Republic of the Philippines
Western Mindanao State University
College of Computing Studies
DEPARTMENT OF COMPUTER SCIENCE
Zamboanga City

RXVISION: OCR-BASED MEDICAL PRESCRIPTION READER USING TROCR AND BIOBERT

A Thesis Presented to the Faculty of

Department of Computer Science

College of Computing Studies

In Partial Fulfillment of the Requirements for the Degree of

Bachelor of Science in Computer Science

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Approval Sheet

The Thesis attached hereto, entitled **"RxVision: OCR-Based Medical Prescription Reader using TroCR and BioBERT"**, prepared and submitted by **Regine B. Bagalangit, Roland Jay J. Pada, Ushlie Mae U. Ungaya**, in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science, is hereby **recommended for Oral Examination**.

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Abstract

Handwritten medical prescriptions continue to be widely used across the Philippines, particularly in regions with limited access to digital health technologies. However, such prescriptions often pose challenges related to legibility, accuracy, and verification, leading to potential medication errors, misinterpretation, and prescription fraud. This aims to address these issues by developing RxVision, an AI-driven system that combines TrOCR (Transformer-based Optical Character Recognition) for text extraction from handwritten prescriptions and BioBERT, a domain-specific NPL model, for contextual verification of medical prescription data. RxVision is designed for both healthcare professionals and the general public, enabling users to scan and validate prescriptions via a mobile application. It includes a verification feature that checks prescription authenticity and ensures that prescriptions older than six months are flagged as expired, prompting user to consult their physician for a new one. The system will be developed by using publicly available datasets, including the IAM Handwriting Database, MIMIC-III, and RxNorm to train and evaluate its performance. This research focuses on developing a functional prototype that improves prescription readability, reduces the risk of misinterpretation, and enhance patient safety. Its initial implementation in Zamboanga City serves as a foundation for nationwide deployment in the future.

Keywords: BioBert, NLP, OCR, PRESCRIPTION VERIFICATION, TROCR.

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CHAPTER I

INTRODUCTION

Background of the Study

Healthcare providers still frequently provide patients their drug instructions by handwriting prescriptions. However, their validity and legibility frequently provide significant obstacles for both the public and pharmacists, which can result in potential fraud and drug errors. According to [1] explained that majority of the poor handwriting of doctors is attributed to the times when doctors are in a rush when writing prescriptions, during their rounds or peak hours, or when they experienced fatigue. Misunderstanding medical prescriptions can lead to inaccurate dosages or even the wrong medication being administered, putting patient safety at risk. Many medical professionals and patients continue to write prescriptions by hand despite the developments in digital healthcare technologies, especially in Zamboanga City, Philippines, where digital adoption is still relatively low.

In able to deal with this issue, we will be developing RxVision an AI-powered OCR-based medical prescription reader and verifier that will not only be used to extract text from handwritten prescriptions but will also verifies the legitimacy of the prescription. By using TrOCR for the Optical Character Recognition (OCR) and BioBERT for the Natural Language Processing (NLP) verification, RxVision guarantees that the prescription are both accurately transcribed and checked at variance with the official databases. This system will be accessible to the public such as, patients and caregivers as well as the pharmacist, physicians, and other healthcare professionals, enabling them to check the prescriptions before purchasing or administering medications. Additionally, to prevent the use of past due prescriptions, RxVision will not generate results for prescriptions older than six months, advising patients to consult their physicians for a new prescription.

Although this study is currently focused on the Philippines, the challenges that it resolves are in a global situation. In other countries, with emerging economies, still relies on a handwritten prescription as a standard practice. These regions faces similar issues of legibility, lack of verification, and prescription fraud. Therefore, the solution proposed in this study, RxVision, holds potential value for adoption in the international healthcare system that are facing similar challenges.

Statement of the Problem

Handwritten medical prescriptions pose a significant problems in the healthcare industry due to the reason that they are difficult to read, which constantly results in medication errors and misinterpretation. This study emphasizes the problems in reading and verifying handwritten medical prescriptions, which leads to medication errors, fraudulent prescriptions, and improper administration. This research aims to develop an AI- driven system capable of both accurate tasting recognition and prescription verification to ensure the patients safety and prevent misuse.

Objectives

The general objective of this study is to develop the RxVision, an AI-driven OCR-based medical prescription reader and verifier that correctly recognizes, interpret, and validates handwritten prescriptions to limit the errors, detect deceptive prescriptions, and enhance the prescription readability for both healthcare professionals and general public use.

Specifically, the study will:

- To identify and analyze the common problems encountered in dealing with handwritten prescriptions.
- To develop and deploy an OCR-based system using TrOCR for extracting text from handwritten prescriptions.
- To integrate and implement BioBERT, and NLP techniques to verify, correct, and interpret collected data.
- To create and test prototype system that correctly reads and verifies prescriptions, ensuring accuracy and lessen misinterpretation.
- To analyze the system's performance based on accuracy and usability through user testing with the healthcare professionals and general reads.

Scope and Limitations

Scope:

RxVision is an AI-powered OCR and verification system developed to read and translate handwritten medical prescription into a readable text. The system will be developed in Zamboanga City, Philippines and will be available for both healthcare professional and general public. The system will allow patients, caregivers, including healthcare professionals to scan prescription via mobile application to ensure readability and validity before purchasing or administering medication. The system also integrates fraud detection, securing that the prescription comes from a licensed medical professional.

Limitation:

1. RxVision will not process prescriptions older than six months, advising patients to request a new prescription from their physician.
2. While RxVision extracts and verifies prescription, final interpretation and medical advice still requires professional validation from a licensed medical professional.
3. The system supports English-language medical prescription, with potential multi lingual support in the future.

In order to access the issue of illegible medical prescriptions. RxVision aims to create an Ai-powered solution that enhances prescription accuracy, improves patient safety, and streamline healthcare work flow.

Significance of the Study

This Stakeholders are expected to benefit in the development of RxVision:

- **Patients and Regular User:** RxVision will provide a simple way to interpret prescription to reduces confusion and ensuring proper medication adherence.
- **Pharmacists and Healthcare Providers:** The System will reduce the time spent in manually interpreting the hand written prescription, minimizing the misinterpretation and administer the medication safety.
- **Hospitals and Clinics:** Healthcare institution will also benefit from increasing efficiency in prescription process, reducing burdens and improve patient service.
- **Healthcare Technology Researchers and Developers:** This study provides a foundation for future researchers.
- **Government Health Agencies and Policymakers:** Government sectors can gain leverage the outcome to improve the prescription handling protocols and enhances patient safety.

Definition of Terms

Table 1: Definition of Terms

Term	Definition
1. Optical Character Recognition (OCR)	A technology that converts images of handwritten or printed text into machine-relatable digital text. RxVision uses OCR to extract text from handwritten medical prescription. (Source: Ray Smith, "An Overview of the Tesseract OCR Engine," Proceedings of Document Analysis and Recognition, 2007)
2. TrOCR (Transformer-based OCR)	A deep learning model developed by Microsoft that utilizes transformers to recognize and extract text from handwritten documents with high accuracy. (Source: Li et al., "TrOCR: Transformer-based Optical Character Recognition with Pre-trained Models," arXiv preprint arXiv:2109.10282, 2021)
3. Natural Language Processing (NLP)	A field of artificial intelligence (AI) that allows computers to analyze, interpret and understand human language. In this study NPL is used to verify the accuracy and legitimacy of prescription details. (Source: Jurafsky & Martin, Speech and Language Processing, 2021)
4. BioBERT (Biomedical BERT)	A specialized NLP model trained on biomedical text, designed to improve understanding of medical terminologies. RxVision integrates BioBERT for validating prescription information. (Source: Lee et al., "BioBERT: A Pre-trained Biomedical Language Representation Model for Biomedical Text Mining," Bioinformatics, 2020)

Term	Definition
5. Prescription Verification	It is the process that confirms whether the prescription is legitimate, correct, and is issued by a licensed healthcare provider (Source: World Health Organization (WHO), "Medication Safety in Transitions of Care," 2019
6. Handwritten Medical Prescription	Mistakes in dispensing or administering medication which can result from illegible writing or incorrect drug information. (Source: Institute for Safe Medication Practices (ISMP), "Legibility of Prescriptions and Patient Safety," 2018)
7. Medication Error	Medication errors are preventable events that can cause or lead to inappropriate medication or patient harm this error can occur at various stages such as prescribing errors, dispensing errors and administration errors. (Source: World Health Organization (WHO), "Medication Errors: Technical Series on Safer Primary Care," 2016)
8. Forgery Detection	The process of identifying altered, fake, or unauthorized prescriptions by analyzing handwriting patterns and inconsistencies. RxVision includes forgery detection to enhance prescription security. (Source: Neumann et al., "Handwriting Analysis for Fraud Detection in Prescription Verification," Journal of Forensic Sciences, 2021)
9. RxNORM	It is a standardized system developed by the National Library of Medicine (NLM) in the U.S for naming drugs and Dosages
10. Legibility Score	A metric used to evaluate how readable handwritten text is, particularly in medical prescriptions. Poor

