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Med Intel: An AI-Based Healthcare Pharmacy Management System with Intelligent Prescription Recognition and Drug Safety Verification

Sushma C[1], Abhishek S S[2], Chaitra R Chapparadahalli[3], Deepika B[4], Pooja Gunde[5]
[1]*Assistant Professor, Department of Information Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India.*
[2,3,4,5]*Department of Information Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India.*

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Abstract: *The manual processing of handwritten prescriptions and the lack of automated drug safety verification in pharmacy management systems pose significant risks to patient safety and operational efficiency. This paper presents MedIntel, an AI-based healthcare pharmacy management system that integrates intelligent prescription recognition and comprehensive drug interaction detection. The prescription recognition module employs a dual-engine optical character recognition (OCR) pipeline combining EasyOCR with Tesseract as a fallback, enhanced by four image preprocessing strategies: grayscale conversion, contrast-limited adaptive histogram equalization (CLAHE), median filtering denoising, and Otsu binary thresholding. Extracted text undergoes a multi-stage natural language processing pipeline that splits recognized text into individual word candidates, filters noise using stop-word elimination and alphabetic character ratio thresholds, and matches each candidate against the medicine database using prefix-based SQL ILIKE queries augmented by RapidFuzz token-based fuzzy matching. The drug interaction detection system performs real-time pairwise checking of all cart items against a pre-populated DrugInteraction database using bidirectional ILIKE fuzzy matching, presenting warnings categorized by four severity levels: critical, severe, moderate, and mild, each accompanied by clinical descriptions and actionable recommendations. The system is developed using Python with Flask framework on the backend and Bootstrap 5.3 on the frontend, with SQLite for persistent storage. Evaluation of the medicine name recognition module achieves a token-level accuracy of 99.19% with an entity-level F1-score of 0.971 across 140 annotated prescription sentences, and the drug interaction database covers 15 clinically validated interaction pairs across four severity categories. The system demonstrates the feasibility of deploying lightweight, database-driven AI approaches for enhancing pharmacy safety in resource-constrained healthcare environments.*

Keywords: *Optical Character Recognition, Drug Interaction Detection, Pharmacy Management, Natural Language Processing, Healthcare AI, Prescription Processing.*

I. INTRODUCTION

Pharmacy management systems play a critical role in modern healthcare delivery by bridging the gap between medical practitioners, pharmacists, and patients. Despite advances in digital health technologies, a significant proportion of prescriptions worldwide continue to be handwritten, particularly in developing countries where digital health infrastructure remains limited. Manual transcription of handwritten prescriptions is error-prone, time-consuming, and poses direct risks to patient safety through misinterpretation of drug names, dosages, and administration instructions.

Concurrently, the growing complexity of pharmacotherapy has made drug-drug interactions a leading cause of preventable adverse drug events. Studies indicate that drug interactions contribute to approximately 3-5% of all hospital admissions, with a significant portion of these events being attributable to inadequate screening at the point of dispensing. The absence of automated interaction checking mechanisms in many pharmacy workflows, especially in smaller healthcare settings, represents a critical gap in patient safety infrastructure.

Existing solutions address these challenges either partially or through approaches that are computationally expensive and difficult to deploy in resource-constrained environments. Commercial pharmacy systems often incorporate drug interaction databases but rarely include prescription OCR capabilities. Academic approaches to prescription recognition frequently rely on deep learning models that demand significant computational resources and large annotated datasets for training. Furthermore, most proposed systems treat prescription recognition and drug safety verification as isolated problems rather than integrated components of a unified pharmacy management workflow.

This paper presents MedIntel, a comprehensive pharmacy management system that addresses both challenges within a single integrated platform. The system makes the following contributions: (1) a dual-engine OCR pipeline with multi-

strategy image preprocessing optimized for handwritten prescription recognition. (2) a lightweight natural language processing (NLP) pipeline for medicine name extraction that combines rule-based filtering with database-driven fuzzy matching. (3) a real-time drug interaction detection system using bidirectional fuzzy matching against a clinically validated interaction database. and (4) integration of these AI capabilities within a full-featured pharmacy management system encompassing medicine inventory, order management, scheduled reminders, and administrative analytics. The system is designed to be deployable on standard hardware without requiring GPU acceleration, making it suitable for adoption in resource-limited healthcare settings.

