Efficiency of Healthcare Systems in Developing Countries During Crisis - A Case Study in India

M506 Research Methods and Scientific Work

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Contents

Abstract

Indian hospitals struggle to handle the enormous number of patients that are admitted to emergency departments each year due to one of the fastest-expanding populations in the world. In order to prevent patients' symptoms from developing into life-threatening circumstances, nurses at the emergency department are responsible for assigning a triage level and ensuring that the patients are seen by professionals within a specific amount of time. Since it defines the treatments and procedures the patient would need to undergo after a diagnosis, it is vital that an accurate triage level is allocated to the patient. It takes a lot of practice, knowledge, and experience to assign a triage number as one needs to consider the information about the patient's vital signs, their chief complaint, and the number of resources they used in the ED.

Artificial intelligence techniques have been utilised to automate the entire procedure in order to prevent mis-triaging, which may happen due to a lack of information, inexperienced nurses, or a time crunch. There are a number of triage systems that are now in use that have been further investigated to create automated triage systems for them, but the Indian triage system, known as the ATP, does not. The purpose of this study is to develop an artificial intelligence-based automated system that would take into account a number of factors, including the triage vitals, chief complaints, and the number of resources used, in order to calculate the ESI value and then determine the appropriate ATP level. This would assist patients to obtain the right care by bridging the gap between inexperienced nurses and the administration of a large population in the ED.

Random Forest (RF) and Gradient Boosting (XG-Boost) were the two methods used to categorise and assign triage levels to patients. With an Area Under Curve (AUC) value of 0.98, it was seen that XG-Boost outperforms RF significantly. Thus, XG-Boost successfully identified patients with "Red" ATP levels with a recall value of 0.73, preventing the misclassification of patients who would otherwise be in danger of dying.

Keywords: Triage, Artificial Intelligence, ESI, ATP.

1. Introduction

India's economy is among the fastest growing in the world regardless of the fact that it is still a developing nation. However, one of India's biggest problems remains to be a severe shortage of trained medical professionals, including doctors, nurses, paramedics, and other basic healthcare workers [1].

Nearly half of all trauma deaths occur in hospitals, emphasising the importance of improving in-hospital treatment. Trauma treatment is extremely time-sensitive, and treating injuries as soon as possible is critical for life. In India, high population density and inadequate pre-hospital treatment exacerbate the problem of overcrowding in Emergency Departments (ED) [2]. Multiple patients being admitted to the ED forces the doctors and nurses to make quick decisions which would be extremely crucial for the patient's treatment. Depending on the severity of the patient's condition, nurses assign them to either receive immediate or delayed medical attention. This process of categorisation is called triaging [3]. Triaging, an extremely critical procedure is a standard hospital protocol followed in the ED, where each patient is assigned a triage number based on their vital signs. A few triage systems that exist with a good accuracy rate are The Australasian Triage Scale (ATS), The Canadian Triage and Acuity Scale (CTAS), The Manchester Triage System (MTS) and The Emergency Severity Index (ESI) [4]. Each of these modern triage systems uses five levels of triage to establish a time frame for receiving medical attention based on key vitals, resources used, or the health history of the patient.

The All India Institute of Medical Sciences Triage Protocol (ATP), used by India's leading medical school since 2010, took into account the country's massive overpopulation as well as the presence of poorly educated staff in the ED who found it challenging to comprehend the complicated five-tier foreign triage system. ATP was created with just three levels of colour-coded categorization: "Red," "Yellow," and "Green" [5] to get over these limitations.

However, mis-triaging, or incorrectly assigning a patient a triage level in the ED, might compromise the patient's care in circumstances where time is of the essence. Mistakes in triage can occur for a variety of reasons, including lack of experience of the nurses, pressure to assign a triage level promptly, and the difficulty of taking into account the primary complaint, vitals, and the number of resources required by the patient in the ED. Under-triaging and over-triaging specifically are the two main types of mis-triaging where patients either do not receive enough resources for their care or undergo unnecessary, potentially risky, and very expensive medical procedures [6].

