AI for Medical Informatics: The Application of Optical Character Recognition Technology in the Transcription of Pharmaceutical Labels

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Abstract—**The growing elderly population in Thailand faces challenges in managing medications, particularly due to vision impairments affecting adherence. This research introduces a novel approach using Optical Character Recognition (OCR) integrated into a mobile platform to automate the extraction of pharmaceutical label information. The system operates in four phases: image capture, quality enhancement, text extraction, and data processing. Text extraction employs advanced techniques such as medication verification via fuzzy matching with Levenshtein distance, dosage instruction using regular expressions, frequency confirmation through dictionary matching, and medical indications with named entity recognition. The system achieved an overall accuracy of 98.67%. The application significantly enhances medication safety for visually impaired elderly users, with positive satisfaction reported for medication entry, scanning, and reminders.**

Keywords—**applied medical informatics, pharmaceutical label data processing, pharmaceutical label transcription, Optical Character Recognition (OCR)**

I. Introduction

Thailand is currently transitioning into a fully developed aging society. In 2018, 16.7% of the Thai population was aged 60 and older, and this proportion is expected to rise to 31.28% by 2040. Older adults are four times more likely to suffer from diseases compared to other age groups [1]. A significant number of elderly individuals are affected by underlying medical conditions that require ongoing treatment and medication during their illnesses. As people age, physical health often declines. Managing daily routines, such as adhering to medication schedules, can pose considerable challenges. Due to their age, elderly individuals may experience confusion and forgetfulness.

Moreover, complications arising from age-related degeneration of the lens in the eye may impede individuals' ability to read medication labels accurately. This impairment can diminish their capacity to comprehend essential information regarding medication administration, leading to potential misunderstandings concerning the timing and type of medication required. Furthermore, blurred vision may result in elderly patients misidentifying pharmacological tablets of similar shapes, jeopardizing their ability to adhere to the medication regimen their healthcare providers prescribe.

Technological innovations have enhanced health outcomes by efficiently managing human wellness, enabling precise disease diagnosis and pharmaceutical development that extends lifespans. Medical technology addresses physical and mental health conditions like adaptive life-sustaining mechanisms [2], using specialized equipment that responds to environmental factors to enhance survival potential.

Health artificial intelligence aims to improve patient care while promoting healthcare equity. Health Information Technology enables systematic patient data documentation, allowing healthcare providers and government agencies to derive insights into effective disease prevention policies while advancing healthcare quality, reducing errors, improving safety, and strengthening provider-patient relationships.

Mobile applications incorporating Optical Character Recognition (OCR) technology enhance pharmaceutical information management systems [3−5]. These applications digitize medication labels, track prescriptions, and provide current drug information. Connecting labels to electronic records improves adherence through automated alerts and scheduling, while reducing errors with accurate

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dosage details, contraindications, and usage instructions. Medical practitioners benefit from immediate access to reliable medication histories and improved compliance tracking.

Consequently, this research develops an elderly-focused medication management system that interprets hard-to-read pharmaceutical labels. Mobile applications with OCR technology link prescription information to digital health records, deliver timely reminders and organized medication schedules. The system provides healthcare professionals with precise medication tracking while helping elderly users achieve improved treatment results through simplified medication identification. This technology ultimately streamlines healthcare delivery and enhances quality of care for elderly.

The primary objective of this research is to implement optical character recognition technology for the automated transcription of pharmaceutical labels within medical informatics systems. The secondary objective is to develop a mobile application interface that employs optical character recognition technology to read and manage pharmaceutical labels. The third objective is to evaluate user satisfaction with the system's performance.

II. Literature Review

Artificial Intelligence (AI) is crucial in medical informatics, especially in automating pharmaceutical label transcription through OCR technology. The practical implementation of OCR markedly improves patient safety and streamlines healthcare operations. This review explores recent advancements, pinpoints challenges, and underscores research gaps associated with utilizing OCR to transcribe pharmaceutical labels within healthcare environments.

The transition from physical to digital medical documentation has become essential for healthcare providers striving for operational efficiency. As traditional data entry methods are deemed insufficient, OCR technology surfaces as a feasible automation solution [6]. This review evaluates the present applications of OCR in healthcare documentation, investigating both the challenges of implementation and the possibilities for technological advancements.

The digitization of medical documentation necessitated the effective implementation of OCR within healthcare settings. A significant study compared three Python OCR libraries: PyOCR, PyTesseract, and TesseOCR, within health information systems. This research evaluated performance through a structured methodology, examining hospital documents across multiple extraction areas while measuring accuracy and processing efficiency. The investigation employed a systematic four-phase approach: document preparation with standardized resolutions, execution of the OCR method with meticulous tracking of processing time, data filtering utilizing regular expressions, and validation of results against expected values. Clinical archive documents from a Portuguese hospital provided real-world testing materials. Notable research gaps identified included inadequate documentation of test material specifications, limited exploration of health information system integration requirements, absence of investigations into parameter optimization, minimal consideration of advanced image pre-processing techniques, unaddressed language variations, a lack of benchmarking against commercial solutions and missing qualitative assessment metrics. This research provided valuable comparative insights while underscoring opportunities for more comprehensive investigations into factors influencing document variability and challenges related to system integration within healthcare environments [7].

Compliance with anti-doping regulations remains a significant challenge in the world of sports despite the regulatory framework established by the World Anti-Doping Agency. This challenge primarily arises from the complexities of interpreting pharmaceutical information. While OCR technology shows promise for improving medication screening processes, previous implementations have encountered notable limitations. Systems such as those developed by Park *et al.* [8] constrained to Korean-language contexts, limiting their broader applicability. A database of prohibited substances was built based on international doping standards, using Korean-language drug names from official pharmaceutical sources. Utilizing the CLOVA OCR model on the Naver Cloud platform, the system enables users to upload prescription images, recognize text, and cross-reference it with the banned substance list. The system was evaluated using a collection of images containing drug ingredient information, yielding a character recognition accuracy of 95.6%, with minimal errors in text extraction. In terms of classification performance, the model achieved an overall accuracy of 92%, demonstrated perfect sensitivity, and reached a level of specificity that supports its readiness for real-world applications [8].

Complementary to the OCR approach, the present research illustrates considerable advancements through a multi-phase development process: initial assessments utilizing Google Tesseract OCR attained a text recognition accuracy of 96.3%, whereas the fully developed system exhibited an improved character recognition accuracy of 98.3%. Notably, the system also registered a 95% degree of accuracy in classifying prohibited substances, reflecting a significant enhancement in doping detection capabilities. However, substantial challenges persist in developing comprehensive international medication databases and validating the system's effectiveness across various clinical and athletic contexts. These findings signify meaningful progress in developing technological solutions for anti-doping compliance, though more research is required to tackle real-world implementation challenges [9].

A recent study proposed an automated method for extracting essential information from cylindrically distorted prescription labels using only a standard camera, without the need for additional hardware. The approach utilized Deep Convolutional Neural Networks (DCNNs) to identify key points on curved labels, achieving high accuracy, with a percentage of correct key 0.03 score of 97%. These key points enabled effective correction of cylindrical distortion through image dewarping and stitching techniques. After image correction, OCR and Natural Language Processing (NLP) were used to extract critical medication details, including patient names, drug names, dosages, and usage instructions. The system performed robustly under various lighting and background conditions, offering a practical solution to minimize manual data entry errors. This is particularly beneficial for elderly patients and contributes to improved medication adherence [10].

