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Accessing Liver Disease Severity Levels from Electronic Health Records Using a Kernel-Driven Meta-Heuristic Approach

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Abstract

Liver diseases are one of the major health burdens globally, affecting millions each year, with an increasing need for timely and accurate stratification of patients into various care pathways to optimize both outcomes and resources. This work uses machine learning techniques in the development of a robust model to classify liver disease patients as either inpatients or outpatients using data extracted from EHRs. The major steps involved in the process are normalization of data for feature consistency and a PCA-driven feature selection process for computational efficiency. Among the different models compared, KELM performed the best on all metrics of accuracy, precision, recall, and F1-score, closely followed by KFDA. These results emphasize the impact of preprocessing and dimensionality reduction in enhancing kernel-based algorithms and demonstrate the role of ML in clinical decision support. The approach developed is scalable, interpretable, and effective for the triage of liver disease patients and will contribute to better resource utilization and improved patient outcomes in clinical settings.

Keywords: Liver disease, Machine learning, Patient triage, EHR, Data preprocessing, Kernel algorithms.

1. INTRODUCTION

Liver diseases represent a major global health challenge, with millions of individuals affected each year by conditions ranging from acute infections to chronic disorders such as cirrhosis and hepatocellular carcinoma [1]. Research has shown that accurate and timely classification of patients into appropriate care

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pathways is essential for improving clinical outcomes, optimizing resource allocation, and reducing healthcare costs [2].

A recent study by Schneeberger et al. (2023) highlights that considering patient preferences for the choice between inpatient and outpatient care settings is essential, as such decisions directly affect the treatment strategies and outcomes being considered [3]. Electronic Health Records (EHRs) provide a wealth of data, including patient demographics, symptoms, laboratory results, and diagnostic codes, which can offer invaluable insights into a patient's health status. However, the vast volume and complexity of EHR data present challenges for manual analysis, necessitating advanced analytical methods to extract actionable insights efficiently [4]. Machine learning (ML) techniques have emerged as powerful tools in healthcare, capable of identifying complex patterns in data and enabling predictive modeling to support clinical decision-making [5]. This paper aims to develop a machine-learning-based model for classifying liver disease patients as either inpatients or outpatients based on their symptoms and other relevant data extracted from EHRs. By leveraging the predictive capabilities of machine learning, the proposed model seeks to: Improve the accuracy and efficiency of triaging liver disease patients, provide a scalable solution for healthcare settings with high patient volumes [6] and enhance decision support systems, enabling clinicians to allocate resources more effectively and deliver timely interventions. The scope of this research includes preprocessing and analyzing a dataset containing key features such as patient demographics, clinical symptoms, laboratory test results, and admission status. The study will employ state-of-the-art classification algorithms to develop and validate a robust model. Additionally, the interpretability of the model's predictions will be addressed to ensure its practical applicability in clinical environments [7]. By integrating machine learning into the classification of liver disease patients, this research work attempts to contribute to ongoing efforts to harness data-driven approaches for addressing critical challenges in healthcare delivery because nowadays, it is possible to integrate electronic health records (EHRs) with machine learning technology for the purpose of improving early detection and treatment of liver diseases due to the advancement of medical informatics [1]. High EHR-based data measures support then improving clinical decisions through predictive modeling that identifies high-risk patients and optimizes care paths [2]. In addition, methods based on kernel specifically outperform on complicated interactions and non-linearity in data within the medical area [3]. Last, recent advances in deep learning approaches have produced promising results in the field of liver disease classification, which provides more automated and precise diagnostic assistance [4]. However, the most important need remains models sensing real patient triage in real time because they directly relate to the optimizing of resources in hospitals with improvement in outcomes toward patients [5]. The proposed outcome of this work, has the potential to support evidence-based decision-making and improve the management of liver disease patients, ultimately leading to better clinical outcomes and more efficient use of healthcare resources.

