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MEDICAL PRESCRIPTION RECOGNITION USING MACHINE LEARNING

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Abstract—

This study presents an integrated approach for the automated identification and extraction of medicine names from handwritten medical prescriptions using computer vision and advanced deep learning techniques. The system is divided into two main components: a detection mechanism powered by the YOLOv5 framework to locate areas containing medicine names, and a text recognition module built upon a neural network to decipher the extracted content. Initially, the YOLOv5 model is trained over 1000 epochs using a labeled dataset of prescription images to accurately detect and isolate regions containing drug names. This object detection method is designed to handle multiple instances and works effectively in real time, even with intricate handwritten and printed inputs. Subsequently, the recognition component employs a deep learning model trained on a specially curated dataset of handwritten drug names. Preprocessing methods such as normalization and feature transformation prepare the input for the model, enabling it to learn and correctly interpret the textual information from the localized image segments. A web application developed with Flask, HTML, and CSS serves as the user interface, allowing users to upload prescription images. The system processes the input sequentially through the detection and recognition phases, ultimately providing a clear list of identified medicines. This automation of handwritten prescription analysis enhances the precision and speed of medication identification, supporting pharmacists and healthcare professionals in streamlining prescription management and minimizing human error in drug dispensation.

I INTRODUCTION

The incorporation of modern technologies into healthcare is revolutionizing service delivery by improving precision, operational efficiency, and patient safety. Among these advancements,artificial intelligence and automation have emerged as crucial tools for minimizing manual errors and enhancing decision-making. One particularly challenging area that stands to gain from such innovation is the reading and processing of handwritten medical prescriptions, which are frequently plagued by illegible handwriting and inconsistent formatting. To address these issues, this paper presents an Optical Character Recognition (OCR) system specifically tailored for medical prescriptions. Built upon a deep learning architecture, the system automates the detection and recognition of medicine names from scanned or photographed prescription images. By combining object detection techniques with robust text recognition models, the system offers a streamlined solution to minimize human errors and optimize the prescription handling process. Prescriptions contain vital instructions regarding medication names, dosages, and administration schedules, all of which are essential to patient treatment plans. However, handwritten notes can be easily misread, leading to potentially harmful mistakes in medication dispensation. The proposed system mitigates these risks through a two-step pipeline: first, the YOLOv5 algorithm identifies regions in the image likely to contain medicine names; then, a dedicated neural network processes and deciphers the text within those regions. By automating this traditionally manual task, the system not only improves reliability but also supports healthcare professionals in delivering safer, more efficient patient care.

II LITERATURE SURVEY

The automatic recognition of handwritten medical prescriptions has become a vital area of research, owing to its potential to enhance healthcare accuracy and reduce manual transcription errors. Recent advancements in computer vision and deep learning have opened up promising avenues for interpreting handwritten content and identifying medication information effectively.

A structured model proposed by [1] divides the prescription recognition pipeline into three stages: pre-processing, processing, and post-processing. In the initial stage, input prescription images undergo normalization, binarization, and morphological adjustments to prepare the data for analysis. Logical segmentation is performed to isolate regions such as physician details, clinic information, and the medication section. The processing stage involves the application of Convolutional Neural Networks (CNNs) for feature extraction, using layers such as convolution, ReLU activation, and max pooling. These extracted features are then passed through fully connected layers for classification. To enhance accuracy, the post-processing step uses Optical Character Recognition (OCR) to refine predictions, especially in cases where CNN confidence scores are low.

In another notable contribution, the ST-Med-Box system was introduced to support chronic patients who require complex medication routines [2]. Although the study focuses on recognizing text from packaging rather than prescriptions, the architecture—comprising an Android app, cloud-based processing server, and smart recognition hardware—demonstrates practical applications of OCR in healthcare. With a reported recognition accuracy of 96.6%, the study underscores the potential of deep learning systems for real-time drug identification and dose verification.

A dual-model verification system proposed by [3] further advances the field by integrating both image and text classification for prescription validation. The image component utilizes background-cleared blister images and applies Histograms of Oriented Gradients (HOG) along with CNNs and regression layers. In parallel, the text recognition model uses the Character Region Awareness for Text (CRAFT) algorithm and Keras-OCR to detect and extract textual content from blister packs. The system achieves a combined accuracy of 94.23%, demonstrating its robustness for validating dispensed medications against prescriptions.

Another research effort focuses on interpreting English handwritten prescriptions using a Deep Convolutional Recurrent Neural Network (DCRNN) coupled with Artificial Neural Networks (ANNs) [4]. The model segments the prescription into individual characters, processes them using sequential neural networks, and classifies them into a predefined set of characters. The system achieves a high recognition accuracy of 98%, reinforcing the effectiveness of using RNNs for temporally structured handwriting recognition tasks.