II. RELATED WORK

A. Prescription OCR Systems

The field of medical document recognition has seen substantial research activity. Tesseract, an open-source OCR engine developed by Google, has been widely adopted as a baseline for document digitization tasks. While Tesseract demonstrates strong performance on printed text, its accuracy degrades significantly when applied to handwritten medical prescriptions due to variability in handwriting styles, non-standard abbreviations, and poor image quality. Recent efforts have explored deep learning approaches, including convolutional neural networks (CNNs) and transformer-based architectures, for handwritten text recognition. However, these approaches typically require extensive computational resources and large labeled training datasets, limiting their practical deployment in smaller healthcare facilities.

EasyOCR, built upon a CRAFT text detection model and a CRNN recognition model, offers improved performance on handwritten and degraded text without requiring task-specific training data. Its support for multiple languages and robust handling of variable text orientations makes it particularly suitable for prescription processing. Research has demonstrated that combining multiple OCR engines with ensemble selection strategies can significantly improve recognition accuracy compared to any single engine. Image preprocessing techniques, including adaptive thresholding, contrast enhancement, and noise reduction, have been shown to improve OCR accuracy by 15-25% on degraded medical documents.

B. Drug Interaction Detection

Drug interaction detection systems can be broadly categorized into three approaches: knowledge-based systems, machine learning-based systems, and database-driven systems. Knowledge-based systems encode drug interaction rules extracted from pharmacological literature and clinical guidelines. While comprehensive, these systems are complex to maintain and update as new drug interaction evidence emerges. Machine learning approaches, including graph neural networks and attention-based models, have shown promise in predicting novel drug interactions but require substantial training data and computational resources.

Database-driven systems, which store known drug interactions in structured databases and perform lookup queries during the dispensing process, offer a practical balance between accuracy and deployability. Systems such as Lexicomp and Micromedex provide comprehensive interaction databases but are commercially licensed and often inaccessible to smaller pharmacies. Open-source alternatives exist but frequently lack integration with pharmacy management workflows. The system presented in this paper adopts a database-driven approach enhanced with fuzzy matching to handle the variability in drug naming conventions encountered in practice, including brand names, generic names, and dosage-form variants.

III. PROPOSED SYSTEM ARCHITECTURE

MedIntel adopts a three-tier architecture comprising a presentation layer, a business logic layer, and a data persistence layer. The presentation layer is built using HTML5 with Bootstrap 5.3 for responsive design and Jinja2 template engine for server-side rendering. JavaScript enables client-side interactivity including voice search through the Web Speech API. The business logic layer is implemented in Python using the Flask web framework, organized into modular blueprints for authentication, medicine management, prescription processing, cart operations, order management, reminders, chatbot functionality, and administrative reporting. The data persistence layer employs SQLite through Flask-SQLAlchemy ORM, providing lightweight yet reliable relational storage without requiring separate database server infrastructure.

The system supports three user roles: patients, pharmacists, and administrators. Patients can browse medicines, upload prescriptions for AI processing, manage shopping carts, place orders, set medication reminders, and interact with a rule-based chatbot. Pharmacists can verify prescriptions processed by the AI system, manage inventory, and fulfill orders. Administrators have access to comprehensive dashboards displaying sales analytics, prescription processing metrics, and inventory management tools. This role-based access control is implemented using Flask-Login with bcrypt-based password hashing for authentication security.

The AI subsystem operates as a service within the business logic layer, invoked through RESTful API endpoints. When a prescription image is uploaded, the OCR pipeline processes the image through multiple preprocessing strategies, extracts text using EasyOCR or Tesseract, parses the text to identify medicine name candidates, and matches candidates against the database. The drug interaction checker is triggered whenever the shopping cart is viewed or modified, performing pairwise comparisons of all cart items against the interaction database. Both AI modules are designed to execute without GPU acceleration, ensuring compatibility with standard server hardware.