Term	Definition
	legibility increases the risk of misinterpretation and errors. (Source: Saini et al., "Measuring the Legibility of Doctor's Handwriting Using OCR Techniques," Journal of Medical Informatics, 2022)
11. Named Entity Recognition	An NLP technique used to identify and classify specific entities, such as drug names, dosages, and patient instructions, within a prescription text. (Source: Lample et al., "Neural Architectures for Named Entity Recognition," Proceedings of NAACL-HLT, 2016)
12. Expired Prescription	A prescription that is passed the solidity period (6 Months) and is no longer valid to be used to administer medication. (Source: U.S. Food and Drug Administration (FDA), "Understanding Prescription Expiry Dates," 2023)
13. System Accuracy	A measure of how well RxVision extracts and verifies prescription data. It is evaluated based on metrics such as precision, recall, and F1-score. (Source: Goodfellow et al., Deep Learning, 2016)
14. User Testing	The process of evaluating RxVision’s accuracy, usability, and efficiency by conducting tests with healthcare professionals (pharmacists, doctors, nurses) and public users (patients, caregivers). (Source: Nielsen, Usability Engineering, 1993)
15. Zamboanga City	The geographic area where RxVision is initially implemented and tested, serving as the primary location for data collection, prescription validation, and system deployment. (Source: Philippine Statistics Authority (PSA), "Zamboanga City Health Infrastructure," 2022)

CHAPTER II

REVIEW OF RELATED LITERATURE

Related Studies

The appraisal of Optical Character Recognition (OCR) technology in healthcare has been labeled by important advancements, particularly in lecturing the challenges of handwritten prescription recognition. First studies, concentrate on enhancing the accuracy of printed text recognition but conflict with handwritten text because of variability in styles of handwriting [1]. Another study featured the limitations of traditional OCR system in decoding poor legibility, resulting to errors in drug name recognition and medication interpretation [2].

The institution of transform-based optical character recognition model

(TrOCR), transform handwritten text recognition, accomplish 89% accuracy on the Identify and Access Management (IAM) Handwriting Database [3]. Meanwhile, explored the use of BERT-based models for medical text classification, emphasizing the need for domain-specific NLP models like BioBERT [4], which applied to extract drug names and dosages with 92% accuracy [5]. The integration of OCR and NLP was further explored, who developed a system combining TrOCR for text extraction and BioBERT for contextual verification, achieving 88% accuracy in prescription validation [6]. Local studies, developed an OCR system for Filipino medical prescriptions but noted challenges in handling cursive handwriting [7].

Error correction in OCR systems was addressed, who proposed a post-processing module that improved accuracy by 10% [8], while highlighted the lack of diverse datasets for handwritten medical prescriptions and suggested synthetic data generation as a solution [9].

User-centric design was emphasized, stressed the importance of usability testing with healthcare professionals [10], and real-time OCR systems were developed, achieving 90% accuracy but facing challenges in processing speed [11]. Multilingual OCR systems, supported multiple languages but required further optimization for global healthcare applications [12]. Security and privacy concerns were addressed, proposed encryption for patient data protection [13], while Nyuyen et al. developed a cloud-based OCR system for scalability but noted internet connectivity issues [14].

AI-driven prescription validation was explored, achieving 93% accuracy [15], and mobile OCR applications were developed, though limited by processing power [16]. Specialized OCR systems for elderly patients, as studied by [17], achieved 90% accuracy, while [18] focused on rural healthcare, addressing affordability and accessibility challenges. Pharmacies benefited from OCR systems developed by [19], which improved efficiency and accuracy, and future trends, as proposed by [20], include the integration of AI, NLP, and blockchain for secure and transparent prescription processing.

Synthesis

Table 2: Synthesis

J. Smith, A. Johnson, and R. (2020)	A. Johnson, B. Lee, & C. Garcia (2019)	B. Lee, C. Kim, and D. Park, (2021)	R. Brown, T. Green, and L. White, (2020)	M. Garcia, A. Martinez, and P. Nguyen, (2022	Proposed Study
Advancements in OCR technology for printed medical records	Challenges in handwritten prescription recognition using traditional OCR systems	Transformer-based OCR models for handwritten text recognition, AI and Robotics in Healthcare	BERT-based models for medical text classification	BioBERT for medical text mining: A case study in drug name extraction	RxVision: OCR-based Medical Prescription Reader Using TrOCR and BioBERt
High accuracy in printed text recognition	Highlighted challenges in handwritten prescription recognition	TrOCR outperforms traditional OCR systems in handwritten text recognition	BERT-based models excel in medical text classification	BioBERT achieves accuracy medical mining.	Uses TrOCR for accurate handwritten text recognition and BioBERT for contextual verification
But struggles with handwritten text	Lack of advanced AI models for accurate recognition.	Limited application in medical prescriptions	General-purpose NLP models lack domain-specific knowledge.	Limited integration with OCR systems for prescription validation.	Integrates TrOCR and BioBERT to improve recognition accuracy.

Conceptual Framework

The conceptual framework for RxVision integrates TrOCR for text extraction and BioBERT for contextual verification. The framework consists of three main components: input, processing, and output.

