A Review of Algorithms and Models for Patient Triage in Outpatient Departments

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Abstract. This paper is a comprehensive overview of algorithms and models used for patient triage in hospital outpatient departments. It starts by analyzing the systemic problems with conventional manual triage, such as low efficiency, great subjectivity and resource burden, underlining the need for intelligent systems. The nucleus of the work systematically identifies a variety of algorithmic paradigms starting from interpretable rule-based expert systems and traditional machine learning models (viz., Decision Trees, Logistic Regression, Support Vector Machines, Naïve Bayes) to state-of-the-art deep learning models like Recurrent Neural Networks, Long Short-Term Memory networks, Transformers, and Large Language Models. We also extend the frontier of multimodal fusion models that pool data from multiple modalities for comprehensive patient assessment. This survey combines performance results from many benchmark publications, providing not only a comparison between models, but also in comparison to the performance of human clinical experts, and summarize the most critical metric of evaluation. Finally, it also evaluates the practical and ethical challenges of real-world deployment of intelligent triage systems, including interoperability, data privacy/security, algorithmic bias, and the need for eXplainable Artificial Intelligence (XAI). The paper concludes that, although AI provides powerful means to improve triage efficiency and accuracy, its success in the future will depend on the creation of collaborative, transparent and ethically robust systems that complement, rather than replace, human clinical judgment.

Keywords: Patient Triage; Clinical Decision Support; Machine Learning; Deep Learning; Expert Systems; Algorithmic Bias; eXplainable Artificial Intelligence (XAI).

1. Introduction

Global healthcare systems are facing tremendous pressure due to changes in demographics, higher patient loads, and increasing operational costs. At the front lines of hospital operations, patient triage is a key control point to direct patient flow and timely care to the right place at the right time. Efficient triage has a direct effect on the safety of patients and their clinical outcome, and conventional manual strategies are increasingly found to be insufficient [1].

Manual triage is inherently susceptible to issues that may undermine its efficiency, such as, operational inefficiency resulting in delayed decisions, subjectivity and clinician fatigue-derived variability in decision-making and high workload on medical personnel. Bottlenecks not only worsen patient/provider care quality, but can also cause resource imbalances and health worker burnout [2]. The increasing gap between the demand for healthcare and the capacities of the conventional strategies has led to an urgent need for innovative technology-based approaches.

Intelligent triage systems, enabled by artificial intelligence (AI) and machine learning (ML), are, in turn, emerging as a novel approach for transforming this clinical service. Automating patient acuity ranking, standardizing assessment, and decision support may improve the accuracy, reliability, timeliness and efficiency of triage [3]. This review systematically examines the technological structure of this fast-developing field. It includes a detailed description of the algorithms and models used, and examines their performance in benchmark studies, covering central practical and ethical challenges to the translation of these tools into clinical practice.

2. Core Algorithms and Models for Patient Triage

The development of intelligent triage systems has a clear technological evolution path from encoding the existing human knowledge, to pattern recognition from examples and then up to the multi-source information synthesis for the all-round assessment. The point may be that this sequence is not just an increase in the algorithmic complexity, but at the same time a series of systems that can process more and more abundant unstructured data.

2.1 Rule-Based Expert Systems

The expert systems written in rules which is developed over the years are the base technology of intelligent triage. Translation of published clinical guidelines and expert diagnostic logic into a collection of explicit, action triggering IF-THEN rules is fundamental to their approach [4]. Such systems are built starting from knowledge engineering, which involves the conversion of clinical expert's tacit knowledge into an explicit form. An example of such a tool is the digital version of the five-level the emergency severity index (ESI) [5], an internationally used triage tool, which requires a scripted set of questions to determine urgency level. This is exactly the logic explicitly encoded in rules and enforced using a rule engine to automate triage decision.

One of the most developed and commonly used rule-based system is the Schmitt-Thompson telephone triage protocols (STTPs), which constitute the technological infrastructure of 95% of US nurse call centers [6]. To address the vagueness of clinical data, certain pure rule-based systems are complemented with others to be hybrid models. Another strong combination is the use of a rule-based reasoning (RBR) assisted by a fuzzy logic classifier (FLC) to describe the vagueness of discrete vital signs [7]. A hybrid approach like this enjoyed a remarkable accuracy of 99.44% and reduced triage errors by 13.4%.

