [22].

Additionally, statistical machine learning techniques, such as support vector machines (SVM) and artificial neural networks (ANN), have been applied to predict liver disease based on clinical and laboratory data. These models often utilize principal component analysis (PCA) and other data preprocessing techniques like SMOTE (Synthetic Minority Over-sampling Technique) to balance datasets and improve model performance [23].

Singh et al. developed a software that employs various classification algorithms, such as logistic regression, random forest, and naive Bayes, to predict liver disease risk using liver function test results [24]. Vijayarani and Dhavanand compared different machine learning techniques and found that support vector machines (SVM) outperformed naive Bayes in diagnosing conditions like cirrhosis, acute and chronic hepatitis, and liver cancers from liver function tests [25]. In another study, an SVM enhanced with particle swarm optimization (PSO) was more effective in identifying crucial features for liver disease detection, achieving higher accuracy compared to SVM alone, random forest, Bayesian networks, and MLP-neural networks [26]. Additionally, SVM was also noted for its superior performance in predicting drug-induced hepatotoxicity using fewer molecular descriptors than Bayesian and other models previously applied [27].

Overall, the literature suggests that machine learning can substantially improve the prediction of cirrhosis and its complications, leading to better patient outcomes through earlier and more accurate diagnoses. The development of these models relies heavily on high-quality data and rigorous validation to ensure their efficacy in clinical settings.

3. Methodology

In this study, our main aim is to develop an effective cirrhosis detection system by using different machine learning models.

3.1. Dataset

Cirrhosis, a severe form of liver scarring due to various liver conditions including hepatitis and chronic alcohol use, was studied in 424 PBC patients [28] who were referred to the Mayo Clinic over a ten-year period. These patients were eligible for a placebo-controlled, randomized trial using the drug D-penicillamine. The dataset includes 312 patients who participated in this trial and for whom comprehensive data is available. The remaining 112 patients, while not participating in the trial, agreed to have essential health metrics recorded and to be monitored for survival outcomes. Figure 1 shows the histogram distribution by Albumin feature. Figure 2 shows the distribution of cholesterol based on gender.

