Research article

Emergency triage classification with machine learning. A Colombian Case

Clasificación de triaje de emergencia con aprendizaje automático. Un caso colombiano

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Abstract

Introduction. This study presents innovative research on classifying emergency department patients using advanced machine-learning techniques. **Objective.** Provide a decision-support tool for identifying patients who require urgent intervention promptly. **Method.** A balanced Random Forest model was developed, which showed promising triage results. The approach created triage subcategories and assigned different priorities based on critical status. **Results.** The results were encouraging, with an accuracy of 80.14% for high-priority patients, 79.45% for referred patients, and 81.29% for patients who ultimately died. **Conclusion.** The findings support the model's effectiveness in improving decision-making in emergency departments. The research aims to enhance patient classification efficiency, optimize resource allocation, and ensure timely care. It provides new insights and can benefit healthcare professionals by improving the quality of emergency care.

Keywords: Machine Learning, Classification Algorithms, Data Analysis, Operations Research, Emergencies, Triage

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Resumen

Introducción. Este estudio presenta una investigación innovadora sobre la clasificación de pacientes en servicios de urgencias mediante técnicas avanzadas de aprendizaje automático. **Objetivo.** Proporcionar una herramienta de apoyo a la toma de decisiones para identificar rápidamente a los pacientes que requieren una intervención urgente. **Método.** Se desarrolló un modelo equilibrado de Random Forest, que mostró resultados prometedores en la clasificación. El enfoque creó subcategorías de clasificación y asignó diferentes prioridades en función del estado crítico. **Resultados.** Los resultados fueron alentadores, con una precisión del 80,14 % para los pacientes de alta prioridad, del 79,45 % para los pacientes derivados y del 81,29 % para los pacientes que finalmente fallecieron. Los resultados respaldan la eficacia del modelo para mejorar la toma de decisiones en los servicios de urgencias. **Conclusiones.** La investigación tiene como objetivo mejorar la eficiencia de la clasificación de pacientes, optimizar la asignación de recursos y garantizar una atención oportuna. Aporta nuevos conocimientos y puede beneficiar a los profesionales sanitarios al mejorar la calidad de la atención de urgencias.

Palabras clave: Aprendizaje automático, Algoritmos de clasificación, Análisis de datos, Investigación operativa, Emergencias, Triaje.

Introduction

Emergency and disaster care present significant challenges for hospitals that treat a high volume of patients requiring critical attention (1). The patient classification system (triage) has been used to manage resources and provide medical assistance in these circumstances (2). This system enables an adequate initial assessment to classify patients based on their injuries, ensuring they receive appropriate treatment in the shortest possible time (3). In Colombia, emergency services reported an average occupancy rate of 99% in 2022 (4), underscoring the country's high demand for medical care. This situation is exacerbated by increasing costs of medical supplies and medications, which have risen by 28% (5). In this context, utilizing resources provides optimal patient care and is crucial in critical situations.

The historical emergence data and multiple digital technologies, such as augmented reality (6), blockchain (7), artificial intelligence (AI) (8), automation and robotics (9), and the Internet of Things (IoT) (10), have expanded the possibilities for addressing uncertainties in the healthcare sector.

These technologies enable decision-making principles applications (11) (12). In this context, machine learning has become a key phenomenon driving the development of new techniques for rapid analysis and data science in patient triage, leveraging hospitals' dynamic capabilities. This is vital for regular emergency processes, because around 40% of patients visiting emergency services have non-urgent problems (9).

This situation is reflected in crowded waiting rooms and extended waiting times. As a result, patients with serious medical conditions are at risk; time is critical in several treatments (10). To improve the triage system, statistical models have been proposed as an alternative for personalized medicating and decision-making (8) (13) (14). In addition, machine learning (ML) techniques have been employed for patient classification, and unlike other methodologies, have achieved accuracy rates ranging from 70% to 80%, thereby positively impacting the optimization of emergency department resources (15). Triage systems must be simple to apply, accurate, fast, reproducible, and discriminative to avoid potentially dangerous and costly under-triage (13). Machine learning techniques have been shown to improve the outcomes of expert-based methods (14). This study aims to develop a patient classification model for Triage III, which refers to the category in the triage system where patients are assessed as having potentially serious conditions that are not immediately life-threatening. These patients require urgent but not immediate medical attention, typically within 30 minutes to 1 hour. The model will create subcategories that allow different priorities to be assigned to patients, addressing patient needs, clinical demands, and healthcare team management (16).