The use of artificial intelligence (AI) models has demonstrated improvements in the ability to forecast and categorise data as well as the correlation of data using a variety of features to produce a much more viable outcome. If the nurses are inexperienced, triaging can become very hard because it needs nurses to take into account numerous factors. AI would be the most suitable method to increase the accuracy and assign proper triage levels in order to decrease mis-triaging and avoid time wastage [9].

2. Problem Statement

ATP in India classifies patients based on both their subjective and objective conditions in the emergency department. The patient's vital signs, medical history, and primary complaints comprise these conditions. Despite being an effective method, life-threatening mis-triages might occur because too many variables must be taken into account before the patient is awarded a triage level in a limited amount of time [6].

3. Research Question

How can the ATP triage system in India be made more automated to speed up the triaging procedure and decrease mis-triages?

4. Objective

To utilise artificial intelligence algorithms to assign a triage level more accurately to a patient in India.

5. Conceptual Framework

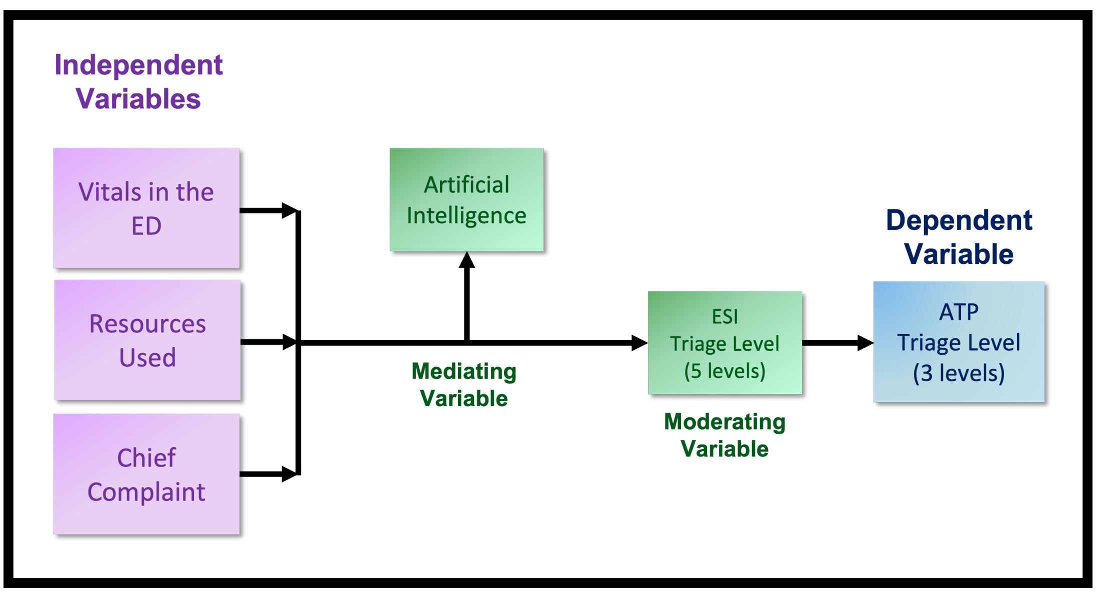

Figure 1: Flow Diagram of the Conceptual Framework

6. Literature Review

Considering that India has the world's largest population, it can be challenging to run hospital emergency rooms when there is a crisis. The absolute necessity of providing patients with sufficient care and attending to them quickly cannot be overstated. Joshi et al. (2020) made this observation while examining a children's hospital in India and found that there wasn't a sufficient system in place to treat the children promptly, forcing them to leave the ED after spending a whole day there. Sahu et al. (2020) proposed ATP, a triage mechanism that makes up for a lack of resources and educated personnel. Yet, because triaging is a manual process and very subjective, mistriaging frequently results. It is exceedingly risky to respond merely using a subjective triage method, which is primarily created in a very short amount of time, to manage such a large population.