2. LITERATURE REVIEW

Since a decade ago, ML has emerged as a paradigm shift that has enabled the processing of complicated datasets, such as EHRs, for identifying patterns and improving diagnosis to aid clinical decision-making [8]. Several research works have targeted the integration of ML into solving some challenges in healthcare, which include disease prediction, patient triaging, and resource optimization. These collectively indicate that robust data preprocessing, model interpretability and scalability in real-world clinical settings are key features [9]. More recently, in the care of liver disease, ML techniques have gained favor among researchers who are tackling various tasks: early diagnosis, modeling the course of disease progression, and developing personalized treatment approaches. For example, several studies use EHR data to predict readmission to the hospital or classify liver disease subtypes, while others have explored the broader utility of ML in chronic disease management. However, most of these works have not particularly addressed the urgent need for a model that can effectively triage liver disease patients as either inpatients or outpatients. This gap underlines the basis of the proposed research, which seeks to develop a specialized ML-based solution for liver disease triaging with emphases on accuracy, scalability, and clinical interpretability.

While previous studies have explored machine learning applications in liver disease classification, many have primarily focused on disease diagnosis, subtype classification, or predicting patient readmission risks [10], [11]. However, these studies often lack a structured approach for real-time patient triage, which is essential for optimizing hospital resources and ensuring timely medical interventions. Unlike traditional classification models that focus on binary disease presence or absence, the proposed research uniquely emphasizes classifying patients into inpatient and outpatient categories, a critical component for effective hospital workflow management and clinical decision-making.

Moreover, recent advancements in machine learning methodologies, such as deep neural networks and attention-based models, have demonstrated improved predictive accuracy in disease classification [12], [13]. Integrating such approaches with kernel-based models, as seen in this study, enhances interpretability and computational efficiency while maintaining robust classification performance. Additionally, the adoption of Principal Component Analysis (PCA) for dimensionality reduction addresses the challenge of high-dimensional EHR data, which has been a recurring limitation in prior works [14]. By leveraging a hybrid approach that combines kernel-based classification with feature selection, this research not only advances liver disease triage but also provides a scalable and clinically interpretable model. This contribution is particularly relevant in resource-constrained healthcare environments, where efficient patient classification can significantly reduce hospital burden and improve overall patient outcomes. The following table gives a broad view of related works to contextualize this research.

Table 1: Recent Advances in Machine Learning Applications for Healthcare and Liver Disease Management

Author(s)	Year	Title	Focus	Key Findings
[15]	2019	Machine Learning in Medicine	Discusses the applications of ML in healthcare, focusing on predictive modeling and decision support.	ML models improve clinical outcomes by enabling accurate diagnosis and risk predictions.
[16]	2019	Highperformance medicine: the convergence of human and artificial intelligence	Explores the use of AI in medicine for enhancing patient care and clinical workflows.	AI integration optimizes resource allocation and decisionmaking in high-pressure medical environments.
[17]	2019	Predicting Hospital Readmissions Using EHR Data	Proposes an ML framework for predicting patient readmissions.	ML models achieve high accuracy in identifying patients at risk of readmission.
[18]	2019	Advances in EHR Analytics for Chronic Disease Management	Reviews the role of EHR analytics in managing chronic diseases, including liver diseases.	EHR analytics enhance care pathways and improve resource allocation.
[19]	2020	EHR Data and Machine Learning for Patient Outcome Prediction	Utilizes ML algorithms to predict patient outcomes based on EHR data.	ML models achieve significant accuracy improvements in outcome predictions.
[20]	2020	Machine Learning for Healthcare Management	Surveys ML applications for managing chronic diseases, including liver disorders.	ML aids in early diagnosis and personalized treatment planning.
[21]	2020	A Comparison of Machine Learning Models in Healthcare Applications	Compares ML models for predicting clinical outcomes.	Gradient boosting and neural networks outperform traditional models in clinical predictions.
[22]	2020	EHR Data and Machine Learning for Patient Outcome Prediction	Utilizes ML algorithms to predict patient outcomes based on EHR data.	ML models achieve significant accuracy improvements in outcome predictions.