The research on drug Label identification through an image and text embedding model (DLI-IT) examines the identification of pharmaceutical labels using complementary technologies. Image-based methods exhibit limitations regarding computational demands and environmental sensitivity. For text processing, the study employs Connectionist Text Proposal Network (CTPN) for detection, followed by a distributed OCR approach in which Tesseract processes multiple sub-images independently before consolidating them into comprehensive documents. Semantic analysis utilizes the Universal Sentence Encoder, chosen for its transfer learning capabilities in specialized pharmaceutical terminology. The Partial Levenshtein Distance technique addresses recognition errors in the extracted pharmaceutical text. A precision of 88% was attained in drug label detection, marking an improvement of up to 35% over conventional approaches. Limitations include a restricted dataset scope and challenges in OCR reliability when processing diverse pharmaceutical packaging under varying conditions [11].

Converting medical documents into machine-readable text was a crucial step in enhancing data management in electronic health records. OCR played a vital role in transforming printed or handwritten medical records into digital text that could be easily accessed and processed. Tesseract OCR extracted raw text, which was then refined through preprocessing. After preprocessing with the Natural Language Toolkit (lowercasing and stopword removal), the top 400 terms were vectorized using term frequency–inverse document frequency and normalized. Analyzed by evaluating Bidirectional Long Short-Term Memory (BiLSTM), Bidirectional Encoder Representations from Transformers (BERT), and ClinicalBERT. These models were pretrained on Electronic Health Record (EHR) data to extract clinical information such as diagnoses, medications, and dosages. The main advantage of OCR was its ability to efficiently digitize large volumes of legacy medical records, reducing the need for manual data entry. Data collection at the University of Texas Medical Branch provided a valuable dataset for evaluating these methods. However, low quality documents, handwriting, and complex layouts caused recognition failures that impaired later NLP analysis. The model demonstrated strong predictive capability, reaching over 94% accuracy and Area Under the receiver operating characteristic curve values near 97.43% for key clinical indicators. Incorporating OCR-derived layout data was shown to improve model accuracy by 3−5%, highlighting the importance of spatial information in clinical document classification and illustrating the role of OCR in boosting the effectiveness of deep learning models [12].

A lightweight pipeline for digitizing paper-based laboratory test reports was developed using OCR and Information Extraction (IE) within the PaddlePaddle deep learning framework. They adopted an OCR system that employs PP-OCR [13] with a MobileNetV3 backbone to perform text detection, direction correction, and recognition. The Information Extraction module consists of five stages: Time Detection, Headline Position, Line Normalization, Conditional Random Field (CRF)-based NER, and Step Detection for multi-column layouts. These stages collectively transform the recognized text into structured data. The system achieved 0.95 character-level accuracy and average accuracy of 0.93 for OCR. Performance validation was conducted using real-world laboratory test reports from Peking University First Hospital. Despite its efficiency, the system's performance depends on OCR accuracy and its ability to handle structured text, which limits its applicability to certain document formats. However, it demonstrates a practical solution for automating medical document processing in resource-limited environments [14].

The use of OCR and AI for automating health insurance claim processing is explored through an Intelligent Document Management System (IDMS). This system extracts the document data from Aadhaar cards, PAN cards, and hospital invoices. It uses Amazon Web Services (AWS) with heuristic rules for unstructured data. While high accuracy (94.09%) is achieved for invoice processing, Aadhaar and PAN card extraction show lower accuracy (83.13% and 70.3%, respectively), revealing limitations in handling fixed-format documents. Converting scanned data into structured formats like JSON and CSV enhances processing speed and reduces manual errors. However, reliance on cloud-based tools and inconsistent performance across document types present challenges. The study highlights OCR's potential in healthcare workflows but emphasizes the need for improved accuracy in structured documents and better multilingual support [15].

In 2025 study a system highlights the potential of computer vision in improving ICU data workflows. One study applied AWS OCR to automate data entry from ICU medical devices by extracting numerical values from smartphone images and mapping them to structured case report forms the system developed using Python, PyTorch, and OpenCV on AWS EC2, showed high accuracy and efficiency in multicenter ICU settings across Hong Kong, Thailand, and Australia. The system achieved 96.9% accuracy and 98.5% completeness, while reducing data entry time to 3.4 min per patient compared to 6.0 min with manual entry. While the approach shows promise, it remains limited by sensitivity to image quality, restricted device compatibility, and the lack of integration with electronic health records. These factors pose challenges for clinical adoption and scalability. Even so, it offers a useful direction for applying affordable, open-source tools in critical care and highlights the need for further work on interoperability and broader device support [16].

The research on AI models for prescription label identification in elderly Thai populations compared two approaches: a two-stage model (EasyOCR with Qwen2-72b-instruct) and a uni-stage model (Qwen2-72b-VL). Using the Visual Question Answering (VQA) form within a Retrieval-Augmented Generation (RAG) framework, both approaches utilized RAG with DrugBank as the reference data source. The two-stage model achieved an accuracy of 94%, excelling in interpreting complex medication instructions, while the uni-stage model provided faster response times for high-volume scenarios. However, the study does not explore multilingual contexts, poor lighting conditions, testing with visually impaired elderly users, or resource efficiency for mobile implementation [17].

Intelligent Document Processing (IDP) is enhancing operational efficiency in healthcare and insurance by tackling problems like manual errors, processing delays, and compliance issues. It uses machine learning (ML), NLP, Robotic Process Automation (RPA), and OCR to automatically extract and verify information from diverse document types, including handwritten ones. OCR plays a key role in automating document processing, achieving over 97% accuracy. Combined with ML, NLP, and RPA, it streamlines workflows, reduces errors, and accelerates approvals. However, despite these advantages, IDP still faces barriers such as high deployment costs and sensitivity to data quality [18].

Wang and Luo explored the use of OCR to extract data from scanned EHRs, aiming to improve efficiency in hospital systems. Their method combined grayscale preprocessing, Tesseract OCR, and NLP to process sleep disorder records. Extracted text was vectorized using a Bag of Words model and classified with Hidden Bayesian Integrated Dense Bi-LSTM (HB-DBi-LSTM) deep learning framework. The model achieved strong accuracy 93.21%, showing improved accuracy over traditional methods. However, challenges included poor scan quality and high computational cost. The study highlighted the potential of optical character recognition in automating clinical data, while noting challenges in scalability and real-time system integration [19].

Notwithstanding the advancements in OCR technology pharmaceutical label transcription, several research gaps remain. In healthcare, especially in digitizing unstructured data such as prescriptions and clinical notes, further development is still needed. Future innovations should focus on multilingual recognition capabilities, environmental adaptability, enhanced accessibility features, and security protocols specific to healthcare. Such enhancements would fortify the implementation of OCR in the management of pharmaceutical data while upholding the standards of healthcare delivery.

III. Materials and Methods

A. Conceptual Framework and Research Design

The framework for transcribing pharmaceutical labels and identifying tablet shapes through image processing and OCR techniques constitutes a significant technological advancement designed to assist elderly individuals. This method employs optical character recognition technology to decode text from pharmaceutical labels accurately and convert it into speech, informing users about the specific type of medication. Furthermore, by utilizing principles of object detection, the solution classifies medication types based on the visual characteristics of the tablets, effectively mitigating the risk of elderly individuals inadvertently consuming incorrect medications. The research framework and conceptual design are illustrated in Fig. 1.

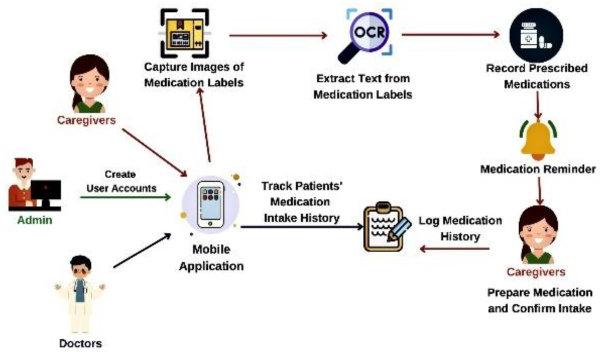

Fig. 1. Conceptual framework and research design.

