TriageIntelli : Développement d'un système de triage assisté par IA en centre de santé, utilisant des données multimodales

MÉMOIRE PRÉSENTÉ

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PAR

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RÉSUMÉ

Face à la surcharge chronique des services d'urgence, notre étude propose une solution concrète pour optimiser le processus de triage des patients à l'aide de l'intelligence artificielle (IA). L'objectif est clair : améliorer la prédiction du niveau de triage attribué aux patients en utilisant des données multimodales, telles que les signes vitaux, les antécédents médicaux et les plaintes exprimées à l'admission.

En s'appuyant sur un jeu de données réel comprenant plus de 1 200 patients, notre recherche évalue les performances de plusieurs algorithmes d'apprentissage automatique : les machines à vecteurs de support (Support Vector Machine, SVM), les forêts aléatoires (Random Forest, RF), les réseaux de neurones (Artificial Neural Networks, ANN), la régression logistique (Logistic Regression, LR), le Gradient Boosting Machine (GBM), l'eXtreme Gradient Boosting (XGBoost), ainsi qu'un modèle empilé. Les résultats montrent que les approches fondées sur l'IA surpassent les méthodes classiques, tant en termes de précision, de rappel que de F1-score. Le modèle empilé, en particulier, atteint une précision de 80,05% et un score F1 de 74,41%, marquant une avancée significative dans ce domaine.

ABSTRACT

In response to the chronic overcrowding of emergency departments, this study proposes a concrete solution to optimize the patient triage process using artificial intelligence (AI). The objective is clear : to improve the prediction of the triage level assigned to patients by using multimodal data, including vital signs, medical history, and presenting complaints at admission.

Relying on a real-world dataset of over 1,200 patients, the study evaluates the performance of several machine learning algorithms : Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), Logistic Regression (LR), Gradient Boosting Machine (GBM), eXtreme Gradient Boosting (XGBoost), and a stacking model. The results show that AI-based approaches outperform traditional methods in terms of precision, recall, and F1-score. The stacking model, in particular, achieves an accuracy of 80.05% and an F1-score of 74.41%, representing a significant advancement in this field.

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LISTE DES ABRÉVIATIONS

AI Artificial Intelligence

ANN Artificial Neural Network

ATS Australasian Triage Scale

CTAS Canadian Triage and Acuity Scale

DL Deep Learning

ED Emergency department

ESI Emergency Severity Index

GBM Gradient Boosting Machines

IA Intelligence Artificielle

JTAS Japan Triage and Acuity Scale

KTAS Korean Triage and Acuity Scale

LR Logistic Regression

ML Machine Learning

MTS Manchester Triage System

RF Random Forest

SMOTE Synthetic Minority Over-sampling Technique

STAS South African Triage Scale

SVM Support Vector Machine

XGBoost eXtreme Gradient Boosting

INTRODUCTION GÉNÉRALE

Le triage des patients dans les services d'urgence remonte à plusieurs siècles et a évolué en fonction des besoins changeants des systèmes de santé. Conçu à l'origine sur les champs de bataille pour donner priorité aux soldats gravement blessés, son objectif initial était d'optimiser des ressources médicales limitées et de sauver le plus grand nombre de vies possible. Cette logique a marqué le début du triage moderne, qui fut ensuite adapté aux hôpitaux et aux services d'urgence civils Iserson and Moskop (2007).

Historiquement, le triage est passé de méthodes simples reposant sur l'observation clinique et le jugement des professionnels de santé, à des systèmes plus structurés et normalisés au XXe siècle, avec notamment l'introduction de l'Index de Gravité des Urgences (Emergency Severity Index, ESI) dans les années 1990. Ces dispositifs permettaient d'évaluer les patients selon cinq niveaux, allant des cas critiques aux situations non urgentes, afin de prioriser les soins en contexte de surcharge hospitalière Gilboy et al. (2011).

Au fil du temps, plusieurs modèles de triage ont été développés pour standardiser et améliorer le processus de triage dans les services d'urgence :

— **Manchester Triage System (MTS)** : développé au Royaume-Uni dans les années 1990, il repose sur des algorithmes décisionnels pour classer les patients en cinq catégories, de "Immediate" à "Non-urgent". Apprécié pour sa simplicité, il a été largement adopté en Europe afin de standardiser les pratiques dans des environnements cliniques complexes Mackway-Jones (1997).

— **Canadian Triage and Acuity Scale (CTAS)** : introduit en 1999, ce système à cinq niveaux est utilisé dans l'ensemble du Canada. Il vise à harmoniser les pratiques et à réduire la variabilité des décisions en classant les patients de « Ressuscitation » (Niveau 1) à « Non-urgent » (Niveau 5) selon la sévérité de leur état Murray et al. (1999).

— **Korean Triage and Acuity Scale (KTAS)** : basé sur le CTAS, il a été adapté aux

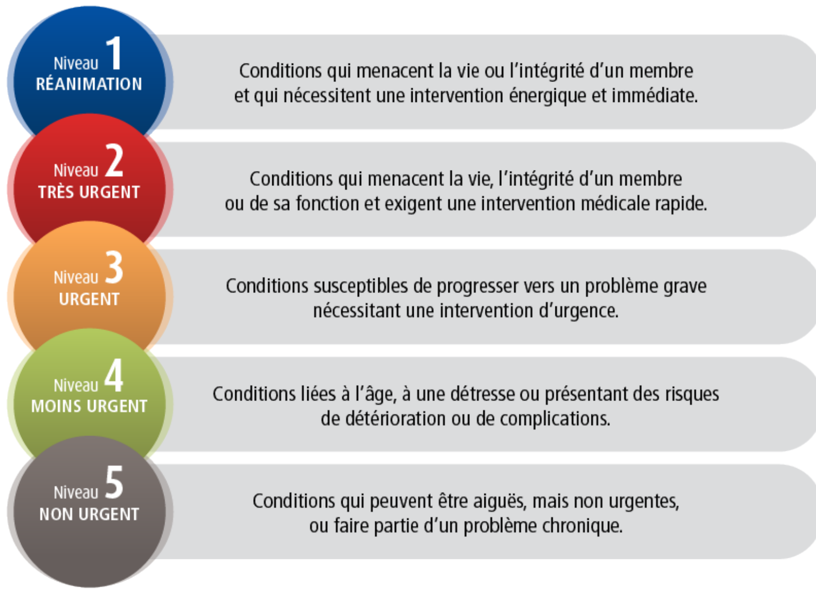

FIGURE 1 – **Niveaux de priorité du triage médical d'urgence**. Vitalité Health Network (2024)

spécificités médicales et de santé publique de la Corée du Sud. Depuis 2012, il classe également les patients en cinq niveaux selon l'urgence des soins Park et al. (2019).

— **Australasian Triage Scale (ATS)** : anciennement « National Triage Scale », il est principalement utilisé en Australie et en Nouvelle-Zélande. Très proche du CTAS et de l'ESI, il adapte cependant ses critères aux réalités des services d'urgence de ces pays Rooke (2010).

— **Japan Triage and Acuity Scale (JTAS)** : dérivé du CTAS, il est employé au Japon en conservant la structure à cinq niveaux tout en l'ajustant aux spécificités du système de santé local Tsuge et al. (2019).

— **South African Triage Scale (SATS)** : conçu pour des contextes de ressources limitées, il classe les patients en quatre niveaux (rouge, orange, jaune, vert). Sa simplicité et sa rapidité en font un outil adapté aux environnements fortement sollicités Robertson and Molyneux (2011).

La Figure 1 illustre les cinq niveaux de gravité utilisés par le CTAS, allant de « Resuscitation » (Niveau 1), correspondant à une menace immédiate pour la vie nécessitant une intervention urgente, à « Non-urgent » (Niveau 5), désignant des conditions mineures ne nécessitant pas de prise en charge immédiate Vitalité Health Network (2024).

Ces modèles, développés pour répondre à des besoins nationaux spécifiques, poursuivent tous un objectif commun : rendre le triage plus rapide, cohérent et efficace. Leur diversité illustre la nécessité d'adapter les outils aux réalités locales, tout en cherchant une standardisation minimale pour permettre des comparaisons internationales.

Cependant, malgré leur utilité, ces systèmes présentent des limites importantes. Ils reposent encore largement sur le jugement clinique subjectif, souvent sous pression, et utilisent généralement des critères simples et unimodaux. Dans des contextes de surcharge, cela entraîne une variabilité marquée et accroît les risques de sur-triage ou de sous-triage. Ces faiblesses réduisent l'efficacité du processus et peuvent compromettre la qualité des soins. C'est précisément sur ce point que se situe l'apport de notre recherche : proposer une approche innovante de triage assisté par l'IA, capable d'intégrer des données multimodales (signes vitaux, antécédents médicaux, plaintes à l'admission) et de s'appuyer sur des modèles prédictifs avancés. L'objectif est d'optimiser la classification des patients selon la gravité réelle de leur état, d'améliorer la gestion des priorités et de réduire les temps d'attente dans les services d'urgence.

Le présent chapitre est organisé selon les sections suivantes :

— **PROBLÉMATIQUE :** Dans cette section, nous aborderons la problématique générale de notre projet de recherche, en mettant l'accent sur les défis du triage manuel et les limites des systèmes actuels.

— **NOTIONS ET CONCEPTS :** Au cours de cette partie, nous présenterons les principales notions clés liées à l'utilisation de l'IA dans le triage des patients aux urgences.

— **OBJECTIF DE L'ÉTUDE :** Dans cette section, nous exposerons les principaux objectifs de notre étude, notamment l'amélioration de la précision du triage grâce à l'IA.

