Automated Techniques for Detecting Healthcare Associated Infections: A Review

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Abstract--- **Automated detection of Healthcare-Associated Infections (HAIs) faces major obstacles due to unclear medical documentation, scarcity of well-annotated data, and multiple symptoms that overlap between HAIs. This review investigates recent advances in using classical machine learning, deep learning, transformers, and natural language processing (NLP) methods in detecting healthcare-associated infections. It examines empirical studies from 2019 to 2025, focusing on models' performance based on various metrics, data issues, and ethical considerations. The study sought to assess and compare the performance of natural language processing (NLP) approaches of detecting Healthcare-Associated Infections (HAIs). Ethical and technical concerns such as data privacy and data imbalance, are critical barriers to implementation of NLP to detection of HAIs. The review underscores the promise of NLP to detection of HAIs while emphasizing the need for standardized metrics for evaluating HAI detection model and ethical frameworks of handling the datasets.**

Keywords--- Healthcare-Associated Infections; Machine Learning; Deep Learning; Natural Language Processing; Transformer; Electronic Health Records

I. INTRODUCTION

Healthcare-Associated Infections (HAIs) continue to present a significant threat to patients' well-being contributing to increased morbidity, mortality, and healthcare expenditure globally [1]. The annual cost of treating HAIs in the US is estimated to range between $28.4 billion to $45 billion a heavy burden on the public health system [2]. It is estimated that 8.9 million healthcare-associated infections are recorded annually in hospitals across Europe [3]. In Africa, a higher rate of mortality among inpatients who suffer HAIs has been reported (22.0%) [4].Traditional HAI surveillance relies on health professionals reviewing data collected from patients to interpret whether there is any presence of HAI or not. Traditional methods for detecting HAIs are time-consuming and prone to delays and inaccuracies [5]. Such approaches typically involve manual chart reviews, microbiology reports analysis, and clinician interviews to confirm infection status, often following standardized case definitions such as those from the Centers for Disease Control and Prevention (CDC). These processes depend heavily on the availability and attentiveness of trained infection prevention staff, which introduces variability and subjective bias. In response to these limitations, machine learning (ML) and natural language processing (NLP) techniques have emerged as powerful tools capable of learning patterns from clinical notes and detecting HAIs.

Recent developments have expanded the scope of ML applications from classical models such as GXBOOST, Support Vector Machines (SVMs), and Decision Trees to advanced deep learning methods like Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Transformers such as Bidirectional Encoder Representations from Transformers (BERT). When these techniques, are applied on structured and unstructured data from Electronic Health Records (EHRs), they provide good predictive performance of HAI's compared to traditional methods and classical methods [6] [7].

Despite these advancements, persistent challenges remain. These challenges include: data imbalance, lack of standardized metrics for evaluating healthcare models' performance, limited generalizability across healthcare settings, and ethical concerns such as data privacy and explainability of models [1]. This review synthesizes the growing body of empirical research on automated detection of HAIs, assesses the effectiveness of various machine learning models developed for detecting HAIs, and explores challenges and gaps in the literature in automating detection of HAIs.

This review examined studies published from 2019 to 2024, where scholars applied classical machine learning, deep learning, NLP, or transformer-based models to the challenge of HAI detection. It also investigated associated data limitations and ethical considerations to guide future model development and clinical implementation.

A. Objective

By the end of this review, the study sought to:

a. evaluate the accuracy of Machine Learning, deep learning, and transformer-based NLP models in detecting HAIs.
b. examine key data and ethical issues in developing HAI detection models.

B. Research Question

This study sought to answer the following questions.

a. How effective are classical machine learning, deep learning, transformers based NLP models in detecting Healthcare-Associated Infections?
b. What data issues and ethical considerations are associated with developing Healthcare-Associated Infection detection models?

II. METHODS

A. Introduction

This section describes specific rigorous methods that were used to identify studies that were relevant for this review.

B. Appraisal Tools and Framework Tools for Analysis

The Critical Appraisal Skills Programme (CASP) [8] checklist for quantitative studies was used to assess the methodological quality of the selected studies. Since not all CASP criteria were relevant, the tool was changed to represent the nature of machine learning and data-driven analyses. Specifically, the appraisal focused on addressing the following questions:

a. Was the study objective or research question clearly stated?
b. Was the methodology appropriate for the type of data or model developed?
c. Was it clear how data sources and data types were selected?
d. Was there a rationale for choosing the algorithms or model architecture used?
e. Did the study report evaluation metrics and validation techniques used?
f. Did the study address data limitations, such as dataset imbalance or over-fitting?

