Triage with Hospital Recommendation

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***Abstract*—The increasing application of Artificial Intelligence (AI) in healthcare has revolutionized the process of triage and patient referral in emergency services. This project introduces an innovative system that leverages machine learning techniques to streamline the triage process by assessing the severity of a patient's condition based on responses to a set of questions encompassing details such as gender, age, physical condition, and vital signs.**

Upon completing a form with this information, the system employs a machine learning model to assign a color representing the urgency of the case. This categorization guides the patient to a section where location and transportation options for medical care are presented. Patients are empowered to choose between waiting a shorter time in the emergency department or opting for the nearest hospital.

The selection of the best alternative involves utilizing the Technique for Order Preference by Similarity to Ideal Solution (Topsis), considering patient preference and analyzing the best available options. This system not only optimizes patient flow in healthcare services but also provides a more personalized and participatory experience for the patient, enabling an informed choice regarding their medical referral.

In summary, the synergy between Artificial Intelligence, machine learning, and multi-criteria decision-making methods facilitates more efficient triage and a patient-centric approach, improving resource management and the quality of care in emergency healthcare services.

Keywords—Triage, Machine Learning, Healthcare, Urgency Classification, Multi-Criteria Decision Making

I. INTRODUCTION

The presence of Artificial Intelligence (AI) today reflects its evolution from Alan Turing [1] with his Turing Test, sparking research, to John McCarthy [3], who coined the term 'Artificial Intelligence' and established AI as a distinct field in 1956. They introduced an innovative method to evaluate machines mimicking human intelligence, triggering extensive research in this field [2].

The healthcare sector is not exempt from this transformative shift in the workforce. AI techniques have extraordinary potential to reshape healthcare, assisting in information analysis and processing, leading to new discoveries and inferences. The impact of AI is evident in three fronts: enhancing image interpretation for healthcare professionals, optimizing the healthcare system by improving workflow and reducing errors, and empowering patients to manage their health information for personal benefits. Our focus is to refine workflow to enhance the healthcare system while simultaneously providing a more satisfying experience for patients, also assisting healthcare professionals [5].

Triage represents the initial point of contact between the user and Emergency Services, constituting an essential procedure in managing this context [6]. In the realm of hospital triage, evaluation methods such as the KTAS (Korean Triage and Acuity Scale) are crucial, enabling patient classification and prioritization based on criteria like vital signs, pain, and specific conditions. These algorithms establish not only patient priority but also waiting times for care and appropriate treatment levels, distinguishing emergencies from non-emergencies [7].

This project introduces a system that employs machine learning to assess patient severity based on provided information. It assigns a color representing urgency, allowing patients to choose between a shorter wait in the emergency department or going to the nearest hospital. The system utilizes the Topsis method to aid in the selection, prioritizing patient preference. This approach improves triage, offering a more personalized and efficient experience, benefiting resource management and the quality of emergency care.

II. STATE OF ART

In the constantly evolving context of technology, advances in the healthcare field have been driven by innovative projects that are shaping how diseases are diagnosed, treatments are administered, and care is provided to patients. Among these advances, the developments in the use of Artificial Intelligence (AI) in sectors such as emergency calls stand out, where more than 110,000 cases were analyzed using a Machine Learning Framework (MLF). This approach revealed remarkable accuracy in detecting cases of cardiac arrest (CA), outperforming human operators by identifying 84.1% of CAs compared to the 72.4% identified by operators. This application of AI stands out for its ability to expedite crucial diagnoses in emergency situations, potentially positively impacting post-CA survival and quick decision-making in critical situations [1].

Another significant achievement is an advanced prioritization system, led by Fernando Teures Redondo, which integrates AI to assess service priority. This system not only streamlines the triage of critical cases but also offers a scalable model to optimize customer service in the healthcare sector [2].

These technological advances in healthcare lead us to the Korean Triage and Acuity Systems (KTAS), an essential methodology in emergency departments. The KTAS, adapted to prioritize medical care in emergency situations, is based on critical assessments performed by emergency nurses, considering vital signs, pain assessment, and other symptoms [3]. However, a recent study on the accuracy of KTAS identified that the main cause of incorrect classifications was the inadequate application of pain scale in the KTAS algorithm [4].