- **MÉTHODOLOGIE :** Au cours de ce volet, nous présenterons la méthodologie adoptée pour aborder la problématique liée à notre sujet de recherche, notamment les techniques d'apprentissage automatique utilisées pour développer notre modèle de triage assisté par l'IA.
- **CONTRIBUTIONS :** Dans cette partie, nous discuterons des apports scientifiques de notre projet de recherche, en mettant en lumière les innovations apportées par l'IA dans l'amélioration des processus de triage.
- **PLAN DU MÉMOIRE :** En dernier lieu, nous présenterons un synopsis du canevas de notre mémoire, décrivant les différentes étapes et sections de notre travail

PROBLÉMATIQUE

La surcharge croissante des services d'urgence constitue un problème majeur à l'échelle mondiale, aggravé par l'augmentation constante du nombre de patients nécessitant une prise en charge immédiate. Au Canada, une étude récente du CADTH a montré que les urgences hospitalières sont régulièrement confrontées à une demande dépassant leurs capacités, entraînant une dégradation notable de la qualité des soins ainsi que des délais d'attente excessivement longs CADTH (2023). En Ontario, une analyse portant sur plus de 36 millions de visites entre 2003 et 2009 a mis en évidence que cette surcharge est accentuée par une utilisation disproportionnée des services d'urgence par les populations défavorisées, accentuant encore la pression exercée sur ces établissements Schull et al. (2011). Aux États-Unis, la problématique est particulièrement marquée dans les zones rurales, où certains hôpitaux enregistrent des temps d'attente pouvant dépasser six heures Valero and others (2023). De même, au Moyen-Orient, plusieurs études soulignent que les périodes de pointe entraînent régulièrement des taux d'occupation extrêmes, atteignant jusqu'à 194 %, ce qui prolonge fortement l'attente des patients classés comme non urgents Isfahani et al. (2020).

Dans ces conditions de surcharge, les systèmes traditionnels de triage révèlent leurs limites. Soumis au stress, à la variabilité inhérente aux décisions humaines et à la contrainte des ressources limitées, ils génèrent fréquemment des erreurs qui compromettent la qualité et l'efficacité des soins. Au Royaume-Uni, par exemple, une étude a montré que la surcharge des urgences conduit souvent à un sur-triage des patients non urgents, retardant la prise en charge des cas réellement critiques Townsend et al. (2023). Des constats similaires ont été observés ailleurs, notamment en Turquie, où les patients passent en moyenne plus de 160 minutes aux urgences lors des périodes de forte affluence Erenler et al. (2016).

Afin de remédier à ces difficultés, l'intégration de l'IA dans les processus de triage apparaît comme une voie prometteuse. L'IA, grâce à sa capacité à traiter simultanément un grand volume de données et à prédire avec précision les niveaux de gravité, pourrait contribuer à améliorer la fiabilité des décisions cliniques. Par exemple, une étude a exploré l'utilisation d'un chatbot basé sur l'IA pour optimiser la prise en charge dans un service d'urgence à forte fréquentation, en améliorant à la fois l'allocation des ressources et la communication entre les professionnels Jacob et al. (2023). Une autre recherche a montré qu'un outil d'aide à la décision reposant sur l'IA permettait de fluidifier le flux des patients et d'améliorer la pertinence du triage effectué Lucke et al. (2018). Toutefois, ces approches demeurent limitées : leur efficacité repose largement sur la diversité et la qualité des données utilisées pour l'entraînement des modèles. Or, dans la pratique, ces solutions n'intègrent pas toujours de manière suffisante la richesse des données cliniques multimodales disponibles (antécédents médicaux détaillés, résultats d'examens de laboratoire, données d'imagerie, etc.). Cette faiblesse empêche souvent les systèmes actuels de saisir pleinement la complexité des situations cliniques rencontrées aux urgences. D'où la question centrale qui guide notre recherche : *Comment dépasser les limites des systèmes traditionnels de triage en développant des approches capables d'exploiter efficacement la richesse des données cliniques multimodales disponibles ?*

NOTIONS ET CONCEPTS

Traditionnellement, le triage repose sur le jugement clinique des professionnels de santé, ce qui peut entraîner des erreurs de sous-triage (lorsqu'un patient critique n'est pas correctement identifié) ou de sur-triage (mobilisation de ressources pour des cas non prioritaires). Ces erreurs peuvent prolonger les temps d'attente et compromettre la qualité des soins. Les systèmes traditionnels, tels que l'ESI, sont largement utilisés pour classer les patients en fonction de leur état. Cependant, ils demeurent dépendants de l'interprétation humaine, ce qui génère une variabilité notable dans les décisions de triage Karlafti et al. (2023).

L'IA, comme évoqué précédemment, vise à améliorer la précision et la cohérence des décisions en s'appuyant sur des algorithmes d'apprentissage automatique. Ces derniers sont capables d'analyser simultanément des données structurées (signes vitaux, mode d'arrivée, etc.) et non structurées (notes cliniques, antécédents médicaux), afin de prédire de manière plus objective et rapide les besoins en soins d'un patient.

Le reste de la section se concentrera sur les deux concepts clés qui constituent le cœur de notre étude, à savoir : le triage et l'IA.

Triage

Le triage est un processus essentiel dans les services d'urgence, conçu pour évaluer rapidement la gravité de l'état des patients dès leur arrivée et prioriser les soins en conséquence. Différents types de triage sont employés selon le contexte :

— **Triage primaire et secondaire** : le triage primaire permet une évaluation initiale rapide afin d'assigner un niveau de priorité, tandis que le triage secondaire consiste en une évaluation plus approfondie après la stabilisation du patient. Ces méthodes, complémentaires, facilitent une organisation adaptée des soins Jeyaraman et al. (2022).

— **Triage avancé** : ce type de triage repose sur l'utilisation de technologies modernes, notamment l'IA et le machine learning, pour accroître la rapidité et la précision des décisions cliniques en fonction des données disponibles Morreel et al. (2021).

- **Triage des catastrophes** : utilisé lors d'événements à grande échelle (catastrophes naturelles, accidents collectifs), ce triage vise à maximiser les chances de survie en allouant prioritairement les ressources aux patients les plus susceptibles de bénéficier de soins immédiats Bazyar et al. (2019).
- **Triage pédiatrique** : spécifiquement adapté aux enfants, ce triage prend en compte leurs particularités physiologiques et cliniques, nécessitant des protocoles dédiés afin de garantir une prise en charge appropriée Doan et al. (2019).
- **Triage téléphonique** : il permet une première évaluation des patients à distance avant leur arrivée à l'hôpital, contribuant à fluidifier les flux et à réduire la surcharge des services d'urgence Marchiori et al. (2020).

Intelligence artificielle et l'apprentissage automatique

L'IA regroupe des techniques qui simulent les processus cognitifs humains à travers des systèmes informatiques. Elle permet de traiter de grandes quantités de données, de reconnaître des patterns complexes et de soutenir la prise de décision, de manière autonome ou semi-autonome. Dans les services d'urgence, l'IA est utilisée pour automatiser certaines étapes du triage, réduire les erreurs humaines et accélérer la prise en charge des patients Klug et al. (2020).

L'apprentissage automatique (machine learning, ML), sous-domaine central de l'IA, consiste à entraîner des modèles à partir de données pour qu'ils puissent ensuite améliorer leurs performances sans être explicitement programmés. Ces modèles prédictifs sont capables d'analyser de nouvelles données et de fournir des estimations fiables. Dans le contexte des urgences, ils peuvent par exemple anticiper la gravité d'un cas, la probabilité d'hospitalisation ou encore les résultats cliniques, à partir d'informations comme les signes vitaux ou les antécédents médicaux Mutegeki et al. (2023).

OBJECTIF DE L’ÉTUDE

Cette étude a pour objectif d’améliorer le processus de triage des patients dans les services d’urgence en développant des modèles d’IA capables de prédire automatiquement le niveau de triage attribué à chaque patient. Pour ce faire, différents algorithmes d’apprentissage automatique seront implémentés et entraînés sur un jeu de données réel, intégrant des informations cliniques multimodales, telles que les signes vitaux, les antécédents médicaux et les plaintes à l’admission.

MÉTHODOLOGIE

Pour mener à bien ce projet, nous avons suivi une démarche méthodologique en plusieurs étapes, allant de la collecte des données jusqu’à la modélisation et l’évaluation des performances. La première étape a consisté à sélectionner un jeu de données pertinent. Nous avons choisi un ensemble de données disponible sur Kaggle, plateforme largement reconnue en science des données pour la qualité et la diversité de ses bases. Ce jeu de données contenait des informations détaillées sur 1 267 patients adultes admis dans deux services d’urgence entre octobre 2016 et septembre 2017, incluant les plaintes principales, les signes vitaux recueillis à l’admission, ainsi que divers résultats cliniques. Cet échantillon, à la fois diversifié et représentatif, constituait une base solide pour l’analyse.

Nous avons ensuite effectué un prétraitement rigoureux des données. Lors de cette étape, nous avons identifié et éliminé des valeurs aberrantes, la correction des erreurs de saisie, la gestion des valeurs manquantes ainsi que la création de nouvelles variables par ingénierie de caractéristiques. Ces opérations visaient à améliorer la qualité des données et à maximiser l’information utile pour l’entraînement des modèles.

L’analyse a été effectuée en Python, en exploitant différentes bibliothèques spécialisées. NumPy et pandas ont été utilisées pour la manipulation et le nettoyage des données, tandis que Matplotlib et Seaborn ont servi à la visualisation, facilitant la détection de tendances et la mise en évidence de relations pertinentes entre variables.

Pour la phase de modélisation, plusieurs algorithmes d'apprentissage automatique ont été testés afin d'identifier ceux les plus adaptés au contexte du triage médical. Nous avons exploré :

— **LR**, méthode classique offrant rapidité et interprétabilité ;
— **SVM**, performant pour les tâches de classification complexes ;
— **RF**, robuste et capable de traiter des données bruitées ;
— **ANN**, apte à capter des relations non linéaires ;
— **GBM** et **XGBoost**, algorithmes d'ensemble puissants optimisant la précision prédictive.

Afin d'améliorer les performances de chaque modèle, nous avons ajusté les hyperparamètres à l'aide de stratégies comme le "grid search" et le "random search". De plus, la méthode SMOTE (Synthetic Minority Over-sampling Technique) a été appliquée pour traiter le déséquilibre des classes, problématique fréquente dans les études de triage.

L'évaluation des modèles s'est appuyée sur plusieurs métriques complémentaires :

— **La précision**, mesurant la proportion globale de prédictions correctes ;
— **Le rappel**, estimant la capacité du modèle à identifier correctement les cas critiques ;
— **Le score F1**, combinant précision et rappel en une mesure harmonisée ;
— **La courbe ROC** et **l'AUC**, permettant de comparer les performances selon différents seuils de décision ;
— **La matrice de confusion**, utile pour analyser finement les erreurs de classification.