The proposed model will enable mass data analysis to optimize decision-making in patient classification, resulting in a significant cost reduction and optimal allocation of resources in the emergency department. The study makes two methodological contributions: a prioritization scheme based on an unsupervised algorithm that considers clinical variables of patients awaiting medical attention, and an interpretable machine learning algorithm that enables understanding of the classification rules and how and why each variable affects patients in real-time.

This article is organized as follows: Section 2 provides a literature review. Section 3 presents the main features of the methodology. Section 4 presents the experimental results obtained from real-world patients. Finally, Section 5 concludes the paper and provides avenues for future research.

Literature Review

Predictive automated tools have been utilized for patient selection in waiting lists.

For instance, researchers developed a hybrid metaheuristic strategy based on simulation that predicts the evolution of prioritized patients (17). The study revealed the methodology and algorithms used to assign optimal priorities to patients on the surgical waiting list (18) and designed mathematical tools that dynamically classify patients awaiting care. The surgical prioritization algorithm demonstrated excellent concordance and correlation with the rankings assigned by expert physicians, consistently stratifying patients who require surgical attention. Researchers have developed various methodologies for patient classification, incorporating new features and pandemic-specific criteria to support informed decision-making (19). Additionally, a decision support strategy for triage in emergency departments and intensive care units (ICU) was proposed (20), along with a framework for training supervised classifiers, suggesting the use of hyperparameter optimization to obtain robust models (21). The resulting accuracy in the studies ranged from 73% to 87%.

The Fuzzy decision matrices are proposed in this study, based on expert opinions and weight criteria derived from the normal distribution, to define a multi-attribute patient prioritization method for the ICU. This method establishes a ranking of patients to support clinical decision-making. The method suggests that errors associated with incorrect interpretations and diagnoses could be reduced by relying on these systems and expert opinions in parts of the decision-making process. On the other hand, a COX-2 regression model was used to estimate the risk of patients with kidney transplants based on the waiting time for a deceased donor kidney transplant (22). The developed model could predict waiting time with good concordance in internal validation, achieving an accuracy of 70%. This strategy offers good predictive performance and provides valuable information to support the healthcare team's decision-making, ultimately benefiting patients. Similarly, developed strategies for characterizing and grouping patients in emergency units using unsupervised machine learning techniques, including k-means, hierarchical methods, and an unsupervised neural network(23). Methodology applications improve capacity planning for healthcare beds, preventing bottlenecks. A data mining (DM) approach to identifying relevant data about patient management provides important information to decision-makers (24), highlighting the usefulness of artificial neural networks in predicting communication risks (25). Finally, predict patient queue and attention time using feedforward artificial neural networks (FFNN) and constraints as patient age, gender, arrival mode, treatment, and medical tests (26). The literature demonstrates the importance of developing decision support strategies in healthcare services through more automated and explanatory processes (23) (25) (26).

In Colombia, the patient classification problem persists due to a lack of operations research methodologies in the medical environment.

The present study aims to fill this gap by proposing a solution based on patient classification in Triage Type III using machine learning techniques in emergency departments. These strategies would help combat excessive demand and long waiting lists, thereby providing timely patient care.

Methodology

This section describes the methodology used to study patient classification in emergency departments. A Level III hospital in Colombia is taken as a case study to illustrate the potential of this approach. The primary sources of information were the works (27) (28) (29). Certain aspects were adapted and integrated into a unified framework. The primary objective is to develop an efficient tool that enables the accurate assignment of patients to specific categories, namely "high priority," "referred," and "deceased," based on clinical and vital signs data. To achieve this, the study involved a series of phases, including data preparation, application of machine learning algorithms, and selection of relevant variables.