Scope of the Study: This project seeks to establish and refine a medication reminder model specifically designed to assist in managing and documenting medication intake among elderly individuals. The primary objective of this model is to enhance convenience, visual accessibility, and reading comprehension, thereby ensuring ease of use for patients. The model that demonstrates effectiveness will subsequently be developed into an application capable of interpreting the text on the front of medication labels.

B. Data Collection

The dataset employed in this study comprises 271 pharmaceutical label images collected from patients receiving treatment at the University of Phayao Hospital, Phayao Province, Thailand, during 2024–2025. The medication dictionary uses real prescription labels from the University of Phayao Hospital, which follow national standards and the Lexicomp database. An internationally recognized drug information resource and data follows Thailand Ministry of Public Health standards. All prescription data was anonymized with patient identifiers removed. The study complies with Thai healthcare regulations, medical research ethics, and Personal Data Protection Act (PDPA) requirements. OCR processing occurs locally without external data transmission. The medication dictionary contains only drug names and medical terminology. These labels were supplemented by a structured medication database derived from the hospital's pharmaceutical records in Table I. To protect patient confidentiality, personally identifiable information was masked prior to analysis. Figs. 2−4 present representative examples of Thai-language pharmaceutical labels, including the original format and their corresponding English translations.

TABLE I. DISTRIBUTION OF ANALYZED CHARACTERS BY TYPE OF PHARMACEUTICAL INFORMATION

Information Category	Number of Characters	Percentage (%)
Medication	123,078	41.02
Dosage Instruction	62,330	20.78
Frequency	70,540	23.51
Medical Indications	44,063	14.69
Total	**300,011**	**100**

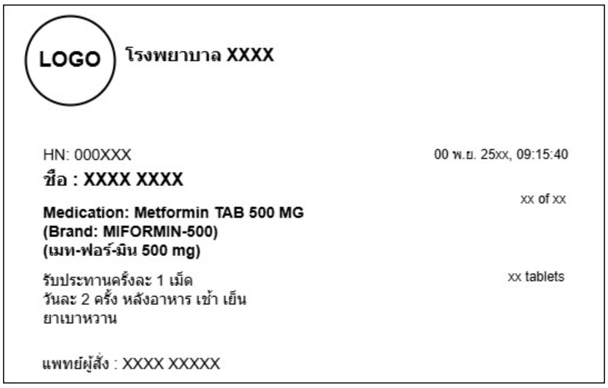

Fig. 2. The Thai format of the pharmaceutical label.

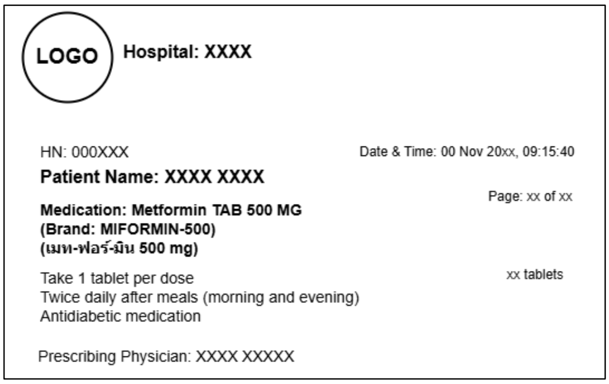

Fig. 3. The English translation of the pharmaceutical label.

Fig. 4. Example of Thai Pharmaceutical Label.

Table I summarizes the distribution of analyzed characters across four key categories of pharmaceutical information: medication, dosage instruction, frequency and medical indications. Medication-related content made up the highest proportion at 41.02%, followed closely by frequency at 23.51%. Dosage instruction and medical indications represented 20.78% and 14.69% of the data, respectively. These figures highlight the variation in content length and layout of Thai pharmaceutical labels. Some labels contained a single line of text, while others required two or three lines to convey complete information. The number of characters also varied, affecting OCR accuracy and necessitating a system capable of handling diverse text structures and formatting styles.

C. Transcription of Pharmaceutical Labels Process

This section delineates a structured methodology for implementing OCR, which refers to converting an image of text into a machine-readable format. For example, when a form or receipt is scanned, the computer captures the resulting scan as an image file; however, a text editor cannot read, edit, search, or count words within such an image file. In contrast, OCR enables the transformation of an image into a text document that encapsulates the content as textual data. Data scientists subsequently categorize it into various OCR technologies based on their specific applications and services. This process comprises multiple steps to enhance recognition accuracy, rectify errors, and ensure structured data output for seamless integration with medical informatics systems, as illustrated in Fig. 5. It is organized into the following four steps.

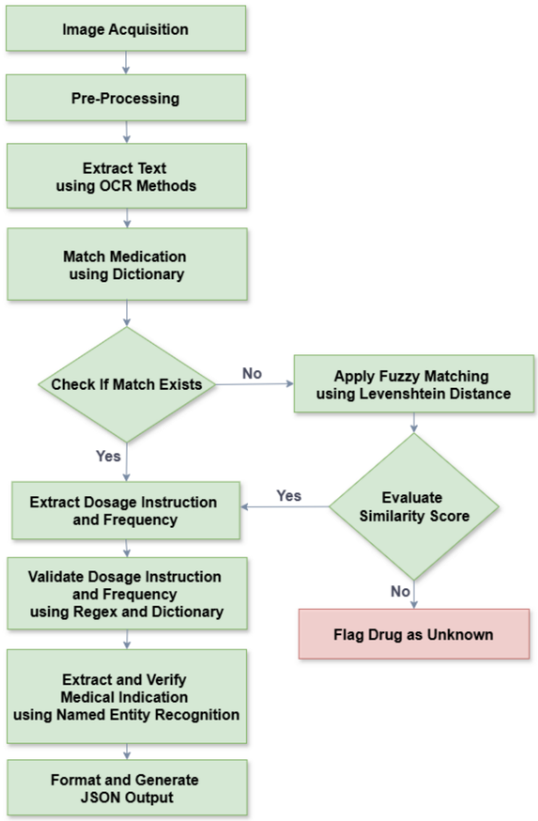

Fig. 5. The flow diagram of OCR-based pharmaceutical label transcription system.

a) Step 1: Image acquisition

The system starts by capturing an image of a pharmaceutical label through a mobile application. Users receive guidelines for optimal image quality, including proper lighting, focus, and angle.

b) Step 2: Pre-processing

OCR software initially undertakes the task of cleansing the image and correcting any errors to ensure accurate reading. The image's quality is paramount in determining the accuracy of text extraction utilizing OCR technology. Various factors may adversely affect character recognition, including inadequate lighting, image blurriness, and reflections. Preprocessing techniques such as grayscale conversion, contrast adjustment, noise elimination, and binarization may be employed to improve image clarity. Such enhancements serve to isolate the text from the background effectively.

c) Step 3: Text extraction using Optical Character Recognition (OCR)

Text extraction using Optical Character Recognition (OCR) is a key process in converting printed information on pharmaceutical labels into digital form. While OCR can identify and interpret text from images, its accuracy may be affected by factors such as font variation, curved packaging, and background noise. In this study, three OCR tools were examined: Easy OCR, Google Cloud Vision and Tesseract OCR. These systems were tested on Thai-language medication labels to evaluate their effectiveness under real-world conditions. The goal is to identify the most reliable approach in terms of recognition accuracy, proper handling of Thai script and completeness of the extracted data.