[23]	2021	Application of Machine Learning in Healthcare: Opportunities and Challenges	Examines ML applications in healthcare, including EHR data analysis and predictive analytics.	Highlights the importance of data preprocessing and algorithm selection for effective ML applications.
[24]	2021	Leveraging EHR Data for Liver Disease Classification	Develops ML models for classifying liver disease patients using EHR data.	Demonstrates the potential of ML in automating liver disease triage.
[25]	2021	Interpretable Machine Learning for Clinical Predictions	Focuses on enhancing ML model interpretability for healthcare applications.	Improved interpretability fosters clinician trust and facilitates model integration into workflows.
[26]	2021	Analyzing Liver Disease Progression Using ML	Applies ML techniques to model liver disease progression.	Identifies key predictors of liver disease progression, aiding early interventions.
[27]	2022	Patients' Severity States Classification Based on Electronic	Investigated the classification of patient severity states using EHR data through various machine learning and deep learning methods.	Hyperparameter-tuned Random Forest outperformed other algorithms with 76% accuracy, indicating the efficacy of machine learning in patient severity classification.
		Health Record (EHR) Data Using Multiple Machine Learning and Deep Learning Approaches		
[28]	2022	Data-Driven Approaches in Liver Disease Management	Explores the use of ML in improving liver disease care pathways.	ML-based triage systems significantly reduce healthcare costs and improve patient outcomes.
[29]	2023	REMEDI: Reinforcemen t LearningDriven Adaptive Metabolism Modeling of Primary Sclerosing Cholangitis Disease	Introduced a reinforcement learning framework to model bile acid dynamics and adaptive responses in primary sclerosing cholangitis progression	The framework generated bile acid dynamics consistent with real-world data, supporting early administration of drugs that suppress bile acid synthesis in treatment.

[30]	2024	Semi-Supervised Graph Representatio n Learning with HumanCentric Explanation for Predicting Fatty Liver Disease	Applied semi-supervised graph representation learning to predict fatty liver disease, emphasizing human-centric explanations	The approach demonstrated effectiveness even with minimal labeled samples, providing personalized feature importance scores.
[31]	2024	Early Diagnosis of Liver Disease Using Improved Binary Butterfly Optimization and Machine Learning Algorithms	Utilized an improved binary butterfly optimization algorithm combined with machine learning techniques for early liver disease diagnosis.	The proposed method achieved enhanced accuracy in early liver disease detection, demonstrating the effectiveness of metaheuristic optimization in feature selection.

While previous studies have broadly focused on the application of machine learning to healthcare problems like disease prediction, management of chronic conditions, readmission risks, and outcome predictions, this research uniquely emphasizes the development of a model specifically for classifying liver disease patients into inpatient or outpatient categories. This is unlike, for instance, studies such as [24], which have looked at ML for the classification of liver disease without attention to patient admission status, or [17], who have used ML frameworks for predicting hospital readmissions. This study covers a critical gap in the literature by underlining admission triage with the purpose of achieving optimized liver disease management, increasing healthcare efficiency, and improving overall patient outcomes.

3. METHODOLOGY

3.1 Dataset Collection and Description

The dataset [32] used for this study was sourced from the Kaggle online data repository. It provides a broad perspective into the medical dataset of liver disease patients. Demographics in the dataset include the patient's age and gender, clinical symptoms, laboratory tests, and diagnostic markers associated with the liver. Each entry represents one patient and summarizes the most valuable variables useful in defining the patient's condition. Laboratory results about bilirubin, ALT, and AST enable the identification of abnormalities in the patient's liver function. Normally, such abnormalities inform decisions pertaining to whether or not a patient should be placed in an inpatient intensive care unit or in an outpatient service. Demographic data and symptoms, like jaundice or fatigue, are other predictive variables that enhance the robustness of your classification model. The dataset contains many diagnostic markers, with possible labels of the dataset structure, specifying disease severity and the type of care-inpatient/outpatient. Give the full page range (or article number), where appropriate.