First, data preparation involved a framework that facilitated the research process by identifying key variables through a comprehensive literature review. This was followed by data preparation, during which ranges of values for vital signs, including heart rate, respiratory rate, oxygen saturation, temperature, and glucose in living patients, were established. This allowed for the elimination of outliers. New variables, including age range and pain intensity on admission, were then introduced to address the presence of missing data and improve the accuracy of the classification.

The Clustering algorithm K-means was used to group patients into clusters based on similarities in their clinical characteristics. This Algorithm made it possible to determine the similarity and disparity between patients, and the optimal number of clusters was selected using the elbow method. This process was instrumental in establishing potential categories of patients. Other clustering algorithms include Hierarchical clustering, T-SNE, UMAP, and affinity propagation. K-means was selected because it performed well in similar use cases (30).

After the clustering stage, model classification considering a balanced Random Forest algorithm was implemented for patient classification. This machine learning model was chosen for its ability to handle unbalanced datasets and to undergo cross-validation on K-folds. This algorithm was chosen to achieve high accuracy, minimize the rate of false negatives, and ensure a balanced classification for all response categories. Subsequently, the importance of variable selection was analyzed to identify which variables contribute significantly to patient classification. This included age, heart rate, respiratory rate, and oxygen saturation variables. Variables of low importance were removed from the model to achieve greater accuracy. Accuracy metrics were used to evaluate the model and accurately measure patients to determine the overall classification. The Area Under the Receiver Operating Characteristic Curve (AUC) was also assessed, as it measures the model's ability to distinguish between classes compared to random classification.

Finally, the main tools used in the study were VosViewer (31) for the literature review, Jupyter Notebook (32) as a development environment, and the Python programming language (33) for data analysis and model design (34) (35). Figure 1 summarizes the overall methodological structure (36) (37). These studies present their phases through flowcharts, which facilitate understanding of the research's structure and development.

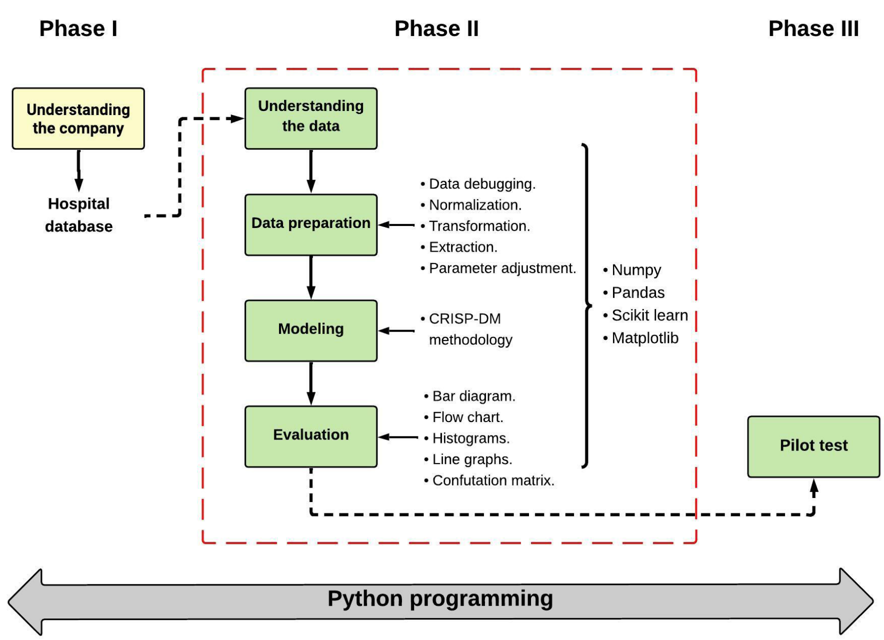

Figure 1. Methodological diagram

Results

Data understanding

The databases analyzed for this study comprise admissions to the emergency department of a Colombian hospital in 2018 and 2019, totaling 183,499 full admission records. Triage III incomplete records were discarded, and missing data were not imputed, as the sample size is too large. Incomplete records were discarded, and missing data were not imputed, as the sample size is too large. The variables used in this research are age, gender, heart rate, respiratory rate, blood pressure, oxygen saturation, and body temperature. These variables are selected because they represent the initial information recorded or tests performed on a patient admitted to the emergency department before referral to a specialist. Therefore, they are essential for making an accurate prediction. Additionally, there are other variables, such as patient name, gender, identification number, and insurance type, as well as temporal variables including admission time, discharge time, the time between consultations, and the patient's final status. Regarding patient outcomes, 94.46% of the patients were discharged, 1.97% were referred, 0.59% had a condition that resulted in death, and 3.29% had other medical outcomes, such as hospitalization, Figure 2.

