Enhancing Medication Safety with ML-Enhanced Decision Support Systems: A Comparative Analysis of Prescription Error Detection

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Abstract

Background: Medication prescription errors are a global issue, leading to significant morbidity and mortality. Traditional rule-based Medical Decision Support Systems (MDSS) are often ineffective, generating numerous false alerts and failing to detect all potential errors. This study assesses a new anomaly detection system integrated with Electronic Health Records (EHR) to improve the accuracy and utility of medication error warnings. Methods: Anomalous prescription detection was implemented alongside an existing MDSS in a real-world inpatient setting over 18 months. The new system utilized Machine Learning (ML) combined with a rule-based MDSS to analyze historical EHR data. It aimed to identify and flag high-risk prescriptions through real-time anomaly detection. The performance of this hybrid system was compared against traditional MDSS and multicriteria query (MQ) methods. A clinical pharmacist reviewed 415 patients (3401 prescriptions) to validate the effectiveness of the system, assessing notifications for accuracy, clinical relevance, and practicality. Results: The ML-enhanced MDSS demonstrated superior performance compared to traditional systems. It achieved a 76% interception rate for prescriptions needing pharmacist review and a precision rate of 75%. The hybrid system outperformed traditional MDSS and MQ methods, with areas under the ROC and PRC curves of 0.84 and 0.79, respectively, compared to 0.66 and 0.57 for MDSS and 0.7 and 0.58 for MQ approaches. Conclusion: Integrating ML with rule-based MDSS significantly improves the detection of high-risk medication prescriptions, reducing false alerts and enhancing accuracy. This hybrid approach offers a more effective tool for identifying potential medication errors and improving patient safety in inpatient settings.

Keywords: Machine Learning, Medical Decision Support System, Electronic Health Record, High-risk prescriptions.

Significance | This study demonstrates that integrating machine learning with decision support systems significantly improves prescription error detection, reducing medication errors and enhancing patient safety.

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Introduction

It is estimated that preventable errors in prescribing medication, along with the harmful effects of drugs, contribute to 1 out of every 132 fatalities in outpatient settings and 1 out of every 853 deaths in inpatient settings in the United States. These errors result in a direct cost of over $21 billion and an accountability cost exceeding $14 billion (Newman-Toker et al., 2024). While these medication errors and Differing Drug Events (DDEs) can be attributed to human error, a significant portion of the fault lies in Electronic Health Record (EHR) systems (Suclupe et al., 2020).

Current methods aimed at reducing these errors involve the use of Medical Decision Support (MDS) alert systems (Mohamed et al., 2024). However, these systems often detect only a small fraction of errors and are plagued by a high rate of false alarms, , leading to

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"alert fatigue" and disrupting workflows (Olakotan & Mohd Yusof, 2021). Moreover, these systems, which rely on predefined databases and rules, often fail to catch errors that are not anticipated or included in the system's protocols (Mohandas et al., 2024). Unlike rule-based systems that observe only the current drug prescription scenario, there is a need for systems capable of dynamically screening for and detecting evolving DDEs throughout hospitalization to intervene early and reduce harm (Swen et al., 2023).

Medical errors represent a significant public health issue and are a leading cause of death. In the United States alone, medical errors cause approximately 250,000 deaths annually, making them the third leading cause of mortality after heart disease and cancer (Surendar et al., 2024; Karande et al., 2021). A report from the Institute of Medicine in 2000 emphasized the need for technology to address the estimated 45,000 to 99,000 deaths annually caused by medical errors. The issue is global, with many countries reporting high levels of health-related DDEs (Malathi et al., 2024). Invasive procedures, hospital-acquired infections, and medications or medical equipment are responsible for most adverse events during hospitalization (Lexow et al., 2022).