In this realm, an investigation was conducted to explore how AI can be used to accurately classify KTAS levels and symptoms. Using speech recognition and natural language processing (NLP) models, classifiers based on ML and BERT were developed to predict KTAS levels and symptoms. These classifiers, utilizing techniques such as SVM, KNN, RF, and BERT, demonstrated notable performance, with AUROC rates ranging from 0.82 to 0.89. These results highlight the potential of automated systems to enhance medical triage by incorporating speech recognition and AI technologies [5].

These advances and current investigations are fundamental to improving the accuracy of medical triage processes and ensuring quality emergency care, highlighting the increasingly significant role of AI in the healthcare field and its potential to optimize clinical and diagnostic processes.

A. *Multi-class Classification*

Multi-class classification is part of supervised learning algorithms and is a classification task with more than two classes, where a sample can only have one label associated with it [6] and can be used to categorize medical images or patient data into diseases. In the context of this problem multi-class classification will be used to predict a patient's triage level based on a set of input data such as vital signs, pain level and mental status.

1) *Decision Trees* are a set of organized rules that efficiently compare a feature's numerical value with a specified threshold. Nodes represent features, and branches show possible outcomes. In this method, samples are classified by following a path from the root to a leaf node, representing a class label.[7][8].
2) *Multi-class Logistic Regression* is an extension of binary logistic regression, it handles more than two classes. Common approaches include one-vs-rest, running a logistic regression for each class, and SoftMax regression, which calculates probabilities for all classes. The model predicts the class by selecting the one with the highest probability. [9] [10]
3) *Support Vector Machines (SVM):* Initially designed for binary classification, SVMs can also handle multi-class problems. They find an optimal hyperplane to separate classes, maximizing the margin (distance between the hyperplane and the nearest data points of each class). SVMs can be linear or non-linear, using functions like polynomial, sigmoid, or radial basis function kernels. [11] [12][13].
4) *K-Nearest Neighbors (KNN):* This algorithm classifies by calculating the distance to the nearest k examples and determining the most represented class among them. The value of k is determined through a validation set or cross-validation. [14].
5) *Naive-Bayes:* predicts based on Bayes' theorem, estimating the probability that a sample belongs to a class by combining prior and class conditional probabilities. It assumes equal importance and statistical independence of attributes, simplifying probability calculations [15] [12]
6) *Artificial Neural Network (ANN):* simulate human brain processing patterns. Comprising input, hidden, and output layers, each node (neuron) connects to others with weights and thresholds. If the output surpasses the threshold, the node activates, sending data to the next layer for parallel computations to discover patterns in extensive data. [16] [17].

These methods have been essential in the evolution of clinical practice, especially in the hospital triage scenario, as evidenced by the examples presented: KATE (Knowledge-based Triage Engine), E-Triage, and the DAM (Deep Attention Model).

KATE is an application developed specifically to enhance the accuracy of the Emergency Severity Index (ESI) triage. This project, utilizing advanced C-NLP techniques, initially extracted crucial information from patients' medical records, such as UMLS dictionaries of clinical terms, social and environmental risk factors, duration of symptoms, and vital signs. The subsequent step involved the application of the XGBoost algorithm, this is a machine learning library that focuses on gradient-boosted decision trees, excelling in solving prediction problems such as classification, regression, and ranking. Supervised learning involves training a model using labeled data to make predictions on new data, relying on patterns identified during this training [18]. The final assessment evaluated the accuracy of the KATE model compared to that of nurses and expert clinicians in triage. The results were striking, demonstrating that the KATE model surpassed the professionals' precision in assigning patient acuity [19].

Similarly, E-Triage, also aiming to improve ESI triage accuracy, employs the Random Forest method. It combines trained decision trees with triage data like vital signs and medical history to predict urgent clinical situations, such as critical care and hospitalization. Analyzing 172,726 emergency service visits, it displayed equal or superior performance to the ESI, excelling in the precise differentiation of patients categorized as level 3 by the ESI [20].

Lastly, the DAM classifies patient severity using ESI as a reference and predicts the number of required medical resources. It employs a bidirectional recurrent neural network architecture with an attention mechanism. It processes structured and unstructured data, including patient complaints, medical history, medication lists, and nurse assessments. The attention scores assigned to nurse annotations provide interpretability to the model, enabling understanding of how specific factors contribute to patient classification in the ESI. The model was trained with over 338,500 emergency department visits spanning three years in an urban hospital. Results showed an approximately 44% accuracy in exact categorization of necessary resources and an Area Under the Curve (AUC) of about 88% in identifying high-need patients, representing a 16% increase compared to nurse assessments. Although the DAM's primary goal isn't patient classification, this analysis is crucial. Besides focusing on triage to minimize errors, the DAM aims to optimize healthcare system effectiveness and improve resource utilization in emergency services [21].