While these optimizations and inaccuracies in text recognition remain a possibility, thereby requiring supplementary correction mechanisms in the subsequent stages. The researchers emphasize the importance of examining the following pertinent information: medication, dosage instruction, frequency, and medical indications (diseases/symptoms). This study delineates a systematic approach to the implementation of an OCR-based transcription system for pharmaceutical labels, integrating advanced error correction and validation techniques as outlined below:

Step 3.1: Correction of Medication Utilizing Dictionary and Fuzzy Matching Techniques—The process of validating pharmaceuticals entails comparing the extracted text against an established drug dictionary (for instance, "Metformin," "Aspirin," "Ibuprofen," "Paracetamol"). In cases where an exact match is identified, the validation process is completed immediately. Conversely, if an exact match is absent, the system employs fuzzy matching methodologies, such as the Levenshtein Distance algorithm, to ascertain the nearest potential match [11]. A predetermined similarity threshold is subsequently utilized to evaluate the match; the corrected medication name is adopted should the score surpass this threshold [11].

Fuzzy matching techniques and Levenshtein Distance offer effective methods for approximate string matching, which are essential for search engines, eliminating duplicate data, and retrieving information despite errors, thereby ensuring greater transcription accuracy [20]. However, if the score drops below the threshold, the entry is flagged for manual review and verification. OCR errors may change medication (e.g., "Metformih" instead of "Metformin"), leading to possible misidentification [20].

Fuzzy matching identifies similarities between non-identical textual strings by quantifying the degree of similarity, unlike exact matching, which requires identical strings. It is helpful in data cleansing, entity resolution, and record linkage. A key technique is Levenshtein Distance (LD), which calculates the minimum number of edits needed to transform one string into another. This allows the detection of approximate matches in noisy data [21].

Levenshtein Distance, introduced by Vladimir Levenshtein, is a widely recognized metric for measuring the difference between two sequences of characters. It measures the minimal operations needed to convert one string into another through insertion, deletion, or substitution. This method is vital in various computational fields, such as NLP, bioinformatics, and information retrieval [22]. To compare two strings, the Levenshtein Distance (LD) indicates the minimum number of editing operations required to transform S into T, with lengths m and n, respectively. Construct a matrix *LD* [*n*+1, *m*+1]. Next, calculate the value of each cell *LD* (*i, j*) in the matrix iteratively using the formula [23], as shown in Eq. (1).

$$LD(i,j) = \begin{cases} 0, & i=0, j=0 \\ j, & i=0, j>0 \\ i, & i>0, j=0 \\ Min, & i>0, j>0 \end{cases}$$

$$Min = min\begin{pmatrix} LD[i-1,j]+1, LD[i,j-1]+1, \\ LD[i-1,j-1]+1 \end{pmatrix} + f(i,j) \quad (1)$$

In this case, $f(i, j) = 1$ if the i^{th} word of *S* differs from the j^{th} word of *T*; otherwise, $f(i, j) = 0$. Finally, the edit distance is provided by the value in the bottom-right corner of the matrix, *LD* (*n, m*). The fuzzy similarity score (*Sim* (*S, T*)) can be calculated using the formula [23], as shown in Eq. (2).

$$Sim(S,T) = \left(1 - \frac{LD}{max(m,n)}\right) \quad (2)$$

This step compares text by defining a reference dataset (drug_dictionary) and target text. Fuzzy matching, utilizing Levenshtein Distance, calculates the similarity score with a threshold of 80 to identify acceptable matches. For instance, comparing "Metformih" to "Metformin" in Fig. 6 yields a Fuzzy Similarity Score of 77.78%, which falls short of the 80% threshold. This suggests that while the strings exhibit similarities, they may not fulfill the established criteria for an exact match.

Step 3.2: Dosage and Quantity Verification uses Regular Expressions to identify dosage patterns (e.g., "1 tablet", "850 mg"), supported by rule-based checks against standard medical formats. This structured methodology enhances accuracy in dosage extraction and mitigates the risk of medication errors by systematically verifying data against established medical standards. For example, the regular expression d+s* (tablet|mg|capsule) is intended to pinpoint numerical values followed by specific dosage units, such as "tablet", "mg", or "capsule". The d+ component captures one or more digits, representing quantities like "1" or "850", while s* permits optional spaces between the number and the unit to accommodate variations in formatting. The final segment (tablet|mg|capsule) ensures that only the specified dosage forms are acknowledged, making this pattern effective for extracting medication dosage information from text.

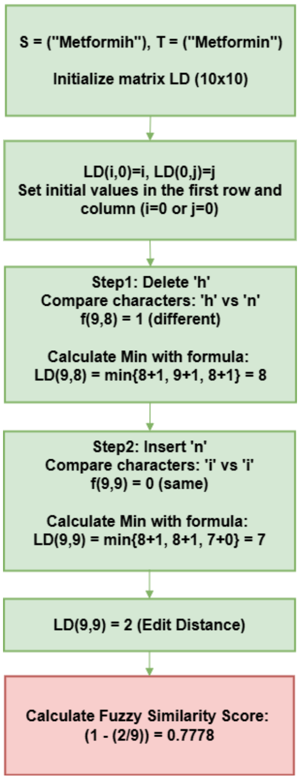

Fig. 6. Edit distance example: “Metformih” vs. “Metformin”.

Step 3.3: Frequency Validation uses dictionary matching to verify extracted timing instructions, reducing OCR errors in key administration details like mealtimes and bedtime dosing. This systematic approach ensures accurate transcription and standardization of temporal medication directives.

Step 3.4: Extraction and validation of indications (Disease/Condition) use NER to identify medication-related conditions. This facilitates accurate therapeutic categorization, which improves clinical decision support and ensures seamless integration with Electronic Health Records.

d) Step 4: Post processing

The validated medication data, including medication, dosages, timing, and indications, undergoes systematic structuring into JSON format to enhance interoperability between medical informatics systems, mobile applications, and databases.

This framework improves OCR-based transcription of pharmaceutical labels for mobile applications and databases by incorporating text extraction, correction, validation, and structured output. Utilizing dictionary-based matching, fuzzy logic, rule-based validation, and NER reduces OCR errors in medication, dosages, schedules, and indications. The structured JSON output guarantees seamless integration with mobile health apps and medical databases.

This section offers a comparative assessment of OCR results using a typical Thai-language pharmaceutical label as the test input. The evaluation centers on four key clinical elements are frequently present on medication labels: medication, dosage instruction, frequency, and medical indication. Table I presents a detailed line-by-line comparison, emphasizing recognition errors and their impact on both language accuracy and patient safety.

In the implementation stage, the development of the system occurs, integrating OCR technology to extract information from medication labels. Finally, the testing phase ensures the verification of the system’s accuracy, functionality, and usability before deployment.

Fig. 7 illustrates a comparative analysis of OCR outputs from Easy OCR, Google Cloud Vision, and Tesseract, applied to a Thai medication label. The ground truth is shown for reference, with OCR errors red boxes. It summarizes OCR errors across systems and highlights key examples.

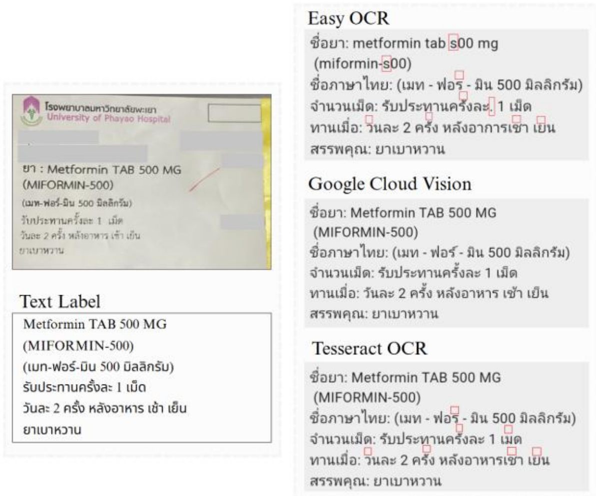

Fig. 7. Comparison of OCR errors.