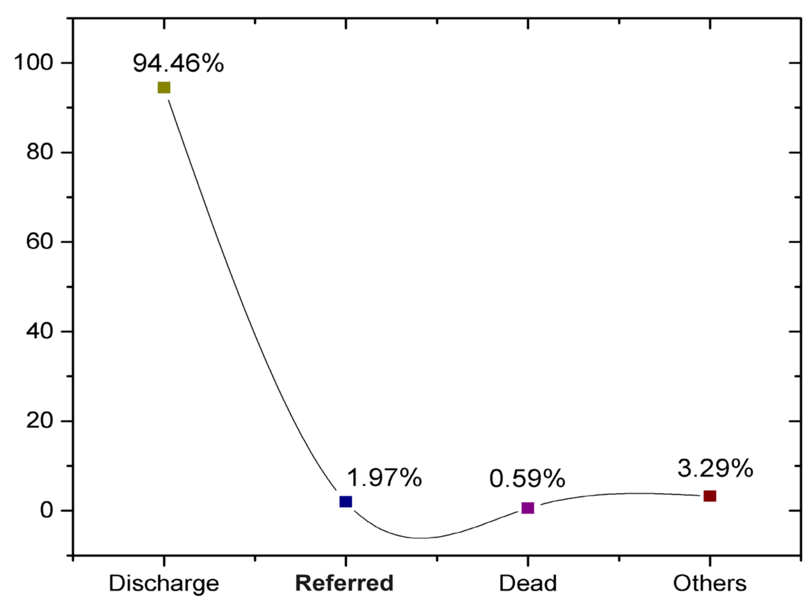

Figure 2. Attendings in emergency room population (percentage)

The quantitative analysis focuses on scalar variables, such as vital signs, body weight, and age, which are measured during the triage classification process. It is identified that the respiratory rate variable has a high presence of outliers in the right tail, which is supported by its high kurtosis value. The variables are shown in Table 1. It is worth noting that some variables have a substantial amount of missing data, as indicated in Table 2. Notably, temperature, heart rate, and respiratory rate have many missing values. This can be attributed to how data is collected and recorded, as well as variations that depend on the patient type, presenting symptoms, and the healthcare professional's judgment.

Table 1. Variable descriptive summary

Variables	Age	Saturation	Temperature	Heart rate	Respiratory rate	Weight (%)	Glucose
mean	37.62	99.99	35.50	82.49	12.99	67.50	112.50
Std	23.12	6.05	3.44	21.93	4.90	7.50	13.28
min	1	90	30	45	5	55	90
25%	21	95	33	64	9	61	101
50%	33	100	36	82	13	68	113
75%	55	105	39	102	17	74	124
max	85	110	41	120	21	80	135

Table 2. Missing data per variable (percentage)

Variable	Count	Equivalence %
Age	226	6%
Saturation	392	11%
Temperature	960	26%
Heart rate	402	11%
Respiratory rate	1100	30%
Weight	325	9%
Glucometry	314	8%

Data preparation

When analyzing the data based on the Glasgow Coma Scale, a tool used to assess and calculate the severity level of a patient (38), it was found that ranges for each vital sign exist, ranging from 0 to a specific upper limit. However, these ranges of values do not completely align with the data available in this investigation, as all individuals assessed are alive. Therefore, during the data preparation process, the possible ranges of values for each vital sign in a living person were established according to the Glasgow Scale, which ranges from 3 (worst state of consciousness) to 15 (best state of consciousness), thereby eliminating most outliers for these variables. These ranges are shown in Table 3.