These projects signify both technological achievements and tangible promises for substantial enhancements in emergency medical care, indicating a promising future for the use of classification methods in hospital practice.

B. Multicriteria Systems

Multicriteria systems apply a methodology of decision support based on a multi-criteria decision analysis. This is a problem-solving methodology that assists decision making in the process of identifying the most preferred actions(s), from a set of possible alternative actions [22]. These systems are utilized in complex decisions involving various criteria. They assess options considering different factors, employing mathematical methods or computational tools to compare and weigh the importance of each criterion, enabling informed decisions in situations where there's no single best option [23].

Multi-Criteria Decision Making (MCDM) is employed when a decision is based on multiple criteria, each representing distinct aspects contributing to the overall evaluation of alternatives. The challenge arises from potential conflicts among these criteria, making it difficult to identify a singularly superior alternative that excels across all criteria simultaneously. Although MCDM represents the major class in decision-making support systems, multi-attribute (MA) and multi-objective decision-making (MODM) represent their subclasses[24].

In MA problems, the number of alternatives is limited, and the attributes are known explicitly, these can be completely defined and assumed feasible, and the attributes may be determinist, probabilistic, fuzzy (or mixed). The problems might be of **choice**, where you select the best alternative, **ranking** where an order of alternatives is drawn, or **sorting**, where the best k alternatives are chosen from a list of $n > k$ [25]

During the COVID-19 pandemic, the utilization of the Analytic Hierarchy Process (AHP), a method for solving multi-attribute problems, in Guayaquil hospitals, Ecuador, was proven to be crucial. The AHP is a theory of measurement for dealing with quantifiable and/or intangible criteria that has found rich applications in decision theory, conflict resolution and in models of the brain [26]. AHP is extensively used in making decisions involving multiple criteria, planning, resource allocation, and conflict resolution. It is a versatile framework that enables both deductive and inductive thinking by considering multiple factors simultaneously, accommodating dependencies and feedback. The method involves making numerical tradeoffs to reach a synthesis or conclusion [27].

In this study case, AHP not only provided a robust framework for analysis but also combined subjective and objective information from experts. This resulted in the identification and selection of more effective triage protocols. By considering criteria such as efficiency, diagnostic accuracy, and speed, AHP allowed for the implementation of more reliable and faster triage practices. This not only increased patients' confidence in the healthcare system but also reduced mortality since decisions based on well-defined and assessed criteria were promptly implemented, ensuring more appropriate and timely treatment [28].

In the research on risk management in the supply of essential medications in level I emergency units of hospitals, the multicriteria system Supply Chain Risk Management (SCRM) was employed. Using various techniques like Risk Matrix, FMEA, multicriteria classification, and ABC criteria, risks linked to critical medication supply were identified. This not only allowed for risk prioritization but also facilitated the development of more precise and efficient stock management strategies. Detailed analysis of these risks resulted in the implementation of inventory policies such as reorder points and buffer levels, ensuring adequate supply of essential medications, reducing operational costs, and guaranteeing timely availability of these medications for critically ill patients [29].

These examples demonstrate how multicriteria systems provide a solid framework for analysis and decision-making in critical situations in the healthcare domain. From enhancing triage protocols to ensuring faster and more accurate treatments, to managing risks in the supply of essential medications, these tools enable more informed decisions and more effective strategies to enhance the quality of healthcare services.

The Analytic Hierarchy Process (AHP) is a useful tool for prioritizing criteria such as diagnostic accuracy, distance to the hospital, and travel time. It allows for comparing and prioritizing these criteria according to patient preferences or medical professionals' perspectives [30].

In addition to the Analytic Hierarchy Process, there are various methods for Multi-Attribute Decision Making (MADM), and TOPSIS, developed by Hwang and Yoon in 1981, is a notable example.

TOPSIS, developed by Hwang and Yoon in 1981, is another instance of Multi-Attribute Decision Making (MADM). This ranking method is straightforward in both its conceptualization and application. The standard TOPSIS approach aims to identify alternatives that possess the shortest distance from the positive ideal solution while maintaining the farthest distance from the negative ideal solution. In this context, the positive ideal solution maximizes benefit criteria and minimizes cost criteria, while the negative ideal solution maximizes cost criteria and minimizes benefit criteria [31].