Enfin, nous avons mis en œuvre une approche de type "stacking" afin de combiner les forces de plusieurs modèles et d'améliorer la robustesse des prédictions finales. Grâce à cette stratégie, nous avons obtenu un système plus fiable et précis pour l'assistance au triage des patients. La Figure 2 illustre ce processus méthodologique, depuis la collecte des données jusqu'à la prédiction du niveau de triage à l'aide des modèles d'IA.

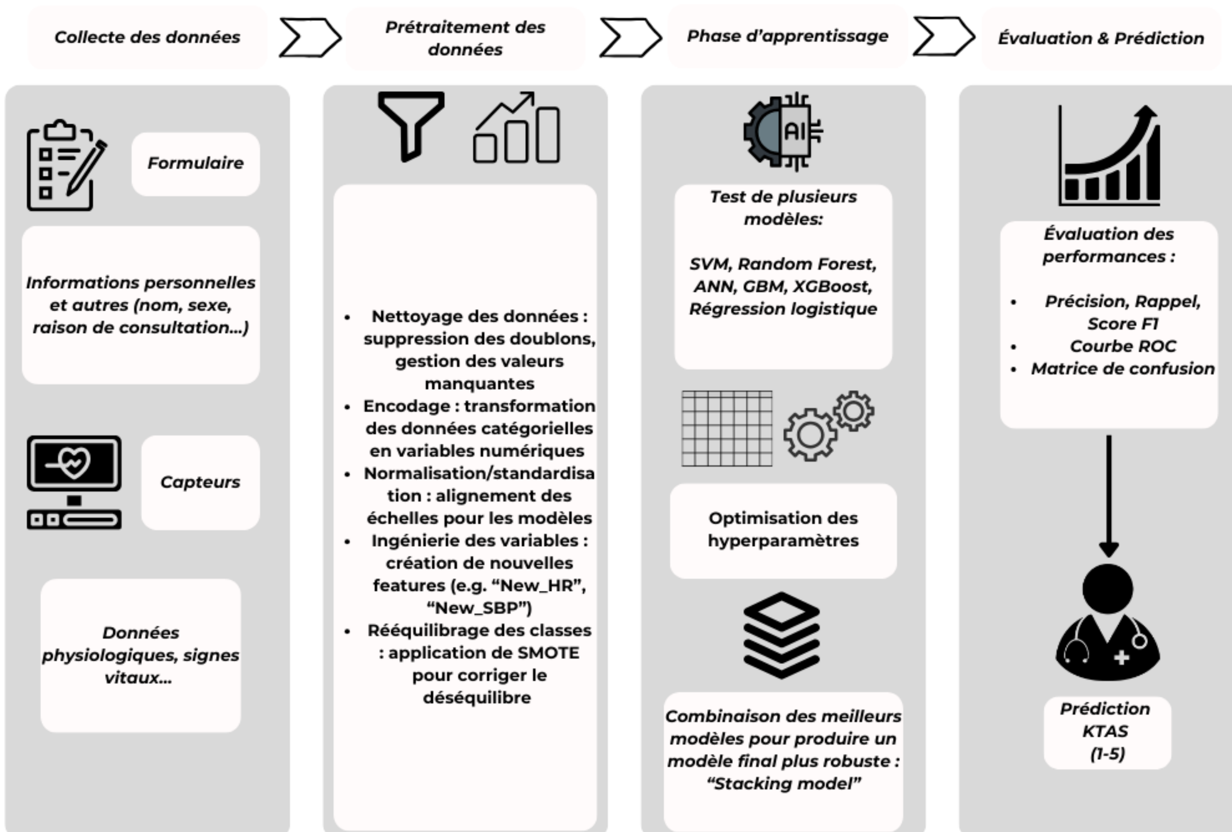

FIGURE 2 – **Processus de prédiction du triage par IA**.

CONTRIBUTIONS

Les résultats de cette étude ont donné lieu à une valorisation scientifique à travers deux publications académiques. Une première contribution a été publiée dans le cadre de la conférence **ICTH 2024**, mettant en lumière les performances des modèles développés et les enjeux associés Araouchi and Adda (2024). De plus, un second article a été également publié dans le cadre de la conférence **ANT 2025**, portant sur une revue de littérature approfondie des avancées et des défis de l'IA appliquée au triage en milieu d'urgence Araouchi and Adda (2025). Ces publications renforcent la visibilité et l'impact des travaux, tant pour la communauté scientifique que pour les praticiens du secteur de la santé.

PLAN DU MÉMOIRE

Ce mémoire par articles, est structuré autour de deux articles, encadrés par une introduction générale et une conclusion générale. L'introduction générale pose les bases du travail en exposant le contexte global de la recherche, les problématiques clés ainsi que les objectifs poursuivis. Elle sert de fil conducteur pour orienter le lecteur à travers les thématiques explorées dans les articles. La conclusion générale, quant à elle, vient clôturer le mémoire en offrant une réflexion sur l'ensemble des résultats obtenus, tout en mettant en perspective les opportunités et les enjeux futurs découlant de cette recherche.

Article 1 : TriageIntelli : A Comprehensive Literature Review on AI-Assisted Multimodal Triage Systems for Health Centers Araouchi and Adda (2025).

Ce premier article, publié dans la conférence 'ANT 2025', est une revue qui explore l'évolution vers des systèmes assistés par l'IA, mettant en avant l'apport des algorithmes d'apprentissage automatique (ML) et d'apprentissage profond (Deep Learning, DL) pour améliorer la précision, optimiser la priorisation des soins et réduire les erreurs humaines. Bien que des progrès notables soient réalisés, des défis subsistent, notamment la dépendance aux données, des préoccupations éthiques et des performances variables selon les contextes. Cet article fournit un cadre critique pour comprendre les opportunités et limites de ces systèmes.

Article 2 : TriageIntelli : AI-Assisted Multimodal Triage System for Health Centers Araouchi and Adda (2024).

Cet article, publié dans la conférence 'ICTH 2024', explore l'intégration de l'IA comme solution innovante pour améliorer le processus de triage. Nous présentons les principales approches et algorithmes d'apprentissage automatique, tels que le SVM, RF, ANN, GBM, LR, XGBoost et les modèles empilés. Enfin, nous détaillons les fondements méthodologiques utilisés pour développer et évaluer ces modèles dans le cadre de cette étude, en mettant en avant leur potentiel pour optimiser le triage médical et répondre aux défis des services d’urgence modernes.

ARTICLE 1

TRIAGEINTELLI: A COMPREHENSIVE LITERATURE REVIEW ON AI-ASSISTED MULTIMODAL TRIAGE SYSTEMS FOR HEALTH CENTERS

Résumé en français du premier article

L'IA est de plus en plus reconnue comme un outil transformateur dans le triage des patients au sein des services d'urgence (Emergency departments, EDs). Les méthodes traditionnelles de triage, telles que l'ESI et le CTAS, ont longtemps été utilisées pour prioriser les soins en fonction de la gravité des patients. Ces systèmes, cependant, rencontrent des défis importants liés à la subjectivité des prises de décision, à la surcharge des services et à l'inefficacité de la distribution des ressources. L'IA offre une solution prometteuse en exploitant des algorithmes de ML pour améliorer la précision des prédictions, optimiser la priorisation des patients et réduire les erreurs humaines. Cette revue explore comment les systèmes de triage ont évolué, passant des modèles conventionnels aux modèles assistés par l'IA, en résumant l'évolution de ces systèmes et en mettant en lumière les avancées et les limitations les plus importantes de l'IA dans la pratique clinique. Les principales conclusions de la littérature récente soulignent les avantages de l'IA dans l'amélioration des résultats de triage, notamment en termes de précision diagnostique et de fluidité des processus dans les flux des ED. Cependant, certaines préoccupations majeures ont été identifiées, telles qu'une forte dépendance à la qualité des données sources, des questions éthiques, et des performances variables selon le contexte des soins de santé.

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A Comprehensive Literature Review on AI-Assisted Multimodal Triage Systems for Health Centers

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Abstract

Artificial intelligence (AI) is increasingly recognized as a transformative tool in emergency department (ED) triage. Traditional triage methods, such as the Emergency Severity Index (ESI) and the Canadian Triage and Acuity Scale (CTAS), prioritize patient care based on acuity but face challenges, including subjectivity, overcrowding, and inefficient resource allocation. AI offers enhanced predictive accuracy, optimized patient prioritization, and reduced human error. This review examines the evolution of triage systems from conventional to AI-assisted models, highlighting advancements and limitations of AI in clinical practice. Recent findings underscore AI's potential to improve diagnostic precision and streamline ED workflows. However, critical concerns include data dependency, ethical challenges, and variable performance across healthcare settings.

Keywords: Patient Prioritization; Emergency Department (ED) Triage; Artificial Intelligence (AI); Machine Learning (ML); Deep Learning (DL)

1. Introduction

Patient triage in emergency departments (EDs) has its origins in the Napoleonic era, where Baron Dominique-Jean Larrey introduced a military triage system to prioritize care based on injury severity. Over time, this concept was adapted for civilian use, becoming integral to managing patient flows in EDs [1]. Modern triage approaches, such as the Emergency Severity Index (ESI) and the Canadian Triage and Acuity Scale (CTAS), enable rapid patient assessment and prioritization based on clinical condition and resource availability.

Despite these structured systems, EDs face persistent challenges, particularly overcrowding, which lengthens wait times and increases the risk of triage errors. These include under-triage (failing to identify critically ill patients) and over-triage (allocating resources to less severe cases) [2]. To address these issues, artificial intelligence (AI) has

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emerged as a transformative tool in triage. Machine learning (ML) algorithms are able to process large volumes of clinical data, enhancing diagnostic accuracy, prioritization, and decision-making efficiency while reducing human error [3].

AI's impact on triage is well-documented in existing literature. For example, Kang et al. (2020) demonstrated that AI models for predicting critical care needs outperformed traditional tools, validating their role in enhancing accuracy and resource allocation [4]. Similarly, Chee et al. (2023) highlighted AI's effectiveness in prehospital emergency care, where it supported prognostic predictions and patient triage in diverse settings [5]. However, much of this prior work focuses narrowly on specific algorithms, datasets, or clinical environments, often neglecting broader issues of implementation, ethical concerns, and system-wide integration.