Table 3. Vital signs range intervals.

Vital sign	Minimum value	Maximum value
Heart rate	28 beats/min	220 beats/minbeats/ min 220 beats/min
Respiratory rate	8 breaths/min	90 breaths/min
Oxygen saturation	50%	100%
Temperature	27 °C	45 °C
Glucose	90 mg/d	130 mg/dL

On the other hand, the "others" variable was removed to limit the database to deceased, referred, and high-priority patients. This allowed for a more precise classification of the patient. In addition, new variables were created: age interval and pain intensity upon admission. The age interval variable corresponds to the developmental stage of a person based on their age and is categorized as infancy, childhood, adolescence, youth, adulthood, and old age. The temperature and pain variables were created as alternatives to handle the high presence of missing data. Although pain is not considered a vital sign, it is an important response for classifying patients. Therefore, its measurement is useful as a complement to vital signs in cases where the symptom has been previously reported.

These variables should thus be analyzed in a binary manner. A value of 0 represents the absence of fever (omission or values below 37.5 °C), while a value of 1 represents the presence of fever (values equal to or above 37.5 °C). This enables the model to interpret this variable accurately and effectively for patient classification.

The database was divided into two sets to develop the classification model. The first part, which comprises 90% of the data, serves as both the training and validation set, while the second partition, consisting of the remaining 10%, is used as the model's testing set. The final composition of the overall database, after performing range cleaning processes on the variables, imputing missing values, and splitting the database into training and testing sets, is presented in Table 4.

Table 4. Vital signs range

Variable Response	Description	Amount of data	Equivalence %
High-priority	Denoting whether the patient's condition was classified as high priority or urgent at triage	153.666	98.96%
Referred	Indicates whether the patient was referred to the emergency department by another healthcare provider	923	0.59%
Deceased	Denotes whether the patient was declared deceased either upon arrival at the emergency department or during their stay	695	0.45%

Clustering algorithm

First, the K-means clustering algorithm was executed with the imputed and normalized database. This algorithm allowed for the grouping of patients with similar characteristics. To determine whether the data points are similar or dissimilar, this method calculates the distance between observations, such that similar records will have a smaller distance between them. The K-means algorithm demonstrated relatively good performance even when referred and deceased cases were rare in the sample. Mixed-variable type PCA was applied as a pre-processing step before K-means to minimize potential unexpected behavior.

The Euclidean distance was used as a distance metric for the k-means algorithm. The elbow method was chosen to determine the optimal number of clusters. This method helps select the appropriate number of clusters when classifying a dataset. This methodology is illustrated in Figure 3, which graphically represents the values obtained by applying the K-means algorithm.

This way, the best stability results were obtained for the optimal value of K = 5 clusters. The stability values, being higher than 95%, indicate that the algorithm's initial centroids do not significantly affect the grouping of patients into the five clusters. Table 5 illustrates the composition of each cluster in terms of the response variable, revealing a strong predominance of the "high-priority" category across all clusters.

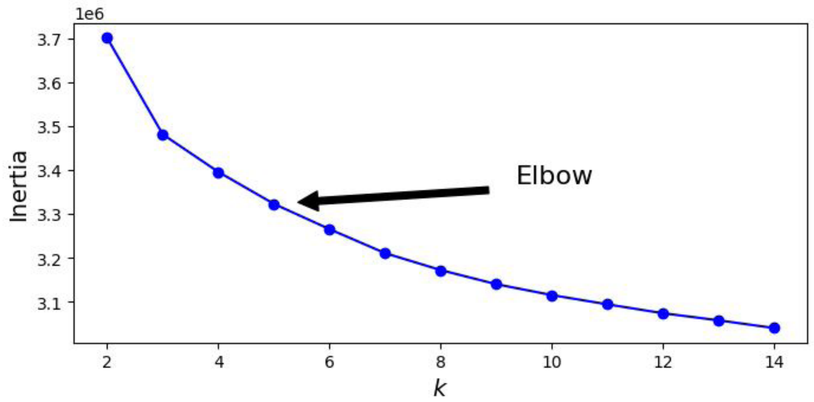

Figure 3. Attendings in emergency room population evolution (percentage)

The figure indicates the best result. Cluster 5 yields a striking balance between the response variables.