Multicriteria systems offer a robust framework for decision-making in complex scenarios, particularly in healthcare. Methods like Analytic Hierarchy Process and TOPSIS stand as valuable tools allowing the assessment and prioritization of multiple criteria, aiding in identifying the best alternatives in situations where conflicts among various aspects need consideration [32].

Multicriteria systems such as AHP and TOPSIS offer invaluable tools for complex decision-making in healthcare. They enable the weighted assessment of multiple criteria, aiding in more informed decisions and more effective strategies. Their application has proven critical, from enhancing triage protocols to managing risks in essential medication supply, leading to more accurate decision making and improvements in the quality of medical care [32].

III. DEVELOPMENT

The development process of this solution is described in this section.

A. *Multi-class* Classification

The group first defined the problem to be solved and then selected a dataset [33] containing 1267 rows and 24 columns of patient condition and triage level data. All columns in the dataset are described in Table 1.

TABLE 1 - Data Description

Column name	Data Description		
	Type	***Description***	***Values***
Group	Categorical Nominal	Group categorization	1 (Local ED); 2 (Regional ED)
Sex	Categorical Nominal	Patient's sex	1 (Female); 2 (Male)
Age	Numerical Discrete	Patient's age	
Patients number per hour	Numerical Discrete	Number of patients per hour in ED per hour	
Arrival mode	Categorical Nominal	How patient arrives at ED	1 (Walking); 2 (Public Ambulance); 3 (Private Vehicle); 4 (Private Ambulance); 5 (Public Transport); 6 (Wheelchair); 7 (Other)
Injury	Categorical Nominal	Whether the patient is injured or not	1 (No); 2 (Yes)
Mental	Categorical Nominal	Mental state of the patient when arrives at ED	1 (Alert); 2 (Verbal Response); 3 (Pain Response); 4 (Unresponsive)
Pain	Binary	Whether the patient has pain or not	0 (No); 1 (Yes)
NRS_pain	Numeric Discrete	Numerical rating scale of patient's pain	
SBP	Numeric Discrete	Systolic Blood Pressure	
DBP	Numeric Discrete	Diastolic Blood Pressure	
HR	Numeric Discrete	Heart Rate	
RR	Numeric Discrete	Respiratory Rate	
BT	Numeric Discrete	Body Temperature	
Saturation	Numeric Discrete	Saturation level using oximeter	
KTAS_RN	Categorical Nominal	Triage level given by nurse in ED	1, 2, 3 (Emergency); 4, 5 (Non-emergency)
Disposition	Categorical Nominal	Action taken after ED	1 (Discharge); 2 (Admission to ward); 3 (Admission to ICU); 4 (AMA discharge); 5 (Transfer); 6 (Death); 7 (OP from ED)
KTAS_expert	Categorical Nominal	Triage level given by experts	1, 2, 3 (Emergency); 4, 5 (Non-emergency)
Error_group	Categorical Nominal		1 (Vital Sign); 2 (Physical Exame); 3 (Psychiatric); 4 (Pain); 5 (Mental); 6 (Underlying disease); 7 (Medical records of other ED); 8 (On set); 9 (Other)
Length of stay_min	Numeric Continuous	Length of stay in ED (minutes)	
KTAS duration_min	Numeric Continuous	Duration of triage process (minutes)	
Mistriage	Categorical Nominal	Whether the triage is correct or incorrect	

1) *Exploratory Data Analysis (EDA)*

After acquiring the data, it was possible to proceed with exploratory data analysis (EDA) that involves identifying general patterns in the data to gain a better understanding of it.[34] During this process, data types, statistical summaries, and unique values of all columns were analysed. It was ensured that each column contained at least two unique values, and therefore, no columns were discarded. After checking for null values, missing information was found in several columns, including Saturation, SBP, DBP, HR, RR, BT, and NRS_pain, which must be filled in the next steps.

To gain a deeper understanding of the data and its application to our problem, hypotheses were formulated and checked, and the data distribution was analysed. It was discovered a direct correlation between the triage level and the patient's age, mental status, vital signs, and saturation level, although not all hypotheses were confirmed.