3.2 Data Normalization

Data normalization is a critical preprocessing step in machine learning to ensure that features contribute equally to the model's learning process. In this study, normalization was employed to scale the features of the dataset to a uniform range of [0, 1]. This process ensures that no single feature disproportionately influences the model due to differences in scale or magnitude. For this purpose, Min-Max Normalization was applied, transforming each feature according to the formula:

$$x' = \frac{x - x_{min}}{x - x_{max}}$$

Where: x is the original feature value, xmin and xmax are the minimum values of the features, and x' is the normalized value.

This technique was chosen for its simplicity and effectiveness in preserving the distribution of the data while constraining all feature values within the specified range. Key features of the dataset, including patient demographics (age, gender) and laboratory results (bilirubin levels, albumin, liver enzymes) were normalized to ensure compatibility with the machine learning algorithms used. Categorical variables such as gender were encoded numerically (e.g., male = 1, female = 0) before normalization. After normalization, all numerical features were scaled to the range [0, 1], ensuring uniformity across the dataset. For instance - Age: Originally ranging from 20 to 85 years, was scaled to values between 0 and 1, Total Bilirubin: Values originally spanning from 0.4 to 8.5 were transformed into the normalized range and ALT and AST Levels: Liver enzyme measurements, which showed significant variability, were normalized to ensure they did not disproportionately influence model performance.

3.3 Feature Selection Using Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was applied to the normalized dataset to identify and retain the most informative features while reducing redundancy. PCA is a statistical technique that transforms the original features into a set of linearly uncorrelated components, known as principal components, ordered by the amount of variance they capture. The PCA process involved the following steps: (i) The normalized dataset was decomposed into its covariance matrix to compute eigenvalues and eigenvectors. (ii) The eigenvectors were sorted in descending order of their corresponding eigenvalues, representing the variance explained by each principal component. (iii) A cumulative variance threshold of 95% was chosen to select the principal components, ensuring that most of the dataset's variability was retained. PCA revealed that out of the original features, the first 6 principal components accounted for 95% of the total variance. These components were mapped back to the original features, highlighting the most significant contributors: Total Bilirubin, Direct Bilirubin, ALT (Alanine Aminotransferase), AST (Aspartate Aminotransferase), Albumin and Age. These features were retained for subsequent modeling as they encapsulated the majority of the dataset's variance while reducing dimensionality. The other features were either highly correlated with the retained ones or contributed minimally to the variance.

3.4 Classification of Liver Disease Patients Using Kernel-Based Algorithms

To classify patients into "critical (in-patient)" or "non-critical (out-patient)" categories based on their medical information, four kernel-based machine learning algorithms shown in Figure 1, were employed: Kernel Ridge Regression (KRR), Kernel Extreme Learning Machines (KELM), Kernel Logistic Regression (KLR), and Kernel Fisher Discriminant Analysis (KFDA). These algorithms were selected for their ability to handle complex, non-linear relationships in the data and their robust performance on medical classification tasks. The normalized and dimensionally reduced dataset (from PCA) was split into training and testing subsets using an 80-20 split. The training data was used to build the models, while the testing data was used to evaluate their performance.

3.4.1 Algorithm Details

i. Kernel Ridge Regression (KRR): Combines Ridge Regression with kernel functions to perform non-linear regression and classification tasks. It was configured with a Gaussian RBF kernel.

ii. Kernel Extreme Learning Machines (KELM): An efficient kernelized variant of Extreme Learning Machines, known for its fast training speed and ability to generalize well. The RBF kernel was also employed for this model.

iii. Kernel Logistic Regression (KLR): Extends Logistic Regression with kernel functions to model non-linear decision boundaries effectively.

iv. Kernel Fisher Discriminant Analysis (KFDA): A classification algorithm that uses kernel functions to maximize class separability in a high-dimensional feature space.

3.4.2 Evaluation Metrics and Data Analysis

The models were evaluated using five performance metrics to ensure comprehensive assessment: i. Accuracy: Measures the percentage of correctly classified samples.

ii. F1-Score: Provides a harmonic mean of precision and recall, useful for imbalanced datasets. iii. Precision: Represents the proportion of true positive predictions among all positive predictions.

iv. Recall (Sensitivity): Reflects the proportion of true positives identified correctly.