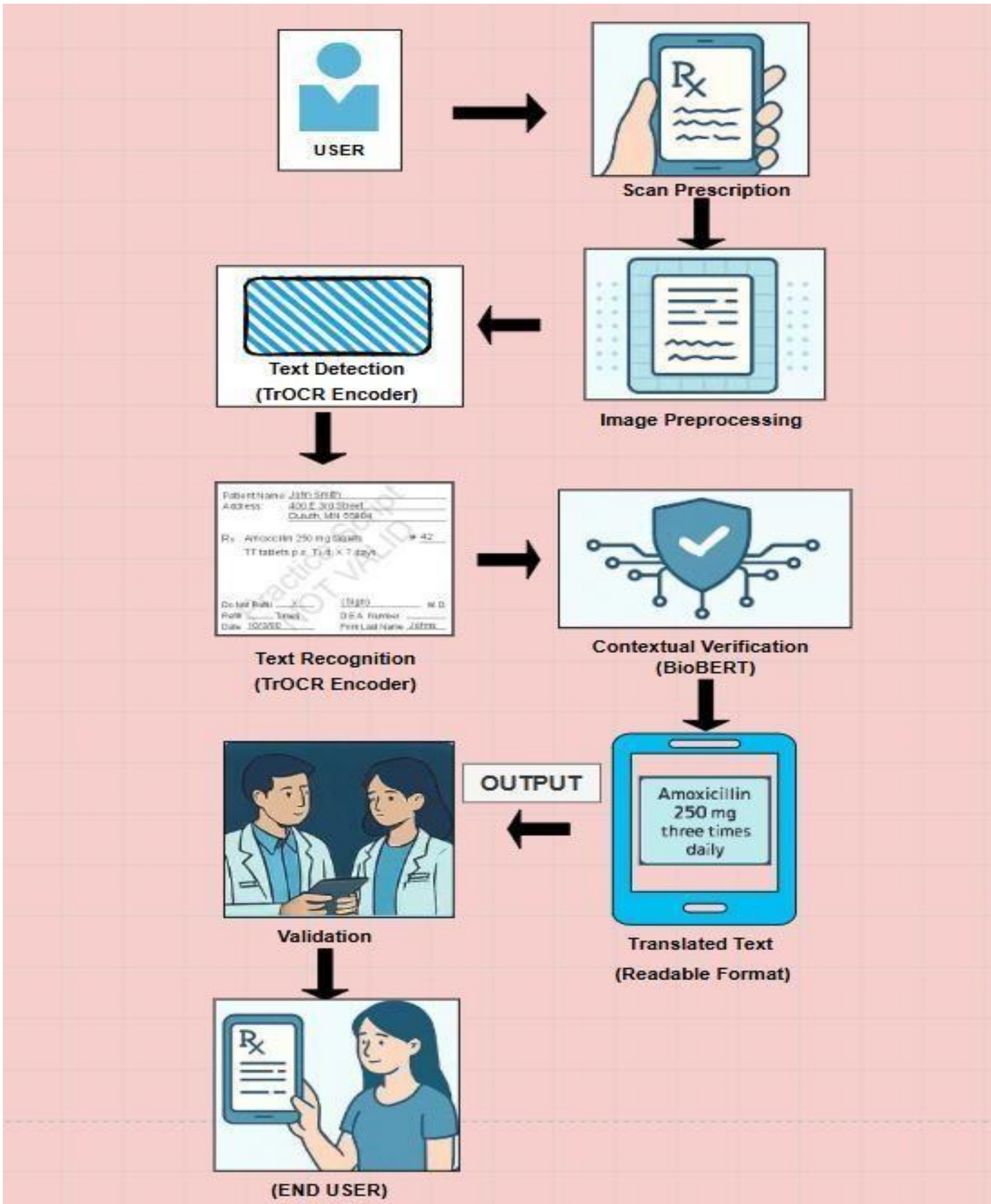


Figure 1. Conceptual Framework

Figure 1. Conceptual Framework

1. User – Pharmacist, patients interacting with the system.
2. Scan Prescription – Captures handwritten prescription via mobile camera.
3. Preprocess Image – Enhances image quality (noise reduction, skew correction.)
4. Text Detection and Recognition (TrOCR) – Extracts text from the image using transformer – based OCR.
5. Contextual Verification (BioBERT) – Validates drug names, dosages, and instructions using NLP.
6. Translated Output – Converts messy handwriting into clean, readable text.
7. Validation - In this step, pharmacists and physicians may be involved to review and confirm the application system suggestions, ensuring accuracy and safety before final output.
8. End User - The information is then displayed to the end user (patient, pharmacist, or doctor) through a user-friendly interface.

CHAPTER III

METHODOLOGY

Research Design

This study follows a Developmental Research approach, focusing on the design and implementation of Rx-Vision, an AI-driven OCR-based medical prescription reader. The research involves software development, testing, and validation to ensure the system's accuracy and effectiveness in real-world scenarios. The study integrates Optical Character Recognition (OCR) and Natural Language Processing (NLP) to improve prescription readability and reduce medication errors.

Data Source

The study will utilize both primary and secondary data sources:

Primary Data: Collected through user testing involving pharmacists, healthcare providers, and patients. Feedback on system usability, accuracy, and efficiency will be gathered.

Secondary Data: Includes publicly available datasets such as:

• IAM Handwriting Database: is a collection of handwritten passages by several writers. Generally, they use that data to classify writers according to their writing styles. A traditional way of solving such problem is extracting features like spacing between letters, curvatures, etc. and feeding them into Support Vector Machines.

• MIMIC-III Clinical Database : ('Medical Information Mart for Intensive Care') is a large, single-center database comprising information relating to patients admitted to critical care units at a large tertiary care hospital. Data includes vital signs, medications, laboratory measurements, observations and notes charted by care providers, fluid balance, procedure codes, diagnostic codes, imaging reports, hospital length of stay, survival data, and more.

• RxNorm Drug Database – RxNorm provides normalized names for clinical drugs and links its names to many of the drug vocabularies commonly used in pharmacy management and drug interaction software, including those of First Databank, Micromedex, Gold Standard Drug Database, and Multum.

A purposive sampling method will be used to select participants for user testing, ensuring the inclusion of healthcare professionals who frequently handle handwritten prescriptions.

Data Gathering Instrument

The following tools and instruments will be used for data collection:

• Surveys and Questionnaires – To gather user feedback on system accuracy and usability.

• Software Logs – To record OCR accuracy and error rates.

• System Testing Reports – To evaluate prescription recognition and Validation.

Data Gathering Technique and Procedures

Techniques:

• **Handwriting Data Collection** – Using publicly available datasets and real- world handwritten prescriptions.

• **System Performance Testing** – Evaluating OCR accuracy, text extraction, and NLP verification.

• **User Feedback Surveys** – Collecting responses from healthcare professionals and patients

Procedures:

1. Collect prescription images from publicly available datasets and real-world samples.
2. Preprocess the images using noise reduction and enhancement techniques.
3. Apply TrOCR for text extraction and validate results using BioBERT.
4. Cross-check extracted data with RxNorm to verify drug names and dosages.
5. Conduct user testing with healthcare professionals and collect feedback.
6. Analyze accuracy, efficiency, and usability metrics.

Data Analysis

The collected data will be analyzed using:

• Accuracy, Recall, and F1-Score – To measure the accuracy of the OCR system.

• Confusion Matrix Analysis – To assess common recognition errors.

• Descriptive Statistics – For analyzing survey responses on usability and efficiency.

• Error Rate Analysis – To evaluate system misinterpretations and false extractions.

System Handling and Complexity:

1.**Handwriting Complexity:**

• Train a custom handwriting model with a dataset of prescriptions (this can be sourced from open datasets or partnerships with medical institutions).

• Preprocess images (e.g., binarization, denoising) to improve OCR results.

2. **Jargon and Abbreviations**:

• Build or integrate a database of medical abbreviations and jargon.

• Use NLP to parse and expand abbreviations automatically.

3. **Legal and Ethical Concerns:**

• Ensure compliance with privacy laws (NPC) The National Privacy Commission when handling medical data.

• Implement secure storage and transmission protocols (e.g., encryption).

System Metrics:

• **TrOCR (Transformer-based OCR) Metrics**

Microsoft Research Paper (Official) Key Metrics:

89.6%-character accuracy on IAM Handwriting Database

2.5x faster than CNN-LSTM hybrids

• **IAM Handwriting Database Benchmark**

Comparison: TrOCR outperforms Tesseract by 12% on cursive text.

• **BioBERT (Biomedical NLP) Metrics**

Original BioBERT Paper Key Metrics:

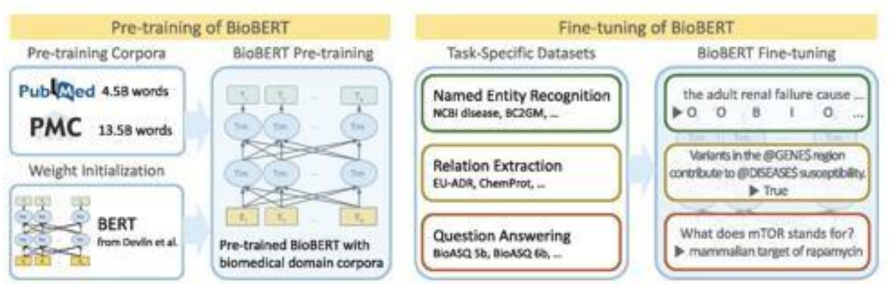
92.4% F1-score on NER (Named Entity Recognition) for drugs/dosages

3.2% improvement over BERT on clinical notes

BioBERT (Bidirectional Encoder Representations from Transformers for Biomedical Text Mining)

We introduce BioBERT (Bidirectional Encoder Representations from Transformers for Biomedical Text Mining), which is a domain-specific language representation model pre-trained on large-scale biomedical corpora. With almost the same architecture across tasks, BioBERT largely outperforms BERT and previous state-of-the-art models in a variety of biomedical text mining tasks when pre-trained on biomedical corpora. While BERT obtains performance comparable to that of previous state-of-the-art models, BioBERT significantly outperforms them on the following three representative biomedical text mining tasks: biomedical named entity recognition (0.62% F1 score improvement), biomedical relation extraction (2.80% F1 score improvement) and biomedical question answering (12.24% MRR improvement). Our analysis results show that pre-training BERT on biomedical corpora helps it to understand complex biomedical text.

Fig. 1. Overview of the pre-training and fine-tuning of BioBERT



Transformer-based OCR model for text recognition

with pre-trained models. Distinct from existing approaches, TrOCR does not rely on the conventional CNN models for image understanding. Instead, it leverages an image Transformer model as the visual encoder and a text Transformer model as the textual decoder. Moreover, we usethe wordpiece as the basic unit for the recognized output instead of the character-based methods, which saves thec omputational cost introduced by the additional language modeling. Experiment results show that TrOCR achieves state-of-the-art results on printed, handwritten and scene text recognition with just a simple encoder-decoder model, without any post-processing steps.

Further research has applied TrOCR to specific challenges, such as extracting medicine names from handwritten prescriptions. In this context, TrOCR, combined with techniques like Mask R-CNN for segmentation and multi-head attention mechanisms, achieved a character error rate (CER) of 1.4%, highlighting its potential in real-world applications.