There are other additional triage systems that are unique to the respective countries. A triaging system that is widely used in the USA is the Emergency Severity Index (ESI), which was devised by N et al. (2005). ESI takes into account both the patient's vitals and the number of resources they utilised in the ED. Furthermore, automation of the triaging process has made significant progress. Various artificial intelligence (AI) strategies are employed to increase accuracy and reduce mis-triaging. Table 1 provides specifics about previously conducted research on triage classification using AI. The common statistic used to assess the performance of the classification models included in this study is the area under the curve (AUC) [14]. The classification model's effectiveness can be inferred if the AUC value is close to 1.

Table I: A literature review of papers which have used artificial intelligence for triaging

Paper	**Objective**	**Algorithm**	**Results**
Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index 2009 [9]	To use a machine learning algorithm to improve ESI triaging	Random forests (RF)	E-triaging is more accurate. AUC = (0.73,0.92)
Predicting hospital admission at emergency department triage using machine learning (2018) [12].	To find out which artificial intelligence model performas better with or without patient history.	• Logistic Regression (LR) • XGradient Boosting (XGBoost) • Deep Neural Networks (DNN)	Without patient history: AUC for LR = 0.87 AUC for XGBoost =0.87 AUC for DNN = 0.87 With patient history: AUC for LR = 0.91 AUC for XGBoost =0.92 AUC for DNN = 0.92
Emergency department triage prediction of clinical outcomes using machine learning models (2019) [11].	To use machine learning approaches for triaging and comparing them to ESI values.	• Lasso regression (LassoR) • Random forest (RF) • Gradient Boosting (XGBoost) • Deep Neural Network (DNN)	Hospitalisation Outcome AUC for LassoR = 0.81 AUC for RF = 0.81 AUC for XGBoost = 0.82 AUC for DNN = 0.82
Developing machine learning models to personalise care levels among emergency room patients for hospital admission (2021) [10]	To find out if patients should receive ICU care or not.	• Gradient Boosting (XGBoost) • Logistic Regression (LR)	AUC for XGBoost = 0.88 AUC for LR = 0.67

7. Methodology

The nature of this research is applied because it aims to discover a practical solution for all Indian hospitals to simplify the triaging procedure. This could assist patients to get the proper care for their conditions and lessen mis-triaging while also managing the rise in trauma and non-trauma patients in the ED. Positivism is the school of thought because this research can be generalised without regard to an individual's personal opinion and has an objective reality. The idea of triaging is one that has been applied in many nations, however, India wasn't successful in implementing it until AIIMS, the most renowned government hospital in India, developed a solution in the year 2020. This provides an opportunity for us to perform deductive research to improve the situation in Indian hospitals as it currently exists and to construct an automated method to aid in the triaging procedure. This style of study is quantitative and uses vast amounts of information on patients at the ED, including their vital signs, primary complaints, and medical history. The data was acquired from [13] using a secondary data collection process using a cross-sectional study method.

Data Analysis and Model Fitting

There are 972 features in the dataset being used for this classification. These aspects include data on the patient's demographics, triage vitals, chief complaint, medical history, and imaging. All of these characteristics aid in the ESI triage classification process. Accurate patient diagnosis is crucial when a patient first reaches the emergency department. Many symptoms exist that would make diagnosis easier. They often have one or more physical complaints, and their vital signs are another sign of illness. Furthermore, it is usually helpful for doctors to be aware of their patient's medical histories, including any medications they have previously taken or surgeries they have had. Also, the ESI triage system gives a triage level mainly based on the resources the patient uses when in the ED.

The columns with more than 50% of the data missing were dropped. The missing data was imputed after the train and test split of 80% and 20% to avoid data leakage. Algorithms such as LR and XGBoost were used to fit the data.

8. Results

The test dataset's patient categorization according to the ESI triage levels, which were used to assess the performance of the AI model, were as follows: ESI 1 = 1058, ESI 2 = 32778, ESI 3 = 46893, ESI 4 = 25116, ESI 5 = 5596. It was observed that the efficiency with which each patient's triage level was assigned by the two AI models varied. To assess how accurately the model predicted the triage values listed in Table 2, the AUC under the ROC curve was calculated.