2) *Data Preprocessing*

To be able to use this data to train models, preprocessing of the data was implemented, which consists of converting the data into a clean dataset that is more suitable for models. [35] The initial step involved converting the values "#BOÞ!" and "??" to null values and replace columns 'Sex' and 'Injury,' with 'Female' and 'Injured', respectively, to get binary values, and replacing all numbers with categorical values in columns like Group, Arrival mode, Mental, Disposition, Error Group and Mistriage. Subsequently, all null values were filled. SimpleImputer was used to replace null values in integer and real columns with median and mean values, respectively and for categorical data, specifically the Diagnosis in ED column, null values were filled with "No Diagnosis." For categorical data, specifically the Diagnosis in ED column, missing values were filled with 'No Diagnosis' and one hot encoding was performed on columns with categorical values using *get dummies* function, from *Pandas* library, which created a new binary column for each value of the categorical values columns.

Following this, the Chief Complain column was analysed to identify repetitive values that could be used in the classification process, as this variable is crucial in predicting triage levels. Furthermore, the blood pressure values were transformed according to medical guidelines [36],and the pain level was categorized. *Get dummies* was used to create binary columns for the categorical values of these columns [37].

To address the issue of numerical data that cannot be converted into categorical data and the potential bias that numerical values may introduce in some models, feature scaling was performed using normalization and standardization. Normalization transforms features to a similar scale, while standardization transforms the standard deviation and mean of column values to 0 and 1, respectively [38]. *MinMaxScaler* was applied for normalization and *StandardScaler* for standardization, both from the *Sklearn* library.

3) Feature Selection

Finally, it was decided which columns to exclude from the problem. To determine this, the importance of all the features was examined using a Random Forest Classifier, a Gradient Boosting Classifier and a Decision Tree Classifier, and calculated the mean of the importance resulting from these three methods. Based on these values, the correlation matrix, and the knowledge of the problem, the following columns were dropped: Group, Disposition, Error Group, Mis-triage, Patients per hour, KTAS RN, Diagnosis in the ED, Length of Stay (minutes), KTAS Duration (minutes), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Chief Complaint, and Numeric Rating Scale (NRS) Pain.

4) Data Spliting

Once all the data had been pre-processed, the target variable was defined and separated from the rest of the data, and the dataset was split into two parts, one with 80% of the data that would later be used for training models - training dataset - and another with 20% of the data that would later be used for testing models - testing dataset.

5) Balancing

The balancing process arose due to a significant disparity among classes, represented by the following values: {0: 20, 1: 165, 2: 365, 3: 344, 4: 56}. This procedure was applied to the training data with the aim of enhancing the models' ability to predict new data. Initially, various balancing techniques were applied to observe how the models performed best. Following this analysis, the four best balancing techniques were selected. The four balancing methods used were: TomekLinks(Removes redundant examples from the majority classes, thus balancing the disparity with the minority classes) SMOTE (Generates synthetic examples for the minority classes) **SMOTETomek** (Combines the SMOTE method with TomekLinks, generating synthetic examples for the minority classes and simultaneously eliminating redundant examples from the majority classes) **RandomOverSample** (Performs oversampling of the minority classes by duplicating or randomly replicating examples from the class) .These four described methods were applied to all models to enable comparison and achieve the best possible model with the most effective balancing technique.

6) Model Selection, Training and Tuning

The model selection was guided by thorough research and testing on the dataset. Initially, two models, LightGBM and Naive Bayes, were excluded due to a lack of significant results, basing our decision on specific performance metrics. We then proceeded with a diverse set of models for training and application on new data, including Support Vector Machine, Decision Trees, K-Nearest Neighbors, Multi-class Logistic Regression, Neural Network, Random Forest, XGBoost, and AdaBoost.

To optimize performance, a suitable range of values for each model was provided, automatically saving the best sets of hyperparameters based on f1 score metric in a text file within the corresponding model folder for future use by the algorithm. It's noteworthy to mention that two distinct and complementary approaches were employed to search for the best hyperparameters: Grid Search and Hyperopt. These techniques facilitated a comprehensive and efficient exploration of the hyperparameter space, significantly contributing to the refinement of the models.

Model training took place after determining the parameters. This logical sequencing ensured that the models were adjusted in the best possible way before being applied to new data. Each carefully planned and executed step aims to provide robust models capable of generalizing effectively and making accurate predictions in practical scenarios.

In the end, the models with the best results, as indicated by the highest F1 scores, were selected. This decision was based solely on the results from hyperopt, as limited computer resources prevented the execution of grid search for all models.

