ISBN: 978-628-95207-8-1. ISSN: 2414-6390. Digital Object Identifier: 10.18687/LACCEI2024.1.1.1130

Use of Machine Learning in Hospital Emergency Care for Patients

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***Abstract*– This paper addresses the design and implementation of a Machine Learning model in the process of patient care in hospital emergencies. With the aim of improving efficiency and quality in the provision of emergency medical services, the application of advanced machine learning techniques is proposed. The central problem lies in optimizing the triage process and the assignment of priorities, crucial aspects in the emergency field. The research is framed within a descriptive and applied approach, using observation as the main data collection technique. The observation sheet, structured on the basis of specific indicators, serves as an instrument to evaluate the performance of the model in practical situations. The main objective of this approach is the effective integration of Machine Learning technology into the workflow of hospital emergency departments, with a view to improving decision-making, resource allocation and, ultimately, patient care.**

***Keywords*—Machine learning, process of care, medical care, artificial intelligence, hospital emergency**

I. INTRODUCTION

Reference [1] indicates that the provision of efficient and timely medical care is an unavoidable necessity in the constant search to improve the quality of life of patients. In a global environment, overcrowding in emergency departments has been identified as a critical and persistent concern. Likewise, in references [2] and [3] it indicates that this challenge transcends geographical borders, highlighting that it is not a problem limited to a specific region, but a global problem that requires cutting-edge and effective solutions. In this context, the proper management of patient flows stands as a fundamental imperative to guarantee safety and effectiveness in the care of emergency situations. This challenge not only implies the need to effectively manage the increased demand for emergency services, but also underscores the importance of implementing innovative practices to optimize healthcare in these critical circumstances.

Reference [4], at the international level, the situation of the hospitals of the Ministry of Health (MINSA) in Peru reflects common challenges in countries with limited resources. Perceived low quality of care, shortages of human resources, and use of outdated technology are issues affecting the ability to provide optimal care in low- and middle-income health systems around the world. This panorama highlights the urgency of addressing not only country-specific deficiencies, but also systemic problems that transcend borders and affect global healthcare.

Digital Object Identifier:(only for complete works, inserted by LACCEI).
ISSN, ISBN:(to be inserted by LACCEI).
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Reference [4], at the national level, in Peru, Ministry of Health (MINSA) hospitals face considerable obstacles that affect the quality of care. The perception of low quality is added to the lack of human resources and operation with outdated technology. This situation is not only particular to Peru; reflects the limitations that low- and middle-income countries around the world face in providing optimal healthcare.

Reference [4], in the Peruvian context, emblematic hospitals such as Cayetano Heredia and María Auxiliadora show alarming mortality rates, exceeding the statistics reported in comparative studies at the Latin American and global level. This situation not only highlights the shortage of human resources, but also highlights the prevailing need for a significant technological upgrade to raise standards of medical care and decrease both morbidity and mortality.

Reference [5], Therefore, it is necessary to apply new telecommunication techniques and algorithms that allow efficient and fast health services to be provided, which can save the patient's life. Telemedicine is presented as an essential solution for remote monitoring, allowing large numbers of different chronic patients to be treated at home. Several studies have investigated various telemedicine activities. Reference [6], these studies involve remote evaluation, diagnosis, and treatment of patients with chronic diseases. Reference [7], the quality of care in the hospitals of the Ministry of Health (MINSA) is perceived as low. The problem is not exclusive to Peru. The quality of care in low- and middle-income countries worldwide is inadequate even though its optimization could save more than eight million lives annually. Deaths from cardiovascular disease have the highest lethality due to the poor quality of care in low- and middle-resource countries. Reference [8], and it is precisely in these pathologies of increasing incidence, where diagnostic studies and therapeutic interventions usually have enormous limitations. Reference [8], the MINSA's human resource deficit is known, with a gap of more than 47,000 professionals estimated for 2016, with a greater deficiency in centers in areas with higher levels of poverty. Reference [8], the deficiencies in technical personnel are possibly greater, but little emphasized. In many hospitals, the lack of technicians who can timely assist patients with their basic needs often forces the cooperation of family members to be able to address this problem. Reference [8], most hospitals operate with outdated technology, which generates delays in the quality of care, just as mortality in medicine services is probably a more realistic marker of the quality of hospital care. A study that analyzed hospital mortality at the Cayetano Heredia Hospital between 1997 and 2008 found a mortality of 9.6% in those under 60 years of age, which increased to 14% in those over 60 years of age. In that same hospital the mortality rate in the previous decade had been 8%. The situation is no different in other hospital centers. At the María Auxiliadora Hospital, mortality in the medicine department during 2014 reached 8.7%, while at the Hipólito Unanue National Hospital during 2018 it was 10.5%. Reference [8], all these figures are significantly higher than those reported in other studies at the Latin American and global level. These numbers are alarming and warrant immediate action.