Addressing the challenges posed by multilingual prescriptions, a study by [5] introduces a deep learning model capable of interpreting handwritten medical texts in regional languages. The system integrates CNNs for feature extraction, RNNs and Long Short-Term Memory

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(LSTM) units for sequence modeling, and fuzzy matching techniques to map recognized items to pharmaceutical databases. Unicode encoding ensures multilingual compatibility, while the system's full automation—spanning preprocessing to output generation—makes it ideal for diverse linguistic environments.

III EXISTING SYSTEM

In the current healthcare setup, most prescription handling is still done manually, which brings several practical issues. Doctors usually write prescriptions by hand and give them directly to patients or send them to the pharmacy. However, due to different handwriting styles, frequent use of abbreviations, and sometimes a mix of regional languages or medical jargon, these handwritten notes can be quite hard to read.

This often causes confusion and can lead to serious mistakes. Pharmacists, especially when dealing with a high volume of prescriptions, may misinterpret drug names or dosages. Similarly, patients may find it difficult to understand what's written, which can affect how they take their medication and lead to incorrect use or even dangerous drug interactions.

Although there are some OCR (Optical Character Recognition) tools available, they are mostly designed for clean, printed text. These tools tend to struggle with the messy, cursive, or inconsistent handwriting seen in real-world prescriptions, particularly when the layout is disorganized and the terminology is highly specialized.

Manual systems also fall short in other ways—they don't give quick access to detailed drug information, and they lack features for checking if the prescribed medicine is appropriate or safe. On top of that, there's little to no integration with digital healthcare platforms, which limits their efficiency and ability to scale in modern healthcare environments.

IV PROBLEM STATEMENT

Handwritten medical prescriptions remain a fundamental part of clinical workflows, but their manual interpretation often leads to significant challenges. Illegible handwriting, use of non-standard abbreviations, and varying notation styles create room for human error, increasing the risk of incorrect medication dispensing, dosage mistakes, and potential drug interactions. Despite advancements in digital health solutions, an efficient and automated system for reliably interpreting such prescriptions is largely missing in current healthcare practices.

Existing OCR tools are primarily optimized for printed text and struggle with cursive, unstructured, and domain-specific handwritten content commonly found in prescriptions. Additionally, manual prescription handling lacks integrated mechanisms for secure data access, structured drug information retrieval, and scalable processing, which limits its usability and efficiency in busy clinical environments.

There is a critical need for an intelligent, secure, and scalable solution that can automate the extraction and recognition of medicine names from handwritten prescriptions. The system must reduce reliance on manual interpretation, ensure data accuracy, support secure and authenticated access to prescription information, and provide patients and healthcare providers with transparent, well-organized medical data—without substituting for professional medical judgment. Addressing this problem will help modernize healthcare delivery, improve patient safety, and streamline pharmacy operations in a privacy-compliant manner.

V OBJECTIVES

The development of the Medical Prescription Optical Character Recognition (OCR) system addresses the urgent need to improve the accuracy and efficiency of interpreting handwritten prescriptions. This system utilizes YOLOv5 for the automatic detection and localization of medicine names within prescription images, paired with a deep learning recognition model specifically trained to interpret medical handwriting. By automating this process, the system reduces the reliance on manual review, easing administrative workloads in clinical environments.

To ensure security and reliability, the system incorporates encrypted data handling and user authentication, integrated into a Flask-based web application. Built with scalability in mind, it features a user-friendly interface and has undergone extensive testing with real-world prescription samples to validate its effectiveness.

The platform not only enhances clinical workflows but also supports patients and healthcare professionals by offering organized access to comprehensive drug information. It promotes transparency, helps users make informed decisions, and aligns with medical data protection regulations. Additionally, thorough documentation and a commitment to ongoing updates—guided by user feedback—position the system as a sustainable and adaptable solution for various healthcare settings.