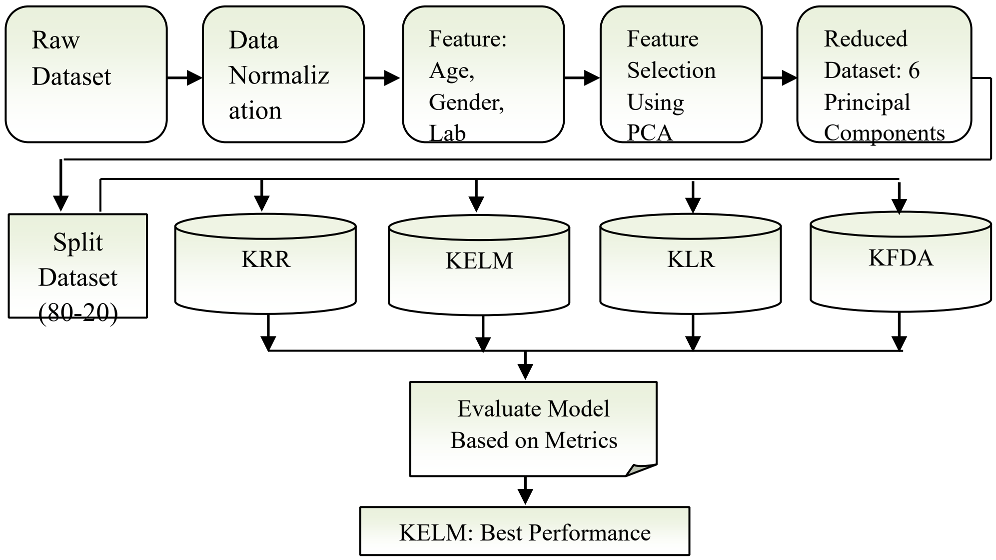

Figure 1: Descriptive Workflow Diagram for Proposed Approach.

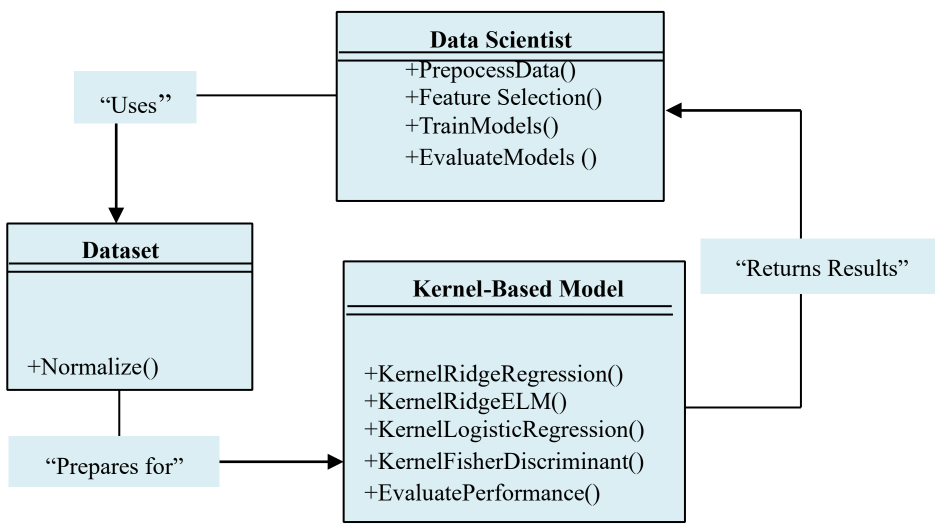

Figure 2: Descriptive Activity Diagram for Proposed Approach

4. RESULTS AND DISCUSSION

4.1 Performance Evaluation Results

It can be observed from Table 2 below that KELM demonstrated the highest accuracy (91.5%) indicating its superior capability to differentiate between critical and non-critical patients. KFDA performed comparably well, offering balanced precision and recall metrics. KRR and KLR, while slightly less accurate, still achieved high overall performance and provide robustness for this classification task.