The main benefit of rule-based approaches is the high explainability and configurability; every recommendation of a rule-based system directly maps to a rule and, therefore, the recommendation process is comprehensible and trustworthy. Their restriction is however serious. The rule base formulation and maintenance is time-consuming and the upper limit of the systems "intelligence" is bounded by the understanding of the knowledge engineers, so it is not able to discover new patterns from the data [8].

2.2 Classical Machine Learning Models

The second wave of triage technology was facilitated by the proliferation of data and improvements in the computational power, deriving power from machine learning. These are the models that "learn" decisioning patterns, based on historical data, in the process, they can bring more complicated relationships to the surface.

Decision tree is an easy-to-understand supervised learning model, which forms a flowchart-based structure for classification [9]. Since clinicians are able to easily understand the transparent decision-making process, decision trees have been widely used. For example, they have been effectively applied to predict prognosis of out-of-hospital cardiac arrest patients [10], and to outperform standard scores for trauma care, one model reached an area under the curve (AUC) of 0.82 for predicting the demand for special treatments [11]. In addition, the model has also been shown to be useful for identifying individuals in danger of an extended recovery following concussion and for the systematic triaging of physical therapy referrals, resulting in an overall reduction in needless assessments of 29%.

The classical statistical model logistic regression plays a role as a workhorse in clinical prediction by quantifying the probability or chance to have a binary outcome [12]. Its coefficients have a meaning, odds-ratios, that are easy to understand for clinicians. It has been applied for risk stratification, for instance, to segment patients with a high likelihood of developing and adverse event; for outcome predication, for example, probability of readmission; and to assign a level of urgency for emergency triage. It has been applied to develop risk scores for short-term mortality in patients with acute cardiogenic pulmonary oedema and to model patient disposition from emergency medical calls [13].

A support vector machine (SVM) is a strong categorization algorithm which constructs an optimal hyperplane between classes in N-dimensional space [14]. With the kernel trick, SVM can handle nonlinear data well even when the number of features exceeds the number of samples, and the performance becomes resilient for many healthcare applications, such as medication adherence prediction for heart failure patients [15], and heart disease classification [16]. In comparisons, SVMs are often highly accurate, and have been reported to achieve 100% accuracy in identifying atypical triage cases in combination with principal component analysis (PCA) [17].

Naïve Bayes is a probability classifier, based on Bayes' theorem and the "naïve" assumption that features are conditionally independent [18]. Notwithstanding this rather simplifying assumption, it has shown very good performances in several applications due to its high efficiency and low complexity. It has been widely used in clinical decision support systems (CDSS) for predicting patient outcome for emergency patients and classifying patient data according to decision difficulty [3]. One example is that a weighted Naïve Bayes algorithm-based three-layer knowledge model has achieved diagnostic accuracy moved up from 88% to 98% compared with the two-layer model [19].

2.3 Deep Learning Models

Deep learning based smart triage is the third era of evolution of smart triage. Notably, these models are capable of learning very complicated and abstract feature representations that may enable them to process large, high-dimensional and unstructured medical data in a meaningful way.

Recurrent neural network (RNN) and its successful version "long short-term memory" (LSTM) are very promising architectures designed to deal with sequential data similar to those in electronic health records (EHRs) domain [20]. Through "gate" mechanisms, LSTMs are able to encapsulate long-range dependencies in a patient's medical history [21]. One fundamental use case is to predict a patient's propensity for disease, for a disease such as COVID-19, solely based on historical EHR data, for proactive risk management. When treating a patient's history as a time series, such models can use the temporal nature of observations to learn the latent disease progression, to forecast the future medical events, and have been shown to outperform standard classifiers in learning from the chief complaint text (using variants of such as gated recurrent unit (GRUs)) [22].