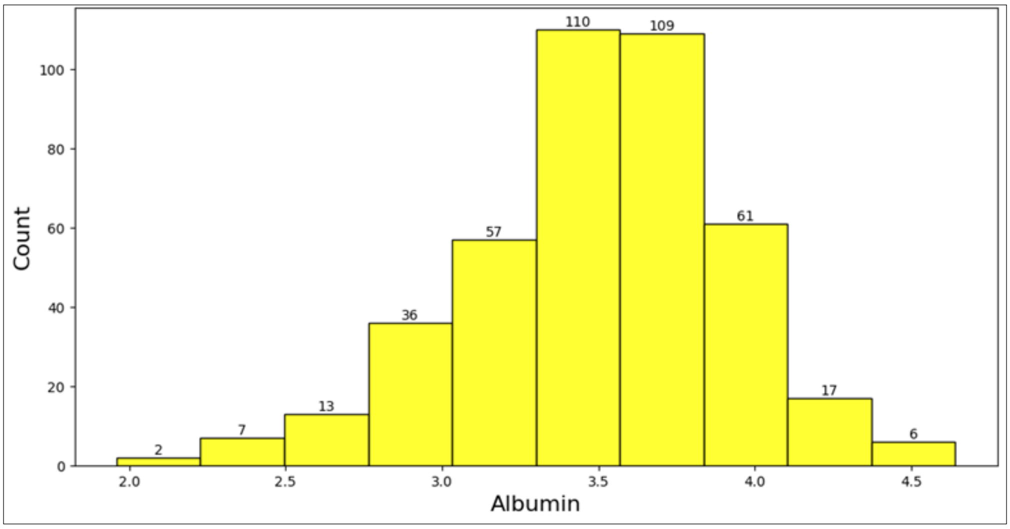

Figure 1 Distribution by Albumin

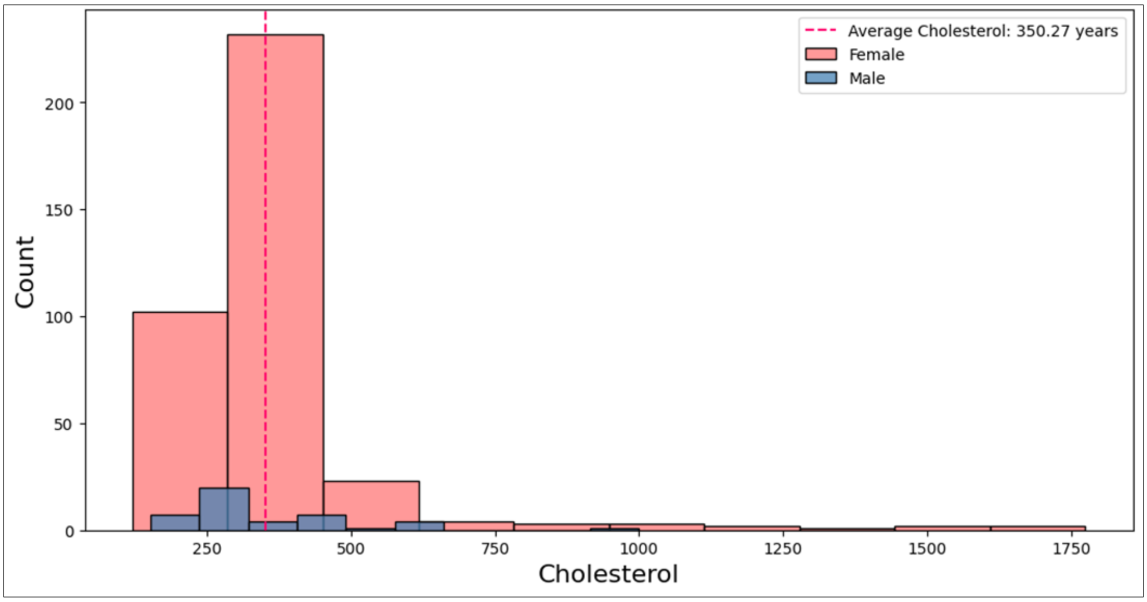

Figure 2 Distribution of Cholesterol based on Gender

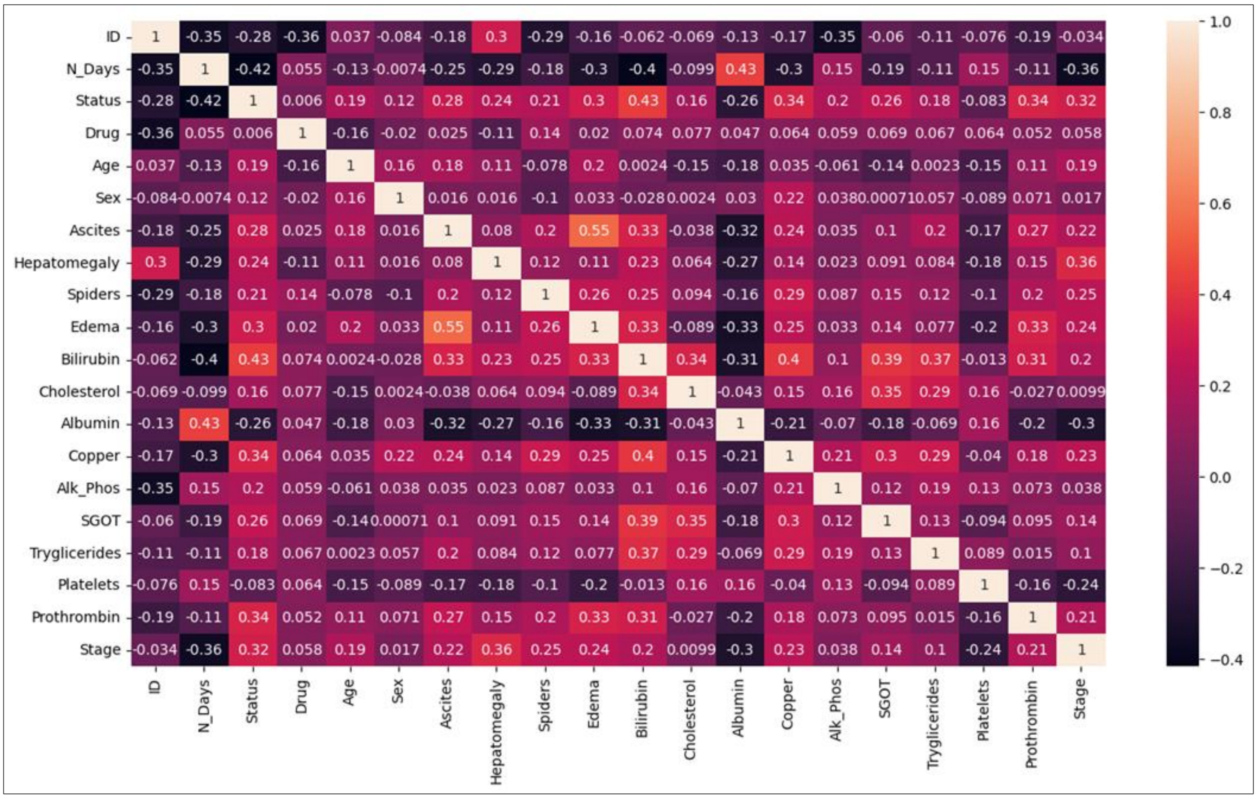

Figure 3 Correlation heatmap

The variables listed in figure 3 along the axes include clinical attributes and test results such as the number of days (N_Days), patient status, medication (Drug), age, sex, presence of ascites, hepatomegaly, spider angiomas (Spiders), edema, levels of bilirubin, cholesterol, albumin, copper, alkaline phosphatase (Alk_Phos), SGOT (a type of liver enzyme), triglycerides, platelets count, prothrombin time, and disease stage. High positive correlations (darker red) are visible between variables like bilirubin and edema, which could indicate that as bilirubin levels increase, so does the severity of edema, a common symptom in advanced liver disease.

Negative correlations (darker blue), though not as strong, are seen in a few spots such as between albumin and bilirubin, suggesting that higher bilirubin levels might be associated with lower albumin levels, a pattern seen in liver dysfunction.

3.2. Description of ML Models

3.2.1. Logistic Regression

Logistic Regression is a statistical model commonly used for binary classification. It predicts the probability of the dependent variable (with two categories) based on one or more independent variables. The model uses the logistic function (or sigmoid function) to squeeze the output of a linear equation between 0 and 1. This probability is then transformed into a binary outcome via a decision threshold (typically 0.5). Logistic Regression is easy to implement and interpret, making it widely used for binary classification problems such as spam detection, disease diagnosis, and credit scoring [37, 38].

3.2.2. Naive Bayes

Naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naive) independence assumptions between the features. They are incredibly efficient in processing large datasets and perform well with categorical input variables compared to numerical variables. Despite their simplicity, Naive Bayes classifiers can outperform more sophisticated classification methods. They are particularly popular in text classification problems such as spam filtering and sentiment analysis due to their effectiveness in handling large volumes of data.

3.2.3. K-Nearest Neighbors (KNN)