*B. M*ulticriteria System

At the project's inception, the aim was to implement the AHP (Analytic Hierarchy Process) method, believing it to be the ideal solution for facilitating effective emergency care selection for users. However, upon careful consideration of the available decision criteria-such as proximity to the hospital and emergency department waiting times-it became apparent that a more suitable approach would be the TOPSIS method (Technique for Order of Preference by Similarity to Ideal Solution). This decision was driven by the intent to develop a project centered precisely around these metrics, ultimately striving to offer the most optimized solution to end-users.

The TOPSIS Model (Technique for Order of Preference by Similarity to Ideal Solution) has been developed to provide patients with an intuitive and effective interface for selecting their preferences in emergency care, also considering the type of emergency through the color assigned during the initial triage. Through this interface, patients can specify their location, mode of transportation, and indicate their preferences between the nearest hospital or the shortest waiting time in the emergency department.

1) General Development

This integration is crucial to guide the TOPSIS algorithm, which relies on information from sources such as the SNS (National Health Service) API and Google Maps. By inputting their location and transportation preferences, the patient allows the algorithm to evaluate and prioritize the relevant criteria for their situation. The resulting matrix is constructed considering the estimated waiting times in the emergency departments of hospitals near the patient's location, as well as the relative distance between them.

These criteria, weighted according to the preferences expressed by the patient, are normalized to ensure a fair comparison. Based on this processed data, TOPSIS determines the ideal and negative solutions, considering both the proximity of the hospital and the estimated waiting time. Subsequently, through the interface, options are presented according to the patient's preferences, offering an objective and personalized selection of emergency care. The integration of TOPSIS in this context aims to provide patients with a more informed and participative experience in choosing an emergency care location, ensuring a more precise alignment with their specific needs. Therefore, the TOPSIS Model, coupled with an interactive interface.

2) Specific Development

The proper selection of hospitals is a critical consideration in many decision-making scenarios. The implemented TOPSIS algorithm operates through several distinct stages to prioritize hospitals based on essential criteria such as proximity and emergency waiting time. The process follows fundamental steps, resulting in an objective evaluation for decision-making.

Decision Matrix: For each hospital, information regarding the distance and emergency waiting time was collected through the APIs. The data was organized into a matrix where each row represents a hospital, and each column signifies an evaluation criterion. Distance and waiting time were treated as key attributes for hospital selection.

Normalization and Weighting of Criteria: The collected data underwent normalization to eliminate scale discrepancies among the criteria. Subsequently, the weights assigned to each criterion were considered, reflecting the importance of each aspect in the final decision.

Identification of Ideal Solutions: Positive and negative ideal solutions were identified for each criterion. This allowed the definition of the best and worst possible values for distance and waiting time, establishing references for comparative analysis.

Separation Measures and Relative Distance: Separation measures were computed to assess the similarity of each hospital concerning the ideal solutions. The relative distance of each hospital from the ideal solution was determined, providing a relative metric for classification.

Hospital Classification: Based on the calculated relative distance, hospitals were classified in order of proximity to the ideal solutions. This yielded a ranking, providing a clear perspective on which hospitals are more aligned with the established criteria.

The application of the TOPSIS technique provided a systematic and structured approach, offering a methodological and robust framework to select the most suitable alternatives according to the specified criteria. By considering proximity and waiting time, patients can make more informed decisions, prioritizing crucial aspects and significantly contributing to the multi-criteria decision-making process in emergency care selection.

IV. TESTS AND RESULTS

1) TOPSIS Application Example

Let's consider three hospitals (A, B, and C) and their respective values for distance and waiting time.

TABLE 2 - Decision Matrix Example

Hospitals	Duration (lower is better)	Waiting Time (lower is better)
Hospital A	240.0s	1200.0s
Hospital B	120.0s	900.0s
Hospital C	300.0s	1500.0s

TABLE 3 - Results

	C^-
0	B
1	A
2	C

The TOPSIS method was applied to evaluate hospitals based on two criteria, distance, and waiting time. Equal weights (0.5) were assigned to both criteria during the process. In the normalization step, the data was normalized by dividing each value by the sum of the squares of the column values, resulting in the normalized matrix.

Next, positive (minimum) and negative (maximum) ideal solutions were identified for each criterion. For distance, the positive ideal solution was 120s (Hospital B), and the negative was 300s (Hospital C). For waiting time, the positive ideal solution was 900s (Hospital B), and the negative was 1500s (Hospital C).

The Euclidean distances from the alternatives to the positive and negative ideal solutions were calculated, and these relative distances were normalized to obtain the measure of relative proximity.

