PIN TO PILL (P2P)

Project Proposal

Habiba Yousry Said	habibayousri46@gmail.com
Haneen Akram Ahmed	Haneenakram3040@gmail.com
Mohammed Mostafa Mohammed	mohammedmostafa2372002@gmail.com
Renad Hossam Mohamed	renad03emara@gmail.com
Shrouk Mohamed Aboalela	Shroudmohamed1@gmail.com

JANUARY 1, 2025

CRISPY TEAM

STP Machathon6.00

I. Introduction

Let's face it—doctors are incredibly busy, often seeing dozens of patients daily. In the midst of their hectic schedules, they frequently rely on handwritten prescriptions to quickly communicate medication details. However, these prescriptions are not always easy to read. Poor handwriting, rushed notes, and complex medical abbreviations can make it challenging for pharmacists, nurses, and even patients to decipher the correct medication, dosage, or instructions. While electronic prescriptions are becoming more common in many healthcare systems, handwritten prescriptions are still widely used, especially in regions where digital systems haven't been fully implemented. This reliance on handwritten notes introduces a significant risk—misinterpretation can lead to patients receiving the wrong medication, incorrect dosages, or even missing essential treatments. Such errors can result in serious health complications, prolonged illnesses, and, in extreme cases, life-threatening consequences. To address this challenge, we are developing an AI-powered model designed to transform handwritten prescriptions into accurate, structured digital text. Our solution not only converts these prescriptions into easily readable formats but also integrates with scheduling systems to ensure timely medication reminders. By automating this process, we aim to enhance patient safety, reduce human error, and improve overall healthcare efficiency.

II. Problem Definition

Handwritten prescriptions remain a prevalent method of communication between healthcare providers and pharmacists. However, it is widely recognized that doctors often have illegible handwriting, which poses a significant challenge in accurately interpreting and dispensing medications. While the prescribing doctor may understand their own notes, other healthcare professionals—such as nurses and pharmacists—frequently encounter difficulties in reading and interpreting the information correctly.

A study conducted at National District Hospital examined the impact of illegible handwriting on prescription errors. Out of 300 analyzed cases, 88% of doctors were able to correctly read their own prescriptions, whereas the accuracy dropped to 82% for nurses and 75% for pharmacists. Notably, pharmacists, who are responsible for dispensing medications, demonstrated the highest rate of misinterpretation. Some of these reading mistakes were critical, posing a serious risk to patient safety, and in certain cases, the errors could lead to life-threatening consequences.

The inability to accurately decipher handwritten prescriptions contributes to medication errors, incorrect dosages, and potential adverse drug interactions. This problem is further exacerbated in multilingual healthcare environments where prescriptions may contain a mix of Arabic and English, increasing the complexity of interpretation. Given the risks associated with prescription misinterpretation, there is a critical need for an automated system that can accurately digitize handwritten prescriptions, extract relevant medical information, and facilitate medication adherence through structured scheduling.

- Challenges:
  - **Misinterpretation of handwritten text**, leading to medical errors.
  - **Difficulty in extracting key prescription details** (medicine names, dosages, appointment instructions).
  - **Mixed-language complexity** (Arabic & English in the same document).
  - **Noise from printed text and layout details** (doctor names, hospital headers).

III. Solution

Phase 1: Handwritten Text Extraction

Implementation Pipeline

Step 1: Image Processing & Segmentation

To enhance the image quality and improve text extraction, the following steps will be applied:

- **Grayscale conversion** to remove unnecessary color information.
- **Adaptive thresholding** to enhance contrast.
- **Morphological operations** (e.g., dilation, opening) to segment handwriting from printed text.
- **Deskewing** to correct orientation.
- **Noise removal** using Gaussian or median filtering to eliminate artifacts.

Step 2: Handwritten vs. Printed Text Segmentation

- **Mask R-CNN Model:**
  - Used for detecting and segmenting handwritten regions in the prescription.
  - Ignores detected printed text (headers, doctor names, etc.).
- **OCR-Based Filtering:**
  - Applies deep learning-based methods to differentiate handwritten from printed text.
  - Handwriting detection is based on irregular stroke patterns and cursive structures.

Step 3: Handwriting Recognition (Arabic & English)

The extracted handwritten text is then processed using Optical Character Recognition (OCR)

- **TrOCR-Base-Handwritten Model:** Recognizes handwritten text in both Arabic and English.
- **Language Identification:** A script identification model detects Arabic and English words separately before applying the respective OCR model.

Step 4: Handling Challenges

- **Misspelling Correction:** Post-processing with language models (spell-checkers) for Arabic and English.
- **Mixed-Script Handling:** Detects and processes Arabic and English text separately.

Evaluation Metrics

- **Word Error Rate (WER)** & **Character Error Rate (CER)** for accuracy.
- **Model Efficiency** to ensure lightweight, real-time performance.

Phase 2: Medicine and Appointment Extraction

Implementation Pipeline

1. **Translate the Entire Text to English (if necessary):**
    - Use a machine translation model (e.g., Google Translate API, MarianMT) to translate Arabic text to English.
    - Ensure the translation preserves the meaning of medical terms and instructions.
2. **Correct misspellings automatically using BERT's masked language Model (MLM).**
    - Use BERT's Masked Language Model (MLM) to predict and correct misspelled words.
    - Mask each word in the text and let BERT predict the correct word.
    - Validate corrected words against a medical dictionary or database.
3. **Correct misspellings in medicine with BioBert or Clinincal Bert.**
    - Use **BioBERT** or **ClinicalBERT** to correct misspellings in medicine names.
    - Fine-tune the model on a dataset of medical terms to improve its performance.
    - Validate corrected medicine names against a medical database.
4. **Fine-tune the NER model on a dataset of medical prescriptions or we could use models like BioBert and MidicalBert that been trained on the medicines.**
    - Collect and annotate a dataset of medical prescriptions with entities like:

  - MEDICINE_NAME: The name of the medicine (e.g., "Paracetamol").
  - APPOINTMENT_INSTRUCTION: The instructions for taking the medicine, including:
    - DOSAGE: The amount of medicine to take (e.g., "2 pills").
    - FREQUENCY: How often to take the medicine (e.g., "every 8 hours").
    - TIMING: When to take the medicine (e.g., "before meals").
- Fine-tune the NER model using frameworks like Hugging Face Transformers.
- Use BioBERT or ClinicalBERT as the base model for better performance on medical text.