Easy OCR shows significant recognition errors. Numerals are frequently misread, such as “500” → “s00,” and Thai text suffers from both character-level distortions, such as “รับประทานครั้งละ 1 เม็ด” → “รับประทานครังละ. 1 เม็ด”. Several lines are omitted or heavily corrupted, making the output unreliable for clinical contexts, such as “วันละ 2 ครั้ง หลังอาหารเช้า เย็น” → “วนละ 2 ครัง หลังอาหารเชา เย็น”.

Google Cloud Vision delivers the most accurate results. It correctly identifies all essential components such as drug name, dosage, and indication, demonstrating strong suitability for Thai medical text.

Tesseract OCR yields partially correct output. Key elements like the drug name are present, but Thai text includes character-level errors, such as “รับประทานครั้งละ 1 เม็ด” → “รับประทานครังละ 1 เม็ด”.

In summary, OCR performance varies significantly. Google Cloud Vision outperforms in both accuracy and completeness, while Easy OCR and Tesseract display distinct error patterns, particularly with Thai script.

D. Mobile Application Development

The system has been developed utilizing the Software Development Life Cycle (SDLC) methodology, thereby ensuring a structured and efficient process. The development phases encompass Planning, Requirements Analysis, Design, Implementation, and Testing.

During the Requirements Analysis phase, user roles and functionalities are defined.

- Caregivers: Access the system, scan pharmaceutical labels, view medication details, notify medications, and record and monitor patients' medication intake.
- Admin: Manage user accounts by creating, deleting, and updating account information.
- Doctors: Log in to track patients' medication adherence and review their intake history.

The design phase occupies a crucial position in the software development lifecycle, facilitating the transformation of system requirements into a comprehensive implementation plan. Employing the principles of Unified Modeling Language (UML) yields a clear and structured representation of the system's architecture, functionality, and interactions, thereby ensuring the seamless integration of all components. This phase necessitates the creation of essential UML diagrams, which include Use Case Diagrams (as depicted in Fig. 8), Activity Diagrams, Class Diagrams (illustrated in Fig. 9), a Data Dictionary, and the User Interface (UI). Furthermore, the system architecture amalgamates Front-End and Back-End components to promote efficient data management and streamlined functionality. Collectively, these components engender a cohesive, scalable, and robust system design, as detailed below.

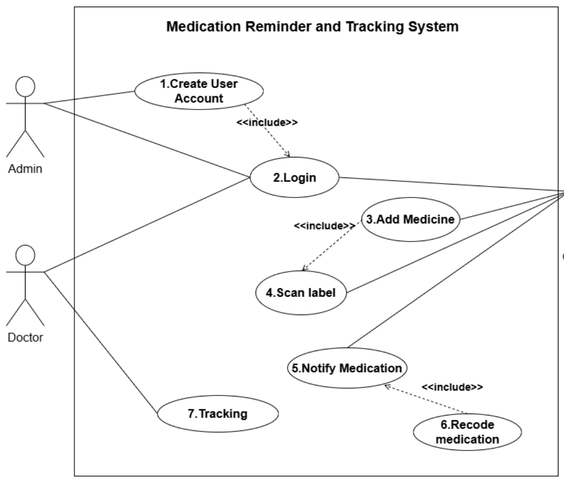

Fig. 8. Use case diagram.

During the development phase, an array of technologies was employed to ensure efficient performance, facilitate seamless integration, and deliver smooth user experience. These tools optimize label recognition, medication management, and application functionality platforms. The system incorporates various backend and frontend technologies to enhance data processing, guarantee effective connectivity, and improve the overall user experience.

In the backend, MySQL Workbench is employed to manage the database, while JavaScript facilitates server-side functionality. Node.js is utilized to enable communication between the backend, the database, and the Google Cloud Vision API with the proposed method. For front-end development, Flutter allows for the creation of cross-platform applications, utilizing Dart as the primary programming language. Visual Studio Code is the principal Integrated Development Environment (IDE) for coding and debugging, whereas Android Studio is designated for testing on Android devices. Figma is employed for User Interface/User Experience (UI/UX) design, assisting in the development of an intuitive and responsive user interface. Collectively, these tools collaborate to deliver a robust and scalable system for pharmaceutical label recognition and medication management.

In the implementation stage, the development of the system occurs, OCR technology to extract information from medication labels. Finally, the testing phase ensures the verification of the system's accuracy, functionality, and usability before deployment.

Fig. 8 illustrates a use case diagram that visually depicts the interactions among various users and the system, emphasizing the specific actions each user role may undertake. For Caregivers, the primary responsibilities involve managing patient medication. These tasks include logging into the system, scanning medication labels, reviewing medication details, receiving alerts, recording medication intake, and monitoring the patient's adherence over time. The administrator role centers on overseeing user accounts. Administrators can log into the system and create, delete, and modify user accounts, thereby ensuring that access control is maintained, and the system remains secure. For Physicians, the focus is on tracking and evaluating medication adherence. Their responsibilities include logging in, accessing patient profiles, monitoring compliance, reviewing medication intake history, and analyzing patterns to ensure appropriate treatment plans are followed.

Fig. 9 demonstrates the class diagram, which provides a comprehensive overview of the system's architecture, highlighting significant classes, attributes, methods, and interactions. This structure is intended to facilitate a medication management system involving administrators, physicians, caregivers, and patients. Central to the system is:

- The "User" class serves as a fundamental framework for all user types. This class encompasses key attributes, which include "userID", "username", and "password". Additionally, it comprises essential methods such as "login()" and "receive Notification()". From this base class, three specialized roles are derived: "Admin", "Doctor", and "Caregiver."
- The "Admin" class provides comprehensive management capabilities by utilizing methods such as "createUserAccount()", "editUserInformation()", and "deleteUserAccount()", thereby ensuring effective user administration and maintaining system security.

