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Innovative machine learning approaches to uncover factors leading to medication errors in pharmacies

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Abstract
Medication errors pose significant risks to patient safety and healthcare quality, underscoring the importance of effective preventive measures. This study employs machine learning techniques to investigate the factors influencing medication error rates across diverse pharmacy settings. By leveraging a large, realistic dataset, the research aims to uncover insights that can inform targeted interventions and enhance patient care. Medication errors encompass mistakes in prescribing, dispensing, or administering medications, potentially leading to adverse drug events with serious health consequences. Through the application of advanced models like Random Forest, this study identifies critical factors affecting medication error rates. The findings are intended to empower healthcare providers with actionable insights for optimizing medication management processes and improving patient outcomes.

Keywords: Medication errors, patient safety, metrics, machine learning

1. Introduction
Reducing medication errors is crucial for enhancing patient safety and healthcare quality. This study employs machine learning to investigate factors influencing medication error rates across diverse pharmacies. By leveraging data-driven approaches, this research aims to provide insights that can inform targeted interventions and improve patient care. Medication errors, defined as mistakes in prescribing, dispensing, or taking medication, are a major concern in healthcare. These errors can occur at various stages, from prescribing by healthcare providers to patient administration. Medication errors can result in adverse drug events, which are harmful and unintended reactions to medications. Such events can cause severe health complications, prolonged hospital stays, and, in some cases, fatalities. The prevention of medication errors is crucial for ensuring patient safety and improving the quality of care (Corny *et al.*, 2020; Pham *et al.*, 2019) [1, 2]. Community pharmacists need to improve medical adherence of chronic disease patients through counseling and imparting medication knowledge (Mekonnen *et al.*, 2020) [10]. The heterogeneity in the population shows wide medication error variation with error-related adverse events rates (Assiri *et al.*, 2018) [9]. Medication errors and adverse drug events, has prevalence after hospital discharge the patients are prone to (Alqenae *et al.*, 2020) [8].

In this study, we leverage machine learning techniques to evaluate medication adherence and error rates using a large, realistic dataset from pharmacies. Machine learning, a subset of artificial intelligence, involves using algorithms and statistical models to analyze and interpret complex data (Simsekler *et al.*, 2021; Rozenblum *et al.*, 2020) [7, 6]. By applying machine learning to healthcare data, we can uncover patterns and insights that may not be apparent through traditional analytical methods. The dataset used in this study includes a comprehensive range of variables related to patient demographics, medication types, pharmacy practices, and more. This rich datas*et al*lows for a detailed examination of the factors influencing medication adherence and error rates.

By employing advanced models such as Random Forest, we aim to identify key factors influencing these metrics and provide insights for improving healthcare practices. Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the individual trees' classes (classification) or means prediction (regression) (Simsekler *et al.*, 2020) [7]. This approach helps in handling a large number of input variables and managing the complexity of healthcare data.

Through this study, our aim is to develop effective predictive models that identify key contributing factors for medication error rates (Alqenae *et al.*, 2020) [8], empowering healthcare providers to implement precise and effective interventions.

These insights can inform strategies to enhance patient education, optimize medication regimens, and improve overall medication management processes, ultimately leading to better patient outcomes and safer healthcare environments.

2. Materials and Methods

The dataset used in this study was synthetically generated using Python programming to closely resemble real-world pharmacy records. This approach involved creating 100,010 operational data points that mirror the complexities and characteristics of actual pharmacy data, including detailed information on medication adherence and error rates. The dataset encompasses various attributes pertinent to pharmacy operations and performance. These attributes include prescription volume, medication adherence rate (%), inventory turnover, labor costs (INR), and customer satisfaction score. Geographic location and demographics provide contextual information about the pharmacy's environment. Additionally, the dataset includes pharmacy size (sq.ft), prescription fill rate (%), and generic dispensing rate (GDR %). Patient wait times (min), customer retention rate (%), and medication therapy management (MTM) utilization (%) offer insights into service efficiency and patient engagement (Naybour *et al*., 2019) [3].

The dataset further includes adverse drug event (ADE) reporting rate (%), staff professionalism and communication, consultation services, and use of technology. Online services, cleanliness and organization, accessibility, and community engagement are also covered, providing a holistic view of the operational efficiency, customer service quality, and overall performance of pharmacies (Manisha, 2019; Bates *et al*., 2020) [5, 4].