While at least 30% of adverse events are preventable, research indicates that adverse events resulting from negligence (such as medical errors) are more likely to harm patients than other DDEs. Therefore, improving patient safety by minimizing pharmaceutical errors has become a critical objective (Sindhusaranya et al., 2023). Errors in prescribing and administering medications frequently cause medication errors; however, they can occur at any point during the medical treatment process (Elshayib & Pawola, 2020; Elliott et al., 2021).

Several technologies, such as digital medicine, computerized prescriber order entry (CPOE), and digital MDS systems, have been developed to improve the prescription process at the point of care (Cornuault et al., 2018). However, it is widely acknowledged that CPOE systems can introduce other prescription errors, such as prescribing the wrong medication (Madhavi et al., 2023). MDS systems are also known for generating excessive and unnecessary alerts, contributing to alert fatigue and inefficiency (Gates et al., 2021). The current gold standard for medication review, performed by clinical pharmacists, is widely recognized as a key step in preventing adverse drug events (Lexow et al., 2022).

Pharmacological interventions initiated during medication reviews are measures taken to address or prevent drug-related problems in patients. However, this process is labor-intensive and, like any human process, is not consistently reproducible. It is crucial to direct these interventions toward patients at the highest risk of prescription errors (Nguyen et al., 2017). In a recent study, factors such as polypharmacy, advanced patient age, and reduced kidney function were associated with a higher incidence of drug-related problems, necessitating increased pharmacological interventions. However, expert predictions and statistical models have not consistently been able to accurately identify high-risk patients (Nguyen et al., 2017).

Although existing systems have slightly improved medication review by targeting high-risk patients, other factors, such as the patient's clinical condition, laboratory results, drug regimens, and drug interactions, must also be considered. The growing availability of EHRs and advancements in data analytics have enabled the use of Artificial Intelligence (AI). AI, powered by complex algorithms capable of analyzing large datasets, has the potential to improve medication review, allowing pharmacists to better predict and intercept drug-related problems, thereby reducing the risk of medication errors (Tekkeşin, 2019). A study evaluating the accuracy of Lumio Medication, a combination of machine learning (ML) and rule-based digital MDS, found that this method provided patient-level predictions rather than estimates about specific prescription rules.

2. Materials and methods

The research examines a digital MDSS that uses ML algorithms to detect and promptly prevent probable mistakes in drug prescriptions. The system utilizes historical EHR to create a mathematical model for each medicine. This framework captures the characteristics of the patient group that is likely to receive the medicine and the medical setting and spatial settings in which it is commonly prescribed. Subsequently, this model may detect prescriptions that deviate significantly from the norm based on patients' clinical conditions. Instances of such outliers include pharmaceuticals that are seldom or never administered to patients in firm circumstances, such as administering birth control drugs to a male infant or prescribing an oral hypoglycemic prescription to a patient who does not have diabetes. The technology identifies such prescriptions as probable drug mistakes during real-time prescription activities. The technology arbitrates at two specific junctures in the doctor's plan: 1) Synchronous notifications are alerts that appear. In contrast, a physician prescribes a medication if the chosen medication is unusual for the patient's clinical characteristics and present circumstances. 2) Asynchronous notifications are generated after an order for medicine has been entered into the system due to an important shift in the patient's profile, such as original laboratory findings or a shift in important signs that make one of the active medicines unusual. Alerts that coincide are referred to as synchronous.

Synchronous time-varying irregularities: a warning has been raised when the information in the patient's outline indicates that the suggested drug is unsuitable or potentially harmful, such as administering an anti-hypertensive medicine to a patient experiencing an infected shock.