Table 2: Test AUC values for the respective AI algorithms.	
Algorithm	**Test AUC (95% CI)**
XGBoost Classifier	0.9869
Random Forest Classifier	0.9355

Plotting the models' precision, recall, and F1 scores provided additional insight into how well they performed by making it easier to see how each group of models performed relative to the others. In distinction to recall, which shows how many of the actual values in a class the model accurately predicted, precision helps determine how many values that were expected to be in a certain class were actually in that class. F1 score is the weighted average of the precision and recall value.

All ESI levels of XG-Boost had precision values of 0.90 or higher, although ESI 1 had a recall value of 0.74 as opposed to the other ESI levels' recall values, which were all kept above 0.90. This demonstrates that, in contrast to the other ESI levels, ESI 1 values were not correctly predicted, refer to Figure 2 for the graphical representation.

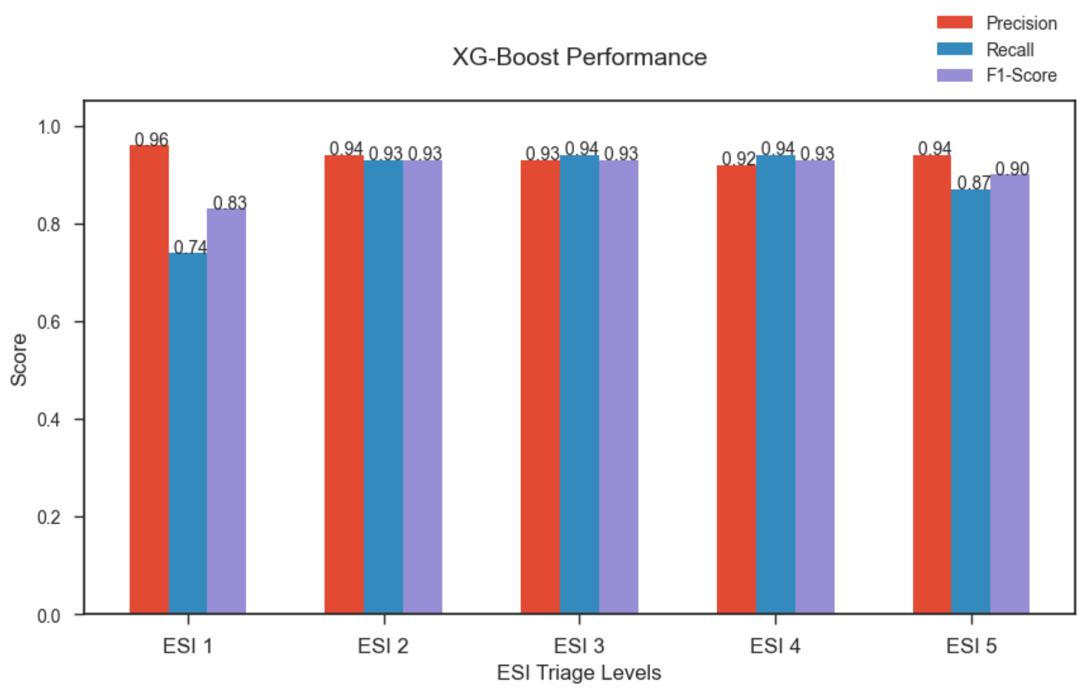

Figure 2: Graphical representation of the performance of XG-Boost algorithm

In contrast, Random Forest performed substantially worse than XG-Boost across all ESI levels in terms of precision and recall scores. On the one hand, ESI 1 has the best precision, but it also has the lowest recall value (0.21), meaning that fewer ESI 1 levels were accurately predicted and ESI 1 mis-triaging was more common. The recall value for ESI 5 is 0.46, which indicates that many ESI 5 data were incorrectly triaged as well, refer to Figure 3 for the graphical representation.