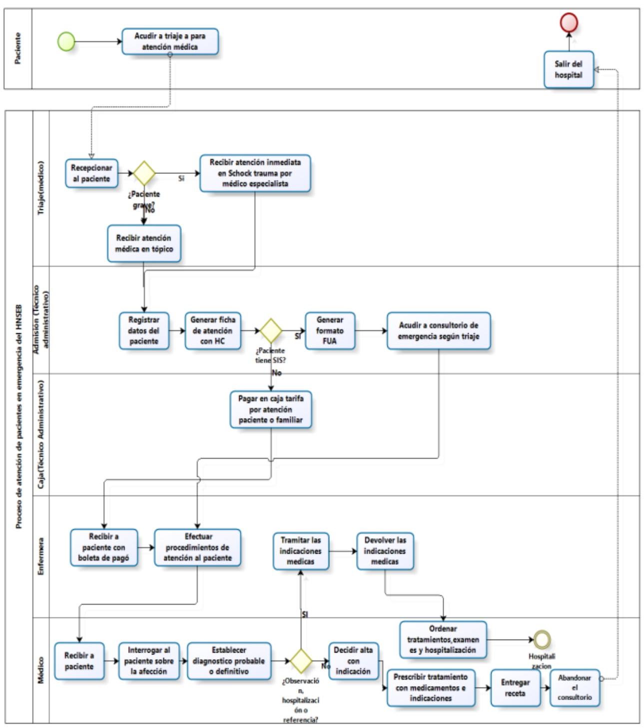

Fig. 1 Patient care process in the hospital emergency area.

The process of caring for a patient in a health center is complicated, especially for the patient who enters through the emergency area, who requires quick and timely attention. In emergencies, care is not taken in order of arrival but rather by severity and priority. According to the arrival of the ambulances, which will enter and leave through the main door of the Emergency service, the patients are transferred to the central patio of the emergency pavilion, where the Triage Team is located, whose function will be to classify patients according to their severity, taking into account the following priorities: emergency, imminent danger of death, immediate attention, prolonged care times that can cause complications in patients, which also cause them to be dissatisfied with the treatment that the clinical entity It can provide what also implies the number of patients seen during the day, hand in hand with the times that are managed in each care and the poor classification that is given for each patient, causing discomfort to them.

Therefore, the objective of this research is to implement a Machine Learning model to improve the patient care process in hospital emergencies, to do so, the following objectives are taken into account, which are: reduce patient waiting time in the hospital. triage in hospital emergencies; increase patient satisfaction in hospital emergency care; increase the percentage of patients per day in hospital emergencies; and optimize the classification of patients according to priority in hospital emergencies.

II. Theoretical Framework

A. Machine Learning

Reference [1], machine Learning (ML) is defined as the design and study of computer tools that use experience to make future decisions, being a field that seeks to generalize unknown rules from previous examples. This approach finds applications in various contexts, highlighting spam filtering, where ML algorithms learn to classify new messages based on thousands of emails previously marked as junk.

Reference [1], ML combines concepts and techniques from areas such as mathematics, statistics, and computer science. There are several types of ML, including:

Reference [2], supervised learning: The algorithm trains on previously labeled data and subsequently predicts results for new unlabeled data. It is like school learning, where problems and their solutions are taught to apply the learned methods in similar situations.

Reference [2], unsupervised learning: The algorithm is trained with unlabeled data, seeking to discover patterns on its own. It is comparable to the process of learning language in childhood, where, at first, we do not understand the meaning, but over time, our brain models how language works.

Reference [2], reinforcement learning: The algorithm learns by observing its environment, receiving feedback in response to its actions. It learns through trial and error, as in games where strategies are tested and refined based on accumulated success.

Reference [2], overfitting: It is the tendency of ML algorithms to fit to specific features of the training data that are not causally related to the objective function. Overfitting can lead to poor performance when applying the model to data not seen during training.

Steps to build a Machine Learning model:

Collect data: Reference [3], data is obtained from various sources, such as websites, APIs, databases, or specific devices. Data collection can be a complicated and time-consuming task.

Preprocess the data: Reference [3], the data is prepared to feed the learning algorithm, ensuring that it is in the correct format. This step usually requires preprocessing tasks.

Explore the data: Reference [3], pre-analysis is performed to correct missing values, identify patterns, and detect potential outliers. Statistical measures and graphs are useful at this stage.