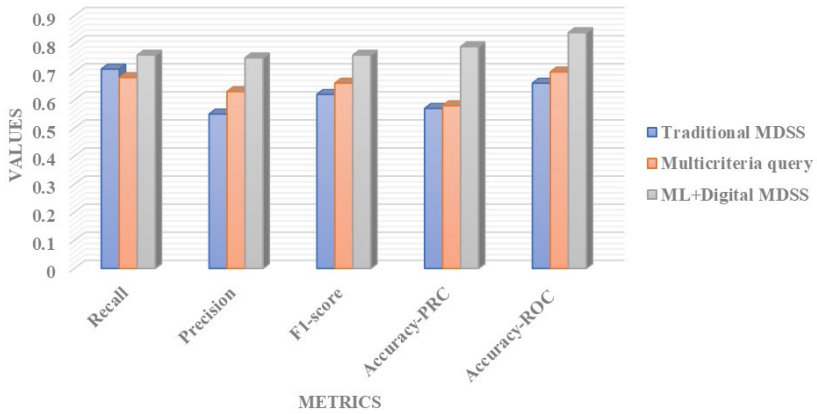

Figure 1. Performance comparison of various metrics to find high-risk prescriptions in an inpatient setting to reduce drug prescription errors

Clinical anomalies: an alarm triggered when a specific prescription is provided to a patient whose clinical characteristics do not align with the typical profile for that medication. For example, if a hypoglycemic drug is supplied to a patient who is not diagnosed with diabetes mellitus or any indications of such a condition (such as high blood sugar levels or past use of hypoglycemic medications).

Dosage anomalies: an alarm is triggered when a medicine dose is identified as an anomaly based on the statistical dispersal of dosages for that drug in the community and the patient's personal medical antiquity (e.g., uncommon dose, uncommon dosage unit, uncommon frequency, uncommon method).

Drug intersect: an alarm is triggered when two drugs from the same group are administered in a way that goes against the recommended utilization of such regimens (e.g., prescribing two kinds of statins simultaneously).

Asynchronous notification types: It encompasses time-varying anomalies. These alerts are triggered when variations in the patient's outline after the prescription has been issued, which makes a certain medication unsuitable or possibly hazardous to continue. For example, if the patient's blood pressure falls, continuing with anti-hypertensive medications could be harmful.

2.1 Input characteristics

To ensure a complete and unbiased selection of characteristics, a multitude of databases were gathered to understand the circumstances of each prescription order and the health status of the patient. Each characteristic is frequently employed for evaluation in regular pharmacy exercise and is associated with a specific patient dataset. These data include lab reports (such as kidney function, potassium levels, and international standardized ratio), demographics (gender and age), medical history (allergy data collected from clarification fields), and biological information (like weight, heartbeat, and blood pressure). Each drug order used a distinct collection of rule-based notifications about the medicine, such as dose, frequency, and route. The frequency of each alarm raised may be considered a definite characteristic with discrete values. The alerts were obtained from the online medication database or created by the hospital pharmacy staff using available literature, ensuring no duplication with the medication database. For instance, if a drug order has a level of potassium chloride of more than 4.5 g/L, it is deemed improper. A regulation was established to tackle this infrequent but potentially dangerous prescribing mistake.

2.2 ML Classifier architecture

The objective was to create a score indicating the likelihood of a prescription order for a certain patient to have at least one drug-related issue deemed a medication mistake. This score helps us determine if a pharmacist needs to review the patient's current set of medicine guidelines. For this purpose, we conducted training on a binary classifier that can detect patients who are probable having one drug-related mistake in their medicine. The chosen classifier was generated from LightGBM, a gradient-boosting architecture that utilizes decision tree algorithms. The two categories of information, patient-related information and prescription-related notifications, were merged as inputs. Every drug order in the progress database was labeled as binary: 1 = a pharmacological involvement, whereas 0 = no pharmacological involvement was implemented.

2.3 Preprocessing

Using ML, the binary classification used 26 designed features derived from diverse inputs, including quantitative values, date/time objects, category values, and natural language processing fields. During the preprocessing stage, all the attributes underwent outlier calibration, standardization, and imputation, while categorical characteristics were encoded using sci-kit-learn and other ML-compatible modules.

2.4 Testing protocol

The tool's effectiveness was assessed using a distinct test database that was not utilized during the creation of the model. The algorithm's accuracy was evaluated and related to the medicine orders examined by pharmacists and to traditional methods such as MDSS notifications and a MQ strategy.