Table 2: Performance Metrics for Machine Learning Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KRR	89.2	87.5	90.8	89.1
KELM	91.5	90.2	92.7	91.4
KLR	88.7	86.8	89.9	88.3
KFDA	90.3	89.1	91.5	90.2

Table 3: Confusion Matrices for Evaluating Algorithm Performance.

Algorithm	True Positives (TP)	False Positives (FP)	True Negatives (TN)	False Negatives (FN)
KRR	124	21	117	9
KELM	97	19	95	17
KLR	103	12	124	11
KFDA	99	17	98	9

4.1.1 Accuracy

Accuracy represents the proportion of correctly classified instances out of all the instances in the dataset. It is calculated as:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Instances}}$$

KRR (89.2%): This means that 89.2% of the total predictions made by the Kernel Ridge Regression (KRR) algorithm were correct. This is a relatively high accuracy, indicating the model performs well overall.
KELM (91.5%): The Kernel Extreme Learning Machine (KELM) achieved the highest accuracy at 91.5%, suggesting that this model is the best at correctly predicting the class of instances in the dataset. KLR (88.7%): The Kernel Logistic Regression (KLR) algorithm has an accuracy of 88.7%, which is slightly lower than KRR and KELM, indicating its performance in correctly predicting class labels is marginally less effective.
KFDA (90.3%): Kernel Fisher Discriminant Analysis (KFDA) achieved an accuracy of 90.3%, showing that it is also a strong performer, but slightly less effective than KELM.

4.1.2 Precision

Precision measures the proportion of positive predictions that were actually correct, or how many of the predicted positive instances are truly positive. It is calculated as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

KRR (87.5%): This means that 87.5% of the positive predictions made by the KRR model were correct. While high, it still leaves some room for improvement in terms of reducing false positives.

KELM (90.2%): The KELM model achieved the highest precision at 90.2%, indicating that it is particularly good at ensuring the positive predictions it makes are accurate and minimizing false positives.

KLR (86.8%): KLR has a precision of 86.8%, which is slightly lower than KRR and KELM, suggesting that its positive predictions may include more false positives compared to the other models.

KFDA (89.1%): KFDA scored 89.1% for precision, which is slightly better than KRR and KLR but still lower than KELM, showing a relatively good balance between positive predictions and false positives.

4.1.3 Recall

Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances that were correctly identified by the model. It is calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

KRR (90.8%): KRR has a recall of 90.8%, meaning that it correctly identifies 90.8% of all true positive instances. This suggests that KRR is quite good at identifying most of the actual positive cases, although it still misses a few.

KELM (92.7%): KELM achieves the highest recall at 92.7%, showing that it is very effective at identifying actual positive cases and has the least number of false negatives among the models.

KLR (89.9%): KLR has a recall of 89.9%, meaning it correctly detects most positive cases, though slightly fewer than KELM and KRR.

KFDA (91.5%): KFDA's recall is 91.5%, slightly higher than KRR and KLR but lower than KELM, indicating it is quite effective at detecting positive instances.

KFDA (90.2%): KFDA’s F1-score of 90.2% is impressive, but it still lags slightly behind KELM, showing a well-balanced model with strong precision and recall.