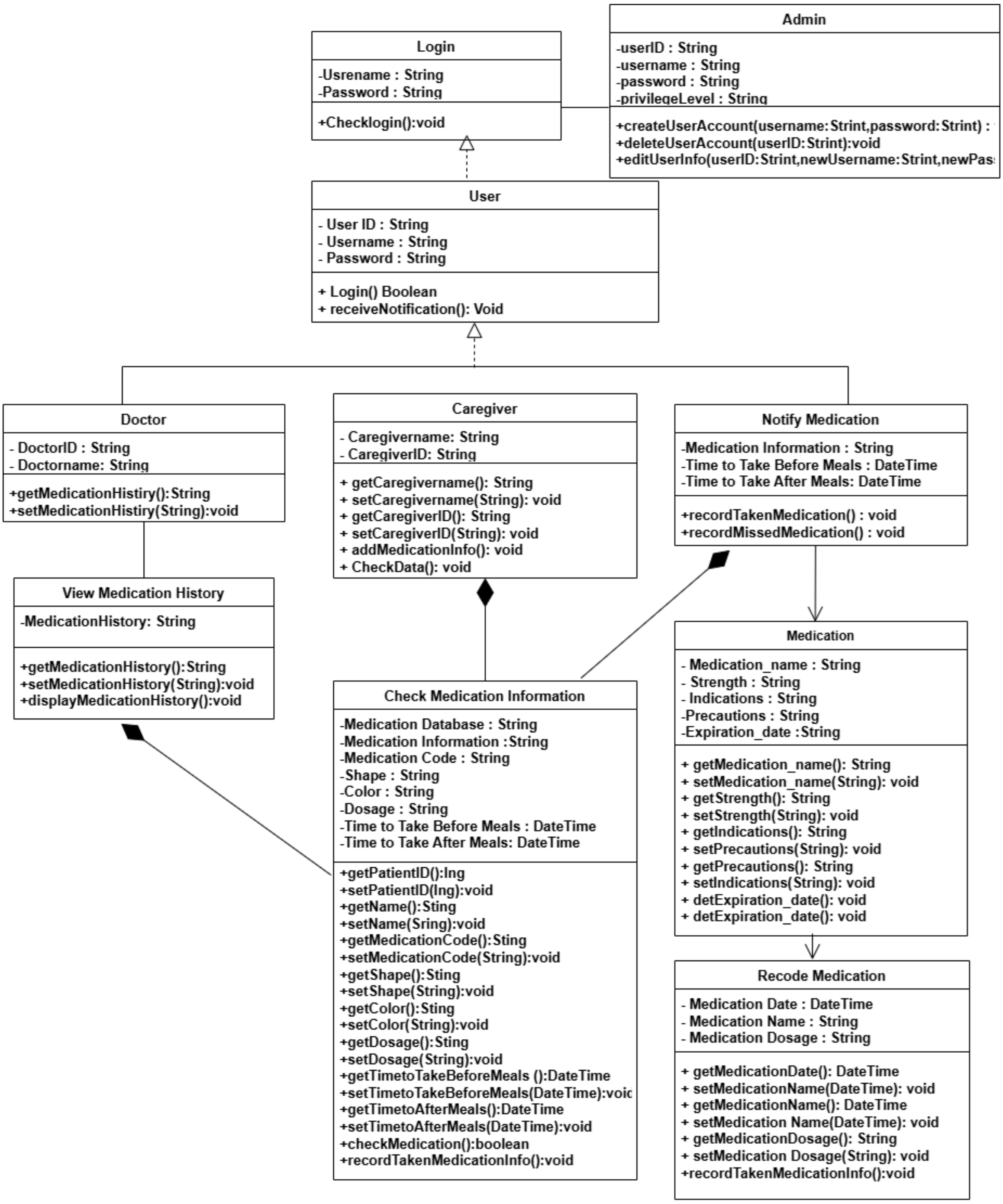

Fig. 9. Class diagram.

- The "Doctor" class utilizes methods such as "getMedicalHistory()" and "setMedicalHistory()" to access and modify patient medication histories. Additionally, physicians can use the "View Medication History" class to present historical information using the "displayMedicalHistory()" method.
- The "Caregiver" class encompasses methods such as "getCaregiverName()", "setCaregiverName()", and "checkPatientData()", which are designed to facilitate the management of patient care and to ensure adherence to treatment protocols. Additionally, the "Check Medication Information" class provides further assistance to caregivers by allowing for the retrieval and documentation of medication-related data.
- The "Medication" class handles medication details and includes methods such as "getMedicationInfo()" and "setMedicationSchedule()".
- The "Notify Medication" class is dedicated to facilitating scheduling reminders and documenting missed doses through the utilization of the "recordMissedMedication()", "execOfTakenMedica tion()" methods.
- The "Recode Medication" class also contributes to ensuring the accuracy of medication records.

Ultimately, the system augments collaboration among administrators, physicians, and caregivers, underscoring the significance of precise and efficient medication management. The meticulously structured class design provides distinct functionalities tailored to each role, contributing to the system's robustness and effectiveness.

E. Evaluating User Satisfaction in Usability and Performance Assessment

The user satisfaction assessment, validated by domain experts, employed a Likert scale to measure attitudes and perceptions based on mean scores [24]. This evaluation focuses on key aspects of the system to assess its performance and user experience, including system access (ease, speed, and security), medication entry and label scanning (precision, efficiency, and user-friendliness), medication reminders (setup simplicity, notification accuracy, and clarity), medication history and records (data input ease, accessibility, and completeness), and the overall application (usability, design, performance, and stability). Each factor is carefully evaluated to ensure effective and user-friendly experience.

- Users review system access based on convenience, speed, and security, ensuring a seamless and safe user entry process.
- Users evaluate the medication entry and label scanning process for its accuracy, efficiency, and user-friendliness, guaranteeing effective handling of medication information.
- Users examine the medication reminder feature for its setup simplicity, notification accuracy, and clarity of information to support adherence to medication schedules.
- Users assess the medication record and history function by focusing on ease of data entry, quick access to past records, and data completeness, which help inform treatment decisions.
- Users evaluate the overall application in terms of usability, design, functionality, and stability to ensure it remains intuitive, reliable, and valuable, enhancing the user experience and supporting effective healthcare management.

IV. Results

A. Application Development Outcomes

This research demonstrates the successful integration of OCR technology to automate extracting information from pharmaceutical labels in healthcare information systems. Additionally, it designs and implements a mobile application interface that leverages OCR technology to read and manage pharmaceutical labels.

The study concentrated on the accurate capture of essential medication details, encompassing medication, dosage specifications, administration frequencies, and timing instructions (including meal-related timing and daily schedules). To augment transcription precision, the system employs a sophisticated amalgamation of methodologies: dictionary-based matching, fuzzy logic, rule-based validation, and NER, all functioning synergistically with the Tesseract OCR engine.

The practical implementation of this technology is manifested in a mobile application meticulously designed and developed for processing pharmaceutical labels on Android devices. The application comprises a comprehensive suite of functionalities, including automated label reading, data storage, medication reminders, adherence tracking, and analytical reporting capabilities, as illustrated in Figs. 10 and 11 for the front end, and Fig. 12 for the backend.

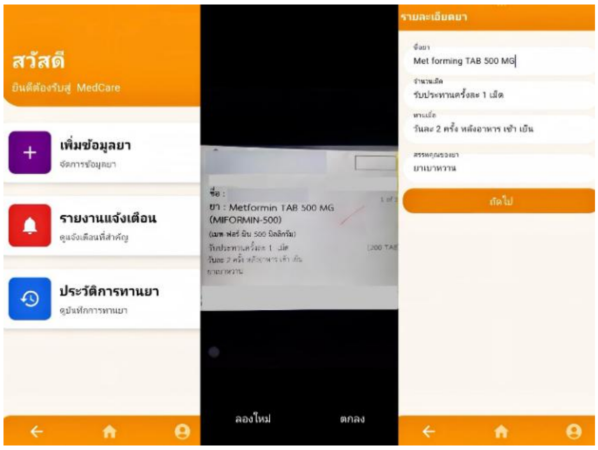

Fig. 10. Add medication interface.

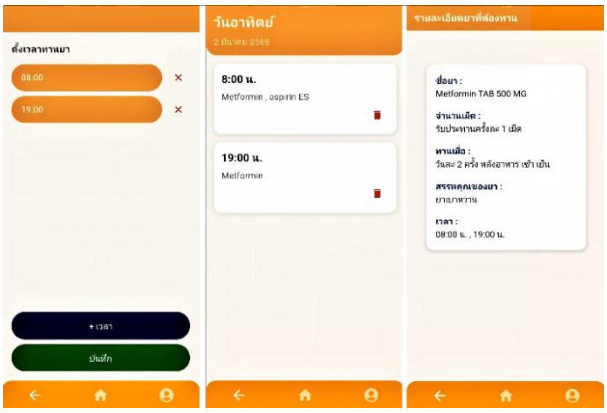

Fig. 11. Reminder interface.

Fig. 12. Monthly medication summary interface.

Fig. 10 illustrates the Medication Addition Interface, wherein users can input pertinent medication details, including the name, dosage, frequency, and other critical information. The Reminder Settings screen, as depicted in Fig. 11, enables users to schedule medication times, establish alerts, and oversee reminders to facilitate timely intake.

Fig. 12 illustrates Monthly Medication and Types Taken by the Patient Interface, providing an overview of the prescribed drugs and their usage frequency.