The studies in the systematic literature review were categorized and analyzed systematically using the Population, Intervention, Comparison, Outcome, and Setting (PICOS) framework [9]. The protocol's development was iterative, and decisions regarding study inclusion, exclusion, and appraisal were further refined during the review.

C. Search Strategy Worksheet

a) Search keywords

During the search for resources for this study, we focused on the following keywords: classical machine learning, deep learning, neural networks, transformers, NLP, healthcare-associated infections, controlling healthcare-associated infections, detecting hospital-acquired infections, electronically assisted surveillance systems, data issues, and ethical considerations.

b) Inclusion Criteria

Research reviewed peer-reviewed publications beginning from 2019 up to 2024. This research examined scientific articles that utilized classical machine learning, deep learning, or transformer-based natural language processing (NLP) techniques to detect Healthcare-Associated Infections (HAIs). The analyzed studies came from empirical research, which presented original data that advanced the knowledge about model development, deployment, and performance assessment. The review admitted research publications that examined either data problems or ethical aspects of HAI detection systems. The analysis required English-only publications because it needed consistent language and easy access for evaluation purposes. The analysis excluded systematic reviews since it concentrated on analyzing the methodologies and datasets in addition to research results stemming from original empirical investigations. Integrating systematic reviews would have added redundant information, making the analysis more complex while using secondary interpretations instead of original firsthand data.

The following studies met the inclusion criteria and were therefore considered: [10], [11], [12], [13] [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26].

c) Exclusion Criteria

Review considered only English-language scientific studies published between 2019 and 2024 so as to capture current technological advancement in detection of HAIs. The research excluded all studies that did not apply classical machine learning, deep learning, or transformer-based natural language processing techniques in detecting healthcare-acquired infections. Research studies that exclusively used secondary data and lacked original empirical studies were excluded from the review assessment. The analysis excluded systematic reviews together with other methods of secondary research to prioritize original investigations. Only studies within the healthcare and clinical informatics domains were admissible for the analysis, while all other studies were excluded to guarantee the applicability of findings in HAI detection.

D. Data Extraction and Synthesis

Information such as publication details, research objectives, machine learning techniques , data source and type, dataset size, evaluation metrics findings, and limitations were noted.
The studies employed heterogeneous methods, including design, algorithms, datasets, and performance metrics, results were synthesized narratively. Comparative performance discussions were presented for studies that included performance of the developed machine learning models, such as recall, F1-score, accuracy, sensitivity, Area Under the Curve, or specificity. Emphasis was paid to ML HAIs' detection trends and the methodological and practical considerations of applying AI to HAI detection in different clinical settings.

III. RESULTS

This systematic literature review critically examines several machine learning models that detect Healthcare-Associated Infections (HAIs) within natural language processing models. Various researchers such as, [27], [10], [11], [12], [13] have done extensive work on classical machine learning techniques such as Support Vector Machines (SVM) for HAI detection. Lopes et al. [27] implemented a model for detecting HAI, where the first scenario yielded an initial accuracy of 85.33%, precision of 18.31%, and a recall of 75.73%. The second scenario achieved 89.78% accuracy and 83.27% recall, but the precision was still very low (19.60%). It is indicated that SVM is sensitive to imbalanced datasets, which is common in medical data scenarios [10]. Sánchez-Hernández et al. [11] complement this by pointing out that SVMs face challenges in unbalanced datasets with unbalanced class distributions, proving that unbalanced datasets lead to poor SVM precision of less than 0%. The study shows that among the ensemble classifiers for clustering-based undersampling methods, the obtained remarkable performance compared to the conventional resampling methods like SMOTE, demonstrating the significance of handling the data imbalance on clinical datasets.