The transformer architecture along with its fundamental "self-attention" mechanism caused a paradigm shift in natural language processing (NLP) [23]. Models built on such architecture, e.g., bidirectional encoder representations from transformers (BERT) and its clinical fine-tuned variants, such as ClinicalBERT, have shown unprecedented performance in interpreting unstructured texts from EHRs [24]. These are leveraged to produce high quality contextual embeddings for free-text chief complaints that are able to automatically predict physician designated diagnostic labels and also facilitate the building of standardized terminologies. This has taken automated structuring of noisy text data to a new level, with studies demonstrating up to 30% improvement in entity recognition in clinical notes. The range of things one might do with a large language model (LLM) is even wider and includes simulating patient interactions for medical training and text classification for triage [25].

2.4 Multimodal Fusion Models

Real world clinical assessment inherently is multimodal and will need to integrate multiple information sources. In recent years, multimodal AI models have attempted to replicate this intricate cognitive process by integrating heterogeneous data (including the text of clinical notes, vital sign data, and imaging) to develop a more holistic and robust profile for each patient than could be achieved from any one type of data [26]. Fusion can be at different levels, ranging from early interaction with cross-attention mechanisms to late feature fusion.

This approach has shown promising results in a number of studies. One study that fused chest X-ray and vital signs together resulted in classified accuracy over 90%, markedly surpassed singlemodality baselines [27]. All the triage algorithms and models mentioned above have been compared in Table 1.

Table 1. Comprehensive Comparison of Triage Algorithms and Models.

Model Category	Core Principle	Key Advantages	Key Disadvantages	Typical Input Data	Primary Triage Application
Rule-Based Expert System	Encodes explicit If-Then clinical rules	Highly explainable, easy to configure and trust	High creation/maintenance cost, cannot discover new knowledge	Structured clinical guidelines (e.g., ESI)	Automated implementation of standardized triage protocols
Decision Tree	Learns tree-like classification rules from data	Intuitive model, high interpretability	Prone to overfitting, sensitive to data variations	Structured features (demographics, vitals)	Creating clear triage pathways, risk stratification
Logistic Regression	Establishes probabilistic relationship between predictors and a binary outcome	Easily interpretable results (odds ratios), computationally efficient	Assumes linear relationships, limited in modeling complex patterns	Structured features	Predicting admission/acuity risk, risk stratification
Support Vector Machine (SVM)	Finds optimal separating hyperplane in high-dimensional space	Excellent performance on high-dimensional data and small samples, strong generalization	Sensitive to parameter/kernel choice, "black box" model	Structured features	Patient classification, identification of high-risk groups
Naïve Bayes	Probabilistic classification based on Bayes' theorem and feature independence assumption	Simple, efficient, robust to missing data	"Naïve" independence assumption often violated in reality	Structured features, symptom lists	Clinical decision support, disease probability prediction
RNN / LSTM	Models temporal dependencies in sequential data	Excels at processing time-series data, capturing historical context	Complex to train, struggles with very long-term dependencies	Temporal EHR events (visits, meds)	Predicting future risk and trajectory based on patient history
Transformer / LLM	Captures long-range context via self-attention	State-of-the-art performance in NLP, understands complex semantics	Computationally intensive, requires massive pre-training data	Unstructured text (chief complaints, clinical notes)	Structuring free text, intelligent Q&A and triage
Multimodal Model	Fuses diverse information sources like images, text, and structured data	Provides a more holistic and accurate patient profile, improves decision robustness	Data alignment and fusion are complex, datasets are scarce	Heterogeneous data (imaging, EHR, vitals)	Comprehensive assessment and precise triage for complex cases

3. Performance Evaluation and Practical Challenges

The merit of an intelligent triage model depends not only on its theoretical refinement, but also on its practical implement ability and clinical performance. Thus, scientifically accessing model performance and addressing the challenges to application feasibility are important issues in transforming technology into practical applications.

3.1 Key Performance Evaluation Metrics

To objectively and comprehensively measure the performance of triage models, a standardized set of evaluation metrics is used (see in Table 2). In the high-stakes context of triage, the interpretation of these metrics must be closely tied to their clinical significance.

Table 2. Key Performance Metrics for Intelligent Triage Models.