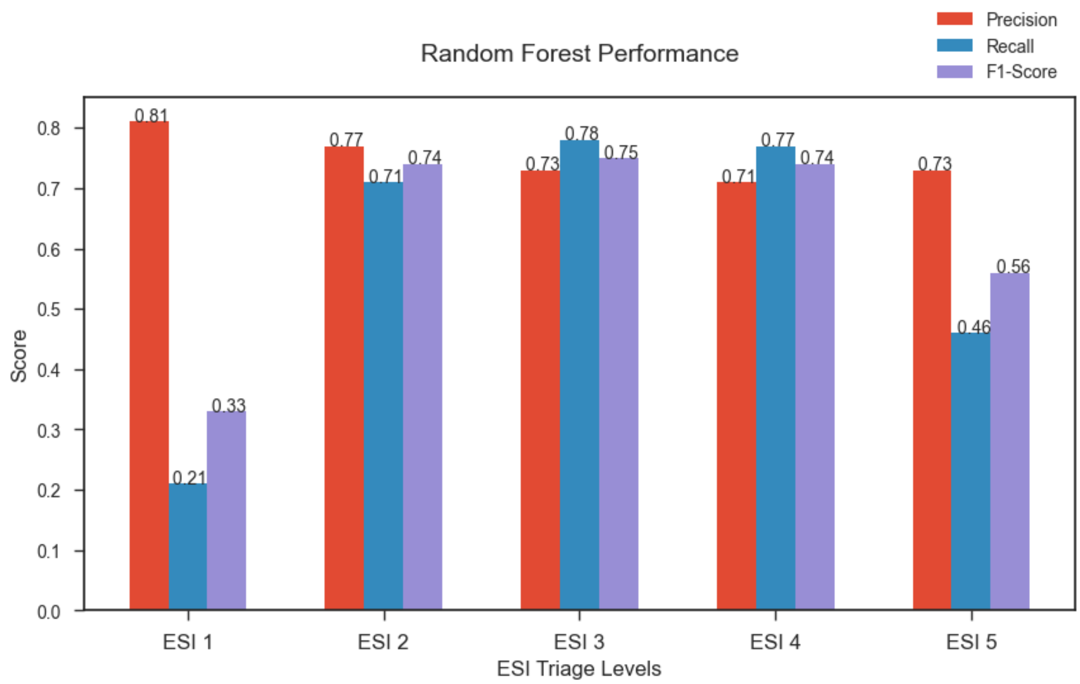

Figure 3: Graphical representation of the performance of Random Forest algorithm

Patients were distributed differently across ESI levels using XG-Boost and RF. The relationship between ESI and ATP triage levels has been described by Sahu et al. in 2020. The ESI levels 1 and 2 are categorised as belonging to the "Red" level of ATP, the ESI levels 3 and 4 as belonging to the "Yellow" level of ATP, and the ESI level 5 as belonging to the "Green" level of ATP. We would be able to accomplish our goal of utilising AI to have an automatic triage classification with regard to ATP by leveraging this relation.

This relationship suggests that patients who need urgent medical attention and are in a high-risk condition are in excruciating pain or suffering, are utilising extensive medical resources, or have dangerous vital signs would be classified in the "Red" Level of ATP. Their treatment must start right away or within the next 10 minutes. The patients who would fall under the "Yellow" group would have potentially fatal illnesses that could progressively worsen into serious morbidity. They utilise one or no resources to relieve their discomfort or to diagnose their sickness, and their symptoms are either mild (low-risk) or persistent. In this situation, medical personnel must act within a half- or hour and provide inpatient care or a thorough examination and provide the appropriate treatment. Last but not least, patients who are only mildly uncomfortable and whose symptoms won't become worse over time are in the "Green" level, where treatment can begin after or within two hours of their arrival at the ED.

Compared to RF, XG-Boost has placed more patients in the "Red" and "Green" categories. On the other hand, RF has categorised a sizable proportion of individuals as belonging to the "Yellow" category. The precise number of patients who were categorised into the ATP triage levels by the AI models utilised for the classification may be found in Fig 4.