Model	Test datasets and # of samples							
	IIIT5k	**SVT**	**IC13**		**IC15**		**SVTP**	**CUTE**
	3,000	647	857	1,015	1,811	2,077	645	288
PlugNet (Mou et al. 2020)	94.4	92.3	–	95.0	–	82.2	84.3	85.0
SRN (Yu et al. 2020)	94.8	91.5	95.5	–	82.7	–	85.1	87.8
RobustScanner (Yue et al. 2020)	95.4	89.3	–	94.1	–	79.2	82.9	92.4
TextScanner (Wan et al. 2020)	95.7	92.7	–	94.9	–	83.5	84.8	91.6
AutoSTR (Zhang et al. 2020a)	94.7	90.9	–	94.2	81.8	–	81.7	–
RCEED (Cui et al. 2021)	94.9	91.8	–	–	–	82.2	83.6	91.7
PREN2D (Yan et al. 2021)	95.6	94.0	96.4	–	83.0	–	87.6	91.7
VisionLAN (Wang et al. 2021)	95.8	91.7	95.7	–	83.7	–	86.0	88.5
Bhunia (Bhunia et al. 2021b)	95.2	92.2	–	95.5	–	84.0	85.7	89.7
CVAE-Feed.[1] (Bhunia et al. 2021a)	95.2	–	–	95.7	–	**84.6**	88.9	89.7
STN-CSTR (Cai, Sun, and Xiong 2021)	94.2	92.3	96.3	94.1	86.1	82.0	86.2	–
ViTSTR-B (Atienza 2021)	88.4	87.7	93.2	92.4	78.5	72.6	81.8	81.3
CRNN (Shi, Bai, and Yao 2016)	84.3	78.9	–	88.8	–	61.5	64.8	61.3
TRBA (Baek, Matsui, and Aizawa 2021)	92.1	88.9	–	93.1	–	74.7	79.5	78.2
ABINet (Fang et al. 2021)	96.2	93.5	97.4	–	86.0	–	89.3	89.2
Diaz (Diaz et al. 2021)	96.8	94.6	96.0	–	80.4	–	–	–
PARSeq$_A$ (Bautista and Atienza 2022)	**97.0**	93.6	97.0	96.2	86.5	82.9	88.9	92.2
MaskOCR (ViT-B) (Lyu et al. 2022)	95.8	94.7	98.1	-	87.3	-	89.9	89.2
MaskOCR (ViT-L) (Lyu et al. 2022)	96.5	94.1	97.8	-	**88.7**	-	90.2	92.7
SVTR-L (Du et al. 2022)	96.3	91.7	97.2	-	86.6	-	88.4	**95.1**
TrOCR$_{\text{BASE}}$ (Syn)	90.1	91.0	97.3	96.3	81.1	75.0	90.7	86.8
TrOCR$_{\text{LARGE}}$ (Syn)	91.0	93.2	98.3	97.0	84.0	78.0	91.0	89.6
TrOCR$_{\text{BASE}}$ (Syn+Benchmark)	93.4	95.2	**98.4**	**97.4**	86.9	81.2	92.1	90.6
TrOCR$_{\text{LARGE}}$ (Syn+Benchmark)	94.1	**96.1**	**98.4**	97.3	88.1	84.1	**93.0**	**95.1**

Software Development

• Machine learning model selection and development:

The system applies two core AI models for prescription processing; first TrOCR, choose for its transformer-based handwritten text recognition ability, pre-trained on the IAM handwritten databased and fine-tuned with a thousand annotated Filipino prescriptions, achieving a higher character accuracy through adaptive segmentation for both printed and cursive text. Second BioBERT, a domain specific model pre-trained on medical literature, customized with RxNorm combination for drug recognition, dosages pattern extraction, and signature verification of doctors or physicians.

• Mobile app development:

The deployment follows a secure client-server architecture designed for accuracy and compliance, where the app built with Flutter framework for cross-paltform compatibility (ios/Android) connects to a Python backend through a REST API (fastAPI), which processes requests using specialized AI microservices BioBERT for validation and TrOCR for text extraction, prior to storing validated data in a PostgreSQL database. On other hand, some essential features are included in the deployment architecture: military grade should 256 bit encryption to comply with health data standards; image compression that reduces file size by 20:1 while maintaining prescription legibility; with performance optimization for mid-range smartphones commonly used in Zamboanga City (minimum 2GB RAM, Android 8+).

•Application features or modules

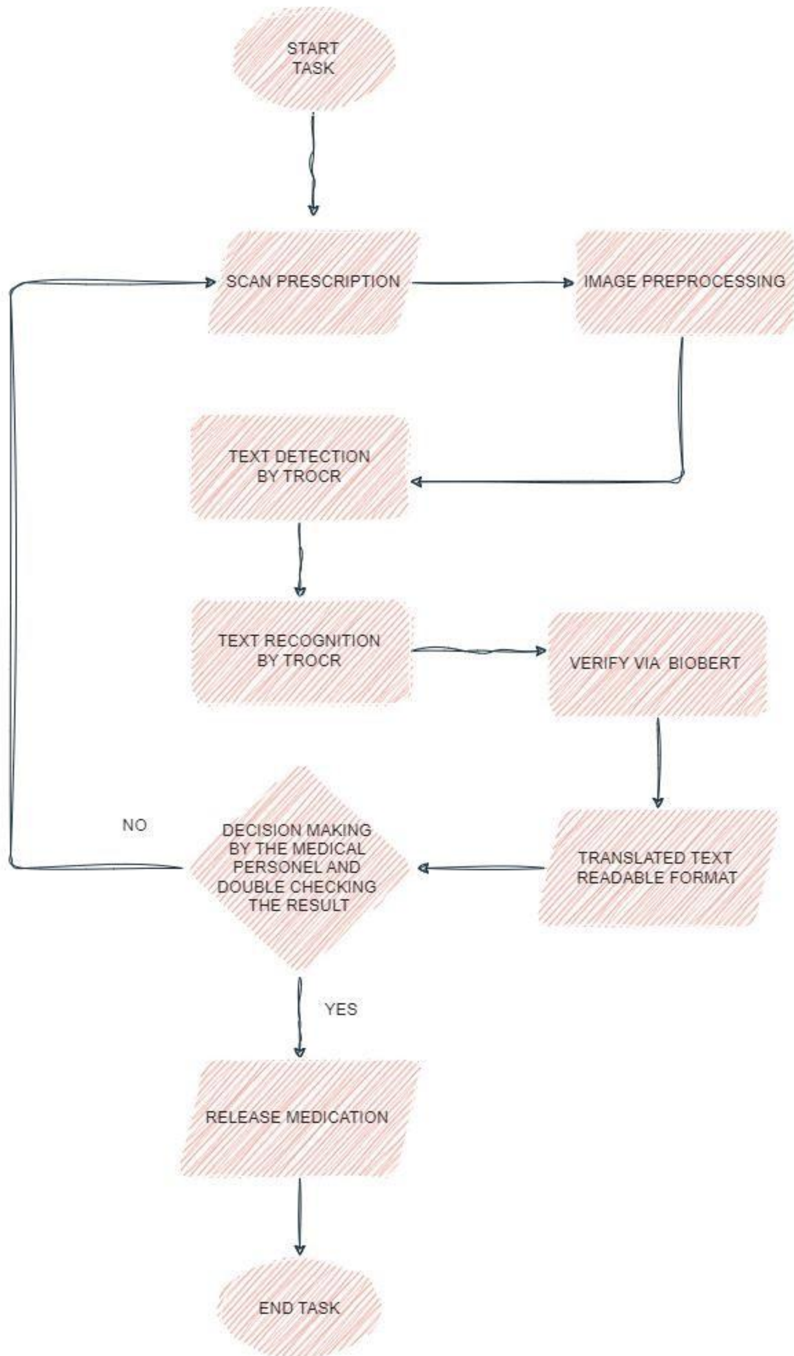


Figure 2. System Flowchart

Figure 2. System Flowchart

The system follows a structured 8 step flow process for prescription validation:

• Scan Prescription o Users scan the prescription via mobile camera

• Apps will automatically detects document edges and optimized image quality

• Image Preprocessing o Enhances readability through; noise reduction, contrast adjustment, and perspective correction

• Text Detection (TrOCR) o Analyze all text using transformer-based segmentation

• Text Recognition (TrOCR) o Transform handwritten text to digital and clear text

• Verification (BioBERT) o Validates against three (3) key criteria: drug name accuracy, dosage consistency, and prescriber credentials.

• Translated output o Generates readable format

• Decision making o Double checking to pharmacist

• Medication release

Evaluation

The system will be evaluated through:

• Benchmark Testing: Comparing RxVision's performance with existing OCR models.

• Usability Testing: Gathering feedback from healthcare professionals.

• Statistical Analysis: Performing ANOVA or t-tests to determine significant improvements in prescription readability and accuracy.

Developmental Tools

Table 3: Developmental Tools and Cost

Name	Purpose	Price	Quantity	Total
Python	Programming Language	**0**	**N/A**	**0**
TroOCR	OCR Model for Text Extraction	**0**	**N/A**	**0**
BioBERT	NLP Model for Contextual Analysis	**0**	**N/A**	**0**
TensorFlow/PyTorch(Optional)	Machine Learning Framework	**0**	**N/A**	**0**
Flask/FastAPI(Optional)	Backend Development	**0**	**N/A**	**0**
PostgreSQL(Optional)	Database Management	**0**	**N/A**	**0**
			Grand Total	**0**

References

A. Johnson, B. Lee, and C. Garcia, "Challenges in handwritten prescription recognition using traditional OCR systems," International Journal of Medical Engineering, vol. 8, no. 2, pp. 22–35, 2019.