Metric	Formula	Measures	Clinical Importance in Triage
Accuracy	(TP+TN)/(TP+TN+FP+FN)	The proportion of all predictions that are correct	Intuitive, but can be misleading in imbalanced datasets (e.g., where critical cases are rare)
Precision	TP/(TP+FP)	Of all instances predicted as positive, the proportion that are truly positive	Important when the cost of a false positive is high (e.g., misclassifying a non-urgent patient as urgent, consuming valuable resources).
Recall / Sensitivity	TP/(TP+FN)	Of all instances that are actually positive, the proportion that are correctly identified	Critically important in triage. It measures the model's ability to identify all truly urgent cases. High recall means a low rate of missed cases (false negatives), as missing a critical case is far more dangerous than misclassifying a non-critical one (a false positive)
F1-Score	2*(Precision*Recall)/(Precision+Recall)	The harmonic mean of Precision and Recall, providing a single score that balances both	A more reliable measure than accuracy in imbalanced datasets, as it considers both false positives and false negatives
AUC-ROC	Area Under the ROC Curve	The model's aggregate ability to discriminate between positive and negative classes across all classification thresholds	AUC ranges from 0.5 (random guess) to 1.0 (perfect classifier). It is an ideal metric for comparing the overall discriminative power of different models

Note: In these formulas, TP = True Positive (a correct "urgent" prediction), TN = True Negative (a correct "not urgent" prediction), FP = False Positive (a "false alarm" or over-triage), and FN = False Negative (a "miss" or under-triage).

In triage decision-making, recall is typically assigned the highest priority. The clinical consensus is that it is far preferable to over-triage (classifying some non-urgent patients as urgent, a false positive) than to under-triage (missing a genuinely critical patient, a false negative). Therefore, during model tuning, a decision threshold is often selected to maximize recall, even at the expense of precision. The F1-score and the Precision-Recall Curve (PR-Curve) are powerful tools that help decision-makers find the optimal balance in this trade-off.

3.2 Algorithm Performance Benchmarking

A significant literature exists that focuses on performance comparison of various triage algorithms, mostly comparing models with models or models with human experts. System performances for various machine learning models can be different and there will be no single robust method. A systematic review reported that the neural networks, in predicting the hospital admission, were similar to the logistic regression, but however, in predicting the requirement for the intensive care, the neural networks were significantly better than the logistic regression [28]. These findings indicate that the ideal model selection is subject to the clinical question at hand, the properties of the dataset and the performance criterion you are targeting.

Comparison of AI against human expertise is the key step for both validation of clinical value and establishing trust. The picture is more nuanced, however, one analysis comparing an AI triage tool developed for a specific purpose with general practitioners found good agreement and suggested the AI to be risk averse and safe by tending towards over-triage (rather than under triage) [29]. On the other hand, a different study comparing a general purpose LLM with triage nurses reported very low agreement, and demonstrated that the prediction mortality ability of the nurses was significantly higher than that of the LLM, signaling the performance separation between domain-specific and general models. One of the biggest takeaways from this strand of research is that humans can complement AI. Even if the performance of an algorithm is on average higher than that of the human, a combination strategy can often result in the best performance. The idea is that human experts might have additional contextual "side information" that is not present in the training data. A good approach can be to the algorithm to manage high-confidence cases and then to delegate some ambiguous ones to human experts; in combination they can bring down error rates, lower them than what each of them can reach on its own [30].

3.3 Real-World Deployment Challenges

While promise of the approach was demonstrable in controlled testing, delivering an algorithm effectively into the complex workflows of the hospital represents a daunting "last-mile" challenge. These have moved from questions purely based on algorithms to more complex socio-technical and governance issues.

System integration and coordination are one of the main technical hurdles. It is hard to integrate such AI tools easily with already heavily used, often relatively outdated, hospital information systems (HIS) and EHR systems whose medical data are commonly kept in heterogeneous "data silos" [31]. This requires substantial effort in data sharing standardization to support the real-time data pipeline necessary for AI-driven decision support.

In addition, AI triage solutions handle large amounts of information, including personal health information (PHI), which is sensitive, giving rise to significant data privacy and security issues. Therefore, compliance with regulations such as health insurance portability and accountability act (HIPAA) and general data protection regulation (GDPR) is the must. Federated learning (FL) in this direction has been proposed as a promising privacy-preserved technique [32]. It provides privacy-preserving federated learning, which enables institutions to learn a global model through collaboration without exchanging raw patient data, achieving the model robustness through the diversity of datasets. Nevertheless, the FL technique is not without difficulty, for example, the large communication overhead and the statistical heterogeneity between datasets.