Train the algorithm: Reference [3], the algorithm is fed with the processed data so that it extracts useful information and can make predictions.

Evaluate the algorithm: Reference [3], the accuracy of the algorithm in its predictions is tested. If the performance is not satisfactory, the algorithm can be tuned and retrained.

Use the model: Reference [3], the model is faced with the real problem and its performance is evaluated. If necessary, the previous steps are reviewed.

B. Patient unit:

The patient unit refers to the set that includes the space of the room, the furniture and the material used during the stay in the hospital. Reference [1], in shared rooms, each unit can be isolated with screens or curtains to preserve privacy. In the Peruvian context, some hospitals seek to have both individual and shared rooms to adapt to the needs of patients. Reference [1], individual rooms are reserved for serious cases, infectious diseases, surgical patients with risk of contagion, immunosuppressed patients, and those with psychological problems.

Reference [1], the bed, an essential component of the patient's unit, must be in optimal condition and allow adequate accommodation of the patient. It is placed in the room so that it has three free sides to facilitate the work of healthcare personnel. Careful bed arrangement contributes to the patient's well-being.

Reference [1], the functions of the nursing assistant in relation to the patient's unit include consciously receiving the patient, considering the sensations and emotional changes they experience upon entering the hospital. In addition, she is responsible for informing the patient about the use of equipment and materials in the unit.

Stages of the process:

Assessment:

Reference [21], assessment is an organized and systematic process of collecting data about the patient's health status. It can be done under "systems and devices" or by "functional health patterns." The collected data is organized and recorded.

Diagnosis:

Reference [21], in the diagnosis stage, the patient's real or potential problem that requires nursing intervention is stated. Diagnoses can be actual, high-risk, possible, or wellness.

Planning:

Reference [21], planning involves organizing the care plan, establishing priorities, objectives, and nursing activities. It is crucial to document and record documentary records of the entire care plan.

Execution:

Reference [21], at this stage, the care plan is carried out, carrying out nursing interventions aimed at solving problems and addressing healthcare needs.

Assessment:

Reference [21], the evaluation, the last phase of the process, assesses the efficiency and effectiveness of the care. It is a continuous process that allows modifications to be made to the care plan to improve care.

C. State of the art

Reference [17], conducted a study titled "Review on the utilization of machine learning technology in the fields of electronic emergency triage and patient priority systems in telemedicine: Coherent taxonomy, motivations, open research challenges and recommendations for smart future jobs." The primary aim of this research, published in the Journal ELSEVIER, was to provide a comprehensive literature review and an in-depth exploration of machine learning functions in electronic emergency triage (E-triage) and patient prioritization for rapid healthcare services in telemedicine applications.

The study emphasized the efficacy of machine learning methods, covering algorithms, input medical data, output results, and machine learning objectives in telemedicine systems for remote healthcare. The researchers introduced a coherent taxonomy, establishing cross-correspondence between machine learning algorithms and telemedicine structure. Various machine learning methods, including specific ones or hybrid approaches, were employed to enhance the performance of E-triage and priority-based systems within telemedicine.

From the machine learning and artificial intelligence perspective, the section aimed to offer researchers an overview of functions, names, and types of machine learning discussed in the study. Consequently, a new cross-correspondence between machine learning methods and telemedicine taxonomy was proposed, aiming to identify the relationship between machine learning algorithms and corresponding telemedicine categories.

The impact of machine learning implementation was evident in proposing a telemedicine architecture based on a synchronous (real-time/online) and asynchronous (store-and-forward/offline) structure. The paper presented lists of machine learning algorithms, performance metrics, input data, and output results. Additionally, it addressed open research challenges, benefits of using machine learning, and recommendations for interdisciplinary research opportunities. The study concluded that a significant contribution was the organization of related works into a clear and coherent taxonomy, mapping the role of machine learning methods in telemedicine through a cross-sector scheme. Comprehensive analysis of relevant research articles helped identify methods and performance measures extensively utilized in telemedicine health monitoring systems, highlighting relevant research challenges, and suggesting directions for future studies beneficial for academic and industrial research.

Reference [18] emphasized the critical role of evaluation in the nursing process. Evaluation supports the foundation of the usefulness and effectiveness of nursing practice, with patient satisfaction being an indicator of a positive prognosis and a definitive determinant of health care quality in the hospital. The main objective of the study was to determine the quality of care in patients at the emergency service of Puente Piedra Hospital. The descriptive study's sample included 198 patients, and data were collected through patient information forms, Satisfaction with Triage scale, and Satisfaction with Nursing scale. Data analysis involved descriptive statistical methods, parametric, and non-parametric tests.