Lopes et al. [27] stated that XGBoost performed better by recording an accuracy of 98.89%, precision of 81.15%, recall of 94.51%, and F1-score of 87.31%. The scores achieved here, remain limited due to the single hospital dataset used and internal validation not warranting broader clinical applicability. Park et al. [12] found that decision trees (DT) are highly interpretable and perform well in predicting urinary tract infection, with the highest performance of all tested models. Despite requiring further pruning and ensemble methods for improved accuracy and generalization, DT is straightforward to interpret, and thus clinically very valuable [13].
Goodwin et al. [22] explored neural network approaches to this task and found that periods were beneficial for sparse datasets. Deep Averaging Network reached 96% sensitivity and an 80% F1-measure. However, performance was affected by dataset size and balance, suggesting the need for more robust training sets. Message Passing (Graph) Neural Networks (MPNN) proposed by [7] have promising results, with an AUROC of 90.27% and a sensitivity of 88.57%. [7] noted that data gathering is highly time and labor-intensive, necessitating impractical, real-world deployment.
Complex deep learning techniques like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) showed better results than the classical machine learning models in the detection of disease. Rabhi et al. [23] pointed out that CNNs have the capability of extracting relevant clinical features automatically more effectively than SVM, and achieve a superior performance of F1=97.7% and AUC=99.8%. In another study, [17] reported slight accuracy improvements using deep attention networks, which is a close relative of LSTM, based on sequential healthcare datasets by handling the temporal dependencies in the same way. The two studies concluded that deep learning has high predictive power. The study also noted that there is a need to improve the interpretability and generalizability of the model.
Finally, there is a lot of promise presented by transformers in general, and Bidirectional Encoder Representations from Transformers (BERT) in particular, in detecting HAI. Li et al. [24] noted that fine-tuned BERT models significantly improved the clinical NLP tasks.Babu and Babu [18] used BERT to create a chatbot that achieved 98% accuracy and 97% precision to ensure ease of communication between the patient and doctor. Additionally,Rasmy et al. [19] showed that Med-BERT works well, with excellent AUC scores even with no fine-tuning. However, these high-performing models are expensive in computational resources and are impossible to deploy in resource-restricted scenarios.
To leverage the information in EHR data, [20] developed NLP–driven models that achieve 97% specificity and perform much better than keyword-based models. Agreeing with them [16], NLP outperforms traditional administrative data with an accuracy of 87%, much more than the manual abstraction. Both studies strongly support that NLP can be a crucial aspect for automated HAI surveillance, as it can extract rich clinical contexts critical for accurate detection.
NLP and ML model efficacy is significantly influenced by data quality and consistency. As shown by [7] and [15] though this dichotomy exists with unstructured data having more clinical nuance, it has lower predictive value than structured data. It is worth mentioning that [25] also pointed out the limit of dataset size, and the bias in single-setting healthcare data, and underlined the necessity to obtain high-quality multicenter datasets to enable model generalizability. Additionally, [26] highlighted heterogeneity in the clinical data sources, which makes it challenging to develop and validate an HAI detection model.
According to Amjad et al. [21], explaining a model makes it trustworthy and effective in healthcare decisions. van Rooden et al. [15]echoed this suggestion, suggesting that data sharing should be done responsibly, patients' privacy should be protected at all costs, and development and deployment should occur within the boundaries set forth by relevant regulations,

such as the General Data Protection Regulation, among other regulatory bodies.

IV. CONCLUSION

This review establishes that machine learning, deep learning, and transformer-based models assist natural language processing to become more effective at identifying Healthcare-Associated Infections (HAIs). The combination of deep learning models, including CNNs, along with LSTMs and BERT as transformer architectures, achieved better unstructured clinical data classification than traditional solutions as demonstrated by [23] and [24]. The detection system's accuracy improved because NLP techniques enabled the extraction of nuanced contextual cues such as temporal relationships, symptom progression, and negations from clinical documents, which are often overlooked by keyword-based or structured-data-only methods. The detection system faces ongoing hurdles, including non-scalable model applications, expensive cost structures, unbalanced data distribution, privacy, and deployment ethical problems as alluded by [14] and [11]. Transformer-based models operate effectively, but they need large computational resources as well as thorough parameter adjustments to remain fair and easy to interpret [19] and [24]. The review emphasizes both the requirement for high-quality, varied datasets and the development of medical and ethically compliant, explainable models. Reaching effective HAI detection in healthcare settings requires both technical developments and data responsibility standards together with systems for standardized evaluation that support safe deployment at scale.

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