MediSafe: AI-Based Medicine Quality Assessment and Disease Recommendation System

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Abstract—Ensuring the quality and safety of medicines is a critical challenge in healthcare systems, particularly in regions affected by counterfeit drugs, improper storage, and lack of regulatory oversight. This work presents MediSafe, an AI-based decision support system for medicine quality assessment and disease-to-medicine recommendation. The system integrates supervised machine learning models trained on physicochemical medicine attributes and symptom-based disease prediction pipelines. A Flask-based web application enables real-time user interaction by loading pretrained models and preprocessing artifacts. Experimental evaluation demonstrates that the proposed system can effectively classify medicine safety levels and provide informed recommendations, highlighting its potential as an assistive healthcare technology.

Keywords—Medicine Quality Assessment, Healthcare AI, Machine Learning, Decision Support Systems, Flask

I. INTRODUCTION

Medicine quality directly impacts treatment outcomes and patient safety. Substandard or improperly stored medicines can lead to therapeutic failure, adverse reactions, and antimicrobial resistance. Traditional quality assessment methods rely on laboratory testing, which is time-consuming and inaccessible to the general public. Recent advances in artificial intelligence and machine learning have enabled data-driven approaches that can analyze multiple quality indicators simultaneously. The objective of this project is to design an AI-powered system that assists users in evaluating medicine quality and predicting diseases based on symptoms, thereby providing informed medicine recommendations across multiple treatment systems.

II. DATASET AND PREPROCESSING

The medicine quality dataset consists of structured tabular data including attributes such as active ingredient, expiry date, storage temperature, dissolution rate, disintegration time, impurity level, assay purity, and presence of warning labels. Data preprocessing steps include handling missing values, normalization of numerical attributes using standard scaling, and encoding of categorical features using label encoders. For disease prediction, symptom-based datasets were transformed into binary feature vectors representing symptom presence.

III. METHODOLOGY

A. Medicine Quality Classification

Supervised machine learning models were trained to classify medicines into safe and unsafe categories. Preprocessed feature vectors were passed through trained classifiers, and the best-performing model was serialized for deployment. Scalers and encoders used during training were also saved to ensure consistency during inference.

B. Disease Prediction and Medicine Recommendation

A symptom-based disease prediction model was implemented using multi-class classification techniques. Predicted disease labels were mapped to corresponding medicine recommendations using lookup tables for Allopathy, Ayurveda, and Homeopathy systems.

IV. TRAINING CONFIGURATION

Models were trained using standard train-test splits with performance evaluated on unseen data. Hyperparameters were tuned experimentally to balance accuracy and generalization. All training experiments were conducted in JupyterLab, and finalized models were exported as pickle files for integration into the web application.

V. RESULTS AND EVALUATION

The system was evaluated using accuracy and class-wise prediction consistency. Manual and bulk testing using the original datasets confirmed that the deployed Flask application produces predictions consistent with offline model evaluation. The results indicate reliable performance for prototype-level deployment.

Model	Use Case	Key Advantage
Random Forest / SVM	Medicine Quality	Robust to noisy tabular data

Symptom Classifier	Disease Prediction	Fast inference for real-time use

VI. DISCUSSION

The MediSafe system demonstrates how machine learning models trained on structured healthcare data can be effectively deployed using lightweight web frameworks. By persisting preprocessing pipelines and models, the system ensures reproducibility and consistency between training and inference. While the current implementation serves as a research prototype, further validation and regulatory considerations are required for real-world clinical use.

VII. CONCLUSION

This project presents an AI-driven approach to medicine quality assessment and disease recommendation. The integration of machine learning models with a Flask-based user interface enables accessible and real-time healthcare decision support. Future work includes model optimization, larger dataset validation, explainability integration, and secure deployment practices.

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