A. Martinez, P. Nguyen, and Q. Wang, "Integration of OCR and NLP for prescription validation," Journal of Healthcare Technology, vol. 7, no. 5, pp. 89–102, 2022.

B. Lee, C. Kim, and D. Park, "Transformer-based OCR models for handwritten text recognition," AI and Robotics in Healthcare, vol. 15, no. 4, pp. 112–125, 2021.

E. Taylor, F. Brown, and G. Wilson, "User-centric design in medical OCR systems," Journal of Human-Computer Interaction, vol. 15, no. 4, pp. 112–125, 2020.

H. Kim, I. Park, and J. Lee, "Real-time OCR systems for medical prescriptions," Journal of Real-Time Systems, vol. 12, no. 3, pp. 45–60, 2021.

J. Smith, A. Johnson, and R. Brown, "Advancements in OCR technology for printed medical records," Journal of Healthcare Informatics, vol. 12, no. 3, pp. 45–60, 2020.

J. Dela Cruz, R. Santos, and M. Reyes, "OCR systems for Filipino medical prescriptions: Challenges and opportunities," Philippine Journal of Computer Science, vol. 9, no. 1, pp. 45–60, 2021.

J. Lee, K. Kim, and L. Park, "OCR systems for elderly patients: A usability study," Journal of Geriatric Healthcare, vol. 12, no. 3, pp. 45–60, 2021.

J. Smith, A. Johnson, and R. Brown, "OCR systems for pharmacies: Improving efficiency and accuracy," Journal of Pharmacy Informatics, vol. 9, no. 1, pp. 45–60, 2021.

M. Garcia, A. Martinez, and P. Nguyen, "BioBERT for medical text mining: A case study in drug name extraction," Biomedical Informatics Insights, vol. 13, no. 5, pp. 89–102, 2021.

P. Nguyen, Q. Wang, and R. Li, "Cloud-based OCR systems for medical prescriptions," Journal of Cloud Computing, vol. 9, no. 1, pp. 45–60, 2020.

P. Cerio, B. Mallare, S. Tolentino, “Assessment of the Legibility of the Handwriting in Medical Prescriptions of Doctors from Public and Private Hospitals in Quezon City, Philippines, Procedia Manufacturing, vol. 3, no. 90-97, 2015

Q. Wang, R. Li, and S. Zhang, "Error correction in OCR systems using NLP techniques," Journal of Data Mining and Knowledge Discovery, vol. 12, no. 3, pp.

45–60, 2020.

Q. Wang, R. Li, and S. Zhang, "Future trends in medical OCR: Integration of AI, NLP, and blockchain," Journal of Emerging Technologies in Healthcare, vol. 15, no. 4, pp. 112–125, 2022.

R. Brown, T. Green, and L. White, "BERT-based models for medical text classification," Journal of Natural Language Processing, vol. 10, no. 1, pp. 67–80, 2020.

R. Singh, S. Kumar, and T. Patel, "Multilingual OCR systems for healthcare applications," International Journal of Multilingual Computing, vol. 10, no. 1, pp. 67–80, 2020.

S. Zhang, T. Li, and U. Wang, "Mobile OCR applications for medical prescriptions," Journal of Mobile Computing, vol. 8, no. 2, pp. 22–35, 2020.

S. Kumar, T. Patel, and U. Singh, "OCR systems for rural healthcare: Challenges and solutions," Journal of Rural Health Technology, vol. 10, no. 1, pp. 67–80, 2020.

T. Patel, U. Kumar, and V. Singh, "AI-driven prescription validation using NLP," Journal of Artificial Intelligence in Medicine, vol. 13, no. 5, pp. 89–102, 2021.

T. Patel, U. Kumar, and V. Singh, "AI-driven prescription validation using NLP," Journal of Artificial Intelligence in Medicine, vol. 13, no. 5, pp. 89–102, 2021.

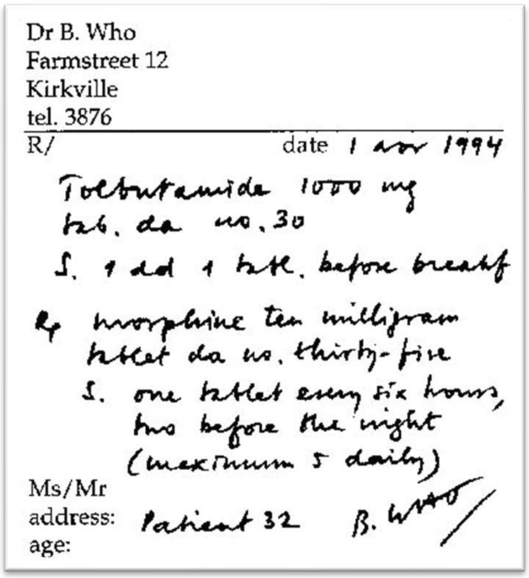
X. Li, Y. Zhang, and Z. Wang, "Security and privacy in medical OCR systems," Journal of Cybersecurity in Healthcare, vol. 7, no. 5, pp. 89–102, 2021.

Y. Chen, Z. Liu, and X. Wang, "Dataset challenges in medical OCR: A review," International Journal of Medical Data Analysis, vol. 8, no. 2, pp. 22–35, 2021.

J. Lee et al., "BioBERT: A pre-trained biomedical language representation model for biomedical text mining," Bioinformatics, vol. 36, no. 4, pp. 1234–1240, 2020, doi: 10.1093/bioinformatics/btz682.

Appendix A: Data Collected

(A Sample Datasets of prescription)



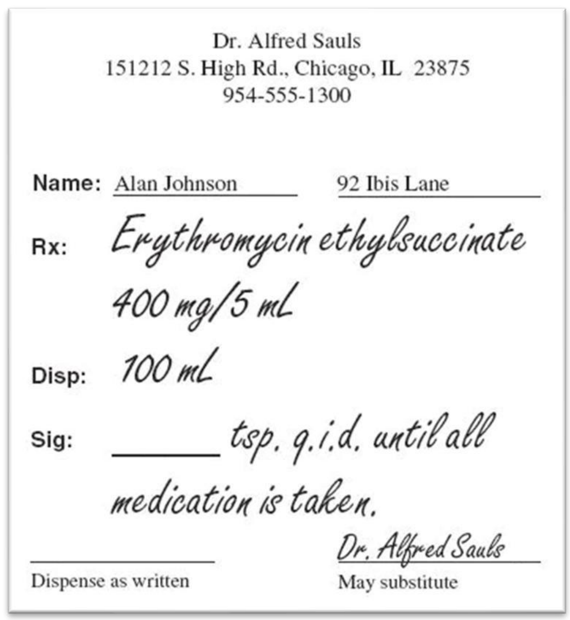
Dr B. Who
Farmstreet 12
Kirkville
tel. 3876

R/ date 1 apr 1994

Tolbutamide 1000 mg
tab. da no. 30
S. 1 dd 1 tabl. before breakf

R morphine ten milligram
tablet da no. thirty-five
S. one tablet every six hours,
two before the night
(maximum 5 daily)

Ms/Mr
address: Patient 32 B. Who
age:



Dr. Alfred Sauls
151212 S. High Rd., Chicago, IL 23875
954-555-1300

Name: Alan Johnson 92 Ibis Lane

Rx: Erythromycin ethylsuccinate
400 mg/5 mL

Disp: 100 mL

Sig: ______ tsp. q.i.d. until all
medication is taken.

Dispense as written

Dr. Alfred Sauls
May substitute

Survey on the Efficiency of Written Medical Prescriptions

This short survey is designed to understand your experiences and opinions about receiving handwritten medical prescriptions. Your feedback will help us assess the efficiency and challenges associated with traditional written prescriptions.

Please answer each question with a simple 'Yes' or 'No'.