In contrast, this review offers a comprehensive synthesis that situates recent AI advancements within the historical evolution of triage systems. Unlike previous studies that examine isolated aspects of AI-assisted triage, this work uniquely addresses the intersection of technical innovations, ethical dilemmas, and real-world clinical adoption barriers. For example, Yin et al. (2021) noted challenges in external validation and routine clinical integration, requiring extensive testing [6]. Issues of data privacy and transparency, as identified by Hosseini et al. (2023), continue to impact clinician trust and patient outcomes [7]. Additionally, Kirubarajan et al. (2020) emphasized the variability of AI performance across different emergency medicine tasks, underlining the need for patient-centered outcome studies before widespread adoption [8]. This review aims to bridge these gaps by synthesizing insights from existing literature and proposing pathways for advancing AI's role in emergency care.

The originality of this review lies in its holistic approach, which critically evaluates AI's potential to optimize decision-making, improve patient outcomes, and address barriers to broader implementation. The remainder of this article is organized as follows. Section 2 outlines the methodology, detailing the literature search process, inclusion and exclusion criteria, and quality assessment methods. Section 3 reviews the historical evolution of patient triage systems, highlighting their progression from traditional approaches to AI-assisted models and discussing the limitations of existing systems. Section 4 examines the integration of artificial intelligence into triage systems, including methodologies, related works, and the challenges faced by these technologies in clinical settings. Section 5 presents a discussion of the findings, emphasizing the benefits of AI in improving emergency department workflows while addressing ethical and operational challenges. Finally, Section 6 concludes by summarizing key insights and proposing directions for future research in AI-driven triage systems.

2. Methodology

The literature review was designed to identify studies that explore the integration of artificial intelligence (AI) into multimodal triage systems in healthcare settings. The search was conducted following a systematic approach, based on established guidelines for the conduct of literature reviews. The literature search strategy is presented in Table1:

Selection criteria were developed to identify those studies that matched the focus of the research. The inclusion and exclusion criteria were as follows:

Inclusion Criteria:

The studies included in this review met the following criteria:

- The articles were written in English and peer-reviewed.
- The study explicitly discussed AI-based triage systems in the ED or similar healthcare environment.
- The research provided quantitative performance measures, such as accuracy, sensitivity, specificity, and AUC.
- The studies dealt with ethical considerations or challenges regarding AI implementation.

Exclusion Criteria:

Studies were excluded if they:

- Were non-peer-reviewed articles, including opinion pieces, editorials, and technical reports not reporting empirical data.
- Did not involve AI in triage systems or lacked a healthcare context.
- Did not report any performance evaluation or provide actionable insights on clinical implications.

Table 1. Summary of the literature search strategy.

Aspect	Details
Databases Searched	PubMed, IEEE Xplore, ScienceDirect, ResearchGate
Search Terms and Boolean Operators	`"AI AND triage systems","Machine learning AND emergency care","Deep learning AND patient prioritization","AI-assisted triage AND healthcare","Neural networks AND emergency triage","AI performance AND (accuracy OR sensitivity OR specificity)","e-triage systems AND (machine learning OR deep learning)","AI implementation AND emergency departments","Ethics in AI AND healthcare triage"`
Timeline	Studies published between 2009 and 2024 were included to capture the latest advancements in the field.
Search Process	The initial search yielded 450 articles. These were screened by reviewing their titles and abstracts for alignment with the research objectives, resulting in the selection of 44 articles for full-text review. Ultimately, 34 articles were included in the final analysis after meeting all inclusion criteria, while 7 articles were included with reservations due to specific limitations.

Certain articles cited in this review, such as historical works, were excluded from the systematic analysis but were referenced to provide additional context or background. Out of those remaining, a systematic quality assessment was carried out to ensure that only studies of sufficient scientific rigor and relevance are included. This step was done using the following criteria:

1. **Relevance to Research Objectives:** Studies were examined to confirm they focused on AI-based triage systems in healthcare, particularly within emergency departments or similar clinical settings. Articles lacking a healthcare context or addressing unrelated AI applications were excluded to maintain alignment with the review's objectives.
2. **Methodological Clarity and Rigor:** The transparency and robustness of each study's methodology were assessed. This included evaluating the design, datasets used, and statistical analyses performed. Preference was given to studies providing detailed descriptions of data preprocessing, algorithm selection, and validation processes. Studies lacking clarity or essential methodological details were considered less reliable.
3. **Performance Metrics:** Quantitative performance indicators such as accuracy, sensitivity, specificity, and AUC were deemed essential. Studies that failed to report these metrics or offered insufficient performance data were deprioritized in the analysis.
4. **Ethical Considerations:** The inclusion of discussions around ethical issues, such as data privacy, fairness, and bias mitigation, was noted. Studies addressing challenges like ensuring diverse and representative datasets were given higher weight.
5. **Credibility of Publication:** The reputation of the publishing journal and the peer-review status of the study were evaluated. Articles from high-impact journals or respected conferences were prioritized, while non-peer-reviewed studies or publications from questionable sources were excluded.

3. Background: From Traditional Triage to AI-Assisted Systems

3.1. Evolution of Patient Triage Systems

Patient triage has evolved significantly, influenced by historical developments and advances in organized medical systems. Originating in the late 18th century, Baron Dominique-Jean Larrey of Napoleon's army developed a prior-

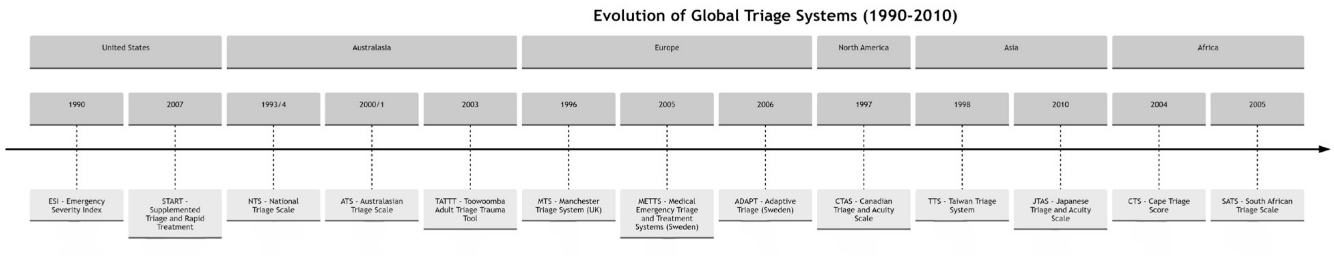

Fig. 1. Evolution of Global Triage Systems (1990–2010)

itization strategy based on injury severity to optimize military medical resources [9]. This military practice laid the foundation for modern triage in civilian healthcare systems.

The Manchester Triage System, developed in the UK in 1996, utilized flowcharts and symptom evaluation to assign patients into one of five categories of urgency. MTS became very popular throughout Europe. It provided standardized guidance for triage nurses and turned out to be effective combined with appropriate training [12]. Also, the Australasian Triage Scale of Australia and New Zealand evolved from the Canadian model. It provided wide guidelines on urgent and non-urgent cases, hence raising efficiency where well applied [13]. Fig.1 presents the chronology of the development of the systems worldwide. The TTS was developed in Asia, as shown by the Taiwan Triage System, and the Cape Triage Score in Africa. Triage systems developed specifically for pediatrics, such as the PedCTAS and the PEWS, were designed with consideration of physiological differences between children, resulting in even more optimized outcomes [14]. For the late 2000s, algorithms used by CDSSs were designed to parse real-time vital signs and symptoms for better prioritization, greatly minimizing human error [15].

Today, AI-enhanced triage represents a significant advancement. AI systems analyze diverse patient data sources, adapt over time, and improve decision-making accuracy. They are particularly valuable in busy EDs, optimizing patient flow and resource allocation [16]. AI has also expanded emergency care access in rural and underserved areas through telemedicine [17]. This evolution underscores the continuous effort to enhance healthcare processes and patient outcomes.

3.2. Limitations of Triage Approaches

Despite advancements, traditional triage systems face limitations. Predictive accuracy remains a significant issue, leading to under-triage or over-triage due to subjective assessments and inconsistent prioritization among clinicians [18]. Tools like the Manchester Triage System, while effective in some contexts, are prone to categorization errors, particularly under high-demand conditions [19].

Resource inefficiency is another challenge. Traditional systems often overlook long-term patient outlooks and medical histories, leading to overcrowding and delays for urgent cases [20]. Additionally, these systems struggle in mass-casualty scenarios, where dynamic, real-time prioritization is critical [21].

Global variations in triage practices further complicate benchmarking and standardization [22]. Although international protocols could enhance consistency, differences in healthcare infrastructure and resources hinder their implementation.

3.3. Introduction of Artificial Intelligence in Triage

Artificial intelligence (AI) has transformed triage by improving accuracy, efficiency, and resource management in emergency departments. Traditional methods rely on subjective human judgment, which AI surpasses through the analysis of extensive datasets [23]. For instance, an AI algorithm predicting critical care needs demonstrated superior performance over tools like the Emergency Severity Index [4].

AI systems use real-time data, including vital signs and medical history, to enhance decision-making [24]. Neural network-based tools have shown high accuracy in patient classification, reducing human error [25]. Gradient boosting models have accurately predicted early mortality, enabling healthcare providers to prioritize high-risk patients effectively [37].

Despite these advancements, clinician trust in AI remains a barrier. Initial skepticism arises from its perceived detachment from hands-on care [28]. Building trust requires consistent reliability and regular model updates [29]. As AI continues to revolutionize triage, thoughtful integration and collaboration with clinicians are essential for maximizing its potential.

4. AI Integration in Patient Triage Systems

4.1. AI Assisted Triage

The integration of artificial intelligence (AI) into emergency department (ED) triage is revolutionizing critical care by enhancing diagnostic accuracy and patient prioritization. AI-driven models can rapidly analyze complex clinical data, offering significant advantages in overcrowded hospital settings. For instance, Raita et al. (2019) demonstrated that machine learning (ML) models outperformed traditional systems like the Emergency Severity Index (ESI), achieving an area under the curve (AUC) of 0.86 in predicting intensive care needs, compared to the ESI's 0.74 [30].

Beyond initial assessment, AI optimizes patient sorting and prioritization. Salman et al. (2021) found that electronic triage (E-triage) systems leveraging ML algorithms reduced human error and improved efficiency, proving highly beneficial for telemedicine and remote patient management [31]. Similarly, Kang et al. (2020) developed a deep learning algorithm that accurately predicted the need for critical care in prehospital settings, outperforming the Korean Triage and Acuity System (KTAS) and the ESI [4].