KNN is a type of instance-based or lazy learning algorithm, where the function is only approximated locally and all computation is deferred until function evaluation. It's a non-parametric method used for both classification and regression. For classification, KNN assigns a class to a new data point based on the majority vote of its 'K' nearest neighbors, where K is a user-specified number. The data point is assigned to the class most common among its nearest neighbors. KNN is very intuitive and simple to implement but becomes significantly slower as the size of the data in use grows [31, 32].

4. Experimental Results

This section describes the experimental results. Jupyter notebook, scikit learn library, python programming is used for the experiment. Figure 4 shows the top features based on feature ranking. SelectKBest is used for raking the features of the dataset. Top feature is Billirubin with a score of 46.9953.

Figure 5 shows classification reports for three ML models where the target classes are C (censored), CL (censored due to liver transplantation), and D (death). LR exhibits strong performance for C and D with high precision, recall, and F1-scores (C: 0.81, 0.95, 0.88; D: 0.91, 0.81, 0.85), but it completely fails to classify CL (precision, recall, F1-score all 0). NB, despite having perfect precision for C, performs poorly due to very low recall (0.16) and similarly struggles with D (precision: 0.79, recall: 0.42, F1-score: 0.55), though it identifies CL accurately (recall: 1.00) with low precision. KNN shows balanced results for C (0.73, 0.91, 0.81) and D (0.86, 0.69, 0.77) but fails to classify CL (all metrics 0). Overall, LR and KNN perform similarly well for C and D, but both models struggle with CL, highlighting a common challenge across these classifiers.

The confusion matrix or evaluation matrix is seen in Figure 7. A machine learning classification algorithm's performance may be evaluated using a confusion matrix. All of the models have been tested using the confusion matrix. The confusion matrix shows how accurate our models are and how inaccurate they are. While false positives and false negatives are attributed to incorrectly predicted values, genuine positives and negative values are assigned to correctly predicted values. The model's accuracy, precision-recall trade-off, and AUC are used to assess its performance after grouping all of the predicted values in a matrix. Figure 8 shows the ROC curve.