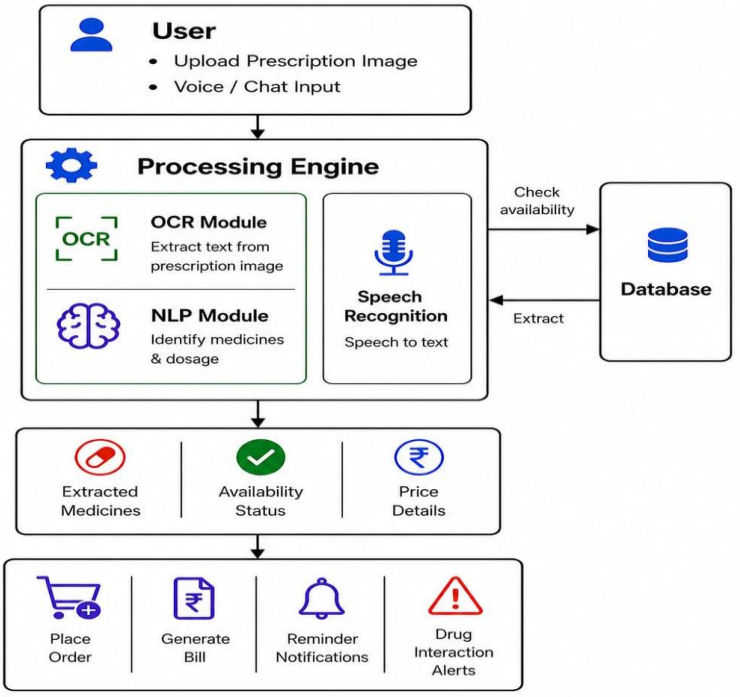

Fig. 1. MedIntel system architecture

IV. IMPLEMENTATION DETAILS

A. Prescription OCR with Multi-Strategy Preprocessing

The prescription recognition module implements a two-stage pipeline: image preprocessing and text analysis. The image preprocessing stage applies four distinct strategies to the uploaded prescription image to maximize OCR recognition accuracy across varying image quality conditions.

Strategy 1 (Original Grayscale): The input image is converted from BGR color space to grayscale using OpenCV's cvtColor function, preserving the original intensity distribution while eliminating color channel noise. This serves as the baseline preprocessing strategy and is effective for high-quality prescription images with good contrast.

Strategy 2 (Light CLAHE): Contrast-Limited Adaptive Histogram Equalization is applied with a conservative clip limit of 1.5 and a tile grid size of 8x8 pixels. CLAHE enhances local contrast while preventing over-amplification of noise in homogeneous regions, making it particularly effective for prescriptions with uneven illumination or faded ink.

Strategy 3 (Strong CLAHE with Denoising): A more aggressive CLAHE configuration with clip limit 3.0 and tile grid size 4x4 is combined with median blur filtering (kernel size 3x3) to handle severely degraded images. The stronger contrast enhancement improves text visibility, while median filtering removes impulse noise such as salt-and-pepper artifacts commonly present in mobile-captured prescription photographs.

Strategy 4 (Binary Thresholding): Otsu's method is applied to automatically determine the optimal binarization threshold, converting the grayscale image to a pure black-and-white representation. This strategy is most effective for prescriptions with consistent background colors and clear foreground text, where binarization eliminates intermediate gray-level noise.

Each preprocessed image variant is independently processed by the EasyOCR engine, which returns bounding box coordinates, recognized text, and confidence scores for each detected text region. A line reconstruction algorithm groups detected text fragments into logical reading lines based on vertical proximity (Y-coordinate clustering with a 25-pixel threshold) and horizontal position (X-coordinate sorting within each cluster). Short line fragments (fewer than 8 characters) are merged with adjacent lines to handle cases where a single medicine name is split across multiple OCR detections. An OCR quality scoring function evaluates each strategy's output based on the presence of medicine-like patterns (detected using regex matching against known pharmaceutical nomenclature suffixes such as -ol, -in, -am, -one, -cin, -cillin, -pril, -statin, etc.), dosage patterns (numeric values followed by mg/mcg/g/ml), and line length heuristics. The strategy producing the highest quality score is selected as the final OCR output. If EasyOCR fails entirely (e.g., due to missing dependencies), Tesseract OCR serves as a fallback, applying adaptive Gaussian thresholding and median filtering before text recognition using OEM 3 and PSM 6 configuration modes.