AI's real-time data processing capabilities enhance decision-making beyond clinician judgment. Shafaf and Malek (2019) highlighted that ML algorithms excel in predicting hospital admissions, mortality rates, and early disease detection, leading to improved emergency patient management Decision support systems integrating AI further assist clinicians in diagnostics. Stewart et al. (2018) noted AI's growing role in emergency medicine, particularly in patient monitoring and optimizing ED operations, although applications like computer vision and robotics remain underutilized [23].

Several studies highlight AI's predictive power in triage efficiency. Liu et al. (2018) emphasized AI's impact on patient monitoring and clinical outcomes, while Tang et al. (2021) demonstrated how AI-driven models reduce waiting times and streamline patient management in congested EDs [32]. Jiang et al. (2021) specifically explored ML applications for cardiovascular patients, showing improved accuracy in triage decisions [33]. Feretzakis et al. (2022) validated Random Forest (RF) models as superior in predicting hospital admissions, particularly in resource-constrained settings [34]. [27].

Combining AI with clinical expertise enhances triage performance. Yu et al. (2021) developed an AI-powered system integrating nurse assessments, utilizing deep neural networks (DNN) and logistic regression to surpass conventional triage tools like KTAS and SOFA [35]. These advancements underscore AI's role in transforming ED workflows and decision-making processes. For a better understanding of AI's impact on triage systems, Fig.2 illustrates key AI branches and their specific applications in patient triage.

4.2. Related Works

Recent studies highlight the transformative role of AI in patient triage, improving both predictive accuracy and efficiency. For example, Kang et al. (2020) developed a deep learning algorithm to predict critical care needs, achieving an AUC of 0.867, outperforming traditional triage tools like the Emergency Severity Index (ESI) and the Korean Triage and Acuity System (KTAS), which had AUCs of 0.839 and 0.824, respectively [4]. Similarly, Shafaf and Malek (2019) reviewed various machine learning (ML) applications in emergency triage. They found that these models consistently reduced under-triage (missing critical cases) and over-triage (using up resources on less urgent cases). The models also improved predictions for things like mortality and hospital admissions, helping to ensure patients get the right level of care [27].

Akhlaghi et al. (2023) evaluated an AI system integrated into an emergency department and found it to be pretty effective, with a 74% accuracy rate in predicting hospital admissions. Even more importantly, it significantly reduced under-triage, ensuring that fewer critical cases were missed [36]. Meanwhile, Klug et al. (2019) used gradient-boosting models to predict mortality, and their results were striking. They achieved an AUC of 0.962 for early mortality and

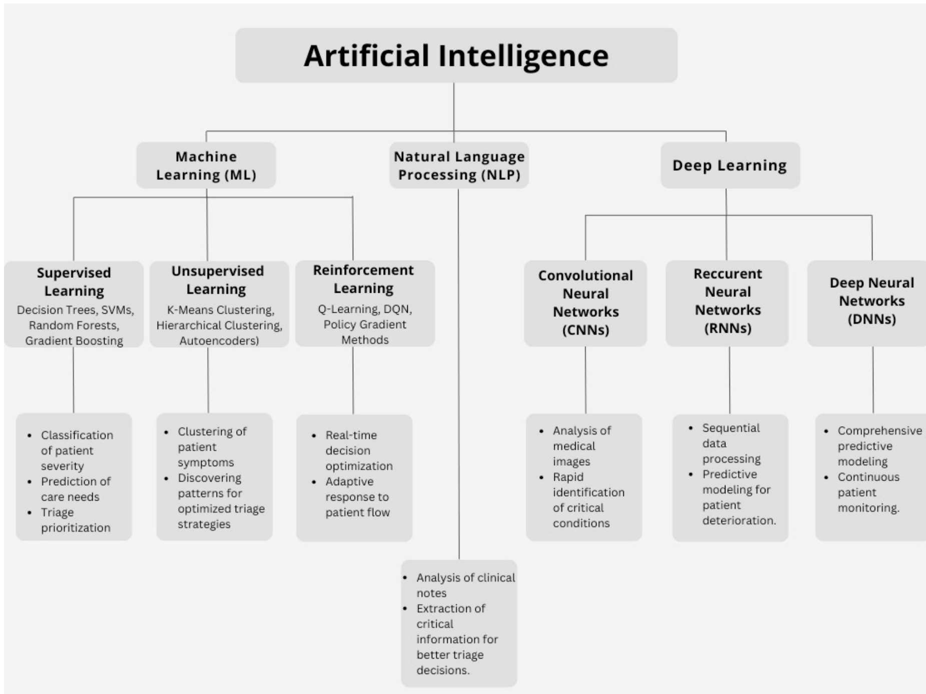

Fig. 2. Overview of AI Branches and Their Applications in Patient Triage

0.923 for short-term mortality. These numbers highlight just how powerful AI can be in making life-or-death decisions in emergency settings [37]. Malycha et al. (2022) also spotlighted AI's role in catching clinical deterioration early. Tools like eCART and the Rothman Index showed high sensitivity in identifying adverse events before they spiraled out of control, giving clinicians a crucial head start [38]. Guzzi et al. (2023) introduced a network science algorithm for triage, and it performed better than manual methods, delivering more accurate and consistent patient prioritization. This kind of innovation could set a new standard for managing emergency patients [39]. Farahmand et al. (2017) used neural networks to triage patients with acute abdominal pain. Their system nailed an 89% accuracy rate for predicting severe cases, even beating out decision tree models when it came to low-priority cases [40]. Stewart et al. (2018) highlighted how AI can boost diagnostic accuracy in emergency departments (EDs). In fact, depending on the condition, AI improved precision by 20-30% compared to traditional methods that relied solely on clinicians [23]. Yin et al. (2021) explored how AI works in real-world clinical settings. They found that AI-driven triage systems reduced error rates by as much as 15% compared to manual approaches, while also improving patient outcomes thanks to early detection [6]. Feretzakis et al. (2022) developed random forest models for predicting ED admissions. Their model scored an impressive AUC of 0.88, outperforming traditional triage scoring in both speed and accuracy [34]. Finally, Kim et al. (2019) showed how AI-powered diagnostic imaging systems could accurately identify critical issues like intracranial hemorrhages with a 92% success rate. Even better, these systems proved reliable across different hospitals during external validation [41]. Table 2 provides a concise summary of key studies discussed in this section, highlighting the AI models used, the triage systems they were applied to, the predictions made, and the metrics used to evaluate their performance.

4.3. Limitations and Challenges in AI-Based Triage Systems

Despite AI's significant potential in patient triage, several limitations hinder its widespread adoption and performance consistency. One major challenge is the lack of transparency in many AI models, often described as "black boxes." These systems generate results without explaining their reasoning, making it difficult for clinicians to fully trust or verify their decisions. In high-stakes environments like emergency departments, accountability is critical. Shafaf and Malek (2019) noted that the opacity of AI could delay its acceptance in healthcare, as clinicians prefer systems that provide interpretable insights [27].

Another significant issue is data quality and standardization. AI models require vast, high-quality datasets, yet healthcare data is often fragmented, inconsistent, or incomplete. Farahmand et al. (2017) found that imbalanced datasets weaken model accuracy, particularly for rare but critical emergency cases. Additionally, biases in training data can lead to unfair predictions that disproportionately affect certain patient groups [40].

AI's performance variability across different clinical settings is another key limitation. A model that performs well in controlled conditions may struggle in real-world hospital environments. Akhlaghi et al. (2023) observed that an AI system with high accuracy during testing showed reduced effectiveness when deployed in live clinical settings, emphasizing the need for continuous recalibration and validation [29].

The ethical and legal implications of AI in healthcare also raise concerns. Patient data privacy and security are paramount, yet integrating AI increases the risk of data breaches. Clark et al. (2023) highlighted the challenge of balancing data protection with compliance to evolving regulations. Additionally, algorithmic biases can exacerbate healthcare disparities if certain demographic groups are underrepresented in training data, leading to unequal treatment recommendations [42].

Over-reliance on AI is another concern. As AI becomes more integrated into triage systems, there is a risk that clinicians may become too dependent on automated decision-making, potentially diminishing their critical thinking skills. Stewart et al. (2018) warned that such dependence could be detrimental, particularly in high-pressure emergencies where AI might fail or encounter unfamiliar situations [23].

Finally, AI models often struggle with the trade-off between sensitivity and specificity. Many models prioritize sensitivity to identify as many critical cases as possible, but this can lead to over-triage and false alarms, straining hospital resources. Malycha et al. (2022) demonstrated that systems like eCART and the Rothman Index tend to sacrifice specificity for heightened sensitivity, underscoring the challenge of achieving balance [38].

In summary, while AI has the potential to enhance triage efficiency and accuracy, several hurdles must be addressed, including transparency, data integrity, ethical concerns, and reliability across diverse clinical settings. The successful implementation of AI in emergency healthcare will require collaboration between developers, clinicians, and policymakers to create systems that are both effective and ethically responsible.

Table 2. Summary of AI Applications in Patient Triage Studies

Author(s)	AI Category	Triage System Used	Prediction Made	Calculated Metrics	Results
Farahmand et al. (2017)	Machine Learning (Neural Network, Decision Tree)	ESI	Triage Level	Accuracy	Accuracy: 89%
Kang et al. (2020)	Deep Learning (DNN)	ESI, KTAS	Critical Care Needs	AUC	AUC: 0.867
Akhlaghi et al. (2023)	Machine Learning (Gradient Boosting)	Custom ED Model	Hospital Admissions	Accuracy	Accuracy: 74%
Klug et al. (2019)	Machine Learning (Gradient Boosting)	Custom ED Model	Early and Short-term Mortality	AUC	AUC: 0.962 (early mortality), 0.923 (short-term mortality)
Malycha et al. (2022)	Machine Learning (eCART, Rothman Index)	Clinical Deterioration Models	Clinical Deterioration	Sensitivity	High sensitivity for adverse event detection
Guzzi et al. (2023)	Network Science Algorithm	Custom Prioritization System	Patient Prioritization	Accuracy	Improved prioritization accuracy using Network Science Algorithm
Yin et al. (2021)	Machine Learning (Various Models)	Real-life Clinical Models	Clinical Accuracy and Efficiency	Error Reduction	Error reduction: 15%
Feretzakis et al. (2021)	Machine Learning (Random Forest)	Custom ED Model	Hospital Admissions	AUC	AUC: 0.88
Kim et al. (2019)	Deep Learning (CNNs)	Diagnostic Imaging	Critical Case Identification	Accuracy	Accuracy: 92%

5. Discussion

The integration of artificial intelligence (AI) into patient triage offers tremendous potential but also raises complex challenges that demand careful consideration. AI's ability to process massive amounts of clinical data in real time is revolutionizing how emergency departments operate, improving both patient care and resource management. For instance, Kang et al. (2020) demonstrated that deep learning models outperform traditional triage tools, such as the Emergency Severity Index (ESI) and the Korean Triage and Acuity System (KTAS), in accurately identifying critical cases [4]. This adaptability is particularly vital in high-pressure environments, where quick and precise decisions can have a direct impact on patient outcomes.