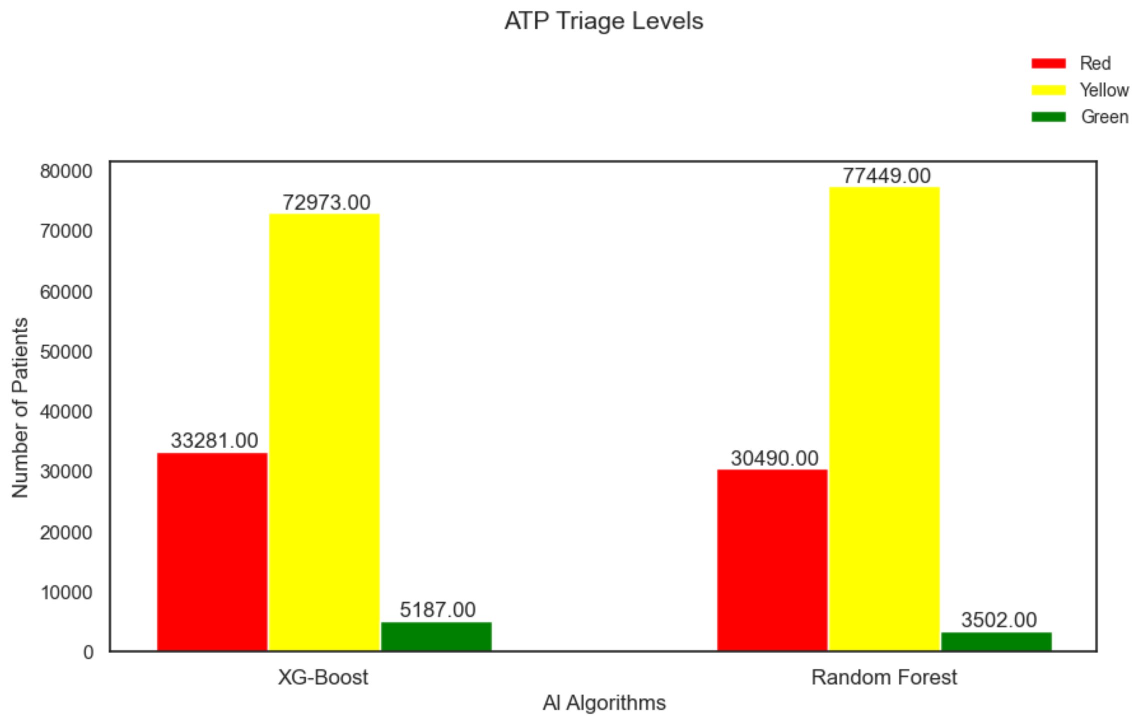

Figure 4: Visualization of ATP Triage Using XG-Boost and RF

9. Conclusion

Both AI models had significantly diverse performances and produced classifications for the ATP triage level that differed considerably. A total of 33836 patients were assigned to the "Red" ATP triage level in the test dataset, 72009 patients were assigned to the "Yellow" level, and the remaining 5596 patients were assigned to the "Green" level. In comparison to RF, XGBoost sends a greater number of patients to "Red," ensuring that a greater number of patients receive immediate medical care. In a similar way, XG-Boost also categorised more patients than RF into the "Green" triage category, ensuring that such patients may be attended to later. Whereas RF assigned the majority of patients to the "Yellow" triage category, as a result, more patients receive treatment in a reasonable amount of time.

XGBoost helps to clearly categorise patients into three levels, ensuring that patients are not over- or under-triaged. In contrast, in RF, patients who may need immediate attention would either be ignored, which would likely worsen their symptoms or people who do not need much medical attention would be attended to first, resulting in unnecessary medical procedures that would also waste resources and precious time of the medical professionals who could have rather attended to patients who were in actual need of their help.

As a result, the ATP triage system can assign triage variables effectively using XG-Boost.

10. Future Work

This paper would be able to accurately validate the proposed model in the presence of a dataset which contained information on patients from India, with demographics specific to India. There are many other countries and regions that do not have a triage system, so if a derivation was to be made in order to help other countries to have their own triage system it would help time, and resources, and assure the citizens of receiving better medical attention.

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Module Title	Research Methods and Scientific Work (WS0123)
Module Tutor	Prof. Dr. Sara Ramzani
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