Table 5. Cluster composition by category of response variable.

Cluster	High-priority	Referred	Deceased
Cluster 1	98.98 %	0,68 %	0.35 %
Cluster 2	90.46 %	0,44 %	0.10 %
Cluster 3	99.21 %	0,54 %	0.25 %
Cluster 4	97.76 %	0,84 %	0.40 %

The classification method was selected based on works with similar characteristics, using the high accuracy criteria, with a minimum threshold of 55% (13).

The balanced Random Forest algorithm with K-fold cross-validation was chosen to guarantee that the algorithm learned from all available data at some point. The model is trained on K-1 subsets and then evaluated on the subset not used for training. This process is repeated K times, with a different subset reserved for testing each time. This testing also aims to minimize the risk of overfitting; the higher the number of folds, the less the chance of overfitting. A hold-out test of 25% size was used to evaluate model capabilities in unseen data.

The selection of predictor variables initially relied on the data availability at the time of triage, using variables such as heart rate, respiratory rate, oxygen saturation, age, temperature, and gender. These variables were used to execute the algorithm. In addition, important graphs of the variables associated with permutation accuracy values and node impurity were constructed. This was done to determine whether there were any variables with low classification power that could be eliminated from the model, Figure 4.

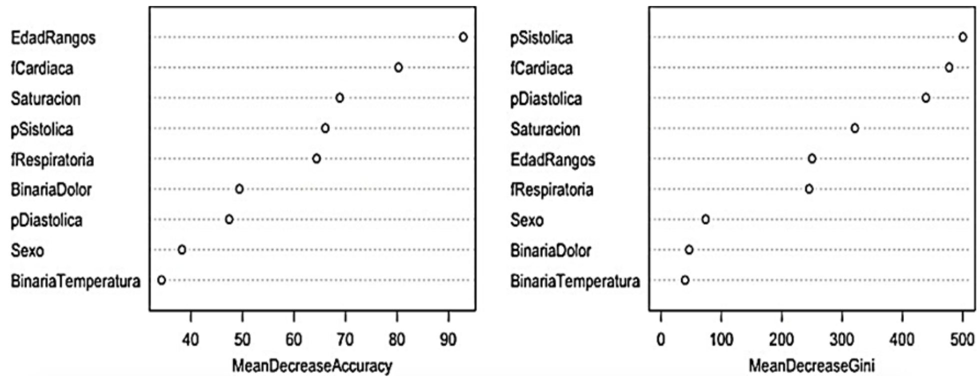

Figure 4. Elbow method graph

The graph selected to establish the importance of predictor variables indicates a decrease in accuracy, as it aligns with the study's objective and the established comparison standard, prioritizing the increase of the accuracy metric. By eliminating the variables of sex and temperature, it was possible to achieve a more precise model with minimal loss of predictive power compared to the original model. For these reasons, the following variables were chosen as predictors for the final model: age, heart rate, respiratory rate, and oxygen saturation. Table 6 presents the results for this indicator by category. The values are quite satisfactory, as the model identified approximately 80% of patients who truly belong to each healthcare outcome.

Table 6. Performance metrics results in the training set

Response variable	Sensitivity	FNR	Accuracy	GMean	AUC ROC
High priority	80.14	19.85	93.76	87.22	87.57
Referred	79.45	20.54	93.72	86.91	87.23
Deceased	81.29	18.70	93.81	87.79	88.15

FNR: False Negative Rate.

Next, false negatives (FN) were calculated to measure the proportion of positive cases the classifier detected as negative. In this study, for the "deceased" category, this rate represents the percentage of patients who will die and will not receive prioritized and timely care, as the model classified them into a different response category. For the obtained model, the false negative rate (FNR) for the "deceased" category is 18.70% (see Table 6).