One of AI's key strengths lies in its ability to evolve continuously by integrating new data, which enhances its predictive capabilities over time. This iterative learning process helps reduce the risks of both under-triage and over-triage, ensuring that high-risk patients receive prompt care while avoiding the unnecessary use of resources on less critical cases. Shafaf and Malek (2019) highlighted that implementing machine learning models significantly lowers error rates, boosting efficiency in managing patients in emergency departments [27]. Moreover, AI-driven optimization of patient flow helps alleviate overcrowding and streamlines operations, making emergency care delivery faster and more efficient.

Looking ahead, AI holds immense promise for further improving the precision and efficiency of triage, particularly in classifying patients based on the severity of their conditions. Recent studies underscore the effectiveness of AI-powered multimodal models in predicting triage levels with remarkable accuracy [43]. Future research should focus on refining these models to minimize errors, reduce delays in patient care, and prioritize critical cases more effectively. Additionally, AI's growing role in telemedicine and remote triage has the potential to expand access to emergency care in resource-limited areas by leveraging data from wearable devices and patient-reported symptoms. These advancements underscore AI's transformative potential to modernize triage protocols, address longstanding inefficiencies, and pave the way for more accurate and effective clinical decision-making.

6. Conclusion

This review describes the development of patient triage systems, from early forms to using AI as a game-changing tool in emergency care. AI has already demonstrated tremendous promise in improving diagnostic accuracy, smoothing ED workflows, and optimizing resource utilization.However, several challenges remain, including issues related to data quality, ethical considerations, and the transparency of AI-driven decisions. To realize AI's full potential in triage, future research should focus on developing explainable AI systems, improving data diversity, and establishing robust mechanisms for continuous performance monitoring. By addressing these challenges, AI can become an integral part of patient triage, enhancing healthcare delivery and improving patient outcomes in emergency settings.

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ARTICLE 2

TRIAGEINTELLI: AI-ASSISTED MULTIMODAL TRIAGE SYSTEM FOR HEALTH CENTERS

Résumé en français du premier article

L’engorgement des ED, aggravé par le vieillissement de la population et la complexité croissante des cas, représente un défi majeur. Le triage, qui priorise les patients selon la gravité de leur état, subit une pression accrue due à des ressources limitées et à un nombre croissant de patients. Cette étude explore l’intégration de l’IA pour améliorer ce processus. Des modèles basés sur l’IA, tels que SVM, RF, ANN, GBM et un modèle empilé, ont été développés et évalués en utilisant le KTAS. Les résultats montrent que les modèles d’IA, en particulier SVM et GBM, augmentent la précision et l’efficacité du triage, tout en réduisant les erreurs humaines et la variabilité des évaluations. Le modèle empilé a affiché la meilleure précision prédictive.

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TriageIntelli: AI-Assisted Multimodal Triage System for Health Centers

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Abstract

The overcrowding of the emergency departments presents a major challenge, exacerbated by an aging population and increasing complex cases. Triage, which prioritizes patients according to severity, faces significant pressure due to limited resources and growing patient numbers. This study explores the integration of artificial intelligence (AI) to enhance the triage process. We developed and evaluated AI-based models, including Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), Gradient Boosting Machines (GBM), Linear Regression (LR), XGBoost and a stacking model, to predict patient triage levels using the Korean Triage and Acuity Scale (KTAS). Our findings demonstrate that AI models, particularly SVM and GBM, delivered the highest prediction accuracies of 79% and 78.7%, respectively. These models also performed well in terms of precision (80.04% and 75.36%), recall (71.94% and 73.36%), and F1-score (72.93% and 72.91%). The remaining algorithms still demonstrated strong predictive capabilities. The developed Stacking Model exhibited the highest prediction, achieving an accuracy of 80.05%, precision of 80.27%, recall of 73.26%, and an F1-score of 74.41%. This incremental gain in performance demonstrates the effectiveness of model stacking, as it capitalizes on the complementary strengths of different algorithms to enhance overall predictive accuracy.

Keywords: Emergency Departments; Triage; Korean Triage and Acuity Scale (KTAS); Machine learning

1. Introduction

The annual number of emergency room visits in Canada and the USA is 142 million [1]. Emergency departments triage patients according to severity to ensure that the most critical cases are dealt with quickly and safely. Emergency department overcrowding, a major challenge since the 1980s, is exacerbated by an aging population and an increase in

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complex cases. Many patients turn to emergency departments out of fear, anxiety, or difficulties accessing local care, often seeing them as the first option for medical attention or as a referral point to specialists. This trend highlights the urgent need to reorganize healthcare services to better regulate emergency admissions and promote ambulatory care [2].

Triage in emergency departments involves assessing the severity of patients' conditions and prioritizing them. It quickly identifies critical cases, ensuring immediate care and efficient allocation of medical resources, thereby reducing waiting times and optimizing care. Nurses responsible for triage face a heavy workload, worsened by the increasing number of patients. This can lead to delays in patient assessment and compromise the quality of care provided. A lack of resources, both personnel and equipment, further complicates the triage process [3].

Historically, triage in emergency departments evolved from informal systems based on healthcare professionals' clinical judgment to more structured and standardized methods. Systems like the Manchester Triage Scale (1990s) and the Canadian Triage and Acuity Scale (CTAS, 1999) are widely used today, improving consistency and reliability but still subject to human limitations such as judgment errors and inter-rater variation [6]. AI and machine learning advancements present new opportunities to automate and enhance these critical processes [7]. Emergency departments face challenges such as patient overload, limited resources, and time-critical requirements, exacerbated by seasonal variations, pandemics, and mass events leading to sudden patient influxes [8]. Improving triage efficiency and accuracy has become a priority for healthcare administrators and policymakers [9]. The demand for Machine Learning algorithms applied to emergency data has increased over the years [10]. Recently, the growing integration of artificial intelligence (AI) in the medical field has garnered increasing interest, particularly in emergency departments [4]. New AI approaches to patient triage have received particular attention due to urgent clinical needs.

Research shows AI can reduce waiting times and improve triage accuracy [4], while also standardizing assessments and reducing variations in clinical judgment [5]. This research project aims to develop practical AI-based solutions to facilitate the triage process for healthcare professionals. The results could benefit healthcare system managers, medical technology developers, and patients requiring emergency care. The study evaluates machine learning models to classify patients using the KTAS [11]. The solution processes medical data to classify patients into one of the 5 levels of KTAS using supervised learning algorithms, with the aim of increasing the trust of clinicians in AI-based models through precision and reliability [12].

The remainder of this paper is organized as follows. Section 2 reviews related studies. Section 3 details the dataset, data preparation, and models used. Section 4 presents the results and a summary of hyperparameters. Section 5 compares our findings with related work. Finally, Section 6 summarizes the key findings.

2. Literature review

Implementing effective triage systems in emergency departments is essential to ensure patients receive appropriate care promptly. Traditionally, these triage systems have been based on manual methods and standardized protocols, such as the Manchester Triage Scale and the Canadian Triage and Acuity Scale (CTAS) [6, 13]. However, although widely used, these methods are limited by inter-rater variability and the risk of human error. Integrating artificial intelligence (AI) and machine learning techniques into emergency triage promises to improve these processes by increasing accuracy and reducing response times. Recent advances in machine learning (ML) technologies have position them as a strong candidate to automate the triage decision-making process. This progress has led many researchers to use ML technologies to develop models that help predict patient hospitalization needs and prioritize them according to the intensity of care registered nurses provide during hospital emergency department (ED) triage. Many studies have demonstrated the superior performance of ML in predicting hospitalization and critical care outcomes compared to traditional triage models, particularly through nursing triage evaluation [14]. Kaldis et al. [15] explored the application of machine learning, particularly GBM, through AutoML, to predict hospital admissions in emergency departments. They used the MIMIC-IV-ED dataset and highlighted the role of key variables like acuity and waiting hours. The study demonstrated the potential of machine learning to improve hospital admission predictions. Raita et al. [16] investigated using machine learning models to predict patients' clinical outcomes during emergency department triage. They used clinical and administrative data, including vital signs and diagnoses, and demonstrated that machine learning models could improve prediction accuracy. Hong, Haimovich, and Taylor [17] developed machine learning algorithms to predict hospital admissions from emergency department triage data. Based on vital signs and diagnoses

Table 1. Summary of studies using various ML models and triage systems.