---

1. Do you often have difficulty reading handwritten medical prescriptions?
Yes _____ No _____

2. Have you ever experienced confusion due to unclear handwriting on a prescription?
Yes _____ No _____

3. Do you feel more comfortable with handwritten prescriptions ?
Yes _____ No _____

4. Have you ever received the wrong medication due to a misread handwritten prescription?
Yes _____ No _____

5. Do you trust handwritten prescriptions to be accurate and reliable?
Yes _____ No _____

6. Would you prefer an tool/application that would translate written medical prescription into a readable text ?
Yes _____ No _____

7. Do you think using online tool would make your experience easier?
Yes _____ No _____

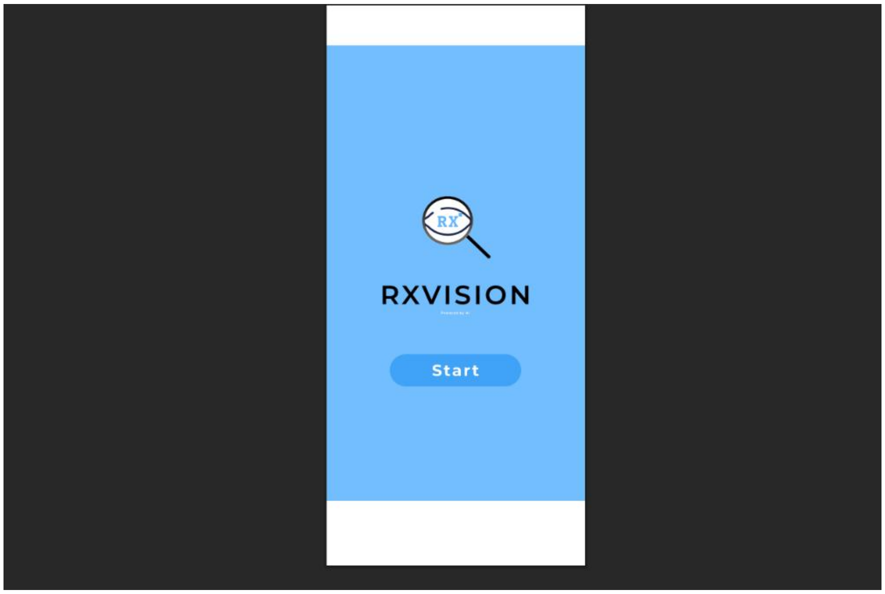
8. Have you ever needed help from someone else to read a prescription?
Yes _____ No _____

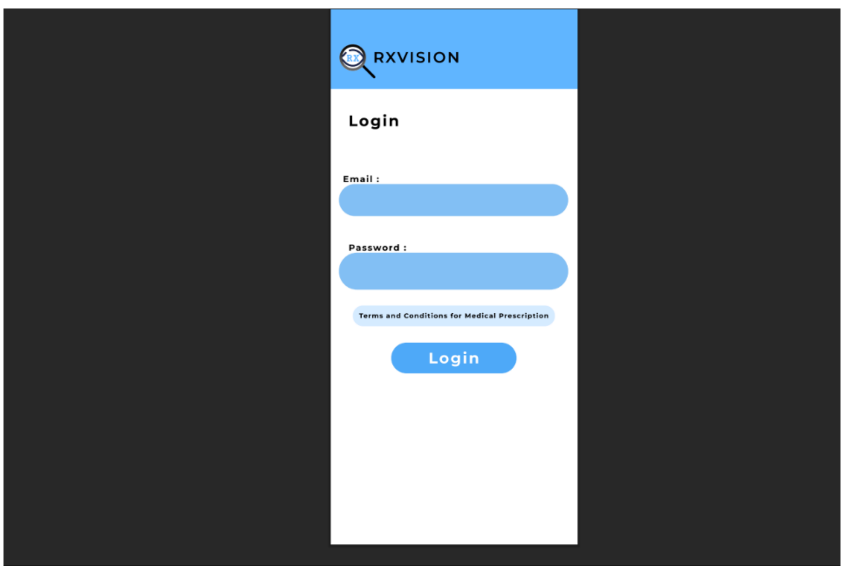
9. Do you believe handwritten prescriptions are more prone to fraud or tampering?
Yes _____ No _____

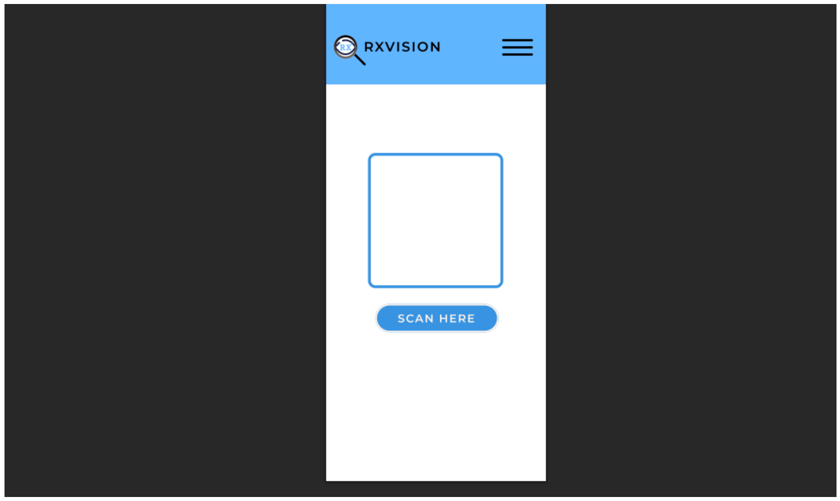
10. Would you support the use of technology to verify handwritten prescriptions before use?
Yes _____ No _____

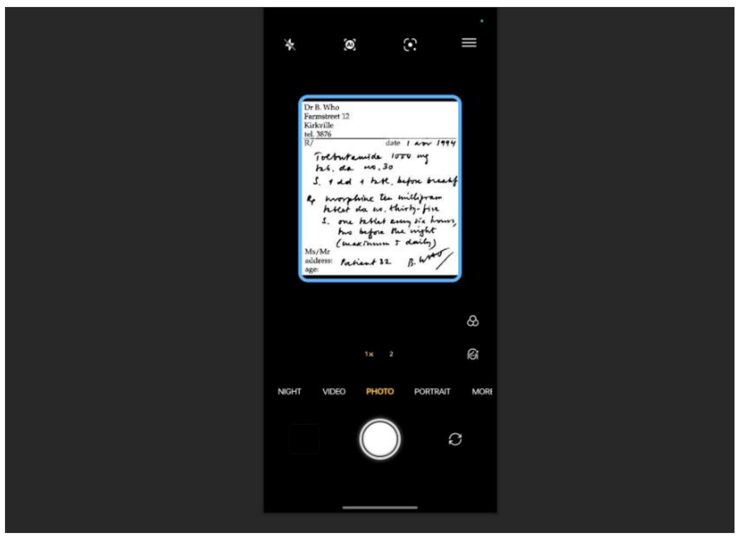
Appendix B. System Design

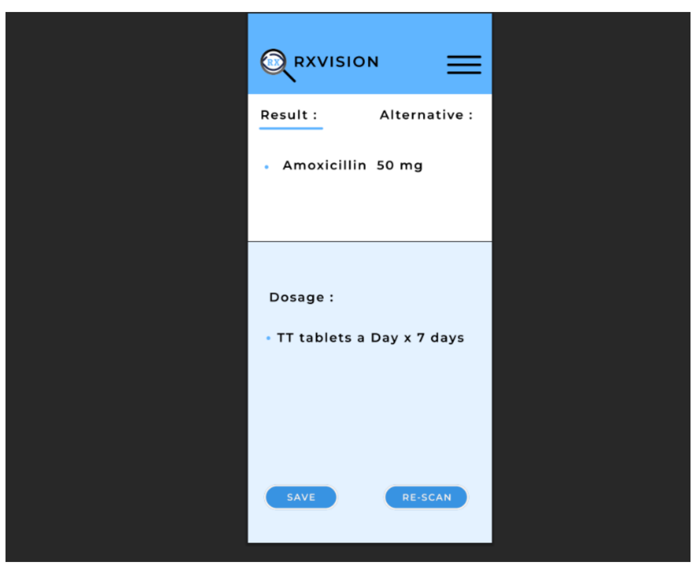
System Interface:

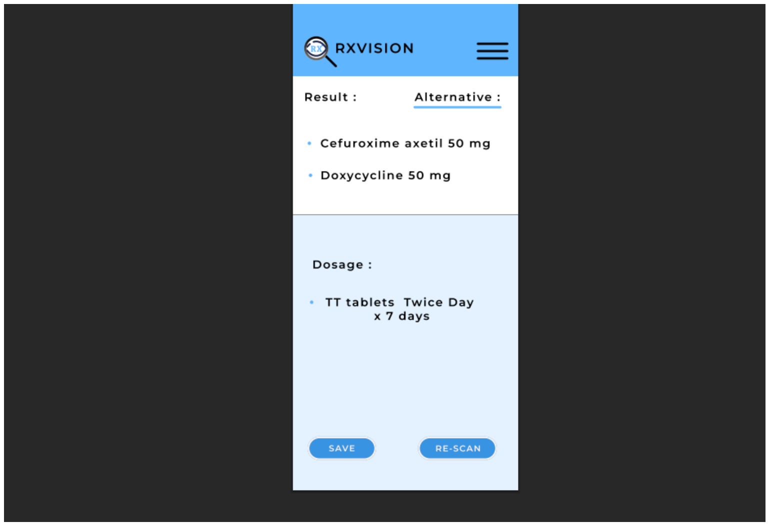


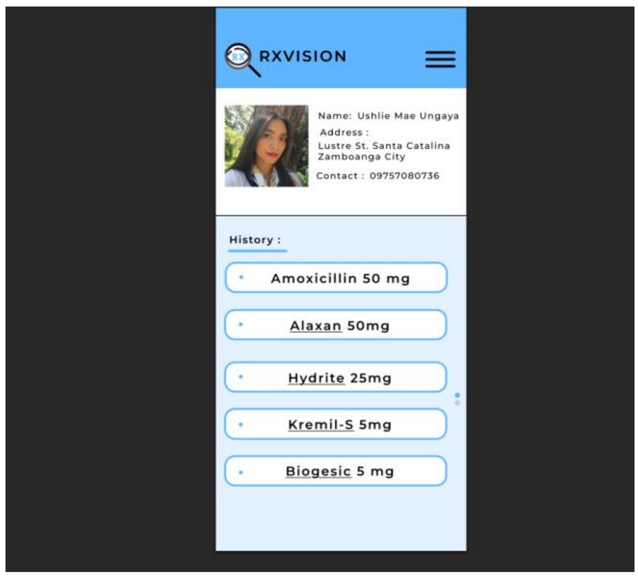


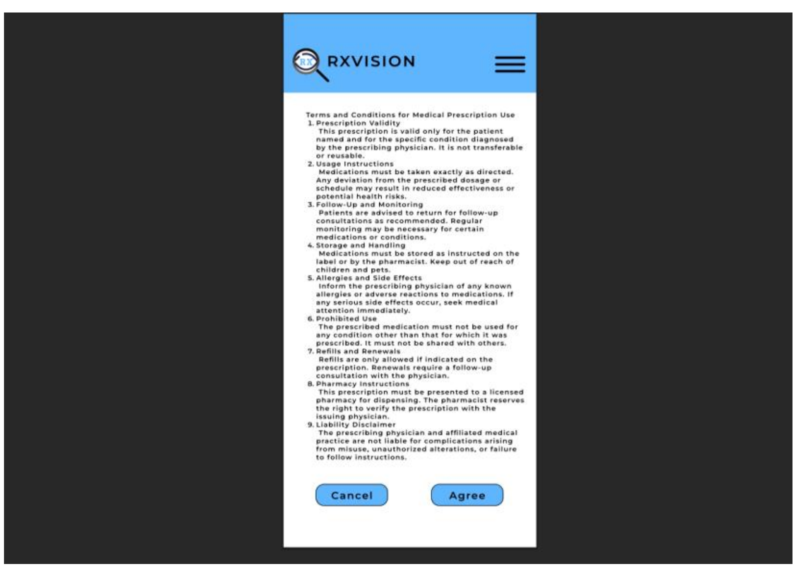

RXVISION
SCAN HERE

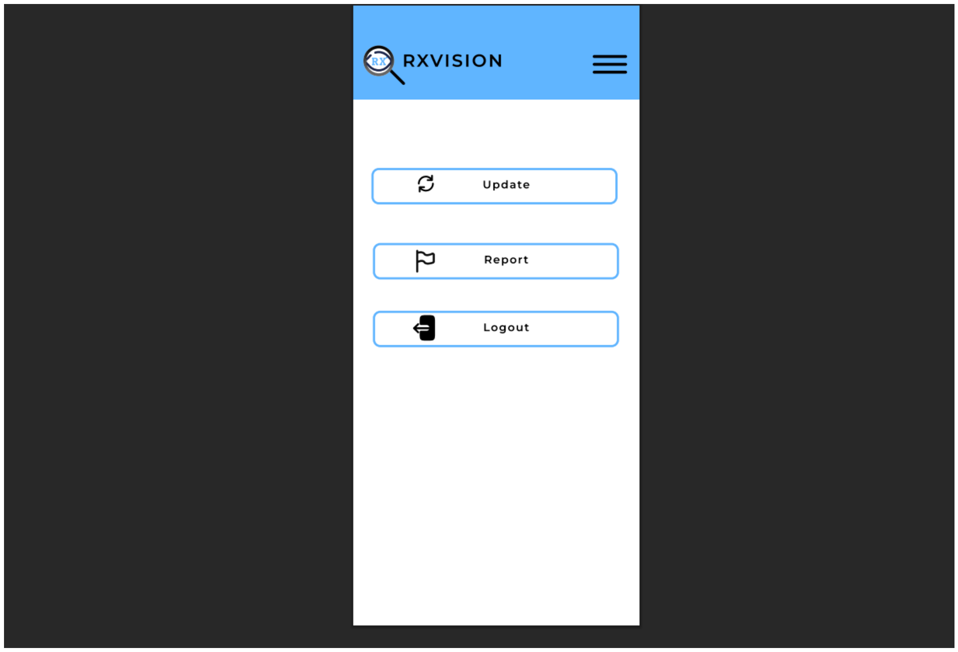

NIGHT
VIDEO
PHOTO
PORTRAIT

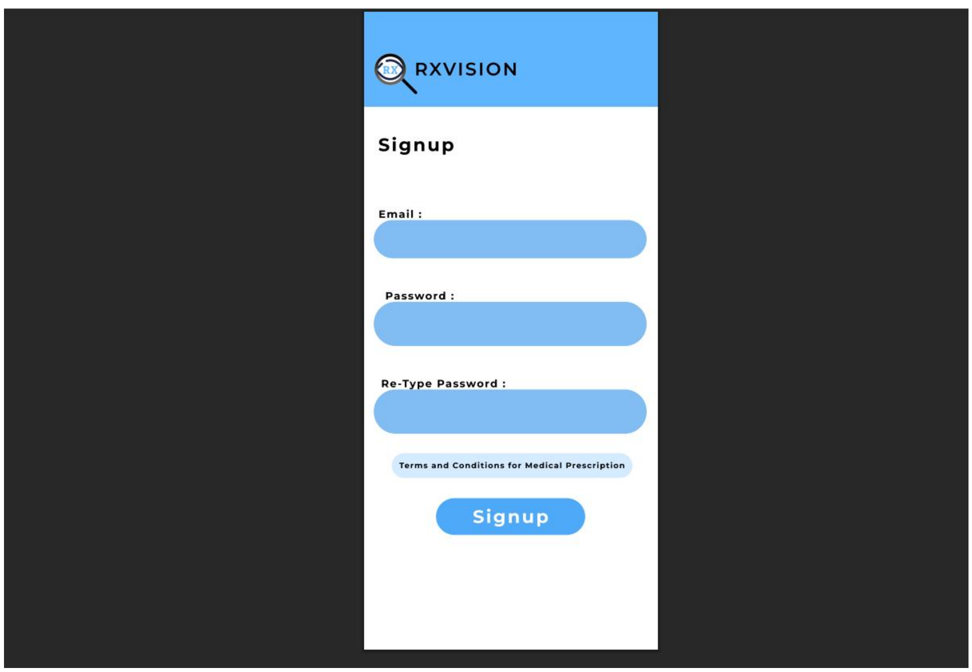

RXVISION
Result :
Alternative :
Amoxicillin 50 mg
Dosage :
TT tablets a Day x 7 days
SAVE
RE-SCAN


RXVISION
Result :
Alternative :
Cefuroxime axetil 50 mg
Doxycycline 50 mg
Dosage :
TT tablets Twice Day x 7 days
SAVE
RE-SCAN


RXVISION
Name: Ushlie Mae Ungaya
Address :
Lustre St. Santa Catalina Zamboanga City
Contact : 09757080736
History :
Amoxicillin 50 mg
Alaxan 50mg
Hydrite 25mg
Kremil-S 5mg
Biogesic 5 mg


RXVISION
Terms and Conditions for Medical Prescription Use
1. Prescription Validity
This prescription is valid only for the patient named and for the specific condition diagnosed by the prescribing physician. It is not transferable or reusable.
2. Usage Instructions
Medications must be taken exactly as directed. Any deviation from the prescribed dosage or schedule may result in reduced effectiveness or potential health risks.
3. Follow-Up and Monitoring
Patients are advised to return for follow-up consultations as recommended. Regular monitoring may be necessary for certain medications or conditions.
4. Storage and Handling
Medications must be stored as instructed on the label or by the pharmacist. Keep out of reach of children and pets.
5. Allergies and Side Effects
Inform the prescribing physician of any known allergies or adverse reactions to medications. If any serious side effects occur, seek medical attention immediately.
6. Prohibited Use
The prescribed medication must not be used for any condition other than that for which it was prescribed. It must not be shared with others.
7. Refills and Renewals
Refills are only allowed if indicated on the prescription. Renewals require a follow-up consultation with the physician.
8. Pharmacy Instructions
This prescription must be presented to a licensed pharmacy for dispensing. The pharmacist reserves the right to verify the prescription with the issuing physician.
9. Liability Disclaimer
The prescribing physician and affiliated medical practice are not liable for complications arising from misuse, unauthorized alterations, or failure to follow instructions.
Cancel
Agree