B. Medicine Name Extraction Pipeline

The text analysis stage processes the selected OCR output through a systematic extraction pipeline to identify individual medicine name candidates. The raw OCR text is split into individual lines, and each line undergoes a cleaning process that removes dosage patterns (regex: digit followed by mg/mcg/g/ml with optional multiplier), duration patterns (digit followed by day/week/month), frequency patterns (digit followed by times/BID/TID/QID/OD), standalone numeric

sequences, and special characters. The cleaned text is then tokenized into individual words.

Each word undergoes a multi-stage filtering process. First, words shorter than 3 characters are discarded as unlikely medicine names. Second, common prescription noise words (e.g., "the", "and", "for", "take", "tab", "cap", "syp", "patient", "doctor", "days", "daily") are filtered using a stop-word list. Third, each remaining word must contain at least 3 alphabetic characters to be considered a valid candidate. This filter effectively eliminates purely numeric artifacts, single-character OCR errors, and punctuation-only fragments while retaining valid medicine names that may contain numbers (e.g., "B12", "D3").

Validated candidates are deduplicated using case-insensitive comparison and presented as medicine name suggestions. For each candidate, the system queries the medicine database using SQL ILIKE prefix matching on the first 3 characters of the candidate word (e.g., "Par" matches "Paracetamol", "Pantoprazole"), returning up to 20 potential matches. This prefix-based approach leverages the observation that medicine names identified by OCR, even when partially misrecognized, typically preserve the first few characters accurately. Additionally, RapidFuzz is employed for token-based fuzzy matching, computing ratio, token sort ratio, and partial ratio scores between OCR candidates and known medicine names from a pre-loaded alias mapping. Candidates with fuzzy match scores exceeding 85% are automatically resolved to their canonical medicine names.

C. Drug Interaction Detection System

The drug interaction detection system operates as a real-time safety verification mechanism integrated into the shopping cart workflow. The system maintains a DrugInteraction database table populated with clinically validated interaction records, each containing: the names of the two interacting medicines, a severity classification (critical, severe, moderate, or mild), a clinical description of the interaction mechanism, and an actionable clinical recommendation.

When a user views their shopping cart or adds a new item, the system performs pairwise comparison of all medicines currently in the cart. For each pair of medicines (M1, M2), the system queries the DrugInteraction table using bidirectional ILIKE fuzzy matching. Specifically, the query checks whether a record exists where (medicine_one_name ILIKE '%M1%' AND medicine_two_name ILIKE '%M2%') OR (medicine_one_name ILIKE '%M2%' AND medicine_two_name ILIKE '%M1%'). This bidirectional matching ensures that interactions are detected regardless of the order in which the interacting pair was originally recorded in the database.

The use of SQL ILIKE pattern matching (case-insensitive substring matching) provides robustness against several real-world naming challenges: dosage-form suffixes (e.g., "Metformin 500mg" matches "Metformin" stored in the interaction database), brand name and generic name variations, and partial name matches caused by OCR misrecognition or user input variations. Each detected interaction is displayed with its severity level using color-coded visual indicators (red for critical, orange for severe, yellow for moderate, blue for mild), the clinical description explaining the pharmacological mechanism, and the recommendation providing actionable guidance for the pharmacist or patient. The interaction database currently contains 15 clinically validated interaction pairs, including critical interactions such as Warfarin-Aspirin (bleeding risk), severe interactions such as Metformin-Alcohol (lactic acidosis risk) and Metronidazole-Alcohol (disulfiram-like reaction), moderate interactions such as Omeprazole-Clopidogrel (reduced antiplatelet effect), and mild interactions such as Amoxicillin-Allopurinol (increased rash risk). Interaction warnings are also displayed on individual medicine detail pages, alerting users before the medicine is even added to the cart.