5. **Normalize Extracted Appointment Instructions Using Rule-Based Systems**
   - Define rules to normalize appointment instructions into a standardized format.
   - Example:
     - Input: "Take 2 pills every 8 hours."
     - Output: "Frequency: Every 8 hours, Dosage: 2 pills."
   - Handle language-specific variations for Arabic and English instructions.

Evaluation Metrics

- **F1 Score**
- **Precision and Recall**
- **Word Error Rate (WER)**
- **Model Efficiency:**
  - **Inference Time:** The time taken to process a single prescription.
  - **Memory Usage**: The amount of memory required to run the model.

Phase 3: Scheduling

Finally, our system will automatically create a digital medication schedule for patients, ensuring they take the right medicine at the right time.

- **Goal:** Ensure the model correctly understands appointment times and can accurately schedule them.
- **Method:** Once the appointment expression is extracted from the previous step, create a set of rules or patterns to identify common time expressions and then map each time expression to its corresponding schedule.
  Example:
  - Every 8 hours: Schedule every 8 hours (8:00 AM, 4:00 PM, 12:00 AM).
  - Before meals: Schedule before breakfast, lunch, and dinner (7:00 AM, 12:00 PM, 6:00 PM).

- Twice daily: Schedule twice a day (8:00 AM, 8:00 PM).

- **How We'll Do It:**

  1- Data Preprocessing: Since the dataset is provided, our first step will be to preprocess the data to make it ready for training. This includes cleaning the images, normalizing text, and handling any inconsistencies in the dataset (e.g., varying handwriting styles, mixed languages, or noise in the images).

  2- Model Development: We'll fine-tune existing AI models (like BERT for NLP and YOLO for computer vision) to handle the unique challenges of prescription data. This includes training the models to recognize Arabic and English text, as well as mixed-language prescriptions.

  3- Testing and Evaluation: We'll test our system on the provided dataset and measure its accuracy using metrics like Word Error Rate (WER) and F1 Score. We'll also ensure the model is lightweight and efficient to avoid performance penalties.

Phase 4: Deployment & Finalization

The objective of this phase is to develop a **user-friendly website** for deploying our AI models, enabling users to upload prescription images for automated text extraction, medicine identification, and appointment-based medication scheduling. This website will serve as an interactive platform demonstrating the end-to-end solution, offering practical applications in healthcare.

1. **Frontend Development**: A responsive web interface built using **React.js** to facilitate image uploads, real-time processing, and structured display of extracted information that is hosted on **GitHub Pages** to ensure accessibility and ease of deployment.
2. **Backend Development**: A backend application developed using **FastAPI** and **Express.js**, integrating AI models for text extraction, medicine and appointment recognition, and scheduling through REST APIs.
3. **AI Model Integration**:
   - **Text Extraction API**: Recognizes and extracts handwritten text from prescriptions in Arabic, English, or a combination of both.
   - **Medicine & Appointment Identification API**: Extracts medicine names and instructions while correcting potential misspellings.
   - **Medication Scheduling API**: Generates structured medication schedules based on extracted appointment instructions.

- Deployed using **Docker containers** for scalability, efficiency, and ease of maintenance.

IV. Conclusion

We believe our AI-driven solution has the potential to make a real difference in healthcare. By automating the process of reading and interpreting handwritten prescriptions, we can reduce errors, save time, and improve patient outcomes. This isn't just a technical project—it's a way to make healthcare safer and more efficient for everyone. We're excited about the opportunity to bring this idea to life through Machathon 6.0, and we hope you'll join us in making this vision a reality.

V. References

- Brits, Hanneke & Botha, A & Niksch, L & Terblanché, R & Venter, K & Joubert, Gina. (2017). Illegible handwriting and other prescription errors on prescriptions at National District Hospital, Bloemfontein. South African Family Practice. 59. 50. 10.4102/safp.v59i1.4658.
- T. Jain, R. Sharma, and R. Malhotra, "Handwriting recognition for medical prescriptions using a cnn-bi-lstm model," 04 2021, pp. 1–4.
- C. E. Mook, C. Poo Lee, K. M. Lim, and J. Yan Lim, "Handwritten character and digit recognition with deep convolutional neural networks: A comparative study," in *2023 11th International Conference on Information and Communication Technology (ICoICT)*, 2023, pp. 137–141.

- Usman Ali Dept. of Computer Science GIFT University Gujranwala, University Gujranwala, Dept. of C. Science GIFT,   , Sahil Ranmbail Dept. of Computer Science GIFT University Gujranwala, Muhammad Nadeem Dept. of Computer Science GIFT University Gujranwala, Waqas Ali Dept. of Electrical Engineering (RCET) University of Engg. & Tech. Lahore Lahore, & Dept. of Electrical Engineering (RCET) University of Engg. & Tech. Lahore Lahore. (n.d.). Leveraging deep learning with multi-head attention for accurate extraction of medicine from handwritten prescriptions. https://arxiv.org/html/2412.18199v1