Based on these measures, hospitals were ranked in order of proximity to the ideal solutions. Consequently, Hospital B, being the closest to the ideal values, was classified as the best option. Following that was Hospital A, and finally, Hospital C. Thus, the TOPSIS method indicated that Hospital B is the most desirable option, followed by Hospital A, and lastly, Hospital C.

This example demonstrates how the TOPSIS technique can be applied in hospital selection, considering multiple criteria, and providing a classification that can assist in making decisions to choose the most suitable hospital based on the established criteria.

2) Classification Tests and Results

The results are presented objectively with accuracy, precision, recall, and F1 score obtained during the testing process. However, to determine the best result, the F1 score was focused.

TABLE 4 - Best Results

Model Name	**Best results**		
	Metrics	***Best Parameters***	***Balance***
Support Vector Machine	Accuracy: 0.681 Precision: 0.645 Recall: 0.681 F1 score: 0.658	C: 0.929	TomekLinks
Decision Tree	Accuracy: 0.574 Precision: 0.551 Recall: 0.574 F1 score: 0.557	criterion: entropy, max_depth: 20.0, max_features: sqrt, min_impurity_decrease: 0.0, min_samples_leaf: 4.0, min_samples_split: 10.0, splitter: best	TomekLinks
K Nearest Neighbors	Accuracy: 0.615 Precision: 0.574 Recall: 0.615 F1 score: 0.572	algorithm: kd_tree, leaf_size: 5, metric: eiclidean, n_neighbors: 28, p: 1, weights: uniform	TomekLinks
Logistic Regression	Accuracy: 0.637 Precision: 0.681 Recall: 0.637 F1 score: 0.653	C: 1.5, max_iter: 919, penalty: 0, solver: sag, tolerance: 0.0, weights: balanced	SMOTETomek
Random Forest	Accuracy: 0.627 Precision: 0.625 Recall: 0.627 F1 score: 0.624	estimators: 18, max_features: log2, min_sample_leaf: 1, n_jobs: 2, oob_score: False, random_state: 7	RandomOverSample
XGBoost	Accuracy: 0.684 Precision: 0.662 Recall: 0.684 F1 score: 0.665	booster: gblinear, estimators: 67, gamma: 0.12, grow_policy: depthwise, learning_rate: 1.1, max_depth: 43, min_child_weight: 0	TomekLinks
AdaBoost	Accuracy: 0.671 Precision: 0.632 Recall: 0.671 F1 score: 0.642	algorithm: SAMME, estimators: 89, learning_rate: 1.2	TomekLinks

V. DISCUSSION OF RESULTS CONCLUSIONS

The development process of this solution intertwines two critical components: the multi-class classification system and the TOPSIS model integrated into a multicriteria decision-making system.

The multi-class classification system began with the selection and analysis of a comprehensive dataset, followed by a detailed exploratory analysis to reveal patterns and correlations between various patient attributes and triage levels. Despite gaps in certain columns, the system proceeded with the understanding that these spaces needed to be addressed in subsequent stages. However, it is worth noting that we conclude that limited computer resources, the lack of more data and the unbalanced nature of the dataset were partly responsible for the lack of better results. We concluded that, considering all tests, the ensemble models such as XGBoost and AdaBoost performed better than the others in multi-class classification.

On the other hand, the TOPSIS model emerged as a crucial tool to empower patients to make informed decisions about their emergency care. The integration of this model into an intuitive interface allowed patients to input preferences related to location, transportation, and urgency level derived from the initial triage. Through an intricate process involving data integration from sources such as the SNS API and Google Maps, the TOPSIS algorithm evaluated and prioritized criteria based on patient preferences. This facilitated the identification of ideal and negative solutions, considering both hospital proximity and estimated waiting times.

The systematic development of the TOPSIS algorithm involved stages encompassing the construction of an evaluation matrix, normalization, weighting criteria, and the computation of relative distances. This methodical approach facilitated the classification of alternatives, enabling a structured output that aids decision-makers in selecting the most suitable emergency care option based on specific criteria.

Ultimately, this innovative system merges AI-driven classification techniques with a robust multicriteria decision-making model, aiming to optimize the patient experience by providing personalized, efficient, and informed choices in emergency care selection. The convergence of these methodologies represents a significant advancement toward patient-centered care in emergency medical services, enhancing the overall quality and effectiveness of healthcare delivery.

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