B. Assessment of the Accuracy of Pharmaceutical Label Transcription

A comprehensive evaluation of character recognition and OCR system performance was conducted at the University of Phayao Hospital in Thailand, involving the analysis of 271 unique pharmaceutical labels across 10 iterations for each label. The analysis concentrated on character recognition accuracy relating to four essential elements: medication, dosage instruction, frequency, and medical indications using Easy OCR, Google Cloud Vision, and Tesseract OCR. For example, Fig. 13 illustrates a comparative analysis of OCR outputs from Easy OCR, Google Cloud Vision, and Tesseract OCR, applied to a Thai medication label. The ground truth is shown for reference, with OCR errors red boxes.

Easy OCR shows significant recognition errors. Numerals are frequently misread (e.g., “500” → “s00”), and Thai text suffers from both character-level distortions e.g., “รับประทานครั้งละ 1 เม็ด” (Take 1 tablet at a time.) → “รับประทานครังละ. 1 เม็ด” (The error is that the top tone is missing.). Several lines are omitted or heavily corrupted, making the output unreliable for clinical contexts e.g., “วันละ 2 ครั้ง หลังอาหารเช้า เย็น” (Twice a day after breakfast and dinner.) → วนละ 2 ครัง หลังอาหารเชา เย็น” (The error is that the top tone is missing.).

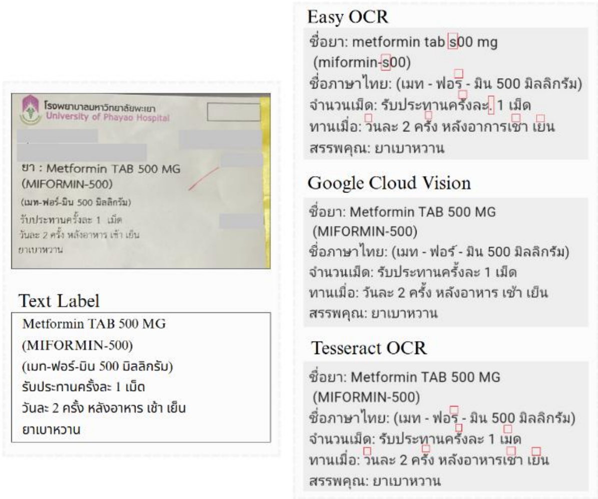

Fig. 13. Comparison of OCR results.

Google Cloud Vision delivers the most accurate results. All essential components—drug name, dosage, and indication—are correctly identified, showing strong suitability for Thai medical text.

Tesseract OCR yields partially correct output. Key elements like the drug name are present, but Thai text includes character-level errors.

The evaluation produced the following results for character transcription in Table II. The evaluation metrics used were Accuracy (Acc.) and Character Error Rate (CER), assessed both before and after applying an OCR integrated with the proposed method.

TABLE II. ASSESSMENT OF THE CHARACTER RECOGNITION ACCURACY IN PHARMACEUTICAL LABEL TRANSCRIPTION

Elements		Pre-Parameters			Post-Parameters		
		EOCR	GCV	TOCR	EOCR	GCV	TOCR
Accuracy (%)	Medication	75.53	94.02	93.04	87.28	**99.27**	94.76
	Dosage Instruction	78.30	92.05	89.70	80.01	99.14	90.09
	Frequency	61.77	90.47	76.56	68.40	97.98	89.85
	Medical Indications	76.60	90.56	93.37	87.46	98.28	94.74
CER (%)	Medication	0.245	0.060	0.070	0.114	0.007	0.062
	Dosage Instruction	0.217	0.079	0.102	0.198	0.008	0.099
	Frequency	0.392	0.100	0.234	0.316	0.020	0.101
	Medical Indications	0.234	0.094	0.066	0.125	**0.017**	0.062
Average Accuracy		73.05	91.78	86.81	80.79	**98.67**	92.26
S.D. (±)		29.04	22.41	18.97	23.99	**6.26**	11.67
Average CER		0.272	0.083	0.083	0.188	**0.013**	0.072
S.D. (±)		29.13	22.44	18.98	23.97	**0.06**	11.73

Note: Easy OCR (EOCR), Google Cloud Vision (GCV), and Tesseract OCR (TOCR)

From Table II, the findings clearly indicate that GCV consistently outperformed the other OCR methods in terms of both accuracy and CER across all evaluated information elements. This trend was particularly pronounced after the application of the post-processing framework. For example, within the Medication element, GCV achieved a top accuracy of 99.27 %, accompanied by an exceptionally low CER of 0.007 %. In contrast, EOCR initially exhibited relatively lower performance but showed considerable improvement following post-processing. This improvement was especially notable in the Frequency element, where the CER decreased from 0.392% to 0.316%, while the accuracy improved from 61.77 % to 68.40 %. TOCR, while demonstrating relatively strong initial performance in elements such as Medication and Medical Indications, showed only moderate gains after post-processing. This pattern suggests that TOCR may have already reached a near-optimal level of performance within the current experimental setup.

To conclude, GCV emerged as the most accurate and reliable OCR method for Thai medical labels. TOCR performed reasonably well, particularly after post-processing, while EOCR requires further improvement to meet medical transcription standards. The post-processing approach proved effective, especially in reducing character-level errors, which is crucial for preserving meaning in Thai script. These findings highlight the importance of OCR enhancement in supporting accurate and dependable clinical data extraction for healthcare.

This summarizes character-level OCR performance, including accuracy, CER, and S.D., with and without the proposed post-processing approach. Among all configurations, GCV combined with the proposed method yielded the highest accuracy, achieving 98.67% (S. D.= ± 6.26) character accuracy and a CER of 0.013 (S. D. = ± 0.06). TOCR, with the method, followed with 92.26% accuracy and 0.072% CER, while EOCR, despite its lowest baseline accuracy 73.05%, improved substantially to 80.79% when augmented with the proposed method. These findings demonstrate the effectiveness of the method in enhancing OCR performance on pharmaceutical labels. Its higher recognition accuracy correlates with lower CER. The standard deviations decreased between 5.05 to 16.15 confirming the system's overall stability and reliability.

In practical testing, several model-specific OCR issues were observed, particularly affecting Thai diacritics, numerals, and domain-specific terminology. EOCR frequently misrecognizes critical elements. For instance, the word "ครั้ง" used in dosage instructions to indicate frequency like, "2 times per day" or "1 tablet per intake". It was incorrectly transcribed as "ครัง," which could lead to incorrect administration. Numerical errors such as rendering "500" as "5oo" or "soo", and time-related errors were also common. For example, "เช้า" (meaning morning) was incorrectly identified as "เข้า" (enter), and "หลังอาหาร" (after a meal, typically referring to after dinner) was misread as "หลังอาการ" (after symptom). Such misinterpretations can significantly disrupt the intended medication schedule.

TOCR showed similar recognition issues, including confusion between digits and visually similar characters, and frequent consonant substitutions likes, "ช" misread as "ข" or "ซ", and "บ" as "ป").

Although GCV achieved superior overall accuracy, it exhibited critical errors in interpreting temporal expressions (e.g., missing space), and some character-level error (e.g., "เที่ยง" (noon) as "เพียง" (only)).

The proposed post-processing method substantially reduced these issues by applying domain-specific correction rules and contextual modeling tailored to Thai medical and pharmaceutical language. This enhancement improves the reliability of OCR outputs, making the system suitable for integration into mobile healthcare applications. It is particularly beneficial for older adults and individuals with limited literacy, supporting safer medication use and adherence in outpatient care.