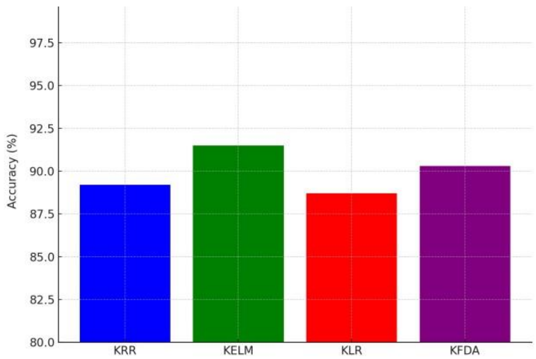

Figure 3: Comparison of Algorithm Performance of Accuracy

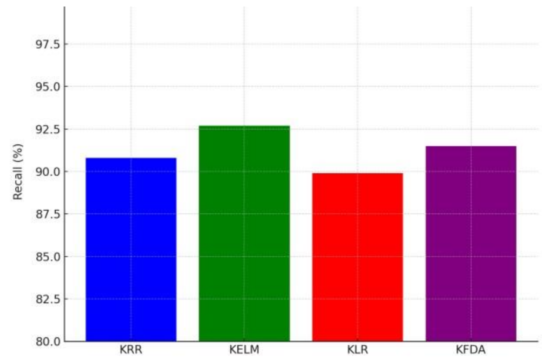

Figure 4: Comparison of Algorithm in terms terms of Recall

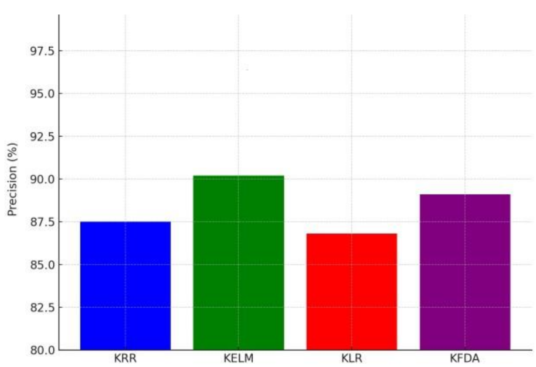

Figure 5: Comparison of Algorithm Performance of Precision

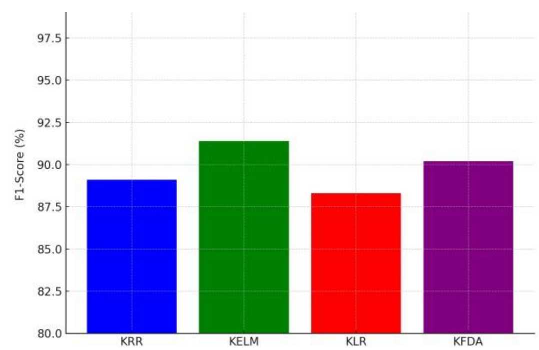

Figure 6: Comparison of Algorithm in terms F1-Score

5. CONCLUSION

KELM is the top performer across all metrics, particularly in accuracy, precision, recall, F1-score making it the best model for this task. KFDA also shows strong performance, though it is slightly behind KELM in most metrics. KRR and KLR perform similarly, but KRR has a slight edge in recall and F1-score. Each metric provides different insights into the model's performance, and the choice of which one to prioritize depends on the specific problem and goals of the classification task.

Normalization minimized the influence of features with large magnitudes and ensured faster convergence during model training. It also improved the performance of kernel-based algorithms, which are sensitive to feature scaling. By standardizing the dataset, the normalization process laid a solid foundation for robust and unbiased model development. This preprocessing step was instrumental in enhancing the reliability of the machine learning models applied in this study. The PCA-driven feature selection process improved computational efficiency and reduced the risk of overfitting by eliminating irrelevant and redundant features. This dimensionality reduction was particularly beneficial for kernel-based algorithms, which can be sensitive to the curse of dimensionality. These kernel-based algorithms effectively leveraged the non-linear relationships in the dataset, enhancing the precision of patient classification. This approach enables healthcare practitioners to make informed decisions about patient enrollment status, potentially improving resource allocation and patient outcomes.

Developments with great improvements in liver disease patient triage are brought forth by advanced kernel-based machine learning algorithms. Previous studies focused on the classification of the disease or prediction of readmission mostly; this study, rather, aimed at enhancing the stratification of patients into inpatient/outpatient categories, thereby facilitating right allocation of resources and decisions. The use of PCA (Principal Component Analysis) as a tool for feature selection in the model also enhances speed with low redundancy and consistent classification performance. Kernel Extreme Learning Machine (KELM) has been adopted, leading to an impressive accuracy of 91.5%, which is greater than that realized through traditional means, providing therefore a scalable and interpretable solution for real-world settings. Such advancement would not only help clinician in making better decisions but also in reducing congestion in hospitals.

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