The accuracy of the classification model was also evaluated. Accuracy is calculated using the equation and represents the overall percentage of patients who have been correctly classified. In this equation, FN represents the false negatives, FP is the false positives, TN indicates the true negatives, and TP refers to the true positives. A higher score in this metric indicates better classification. The model achieved an accuracy of 80.15% in the test set result, which is considered good according to the literature (35).

The false-negative rate of 18.70% in the "high-priority" category is ethically significant, as it implies a risk of failing to identify critically ill patients who may not receive timely care. The same holds for the "Deceased" category. While the model shows promising performance, this limitation underscores its importance as a support tool rather than a replacement for clinical judgment.

The accuracy (ACC) of the classification model was also evaluated. Accuracy was calculated using the equation and represents the overall percentage of patients who were correctly classified. In this equation, FN represents false negatives, FP is false positives, TN indicates true negatives, and TP refers to true positives. A higher score on this metric indicates better classification ability. Our model achieved an accuracy of 80.15% on the test set, a result considered good according to the literature (25).

On the other hand, the area under the ROC curve was also evaluated as a metric. The ROC curve is a statistical tool used to assess the discriminative capacity of a dichotomous diagnostic test. This curve represents sensitivity as a function of false positives (complementary to specificity) at different cutoff points. This evaluation allowed for comparing the model's performance in classifying patients with the classification obtained by random assignment. For the model to be considered satisfactory, the variables must exceed the 0.5 threshold in the area under the ROC curve, indicating that the algorithm effectively discriminates between different cases better than random allocation (39). Figure 5 shows the ROC curve, in which purple represents the "high priority" category, red represents the "referred" category, and green represents the "deceased" category.

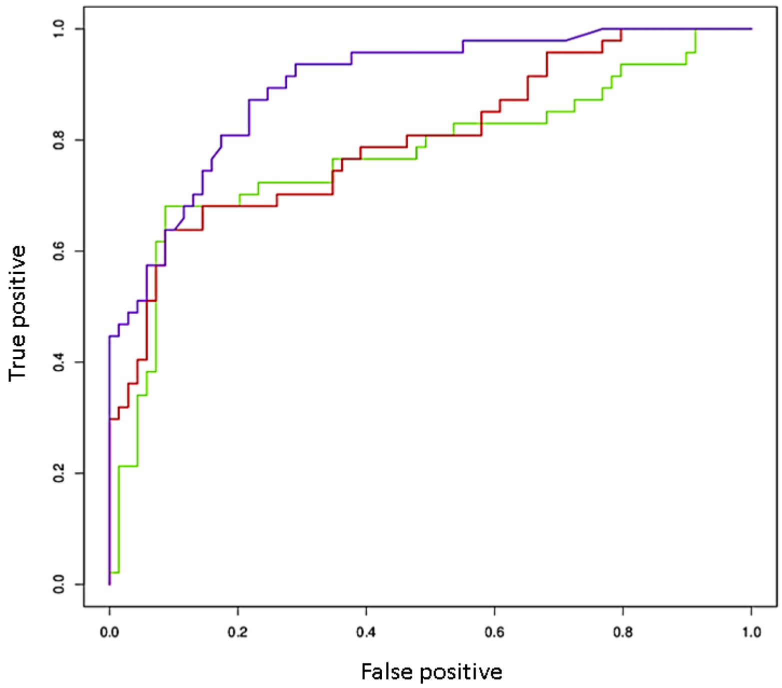

Figure 5. ROC Curve

Discussion

This study uses machine learning models to classify patients referred to the emergency department of a hospital in Colombia. The results are very promising, as the classification models achieved an average accuracy of 80.15%, with sensitivities of 80.14% for patients classified as "high priority," 79.45% for those classified as "referred," and 81.29% for those classified as "deceased." This is of the utmost importance in emergency medical care, where speed and accuracy in decision-making can make the difference between life and death.

The categorization methodology proposed here, which encompasses the labels "high priority," "referred," and "deceased," has proven to be highly effective and is supported by high sensitivities in each category. These results align with previous research (40). The Random Forest-based model achieved the highest accuracy, at 77%, a sensitivity of 65%, and a specificity of 72%. In addition, this model was notable for a significant reduction in the false-negative rate (35%) and, almost as importantly, a notable decrease in the false-positive rate (16%).