C. Usability and Performance Assessment Results

Based on the experimental findings, the researchers selected Google Cloud Vision API as the foundational OCR engine due to its consistently high performance during preliminary testing. To further improve recognition accuracy, a hybrid error correction framework was introduced. This framework employs a combination of post-processing methods, including dictionary-based matching, fuzzy logic inference, rule-based validation, and NER. These techniques are organized within a multi-layered architecture, which effectively minimizes OCR errors, particularly in mobile text recognition contexts where input data quality is often variable. To evaluate the system in a real-world context, thirty participants who were caregivers or family members of patients with long-term health issues tested the application and provided feedback on its effectiveness, usability, and overall experience. A standardized questionnaire was used to ensure consistency in the evaluation. The results are summarized in Table III.

TABLE III. EVALUATION OF USER SATISFACTION ON SYSTEM USABILITY

Category	Mean	Level
System Access	3.35	Moderate
Medication Entry and Label Scanning	3.67	Good
Medication Reminder	3.67	Good
Medication Record and History	3.61	Good
Overall Application	3.38	Moderate
Overall Average	**3.54**	**Good**

Table III summarizes user satisfaction across various systems. The overall average score was 3.54, indicating a positive response. System Access (3.35) and Overall Application (3.38) received moderate ratings, suggesting potential areas for improvement. On the other hand, Medication Entry and Label Scanning (3.67), Medication Reminder (3.67), and Medication Record and History (3.61) were positively rated, though slight improvements could optimize these features further.

Medication entry and label scanning and medication reminder were particularly effective for hospital tasks, while system access and overall application may require enhancements to improve usability and efficiency.

User feedback reveals both the system's strengths and areas for potential improvement. Healthcare professionals praised its effectiveness in tracking medication adherence and supporting treatment planning by providing easy access to patient medication histories. One user commented, "The system helps us spot whether patients are sticking to their meds or not". For caregivers, the system alleviates the challenges of managing medication schedules. One caregiver noted, "I use the application to help my dad with his meds. The logs and reminders keep us both worry-free".

A key recommendation was to enhance data visualization by offering more flexible viewing options, making it easier to understand and compare medication data. One user suggested, "If there were more ways to view the data, it would make things easier to read and compare".

Additionally, feedback emphasized the need to refine the preprocessing techniques and OCR system for greater accuracy. Faded or unclear labels can lead to misinterpretation, making careful data review essential to ensuring accuracy and reducing errors. As one user explained, "Faded or unclear label text occasionally caused character misinterpretation, requiring careful review to ensure accuracy".

V. Discussion

The proposed system demonstrates strong performance in recognizing structured pharmaceutical data, particularly in identifying medication names and dosage units, which is essential for safe and effective medication management. Among the tested configurations, the combination of Google Cloud Vision with the proposed post-processing method achieved the highest performance, reaching 98.67%-character accuracy and a CER of 0.013. This performance surpasses previous studies, including 95.70% [8], 97.00% [10], 93.0% [14], 94.09% [15], 96.90% [16], 94.00% [17], and 93.20% [19], and remains competitive with 98.30% [9].

Compared to other cloud-based OCR services, the proposed method outperformed AWS OCR combined with heuristics [15], standard AWS OCR [16], and CLOVA OCR [8] by 4.67%, 1.77%, and 3.00%, respectively. These improvements to the integration of domain-specific dictionaries, fuzzy logic inference, rule-based validation, and named entity recognition tailored to Thai-language medical documents. These techniques help mitigate linguistic challenges such as Thai morphological ambiguities and inconsistencies in scanned prescriptions.

Performance varied significantly depending on which OCR engine the system employed. For instance, EasyOCR combined with the proposed method improved from a baseline of 73.05% to 80.79%. However, this result remained lower than the 94.0% accuracy reported in the research by Thetbanthad *et al*. [17], which employed the Qwen2-72B-instruct model with an integrated VQA component under a RAG framework, combining document retrieval with response generation to enhance language understanding. It does not fully incorporate instruction-tuned large language models or advanced multimodal reasoning, which are specifically optimized for task-oriented prompt following. This may contribute to the observed performance gap.

Tesseract OCR, when enhanced by the proposed method, reached 92.26% accuracy with a CER of 0.072. While this is slightly lower than in the study by Wang and Luo [19] (93.21%), which utilizes a HB-DBi-LSTM-based model, the result is still competitive. The researchers suspect that the discrepancy arises from Tesseract's limitations in handling Thai script, especially under varied font styles, layouts, and image quality.

Challenges specific to Thai-language medical texts include morphological ambiguities, such as confusion between similar-looking words. Visual noise from degraded labels also poses difficulties. English-based studies tend to exhibit these issues less prominently such as the work by Lee *et al*. [9], which often use high-quality digital inputs. In real-world clinical environments, printed prescriptions often suffer from poor contrast, faded ink, and scanning artifacts. These factors reduce recognition accuracy, especially given the frequency of such issues and the critical importance of medical indications.

Despite these challenges, the proposed method consistently outperforms baseline systems and shows strong potential for clinical deployment, particularly in rural or underserved areas where manual verification is limited. Accurate transcription of medication labels is crucial, as misinterpretation can lead to adverse drug events and reduced patient adherence.

To promote real-world usability, researchers have developed a mobile application based on the proposed system. This tool supports patients, especially those with visual impairments by providing clear interpretations of pharmaceutical labels. It also addresses healthcare accessibility gaps, which are prominent in many regions of Thailand.

Future development will focus on reducing character error rates with advanced pattern recognition techniques, expansion of the pharmaceutical lexicon, and image preprocessing methods such as noise reduction and contrast enhancement. Expansion of the pharmaceutical lexicon, as well as adaptive learning mechanisms and user interface improvements guided by human-centered design principles, as improvements in Ref. [16]. To further improve mobile performance, researchers will apply model quantization to reduce memory usage and accelerate real-time inference on resource-limited devices. Researchers will also explore federated learning to enable on-device model updates using local user data, enhancing personalization while preserving patient privacy. While the current system relies on cloud-based inference, future deployment will consider on-device solutions via TensorFlow Lite or ONNX Runtime Mobile to reduce latency and support offline use.

VI. Conclusion

In conclusion, this research highlights the potential of OCR technology in automating the extraction of critical information from pharmaceutical labels. The mobile application successfully captured key medication details, including medication, dosages, administration times, and medical indications, with high accuracy. However, the recognition of frequency and medical indications was slightly less accurate. These challenges stemmed from the complexity of pharmaceutical terminology, label design, and image quality. Despite these issues, the system demonstrates significant promise in enhancing medication safety and patient care.

Overall, user satisfaction is positive, with high praise for medication entry, label scanning, and reminders. However, system access and overall application performance were rated lower, highlighting the need for improvements in usability. In conclusion, while the system effectively promotes adherence and supports treatment planning, enhancing data visualization would improve usability and decision-making for both healthcare professionals and caregivers.

Multilingual scalability presents challenges due to linguistic diversity, especially in low-resource languages, requiring adaptive OCR and preprocessing techniques. Future improvements will focus on integrating language-agnostic models, multilingual resources, and additional international databases to enhance system flexibility, scalability, and interoperability. To further enhance recognition across diverse scripts, script-aware preprocessing will be used to tailor image processing to script-specific features. Techniques such as language-specific feature extraction and multi-task learning will address structural and contextual variations. Together with improved OCR, advanced NLP, and mobile support, these upgrades enable scalable use in multilingual healthcare settings.

This study acknowledges certain limitations. Users with impaired vision often require caregiver assistance, and OCR accuracy is affected by image quality issues like blurriness and poor lighting. Challenges also arise from inconsistent pharmaceutical terminology and unstructured text, as well as label degradation and privacy concerns during data collection.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Wongpanya S. Nuankaew conducted the research; while Fapratan Jailangka, Atthakit Khampraphai, and Apatsara Kamka gathered the data; Patchara Nasa-Ngium analyzed the data, and Pratya Nuankaew wrote the manuscript. All authors approved the final version.

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