Author	ML Model Used	Triage System Used	Prediction Made	Calculated Metrics
V. Kaldis et al [15]	AutoML, Gradient Boosting Machines (GBM)	Not specified	Hospital admissions	AUC
Y. Raita et al [16].	Lasso regression, random forest, gradient boosted decision tree, deep neural network	Emergency Severity Index (ESI)	ICU admission or in-hospital death	AUC, net benefit
Woo Suk Hong et al [17].	Logistic regression, XGBoost, deep neural networks	Emergency Severity Index (ESI)	Hospital admission	AUC
G. Feretzakis et al [19].	Random Forest, Logistic Regression, Naive Bayes, Support Vector Machine (SVM), Decision Tree, Neural Network	Not specified (clinical features used)	Hospital Admission	F-measure, ROC Area
Yu et al [20].	Logistic Regression, Random Forest, Deep Neural Network	Initial Nursing Assessment, KTAS, SOFA	ICU admission, ER death	AUC
Yun et al [21].	XGBoost, Deep Neural Network	Korean Triage and Acuity Scale (KTAS)	Critical care outcome	AUC
Choi et al [22].	Logistic Regression, Random Forest, XGBoost	Korean Triage and Acuity Scale (KTAS)	KTAS level prediction	AUROC
Huilin Jiang et al [23].	Multinomial logistic regression, XGBoost, random forest, gradient-boosted decision tree	Emergency Severity Index (ESI)	Triage level	AUC, accuracy, macro-F1

from electronic medical records, their model showed superior performance in identifying patients requiring urgent hospitalization. However, they highlighted a lack of direct comparative studies between different machine learning algorithms for triage, making it difficult to determine the most effective approaches. Goto et al. [18] used machine learning to predict clinical outcomes for children in emergency departments, but their study was limited to a specific pediatric population, raising questions about the generalizability of the results. Feretzakis et al. [19] explored the application of machine learning models to predict hospital admissions from emergency department data, demonstrating overall strong results with several algorithms, particularly RF, which showed superior performance and potential for clinical decision-making support. Yu et al. [20] developed a machine learning and initial nursing assessment-based triage system for emergency departments to predict adverse clinical outcomes. The study evaluated various ML algorithms, including LR, RF, and Deep Neural Network (DNN), using both the full and low-dimensional (LD) datasets. The results demonstrated that the ML and initial nursing assessment-based triage system outperformed existing triage systems like KTAS and Sequential Organ Failure Assessment (SOFA). This study highlights the potential of integrating ML with nursing assessments to enhance the accuracy and efficiency of triage in emergency departments. Yun et al. [21] developed a machine-learning model to predict critical care outcomes for adult patients presenting to the emergency department using initial triage information. The study compared the performance of XGBoost and DNN models with the conventional KTAS model developed using LR. The study concluded that the XGBoost model outperformed the conventional triage model in predicting critical care outcomes, demonstrating the potential of machine learning to improve triage accuracy in emergency settings. Choi et al. [22] developed machine learning models to predict the KTAS levels for patients in the emergency department. The study employed LR, RF, and XGBoost models. The models demonstrated high predictive performance for both Random Forest and XGBoost, suggesting the potential of ML to enhance triage accuracy. Jiang et al. [23] developed machine learning models to support emergency department triage for patients with suspected cardiovascular disease. The study used data from 17,661 patients and evaluated various algorithms including multinomial logistic regression (MLR), XGBoost, RF, and gradient-boosted decision trees (GBDT). Key predictive variables included blood pressure, heart rate, oxygen saturation, and age. The study demonstrates the potential of machine learning to enhance the accuracy of triage in emergency settings for cardiovascular conditions.
Table 1 presents recent academic publications that have explored the use of ML techniques to predict triage outcomes.

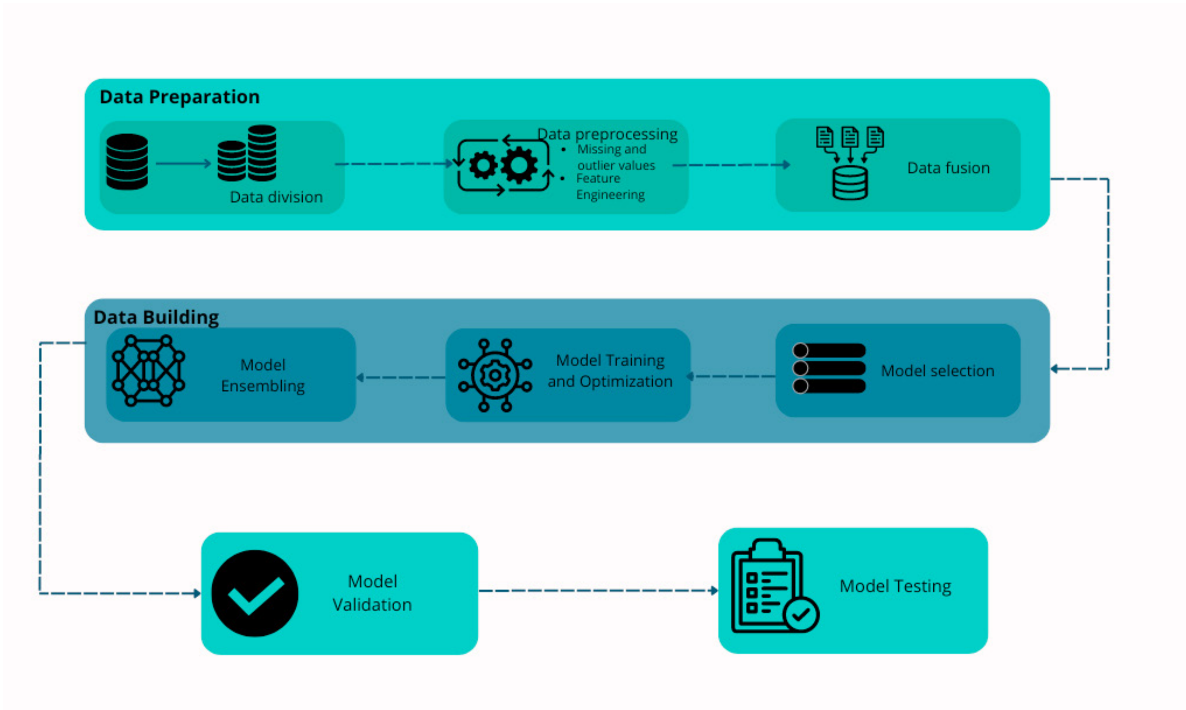

Fig. 1. Study design workflow.

3. Materials and Methods

3.1. Study design and setting

The data was obtained from Kaggle [24] which provided a well-structured dataset ideal for our analysis. The dataset ensured a diverse and representative sample that aligns with the study's objectives, with data points selected based on relevance, completeness, and diversity to provide a comprehensive view of the subject matter.

We conducted our analysis using Google Colab and Python version 3.10. Google Colab's cloud-based environment offered the flexibility and power needed for our computational tasks and the convenience of easy collaboration. The essential libraries for this project included NumPy for numerical operations, allowing us to handle large arrays and matrices of numerical data efficiently. We used pandas for data manipulation, which provided versatile data structures and functions designed to make data analysis fast and easy. For data visualization, we relied on Matplotlib and Seaborn, which enabled us to create informative and aesthetically pleasing graphs and plots, crucial for interpreting the results of our analysis. Lastly, we utilized scikit-learn for machine learning algorithms, offering a robust suite of tools for model training, evaluation, and validation.

These tools collectively facilitated a comprehensive and efficient workflow, enabling us to perform in-depth data analysis, generate meaningful visualizations, and develop robust predictive models. Integrating these libraries in Google Colab's environment allowed for seamless execution and sharing of our notebooks, enhancing our productivity and the quality of our research findings. The steps of our model are presented in Figure 1.

3.2. Data collection and processing

The data was collected from 1,267 systematically selected records of adult patients admitted to two emergency departments from October 2016 to September 2017. Twenty-four variables were evaluated, including chief complaints, initial vital signs recorded by nursing staff, and clinical outcomes. The true KTAS was determined by three triage experts: a certified emergency nurse, a KTAS provider and instructor, and a highly recommended nurse with outstanding emergency department experience and competence [11].

After collecting the data, we divided it into two datasets. Unnecessary attributes were carefully removed to streamline the analysis, while ensuring that the KTAS expert attribute was preserved as the target variable. Subsequently, we applied a series of preprocessing steps to each dataset, including handling missing values, addressing outliers, and performing feature engineering to enhance the quality and relevance of the data. This meticulous preprocessing ensured that both datasets were clean, consistent, and suitable for further analysis. For missing values, we identified three attributes 'Saturation', 'NRS_pain', and 'Diagnosis in ED' that were incomplete, and imputed them by filling in the most frequently occurring value for each case. Additionally, for outlier values, we replaced these with boundary values, moderating the effect of extreme data points without fully discarding them. In terms of feature engineering, categorical data initially represented as numerical values were transformed into meaningful categorical features, which enhanced the interpretability and utility of the data for modeling. Once preprocessing was complete, both datasets were merged into a comprehensive dataset. This combined dataset provided a holistic view of the patient's information, ready for further analysis and modeling.

3.3. Model Development

Since this research project focuses on a multiclass classification problem, specifically predicting the patient's emergency code. For our study, we evaluated six machine learning models: SVM, RF, ANN, GBM, LR, and XGBoost. Each of these models was selected for its distinct advantages and effectiveness in handling various types of data. SVMs are powerful for classification tasks, especially when data have clear separation margins, and they perform well in high-dimensional spaces [25]. LR, though a simpler model, remains highly interpretable and performs well in both binary and multiclass classification problems, serving as a robust baseline model. RF is an ensemble learning method that combines multiple decision trees to improve predictive performance and control overfitting, making it highly versatile and reliable [26]. ANNs, inspired by the human brain, are particularly useful for capturing complex patterns in data and are well-suited for tasks involving non-linear relationships due to their multi-layer structure. GBMs, known for their high predictive accuracy, build models in a stage-wise fashion and are particularly effective for both regression and classification tasks, especially when dealing with structured data [27]. XGBoost, an advanced implementation of gradient boosting, is recognized for its speed and superior performance in structured data scenarios, often outperforming other models due to its optimized boosting techniques. By comparing the performance of all six models, we aimed to determine which provided the best balance of accuracy, interpretability, and efficiency for predicting patient emergency codes. The inclusion of these diverse models ensured a comprehensive evaluation, allowing us to identify the most effective approach for this critical classification task. Training these models effectively requires careful tuning of hyperparameters, which is crucial for optimizing model performance. Hyperparameters control the learning process and can significantly affect models' accuracy, efficiency, and generalizability. In this study, we performed fine-tuning by testing various values for each hyperparameter across the six models.We employed techniques like grid search and random search to explore the hyperparameter space. Multiple combinations of hyperparameters were tested, and model performance was evaluated using cross-validation to avoid overfitting and ensure robust results. After comparing the outcomes across different hyperparameter configurations, we selected the values that yielded the best results in terms of accuracy, precision, recall, and F1-score. This detailed fine-tuning process was crucial in ensuring that each model was fully optimized for the multiclass classification task, allowing us to deliver high-performance models.