2.5 Method

During a 14-day timeframe, a proficient clinical pharmacist systematically examined patient prescription orders from various wards and recorded any subsequent actions. The prescription orders were selected from an automated everyday abstraction of the medical program, which recorded all patients with at least one medication prescription. The pharmacist assessed a maximum number of patients over the 2-week duration. The data analysts were unaware of the specific medicinal treatments. The prescription orders' information was employed as inputs for the algorithm, which was then evaluated on all divisions. Subsequently, all projected rates (an incessant factor representing the likelihood of mistakes in a prescription order) were juxtaposed with the binary value: 1 = A pharmacological interference was conducted as part of the medication review, whereas 0 = No pharmaceutical intervention was performed. To address drug-related issues that were not detected by the test, a team consisting of two doctors and two pharmacists assessed the severity level on a scale of 1 (minimal) to 4 (life-threatening). A thorough examination of the patient's medical records was conducted to evaluate this risk, focusing on the possibility of immediate or long-term damage.

3. Results and discussion

The pharmacist examined 415 patients (3401 prescription orders) in a separate testing dataset. Out of the 415 distinct patients (with a total of 3401 prescriptions) randomly chosen for study in the test

dataset, a minimum of 1 pharmacological intervention was suggested for 175 individuals, accounting for 43% of the sample. There were 213 instances when medicinal interventions were made, accounting for 6.4% of all medicine requests. Within the testing database, 65.7% of the input originated from various departments, including trauma and emergency care, cardiovascular medicine, pregnancy, orthopedic surgery, and diabetes.

Figure 1 depicts the performance comparison of various metrics to find high-risk prescriptions in an inpatient setting to reduce drug prescription errors. To compute recall and accuracy with constant rating, including the outcome of the hybrid algorithm (ML+Digital MDSS), we determined the level of classification that optimizes the F1 score. The Digital MDSS demonstrated superior performance compared to traditional systems in terms of its ability to identify patients with medication errors (recall or sensitivity) and minimize false warnings. The proposed algorithm (ML+Digital MDSS) achieved a 76% interception rate for prescription orders requiring pharmacist intervention in the testing database, using the classification cutoff that optimizes the F1-score. Additionally, it demonstrated a precision rate of 75%. Of the remaining prescriptions that needed pharmacist intervention but were not detected by the algorithm (false negatives), none posed a risk to life. The resulting F1 score demonstrated a 16.2% higher level of accurateness compared to MQ approaches and a 23% higher level of accurateness compared to the MDSS. The algorithm demonstrated much higher accuracy than MQ approaches and the MDSS, as shown by the Accuracy-PRC (Precision-Recall Curve) and Accuracy-ROC scores, which showed a 34% and 21% increase, respectively, in accuracy.

4. Conclusion

This study assessed the efficacy of an advanced Medical Error (ME) warning system that combines Machine Learning (ML) and a rule-based Digital Medical Decision Support System (MDSS) within an Electronic Health Record (EHR) framework. Over 15 months, the new system's performance was compared against traditional MDSS and multicriteria query methods. The ML+Digital MDSS demonstrated superior accuracy, with an interception rate of 76% for prescription orders needing pharmacist intervention, and a precision rate of 75%. The system outperformed traditional methods, reflected in higher areas under the ROC and PRC curves—0.84 and 0.79, respectively, compared to 0.66 and 0.57 for MDSS and 0.7 and 0.58 for MQ approaches. These findings highlight the effectiveness of integrating ML with existing decision support tools to enhance medication safety by reducing prescription errors and improving alert precision.

Author contributions

F.R. led the study's design, data analysis, and manuscript preparation. L. contributed to data collection, interpretation of results, and manuscript revision. Both authors reviewed and approved the final manuscript.

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Competing financial interests

The authors have no conflict of interest.

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