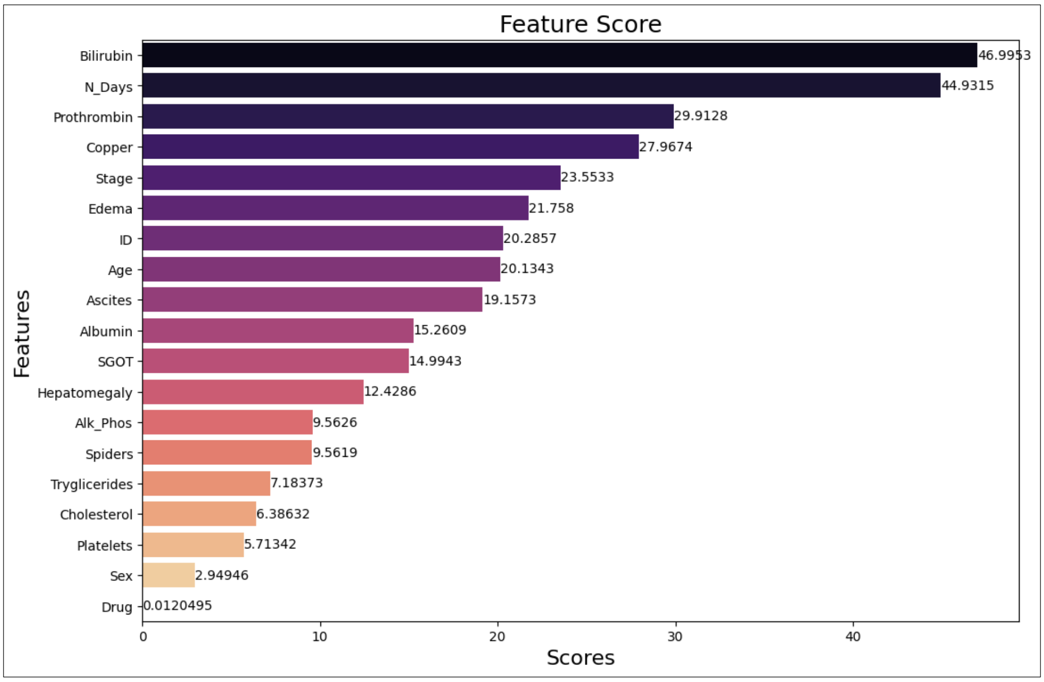

Figure 4 Feature Ranking

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Classification Report for LogisticRegression:
              precision    recall  f1-score   support

           0       0.81      0.95      0.88        44
           1       0.00      0.00      0.00         4
           2       0.91      0.81      0.85        36

    accuracy                           0.85        84
   macro avg       0.57      0.59      0.58        84
weighted avg       0.81      0.85      0.82        84

Classification Report for NaiveBayes:
              precision    recall  f1-score   support

           0       1.00      0.16      0.27        44
           1       0.07      1.00      0.13         4
           2       0.79      0.42      0.55        36

    accuracy                           0.31        84
   macro avg       0.62      0.53      0.32        84
weighted avg       0.87      0.31      0.38        84

Classification Report for KNN:
              precision    recall  f1-score   support

           0       0.73      0.91      0.81        44
           1       0.00      0.00      0.00         4
           2       0.86      0.69      0.77        36