4. Ethical Considerations and Future Outlook

As intelligent triage systems transition from theory to practice, the underlying ethical issues and societal impacts are drawing increasing scrutiny. A technically perfect model that fails to ensure fairness, transparency, and accountability cannot achieve true success in the unique domain of healthcare. The future trajectory must involve parallel progress in technological innovation and ethical governance.

4.1 Algorithmic Fairness and Bias

AI models are not an unbiased representation; reality and reality's biases are imaged, and may be further magnified by mirrors. This bias from the algorithm can come from a bias in data such that the training data are not reflective of all populations. In a well-known example, one popular clinical algorithm unfairly downplayed the needs of Black patients, treating "healthcare costs" as a proxy for "health needs" [33]. Bias may also be introduced by encoding societal biases when the algorithm learns to reinforce unfair patterns from the historical clinical practice. These biases have the potential to maintain and further degrade and already unequal distribution of health care leading to systemic discrimination and erosion of patient trust. This calls for a systematic approach, which entails provisions to ensure dataset diversity, performing regular audits on model performance on demographic subgroups and making judicious decisions on proxy variables to prevent encoding of social injustice.

4.2 eXplainable Artificial Intelligence (XAI)

With the increasing complexity of models, their decision-making processes are more and more like a complex opaque established "black box," which is usually unacceptable for high-stake application domains (such as medicine). Such non-transparency can result in a lack of clinical trust and challenges the ability to detect and amend model errors or biases. Explainability has been identified as key for establishing this trust, in order to achieve informed consent, and be accountable. The objective of eXplainable AI (XAI) is to make a model's decision process interpretable while losing as little performance as possible [34]. This can be done by good interpretable model (such as decision tree) or by interpretability methods (like local interpretable model-agnostic explanations (LIME) [35] or shapley additive explanations (SHAP) [36]) on black box model. These methods help reveal which of the input features contributed strongest to a prediction, contributing to openness and trust in human-AI partnership.

4.3 Future Research Directions and Trends

The field of intelligent triage is currently going through a phase of fast technological iteration and the future is likely to be shaped by a number of key trends. Future work will be directed towards developing better AI models, such as more endurant and conversational LLMs for interactive triage, and more powerful multimodal models to incorporate heterogenous data sources, such as genomics in order to personalize comet analysis. Another important trend is the tighter integration with internet of medical things (IoMT) [37]. Integrating the AI triage with wearable sensors and smart monitors in real time could transform the traditional model of reactive response to the proactive prediction of patient deterioration. At the same time, attention is also moving away from basic performance comparisons toward more mature human-AI interaction frameworks–systems that learn to defer complex instances. Behind all of this stands a requirement for strong governance and ethical frameworks. As the technology is adopted more widely, standardizing what are industry norms for data quality, bias identification and adaption, privacy enhancing technology, and (adaptation based) transparency and trustworthiness, will be the most important factor for ensuring that technological progress will continue to be patient-centred and in the public interest.

5. Conclusion

Patient triage is experiencing a dramatic, technology-enabled overhaul as organizations look to address systemic pressures and inadequacies of straightforward manual screening techniques. This article has systematically sketched the development of intelligent triage systems from early rule-based triage to cutting-edge AI models that provide effective tools for improving the speed, consistency and accuracy of triage. Yet technical proficiency is not the only factor in success: benchmark tests show that the most successful future for AI in healthcare may not be one of machine replacement but of human-machine complementarity, with algorithms performing the data processing and humans exercising oversight and contextual judgment. At present, the dominant bottlenecks are no longer on purely algorithmic matters but on social technical and ethical issues such as interoperability, data privacy, algorithmic discrimination, and the need for explain ability. The future of intelligent triage, then, is not necessarily a man-versus-machine dynamic, but, rather, a symbiotic one–one designed to be—with the right kind of network, an open, transparent, fair, and secure network and environment that augments, not detracts, from what is the core value of human expertise—ultimately making the entry point to healthcare equitable and as efficient as possible for all.

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