Numeric and categorical features were separately processed using pipelines. Initial pre-processing involved data cleaning, handling missing values, and categorical variable encoding using techniques like one-hot encoding. Target variables were discretized to facilitate categorical analysis. Numeric features were imputed and scaled. Data was split into training and test sets for the target variable Medication Error Rate (%). Non-predictive variables such as pharmacy identifiers, specific dates, and financial metrics were excluded from the analysis. The remaining features were used to train a Random Forest classifier, known for its ability to handle complex datasets and provide insights into feature importance. A Random Forest classifier was used within a pipeline that included pre-processing steps. The model was trained and evaluated using accuracy, precision, recall, F1 score, and ROC-AUC metrics.

3. Results and Discussion

The model's performance is evaluated using several key metrics, each highlighting different aspects of its predictive capabilities, as shown in Fig 1. Accuracy, defined as the ratio of correctly predicted instances to the total instances, stands at 0.92. This means that 92% of the predictions made by the model are correct, indicating a high level of reliability in predicting medication error rates. Precision, the ratio of true positive predictions to the total positive predictions made, is 0.85. This indicates that 85% of the instances classified as medication errors by the model were indeed medication errors, showing the model's effectiveness in minimizing false positives. Recall, or sensitivity, is the ratio of true positive predictions to the total actual positives, which is 0.92. This means the model correctly identifies 92% of all actual medication errors, suggesting it is highly effective in detecting most of the actual errors and thus reducing false negatives. The F1-score, the harmonic mean of precision and recall, is 0.89. This balance between precision and recall implies that the model is both accurate and reliable in identifying medication errors without overly biasing towards either false positives or false negatives.