    accuracy                           0.77        84
   macro avg       0.53      0.53      0.53        84
weighted avg       0.75      0.77      0.75        84
```

Figure 5 Classification report of Logistic Regression, Naïve Bayes and KNN

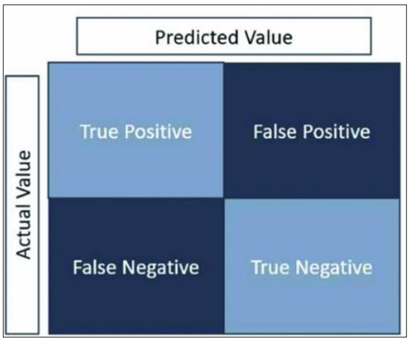

Figure 6 Confusion Matrix [2]

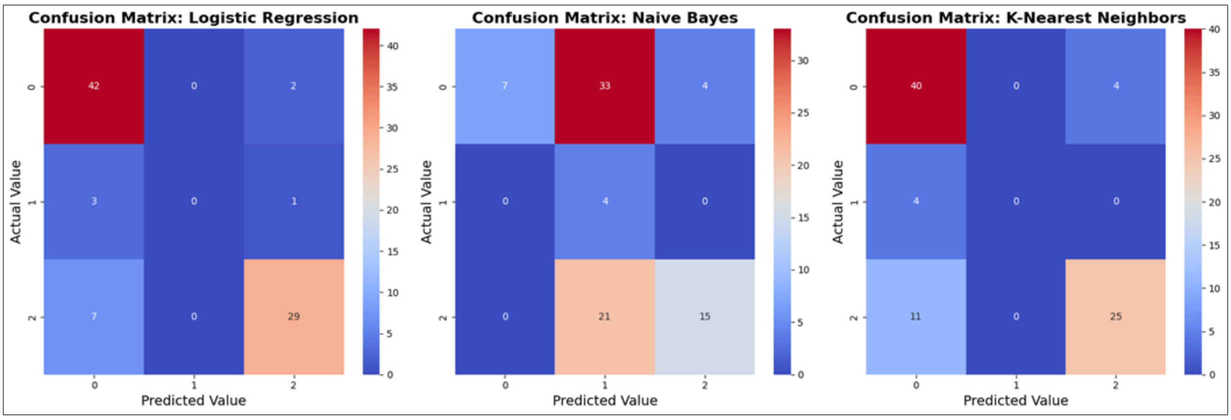

Figure 7 Confusion Matrix of three ML models

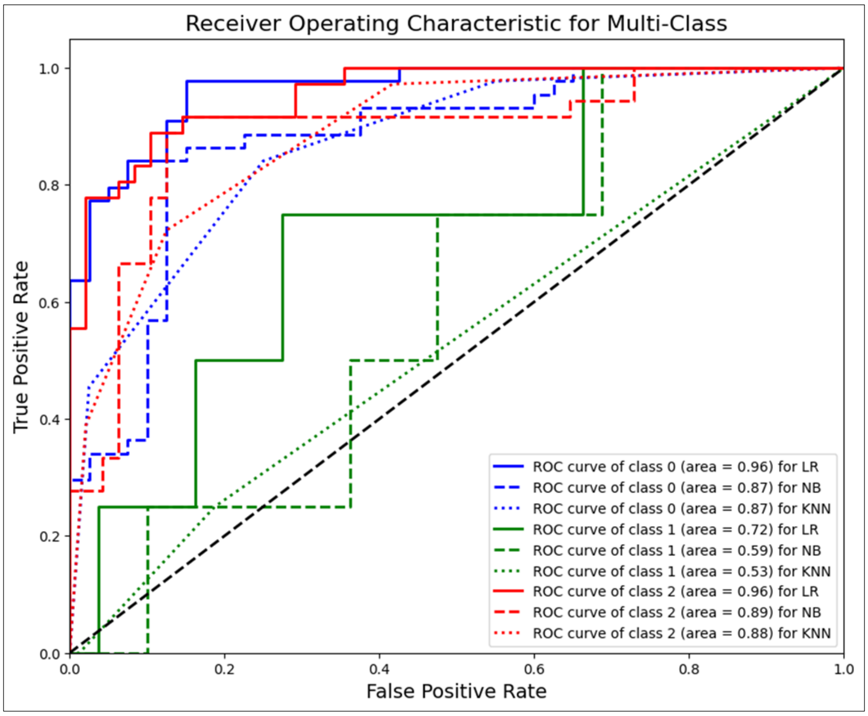

Figure 8 ROC curve

5. Conclusion

Cirrhosis, a potentially deadly infection, requires immediate attention to prevent severe health issues. Developing machine learning models could significantly aid in detecting cirrhosis early, potentially reducing its long-term detrimental health effects. Various machine learning algorithms have been tested for their ability to predict liver infections from different physiological indicators, showing promise for future enhancements in medical frameworks. These enhancements are expected to bolster the reliability and functionality of these systems. Moreover, machine learning solutions could assist the general public in assessing the risk of serious conditions like stroke in adults. Ideally, patients with liver disease (LD) would benefit from early diagnosis and treatment, allowing them a chance to effectively manage and recover from their condition.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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