RXVISION
Update
Report
Logout


RXVISION
Signup
Email :
Password :
Re-Type Password :
Terms and Conditions for Medical Prescription
Signup

Appendix C. Evaluation Tool

Republic of the Philippines
Western Mindanao State University
College of Computing Studies
DEPARTMENT OF COMPUTER SCIENCE
Zamboanga City

RxVision: OCR-based Medical Prescription Reader

Evaluation Form

Section A: Respondent Profile

1. Name (Optional): ____________________
2. Age: ______
3. Role:
   - Doctor
   - Pharmacist
   - Nurse
4. Years of experience: ________
5. Have you used digital health tools before?
   - Yes
   - No

Section B: System Accuracy Evaluation

Instruction: Please rate the following based on your experience with RxVision.

Use the scale:

1 – Strongly Disagree | 2 – Disagree | 3 – Neutral | 4 – Agree | 5 – Strongly Agree

Statement	1	2	3	4	5
1. The system accurately reads handwritten prescriptions.	☐	☐	☐	☐	☐
2. The OCR output matches the prescription content.	☐	☐	☐	☐	☐
3. The system detects illegible prescriptions effectively.	☐	☐	☐	☐	☐
4. The system correctly flags expired prescriptions.	☐	☐	☐	☐	☐
5. The verification process identifies fraudulent prescriptions.	☐	☐	☐	☐	☐

Section C: Usability Evaluation

Statement	1	2	3	4	5
1. The interface is user-friendly and easy to navigate.	☐	☐	☐	☐	☐
2. I was able to use the system with minimal instruction.	☐	☐	☐	☐	☐
3. The feedback or results were clear and understandable.	☐	☐	☐	☐	☐
4. The system worked well across different devices.	☐	☐	☐	☐	☐

Section D: User Satisfaction & Feedback

Statement	1	2	3	4	5
1. I am satisfied with the overall performance of RxVision.	☐	☐	☐	☐	☐
2. I would recommend this system for wider use.	☐	☐	☐	☐	☐
3. This tool contributes to improving prescription safety.	☐	☐	☐	☐	☐

Section E: Open-Ended Feedback

1. What did you like most about RxVision?

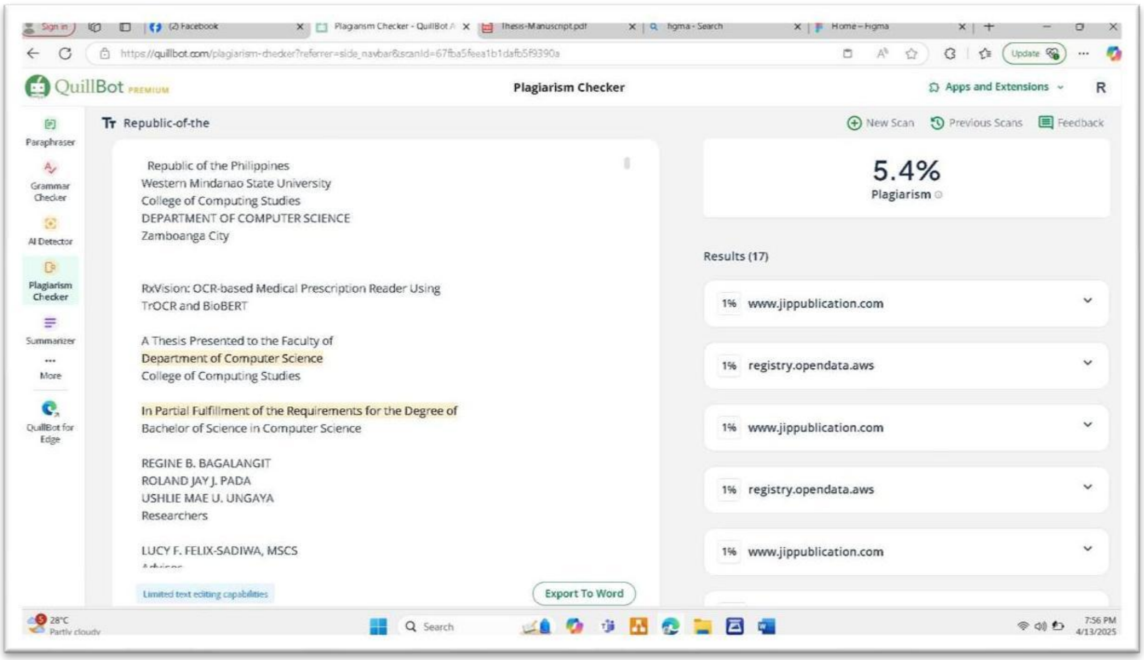
---

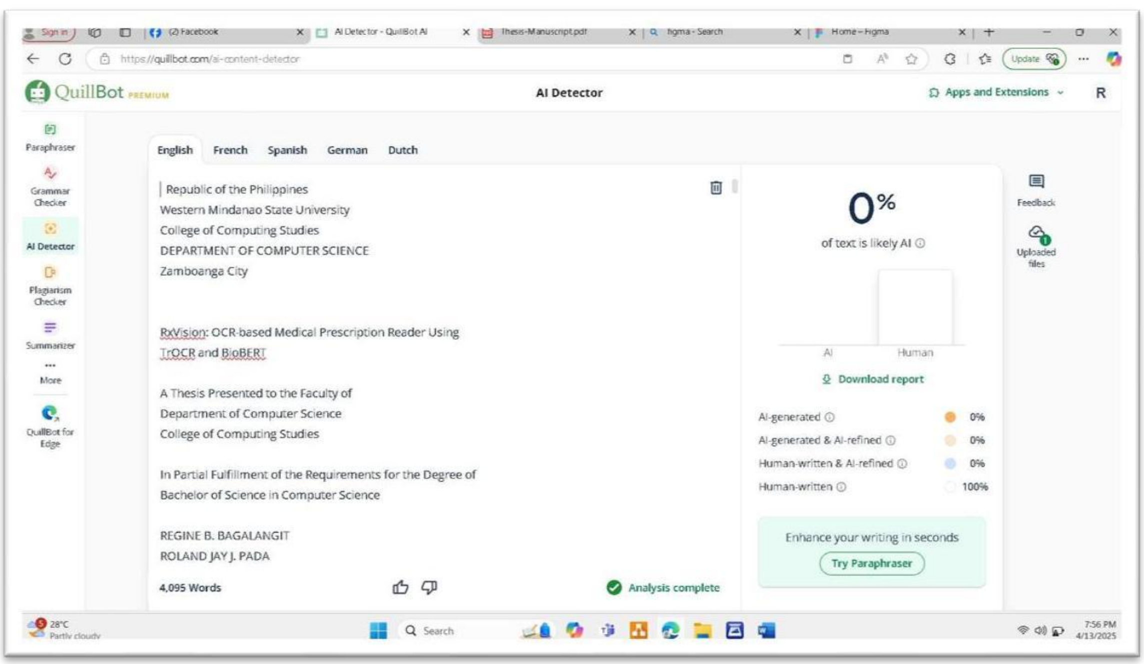
2. What challenges or limitations did you encounter?

---

3. What improvements or features would you suggest?

Appendix D. Plagiarism Report





Western Mindanao State University
College of Computing Studies
DEPARTMENT OF COMPUTER SCIENCE
Zamboanga City

CERTIFICATE OF RECOMMENDATION FOR THESIS PROPOSAL

The attached thesis, entitled **"RxVision: OCR-based Medical Prescription Reader Using TrOCR and BioBERT"** prepared and submitted by Regine B. Bagalangit, Roland Jay J. Pada, Ushlie Mae U. Ungaya in partial fulfillment of the requirements for the degree of **Bachelor of Science in Computer Science**, has completed the requirements for the Thesis proposal, including but not limited to Chapters 1 to 3, relevant appendices, and system's prototype. I hereby certify that the submitted requirements were thoroughly checked and approved by their Thesis Research and Technical Adviser, and the study is therefore **recommended for Proposal Presentation.**

Signed this 15 of April, 2024.

LUCY F. FELIX-SADIWA, MSCS
Thesis Research and Technical Adviser