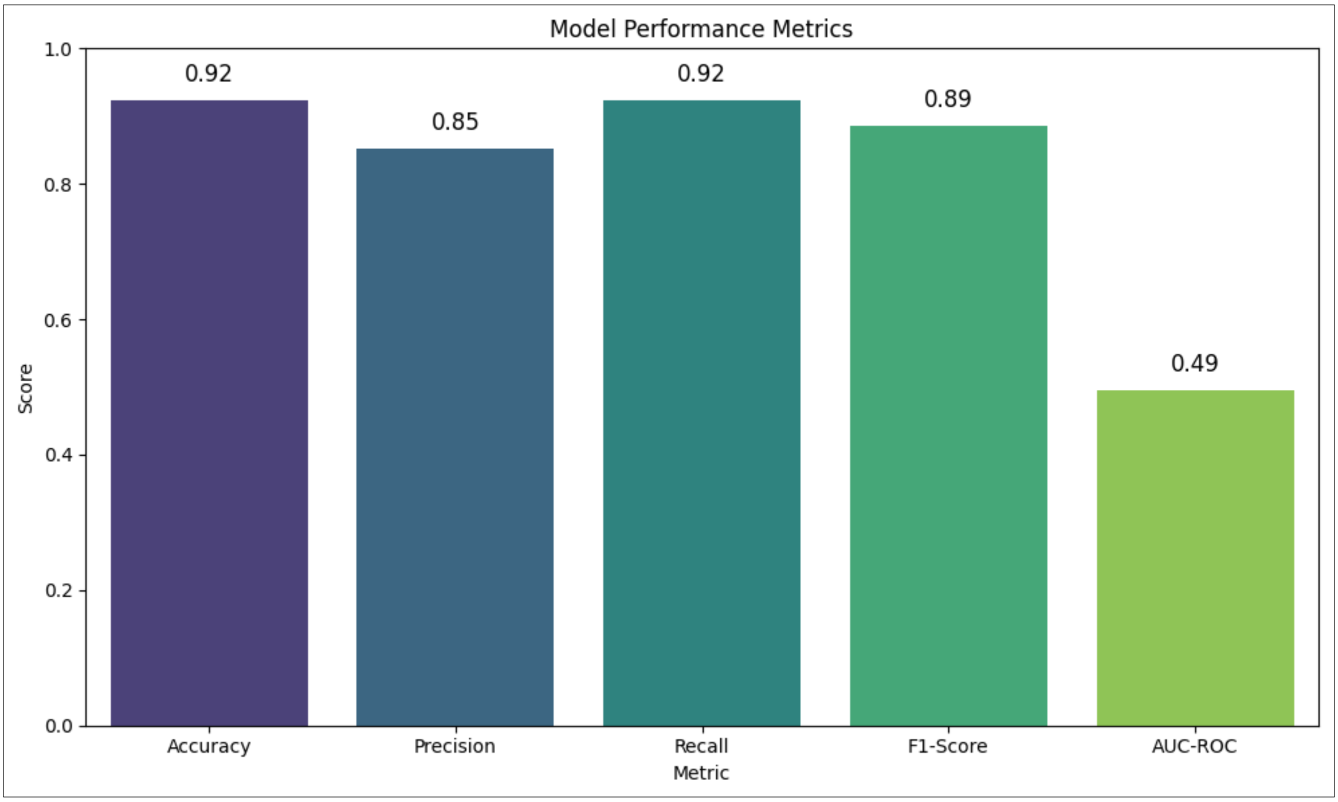

Fig 1: Model Performance Metrics

The high accuracy, recall, and F1-score values indicate that the model performs well in correctly predicting medication errors and balancing precision and recall. This suggests that the model is reliable for real-world scenarios where accurately identifying medication errors is crucial. The precision score of 0.85 is good but indicates room for improvement in reducing false positives. This level of precision is acceptable in many practical applications, especially in critical areas like medication error detection, where missing an error (false negative) is often more critical than a false alarm (false positive). Compared to other metrics, the significantly lower AUC-ROC score highlights a potential issue with the model's overall discriminative power. This suggests that while the model performs well on the training and testing sets, it might struggle with unseen data or different data distributions. Further model tuning, additional features, or alternative algorithms could be explored to improve the AUC-ROC score. Overall, the model demonstrates strong accuracy, precision, recall, and F1-score performance, indicating it is effective for identifying medication errors. However, the low AUC-ROC score suggests a need for further evaluation and potential improvements to enhance the model's generalizability and robustness in distinguishing between different classes.