The present study achieved greater accuracy than previous research results, suggesting a significant advance in applying machine learning models to emergency triage. This approach provides high classification accuracy and effectively prioritizes high-demand emergency medical care situations.

Such a capability is essential in optimizing resource allocation and improving the quality of care provided to patients.

However, it is important to note that in the "deceased" category, an FNR of 18.70% was recorded. This means that the model incorrectly classifies as negative about 18.70% of patients who will ultimately die, implying that they will not receive timely and prioritized care. Despite our achievements in classification, this finding underscores the need to refine the models further and address limitations, such as missing data on key variables. This suggests the need to collect more complete and detailed data and consider additional variables to help reduce FNR and improve care for critically ill patients. However, overall, the study's results support the utility of machine learning models in patient classification within emergency departments, offering valuable insights for optimizing resources and making informed medical decisions in critical situations. However, identifying the FNR highlights the importance of further refining our approaches to ensure no urgent care patient is left unattended.

Regarding the interpretability of results, it is worth noting that imbalanced data can be challenging to interpret, as the relationships between predictive features and the outcome may be non-linear and involve interactions between these features (41). Partial dependence plots and SHAP values are the standard methods for interpreting supervised learning classifiers. These methods analyze how predictions change in response to variations in the predictive features. While SHAP values account for potential correlations among predictive features, partial dependence plots assume that the predictive features are independent (42). The estimation of SHAP values and partial dependence plots is left for future research, as this paper focuses on demonstrating the predictive performance of supervised learning classifiers and proposing operational strategies through feature selection.

Conclusions

The study has proven to be highly promising in emergency triage. The methodology of classification into specific categories, including "high priority", "referred," and "deceased," yielded results consistent with previous research, indicating that the application of machine learning models to emergency triage is an effective way to make crucial medical decisions. By achieving an average accuracy of 80.15% and high sensitivities in each category, it offers a tool to make a difference between life and death in high-demand emergency medical care situations.

The methodology, which combines the K-Means algorithm for initial patient clustering and utilizes Random Forest for final classification, has proven effective. Clustering enabled the initial grouping of patients with similar characteristics, leading to more accurate subsequent classification. Variable selection based on importance contributed to more precise classification by eliminating irrelevant variables. This combination of methods offers a robust approach to medical decision-making in emergency settings.

The study focused not only on classification accuracy but also on the ability to assign priorities effectively. This feature is critically important in high-demand emergency medical care situations, as it plays a crucial role in ensuring that patients receive the necessary care at the right time. Reducing the false negative rate mitigates the risk of critical patients not receiving the required priority care. This improvement in medical decision-making can not only save lives but also optimize the allocation of hospital resources.

We acknowledge that the focus on a single hospital limits the generalizability of our findings. While this setting provided a controlled environment for developing and testing our machine learning models, we recognize that patient demographics, triage protocols, and healthcare delivery can vary significantly across institutions. Therefore, future research should aim to validate the model across multiple hospitals and diverse geographic and clinical settings to ensure broader applicability and robustness. Expanding the study this way will help assess the model's performance under varying operational conditions and enhance its potential for real-world implementation.

Future research might explore additional approaches, such as sequential algorithms, and consider collecting more detailed patient information. Additionally, it would be beneficial to evaluate the implementation of advanced machine learning or deep learning techniques to enhance the model's predictive performance further. These investigations could lead to significant advances in accurately predicting patient classification in emergencies, which would positively impact medical decision-making and the efficiency of healthcare resources.

Ethical Considerations

In our study, all patient records were de-identified prior to analysis to ensure compliance with data protection regulations and to protect individual privacy. The dataset was obtained from a secure institutional database with appropriate ethical approval and authorization for secondary use in research. No identifiable personal information was accessed or used at any analysis stage. Additionally, we recognize the importance of addressing potential algorithmic bias and ensuring fairness in predictive modeling. As such, we have discussed ethical safeguards, data governance, and model transparency in the revised manuscript to clarify our commitment to ethical research practices.

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