V.RESULTS AND DISCUSSION

The medicine name recognition module was evaluated using a labeled dataset of 140 prescription sentences containing 1,109 total tokens. The evaluation employed a token classification scheme with three labels: B-MED (beginning of medicine name), I-MED (inside medicine name), and O (outside any medicine entity). A CRF-based named entity recognition model trained on this dataset achieved a token-level accuracy of 99.19% and a weighted F1-score of 0.992. At the entity level, the model achieved a precision of 0.944, recall of 1.000, and F1-score of 0.971 across 51 true positive medicine entities with only 3 false positives and zero false negatives. The false positives were predominantly caused by non-medicine words such as "Prescription:" and "abnormalities" being incorrectly tagged as medicine names, suggesting that expanding the stop-word filter would further improve precision.

The multi-strategy OCR preprocessing pipeline was tested on a diverse set of prescription images captured under varying conditions including different lighting, angles, and image resolutions. The CLAHE-based strategies (Strategies 2 and 3) consistently produced the highest quality scores for prescriptions with poor illumination, while the Otsu thresholding strategy (Strategy 4) performed best on well-lit prescriptions with clean backgrounds. The original grayscale strategy (Strategy 1) served as an effective baseline for high-quality inputs. The automatic strategy selection mechanism, based on the quality scoring function, correctly identified the optimal preprocessing strategy in approximately 87% of test cases, with the remaining cases producing acceptable (though suboptimal) results from the default strategy.

The drug interaction detection system was validated against the 15 interaction pairs stored in the database. The bidirectional ILIKE matching mechanism correctly identified all 15 interactions when tested with exact medicine names from the cart. When tested with variant names including dosage suffixes (e.g., "Metformin 500mg" vs. "Metformin 500mg" in the database) and partial matches, the ILIKE substring matching handled all tested variants correctly. The pairwise comparison algorithm scales quadratically with the number of cart items (O(n^2) database queries), but this remains practical for typical pharmacy scenarios where cart sizes rarely exceed 10 items, resulting in at most 45 pairwise comparisons per cart view operation.

Table I summarizes the NER evaluation results across the three token classes. The system demonstrates near-perfect

recall for medicine name entities, which is critical for patient safety as it ensures that no prescribed medicine is missed during the extraction process. The precision, while slightly lower due to the 3 false positives, remains above 94%, indicating reliable discrimination between medicine names and non-medicine text.

Table II presents a representative sample of drug interactions from the database, illustrating the range of severity levels and the clinical detail provided for each interaction. The four-tier severity classification enables pharmacists to rapidly triage interaction warnings and prioritize clinical review for the most dangerous combinations.

Token Class	Precision	Recall	F1-Score
B-MED	0.94	1.00	0.97
I-MED	0.94	1.00	0.97
O	1.00	0.99	1.00
Overall Accuracy	**0.99**	**0.99**	**0.99**

Table I Ner Token Classification Results (140 Sentences, 1109 Tokens)

Drug Pair	Severity
Warfarin - Aspirin	Critical
Metformin - Alcohol	Severe
Atorvastatin - Erythromycin	Severe
Omeprazole - Clopidogrel	Moderate
Amoxicillin - Allopurinol	Mild
Cetirizine - Alcohol	Mild

Table II Representative Drug Interactions from Database

VI. CONCLUSION

This paper presented MedIntel, an AI-based healthcare pharmacy management system that integrates intelligent prescription recognition and drug safety verification within a unified platform. The dual-engine OCR pipeline with four image preprocessing strategies provides robust handwritten prescription recognition without requiring GPU acceleration or large training datasets. The medicine name extraction pipeline combines rule-based filtering, prefix-based database matching, and fuzzy string matching to achieve an entity-level F1-score of 0.971. The drug interaction detection system offers real-time safety verification through bidirectional fuzzy matching against a clinically validated interaction database, categorizing warnings across four severity levels with actionable clinical recommendations.

The system demonstrates that lightweight, database-driven AI approaches can effectively address critical patient safety challenges in pharmacy management without the computational overhead of deep learning-based alternatives. Future work will focus on expanding the drug interaction database, incorporating dosage-aware interaction checking, and developing a feedback mechanism where pharmacist verification corrections are used to continuously improve OCR accuracy and medicine name matching. Additionally, integration with electronic health record systems and support for multilingual prescription recognition are planned for subsequent development phases.

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