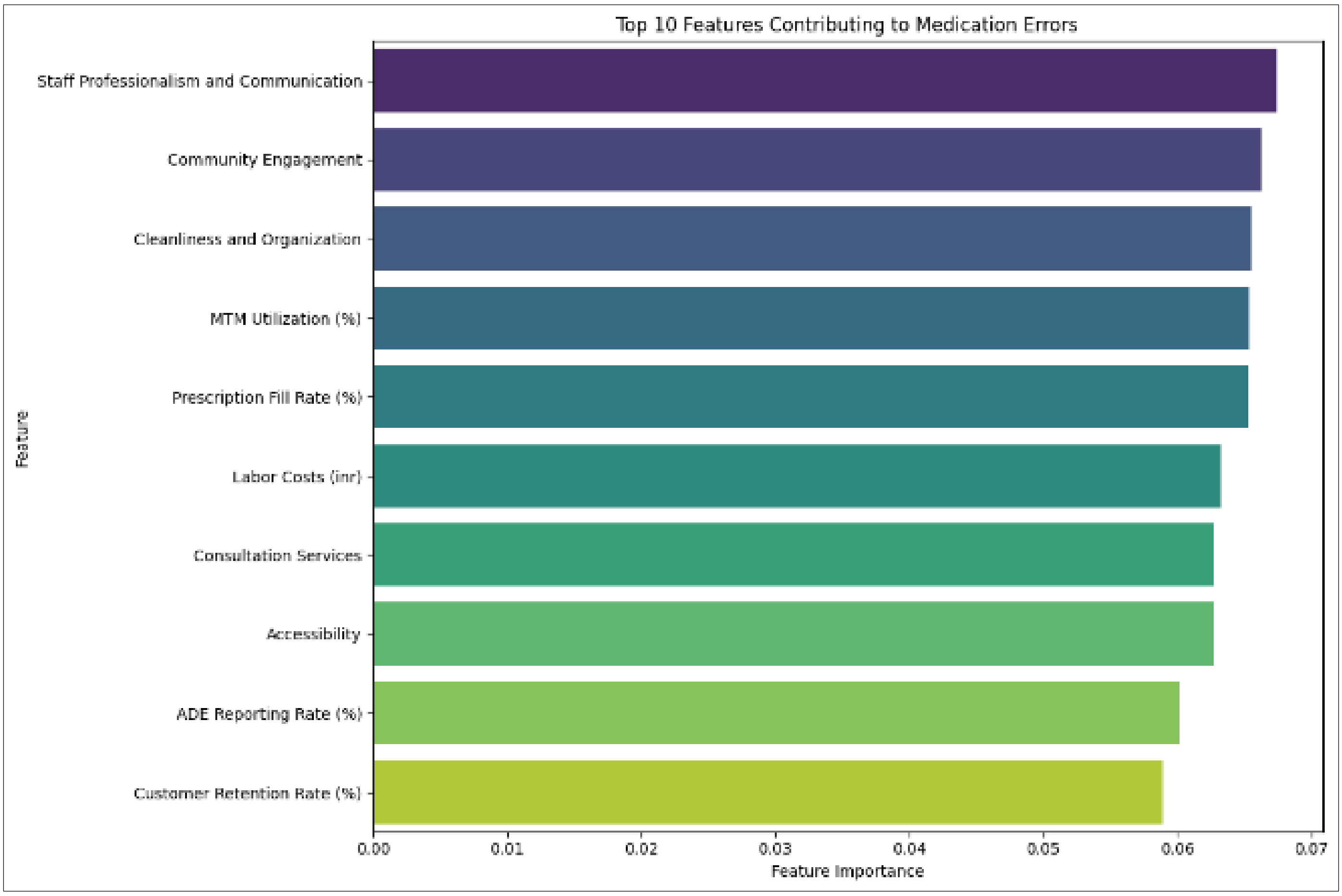

Fig 2: Top 10 Features Importance for Medical Error

The chart in Fig 2 highlights operational factors that significantly minimize medication errors in community pharmacies. The chart titled "Top 10 Features Importance for Medical Error" highlights the relative importance of various factors in contributing to medication errors. The most significant factor is staff professionalism and communication, indicating that the skills and communication abilities of staff play a crucial role in preventing errors. Community engagement follows as the second most important feature, suggesting that the level of interaction and involvement with the community impacts medication error rates significantly.

Cleanliness and organization of the facility rank third in importance, implying that a well-organized and clean environment can help reduce the chances of errors. Medication Therapy Management (MTM) utilization is the fourth most important factor, showing that the extent to which MTM services are used affects medication error rates. The prescription fill rate is the fifth key feature, highlighting its influence on errors. Labor costs are the sixth most significant factor, suggesting that financial aspects related to staffing may influence error rates. The availability and quality of consultation services rank seventh, emphasizing their role in preventing medication errors. Accessibility, which refers to how easily patients can access pharmacy services, is the eighth most important factor impacting error rates. The Adverse Drug Event (ADE) reporting rate is the ninth significant feature, indicating that effective reporting can influence the rate of medication errors. Finally, customer retention rate is the tenth key factor, suggesting that higher retention rates might be associated with better service quality and fewer errors. Overall, the chart emphasizes the importance of various aspects of pharmacy operations, with staff professionalism and communication being the most critical in reducing medication errors.

The importance scores suggest that improvements in these top features can substantially impact the accuracy and safety of pharmacy medication dispensing. Pharmacies should focus on enhancing these key areas to reduce medication error rates effectively. This detailed analysis helps prioritize areas for improvement to ensure better patient outcomes and reduce the incidence of medication-related issues.

4. Conclusion

Reducing medication errors is paramount in safeguarding patient well-being and improving healthcare delivery. This study utilized machine learning methodologies to analyze a comprehensive dataset encompassing various attributes related to pharmacy operations and patient demographics. The results demonstrated the model's robust performance in accuracy, recall, and F1-score metrics, indicating its efficacy in predicting medication errors and balancing between precision and recall. While the model accurately identified medication errors, achieving an AUC-ROC score slightly above random guessing suggests opportunities for enhancing its discriminative power. Future research could focus on refining the model's performance through additional feature engineering, algorithmic improvements, and validation of diverse datasets. Overall, this study underscores the potential of machine learning in enhancing medication safety practices and underscores the ongoing need for innovative approaches in healthcare analytics to improve patient care outcomes.

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