The findings highlighted that patient satisfaction with nursing care is indicative of a positive patient prognosis and a crucial determinant of healthcare quality. The study emphasized that evaluating user satisfaction with nursing services is essential for enhancing patient perception after treatment. In emergency units, nursing professionals often serve as the first point of contact for patients, and the relationship established can significantly impact patient satisfaction with the hospital. The conclusion indicated that patients in the emergency unit were generally satisfied with triage and nursing care practices, although satisfaction levels related to health status and psychological support were identified as low.

Reference [19], in their research titled "A novel approach for predicting acute hospitalizations among elderly recipients of home care. A model development study," aimed to investigate predictors and performance of machine learning algorithms for predicting acute hospitalizations in elderly recipients of home care services. The developmental study utilized a retrospective cohort from the social sector with 1,282 participants aged 65 or older, receiving home care services in Aalborg Municipality. Data collection involved a newly developed triage tool and routinely collected administrative and clinical data in the Danish health and social care sector. The study tested and evaluated 857 predictors based on the area under the precision-recall curve (PR-AUC), employing a sliding window approach with random subsampling and a boosting algorithm (RUS Boost).

The findings revealed that the RUS Boost algorithm outperformed standard logistic regression, achieving a higher PR-AUC. Four of the five most important predictors for accurately predicting acute hospitalization were identified, including the total number of services provided, personal care records, medication management and records, and physical complaints from the triage tool. The study concluded that municipalities routinely collect valuable data for early prediction of acute hospitalizations, with the need for future studies to validate these results.

Reference [20], in their thesis titled "The role of machine learning algorithms for diagnosing diseases," aimed to provide an overview of automatic learning algorithms applied for identifying and predicting various diseases, such as Naïve Bayes, logistic regression, support vector machine, K-nearest neighbor, K-means clustering, decision tree, and random forest. The study reviewed previous research using machine learning algorithms for disease detection in the medical field over the last three years.

The methodology involved machine learning models learning from patterns in training examples without explicit instructions, and the study focused on classification methods widely used in the medical field to identify and predict diseases more accurately. Various diseases, including liver cancer, chronic kidney disease, breast cancer, diabetes, and cardiac syndrome, were explored. The study highlighted the significance of machine learning techniques in classification for medical applications and discussed different algorithms' applications on standard datasets.

The results indicated that many machine learning algorithms, such as logistic regression, K-nearest neighbors, support vector machine, K-means, decision tree, random forest, and ensemble models, showed promising accuracy in predicting diseases. The study acknowledged the importance of considering factors like datasets, feature selection, and the number of features influencing the accuracy and performance of the model. The article provided a comprehensive review of different machine learning algorithms for predicting diseases and presented a tabulated list of results from various studies using different models. The conclusion emphasized the role of machine learning in the medical sector for data analysis related to diseases, particularly in early disease detection.

Reference [21] in his thesis titled “Machine Learning techniques applied to precision oncological diagnosis and treatment through the analysis of omics data” whose main objective is to explore the use of Machine Learning methodologies used in precision oncological research to from omics data. Identify possible methodological weaknesses to develop subsequent robust and reproducible Machine Learning models that help their application in routine clinical practice. Develop models based on Machine Learning that allow the discovery and repositioning of drugs in the context of Precision Medicine. Use of Machine Learning algorithms for the identification of altered biomarkers and pathways in cancer patients to help stratify patients to search for specific treatments. As a methodology, studying previous works that used TCGA data, more than 150 published articles that applied ML techniques to analyze said data. Most of the reviewed works applied training solutions: supervised and unsupervised. Furthermore, the works are classified according to the biological problem, the algorithm and the type of omics data used. The characteristics of the TCGA repository (large databases of different omics) provide an ideal environment for the comparison of methodologies. In this way, based on the same data, the application of different ML-based methodologies can be compared to solve various problems. During the development of the review, weaknesses in the application of the methodologies are identified: mainly, the lack of reproducibility of the results and overtraining of the models. The review of articles helped design guidelines for applying ML models in the analysis of omics data. Following these guidelines, ML models were applied to solve two problems in biomedicine: 1) identification of signatures and/or biomarkers altered in patients with colon cancer 2) automatic screening of anti-tumor drugs. Both problems follow the objectives of Precision Medicine. Regarding the trends of the reviewed works, kernel-based models and specifically, the SVM model and its variants are the most used in this field, followed by models based on decision trees. A growing trend has been detected in the use of neural networks, mainly with Deep Learning topologies, although they present great difficulties for their application in omics databases, due to the low number of samples presented in these studies. Finally, a classification of the biological problems addressed by each type of cancer is made, such as results, most of the reviewed works applied training solutions previously mentioned in this doctoral thesis:

supervised and unsupervised. Furthermore, the works are classified according to the biological problem, the algorithm and the type of omics data used. The characteristics of the TCGA repository (large databases of different omics) provide an ideal environment for the comparison of methodologies. In this way, based on the same data, the application of different ML-based methodologies can be compared to solve various problems. During the development of the review, weaknesses in the application of the methodologies are identified: mainly, the lack of reproducibility of the results and overtraining of the models. The review of articles helped design guidelines for applying ML models in the analysis of omics data. Following these guidelines, ML models were applied to solve two problems in biomedicine: 1) identification of signatures and/or biomarkers altered in patients with colon cancer (see section 3.2); 2) automatic screening of anti-tumor drugs (see section 3.3). Both problems follow the objectives of Precision Medicine. Regarding the trends of the reviewed works, kernel-based models and specifically, the SVM model and its variants are the most used in this field, followed by models based on decision trees. A growing trend has been detected in the use of neural networks, mainly with Deep Learning topologies, although they present great difficulties for their application in omics databases, due to the low number of samples presented in these studies. On the other hand, gene expression data are the most frequently used. Their use, combined with other omics data, such as miRNA and/or methylation data, obtain better model performances, as indicated in the review. The work also discusses the ways and performances achieved with different forms of omics data integration. Finally, a classification of the biological problems addressed by each type of cancer is made. It is observed, for example, that the glioblastoma cohort is the one with the most survival studies, mainly due to the high mortality, which implies a greater number of events and increases the power of this type of analysis. On the contrary, the breast and kidney cohorts emerge as the most frequently employed datasets in the quest for new subtypes, utilizing unsupervised learning techniques. The findings suggest that the application of machine learning (ML) techniques to omics data reveals patterns and variables of interest that conventional methods, such as statistical inference, hypothesis testing, or differential expression analysis, may fail to identify. Reference [1] illustrates the prevalence of supervised learning as the predominant type. This approach is predominantly applied to expression data, particularly RNA Sequencing (RNA Seq), with kernel-based models, specifically the Support Vector Machine (SVM) algorithm, emerging as the most frequently utilized. It is important to note that no single model stands out as significantly superior across all cases. Neural networks, particularly those employing Deep Learning topologies, play a significant role in these analyses, with the primary limitation being the sample size of the cohorts. Reference [21] focuses on predicting the number of students approved and failed in the courses of the Basic Studies Program at Ricardo Palma University through the application of Machine Learning algorithms. The methodology involves dividing the study population into two segments: one termed "train," which is dedicated to model development (comprising 70% of the population), and the other for performance testing of the developed model (30% of the population), referred to as the "test" segment. The operationalization of the model's performance is gauged through the Accuracy indicator, representing the success rate of the confusion matrix. This indicator reflects the proportion of correct predictions, both positive and negative, in relation to the total number of predictions (observations). The study concludes based on the accuracy achieved by the model. The work method used to develop this research was the CRISP Methodology. -DM, its use was very useful to obtain ideas and be able to structure a path where it was easy to complete each stage, not because of the complexity of the research, but because of the goal that had to be achieved in each one.

III. Method

A. Type of research

Descriptive research: it is descriptive research, because it has a dependent variable (Machine Learning), independent variable (Patient care process in the hospital emergency area)

Applied Research: The application will be carried out in the Machine Learning model to solve the practical problem in our case, the patient care process in hospital emergencies.

B. Procedures and instruments

For the data collection technique, it was decided to use observation where the observation sheet will be used as an instrument based on the indicators proposed in the objectives.

IV. Conclusions

The introduction of machine learning systems in the field of hospital emergencies demonstrates a significant improvement in the effectiveness of the patient care process, optimizing resources and response times.

The predictive capacity of machine learning models contributes to the early identification of critical medical conditions, reducing morbidity by anticipating emergencies and facilitating preventive interventions.

The application of machine learning algorithms in the care of emergency patients allows for a more efficient allocation of hospital resources, guaranteeing adequate management of beds, personnel, and supplies at critical times.

The integration of machine learning models in the emergency care process provides medical professionals with accurate and timely information, improving clinical decision making and allowing more personalized treatment.

The quality of care is reinforced through the implementation of machine learning models, if continuous validation and adjustments are carried out according to clinical feedback, ensuring the reliability and effectiveness of the system in dynamic emergency care environments.

Acknowledgment

We thank the whole team for their mutual effort.

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