Our model pipeline was designed to ensure a consistent and robust data preparation and training process. The pipeline included several key steps: data preparation, data balancing, and model training. During the data preparation phase, we transformed categorical variables into numerical formats through encoding. To address class imbalance, we utilized SMOTE (Synthetic Minority Over-sampling Technique), which oversamples the minority class to prevent the models from being biased toward the majority class. While SMOTE is effective in balancing the dataset and preventing skewed model performance, it is important to consider its impact on the overall performance of the model. Synthetic data generated by techniques like SMOTE can sometimes lead to models that appear overly optimistic in their performance metrics, such as accuracy and F1-score. This is because the model learns from synthetic samples that may not fully represent the complexity of real-world, unseen data. As a result, while the model may perform well on the training and validation sets, it may struggle to generalize effectively when applied to new, unseen datasets. Despite this potential drawback, we chose to work with SMOTE because it provides a valuable approach to mitigating class imbalance, which is a common challenge in healthcare datasets where critical cases may be underrepresented. Without addressing this imbalance, the models could become biased toward the majority class, leading to suboptimal predictions for minority class instances. By using SMOTE, we aimed to improve the model's ability to identify these rare cases, while remaining mindful of the need for further validation on real-world data to ensure the models' generalizability. The model training phase involved training various classification models (SVM, RF, ANN, GBM, LR, XGBoost) on the processed data. The pipeline ensured that the same transformations were consistently applied to both the training and test sets, ensuring that the models were trained and tested on identically processed data. Evaluating model performance is essential to understand how well the models generalize to new data. We used a comprehensive set of metrics to assess our models: accuracy, precision, recall, F1 score, AUC (area under the curve), ROC curve (receiver operating characteristic curve) and confusion matrix. Accuracy measures the overall correctness of the model, while precision evaluates the proportion of true positive predictions among all positive predictions. Recall assesses the proportion of true positive predictions among all actual positive cases, and the F1 score, as the harmonic mean of precision and recall, provides a balance between the two. The AUC represents the model's ability to distinguish between classes, and the ROC curve visualizes the trade-off between the true positive rate and the false positive rate. The confusion matrix summarizes the true positives, true negatives, false positives, and false negatives, providing a detailed breakdown of the model's performance [28, 29].

Finally, we combined our models using stacking, which integrates multiple models to improve overall performance. Stacking allows us to leverage the strengths of each individual model by combining their predictions through a meta-model, typically resulting in better generalization and performance than any single model on its own. By using stacking, we capitalize on the diversity of the underlying models, where each model may capture different patterns or nuances in the data. This synergy helps mitigate individual weaknesses, making the overall system more robust [30]. After combining the models, we calculated the metrics to evaluate the effectiveness of the stacked model and then tested it on new inputs to ensure its robustness and accuracy in practical applications. This approach allowed us to improve both prediction accuracy and model reliability. The decision to work with a stacking model is justified by its ability to reduce overfitting and enhance predictive performance by aggregating the insights from different algorithms. Stacking, by fusing models with varying strengths, helps produce a more balanced predictive system that is less prone to the biases or limitations of any single model, making it especially valuable for complex tasks like patient triage predictions.

4. Results

We evaluated various machine learning models, including SVM, RF, ANN, LR, XGBoost and GBM. A total of 6 models were trained and tested in the data set, yielding prediction precision as shown in Table 2. The results showed that GBM and SVM models delivered the highest prediction accuracies of 79% and 78.7%, respectively. These models performed well in precision (80.04% and 75.36%), recall (71.94% and 73.36%), and F1-score (72.93% and 72.91%).

While SVM and GBM achieved the highest accuracies, the remaining models still delivered commendable performance metrics, showcasing their effectiveness in predicting triage patient outcomes. The close accuracy scores of the other models highlight the overall efficacy of our model selection and parameter tuning process, underscoring the reliability and versatility of various machine learning approaches in handling complex classification tasks.

After testing multiple combinations, we developed a Stacking-Model that combining the best three-performed models. This ensemble model demonstrated a slight improvement in performance compared to the base models as shown in Table 3. The Stacking-Model's ability to leverage the strengths of each contributing model resulted in a more robust and accurate prediction, showcasing its potential advantage over standalone models. This minor performance boost highlights the efficacy of model stacking in enhancing predictive accuracy by combining the complementary strengths of different algorithms.

5. Discussion

Among the models tested in this study, the stacking model that combined SVM, GBM, and LR outperformed individual models. It achieved an accuracy of 80.05%, surpassing MLP, RF, XGBoost, and GBDT models from [23] by 5.75%, 5.55%, 1.55%, and 3.35%, respectively. Furthermore, the AUROC of our stacking model reached 93%, outperforming the LR, RF, and XGBoost models in [22] by 30%, 10%, and 10%, respectively, as detailed in our experiments notebook in [31].

Table 2. Performance metrics of various models.

Model	Hyperparameters	Accuracy	Precision	Recall	F1-score	AUC
SVM	kernel: ’rbf’, C: 10, gamma: 0.01	78.74%	75.36%	73.36%	72.91%	0.9308
RF	n_estimators: 100, max_depth: 10, min_samples_split: 5, min_samples_leaf: 2, bootstrap: True, random_state: 42	76.90%	73.81%	73.83%	72.68%	0.9059
ANN	hidden_layer_sizes: (50, 25), activation: ’relu’, solver: ’adam’, alpha: 0.001, learning_rate: ’adaptive’, max_iter: 500, random_state: 42, early_stopping: True, validation_fraction: 0.1	75.06%	71.51%	70.87%	69.67%	0.92
GBM	n_estimators: 100, learning_rate: 0.1, max_depth: 3, random_state: 42	79.00%	80.04%	71.94%	72.93%	0.9203
LR	penalty: ’elasticnet’, l1_ratio: 0.5, C: 1, solver: ’saga’, max_iter: 200	75.85%	77.90%	72.60%	74.14%	0.9068
XGBoost	n_estimators: 100, learning_rate: 0.1, max_depth: 3, random_state: 42	76.90%	76.14%	70.63%	72.05%	0.9199

Table 3. Performance metrics of the Stacking-Model.

Model	Base models	Accuracy	Precision	Recall	F1-score	AUC
Stacking-Model	SVM, GBM, LR	80.05%	80.27%	73.26%	74.41%	0.9298

Most existing research as noted in our literature review, focuses on predicting patient outcomes, but this study highlights the importance of accurate triage level predictions, which directly impact those outcomes. Precise triage helps identify high-risk patients early, enabling timely interventions, reducing complications, and improving survival rates. Errors in triage, such as over- or under-triage, can lead to delays in treatment and worsened patient conditions as noted by [11]. Therefore, improving triage accuracy through machine learning enhances emergency department operations and strengthens overall patient care quality by minimizing these misclassification errors.

6. Conclusion

This study highlights the potential of AI to enhance emergency department triage by improving the accuracy and efficiency of patient severity assessments through advanced machine learning models. Despite the promising results, a key limitation is the reliance on a single dataset, which may hinder the generalizability of the models to other clinical environments with varying demographics, seasonal factors, and hospital contexts. To address these limitations, future work will involve expanding the dataset to incorporate diverse clinical conditions, demographic variations, and seasonal patterns. This will improve the robustness and applicability of the models across different emergency department scenarios. Additionally, validating the models on new datasets will be crucial to ensuring their performance and adaptability in different healthcare settings. By increasing the diversity of data and testing the models in real-world environments, future research aims to strengthen the generalizability and reliability of AI-driven triage systems, ultimately improving patient outcomes and resource management in emergency care.

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CONCLUSION GÉNÉRALE

Le triage en milieu hospitalier demeure l'une des étapes les plus sensibles et décisives du parcours de soins en situation d'urgence. La complexité des cas et les limites humaines de l'évaluation initiale posent de sérieux défis, particulièrement dans un contexte de surcharge chronique des services. Face à ces enjeux, l'émergence de l'IA, et sa capacité à traiter des données hétérogènes à grande échelle, ouvre de nouvelles perspectives pour renforcer la fiabilité et l'objectivité des décisions médicales à l'entrée des urgences.

Dans cette étude, plusieurs modèles d'apprentissage automatique ont été développés et comparés à partir d'un jeu de données réel de plus de 1 200 patients intégrant des informations cliniques multimodales. Les algorithmes testés comprenaient le SVM, RF, ANN, LR, GBM, XGBoost, ainsi qu'un modèle empilé. Ce dernier a obtenu les meilleures performances, avec une précision de 80,05% et un F1-score de 74,41%, dépassant les modèles individuels tels que le GBM (72,93%) et le SVM (72,91%). Ces résultats confirment les conclusions de plusieurs travaux antérieurs soulignant la supériorité des approches d'ensemble dans les contextes médicaux complexes. Notre étude se distingue toutefois par l'utilisation de données cliniques réelles et multimodales, ainsi que par la rigueur méthodologique adoptée dans la comparaison des modèles. Deux publications scientifiques sont venues valoriser ces apports : un premier article, présentant la méthodologie et les résultats détaillés, a été publié dans le cadre de la conférence ICTH 2024 Araouchi and Adda (2024), tandis qu'un second article, portant sur une revue des avancées en IA appliquée au triage, a été publié dans la conférence ANT 2025 Araouchi and Adda (2025).

Néanmoins, certaines limites doivent être reconnues. Premièrement, les résultats reposent sur un ensemble de données restreint à un contexte hospitalier précis, ce qui peut limiter leur généralisation immédiate. Deuxièmement, bien que diverses modalités aient été intégrées, certaines sources pertinentes, comme l'imagerie médicale avancée ou les notes cliniques non structurées, n'ont pas été pleinement exploitées. Troisièmement, les techniques d'apprentissage utilisées, malgré leur efficacité, nécessitent une optimisation plus poussée des paramètres ainsi qu'un recours à des bases de données plus vastes. Enfin, le déploiement concret de ces modèles en milieu hospitalier réel soulève plusieurs défis pratiques : interopérabilité avec les systèmes existants, formation du personnel médical, mais aussi enjeux éthiques et juridiques liés à la confidentialité des données. Ces limites ouvrent ainsi plusieurs pistes de recherche futures : élargir et diversifier les jeux de données, intégrer des modalités additionnelles et approfondir les conditions nécessaires à l'implémentation efficace et éthique de l'IA dans les services d'urgence.

En conclusion, cette étude met en évidence le potentiel de l'IA pour améliorer de manière significative le triage des patients aux urgences, tout en soulignant les défis à relever pour une adoption clinique réussie. Elle contribue à la fois à la littérature scientifique et à la pratique hospitalière, en posant les bases d'une transition progressive vers un triage assisté par l'IA, plus sûr et plus équitable.

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