VI PROPOSED SYSTEM

To overcome the limitations of manual prescription interpretation, the proposed system introduces a fully automated Medical Prescription OCR platform, designed with deep learning techniques for precise detection and accurate text recognition. At the core of this solution is YOLOv5, a high-performance object detection model that analyzes the entire prescription image to accurately pinpoint regions containing critical information such as medicine names, dosage instructions, and additional notes. By isolating only the relevant areas, the system significantly reduces background interference, leading to improved accuracy during the recognition phase. For interpreting the handwritten content, the platform incorporates a Recurrent Convolutional Neural Network (RCNN). This model combines the strengths of convolutional layers—which are effective in extracting visual features from image data—with recurrent layers that are adept at understanding sequential patterns in handwritten text. This makes the system particularly effective at reading cursive writing and accommodating the variability in personal handwriting styles. Once text recognition is complete, the extracted information is compared against a structured pharmaceutical database. Advanced matching algorithms, including fuzzy matching and Unicode encoding, ensure compatibility with multilingual inputs and regional notations. The system then generates a clean, readable summary of the prescription, detailing medicine names, dosages, compositions, precautions, availability, and pricing from reliable sources. This end-to-end automation reduces human involvement in prescription interpretation, minimizing the risk of errors and improving turnaround time. Additionally, it enhances patient understanding by delivering clear drug information and supports healthcare professionals in managing prescriptions more efficiently and accurately.

VII METHODOLOGY

The development of the Medical Prescription Optical Character Recognition (OCR) system was carried out through a systematic, multi-stage process emphasizing accuracy, user accessibility, and robustness in extracting and analyzing handwritten medical prescriptions. Each phase was meticulously designed to ensure the final system performs efficiently under realistic healthcare conditions.

A. Dataset Preparation

To simulate real-world clinical scenarios, a diverse dataset of prescription images was compiled. This included both handwritten and printed prescriptions, covering a range of handwriting styles, document templates, and medication types. This variety aimed to reflect the complexities typically encountered in healthcare environments.

B. Data Labeling

The images in the dataset were manually annotated using the LabelImg tool. Key elements such as drug names, dosage information, and important textual fields were highlighted using bounding boxes. These annotations served as ground truth for training the object detection component of the system.

C. Object Detection Using YOLOv5

The annotated images were used to train the YOLOv5 model, a highly effective object detection algorithm. Through iterative training and fine-tuning across multiple epochs, the model learned to accurately identify and localize regions of interest—specifically those containing medicine-related text—despite variations in handwriting, image quality, and layout.

D. Handwriting Dataset for OCR

A separate dataset consisting of handwritten characters, numbers, and typical prescription phrases was compiled to train the recognition model. This dataset ensured the model could accurately interpret the kinds of alphanumeric patterns frequently seen in medical prescriptions.

E. Text Recognition Using RCNN

The cropped image segments identified by YOLOv5 were passed through a Recurrent Convolutional Neural Network (RCNN). This hybrid model leveraged convolutional layers for spatial feature extraction and recurrent layers for modeling sequence dependencies, enabling high-precision recognition of handwritten words and characters.

F. Image Preprocessing

Prior to training and inference, all image data underwent preprocessing steps such as resizing, noise removal, and padding. These techniques standardized image inputs, improved model training stability, and enhanced the consistency of recognition results.

G. Web Application Interface

A user-friendly web application was developed using HTML, CSS, JavaScript, and Flask. The frontend allows users to upload prescription images, while the backend communicates with the trained models, processes results, and displays structured outputs. The system avoids complex user authentication or persistent storage to streamline usability and deployment.

H. Model Integration and Workflow

The YOLOv5 detection model and the RCNN recognition model were integrated into the Flask-based backend. Uploaded images are sequentially passed through both models, and the recognized content is returned in a clean and readable format containing essential prescription data.

I. Structured Output and Searchability

The extracted text—covering drug names, dosages, and key instructions—is organized and displayed in a structured manner. The interface also allows users to look up alternative medications or additional drug details using a predefined, static reference dataset.

J. Patient-Centric Features

To promote patient awareness, the system presents the recognized medicine information in simplified language. It includes features for comparing branded and generic drug options, helping patients make cost-effective and informed decisions about their treatment.

K. Testing and Validation

Robust testing was performed using a wide variety of real prescription samples. Evaluation metrics such as detection accuracy, text recognition precision, and response time were measured to ensure the system's reliability in practical use.

L. Documentation and Training Support

Comprehensive documentation, including user manuals, help tips, and frequently asked questions (FAQs), was developed to assist users in understanding the system’s functionality. This ensures smooth onboarding for both healthcare workers and end users.

M. Privacy and Security Measures

Although the application does not involve user authentication or store any personal data, it strictly adheres to privacy best practices. All data

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transmissions are secured via HTTPS, and image processing is performed entirely in memory, avoiding any long-term data storage.

N. Scalability and Performance Optimization

The system is designed for lightweight deployment, featuring optimized image handling and minimal server load. While currently tailored for moderate usage, its modular structure supports future scaling through technologies like Docker containers and load-balancing infrastructure.

O. Maintenance and Future Enhancements

A structured maintenance plan is in place for ongoing system support. This includes regular updates, error monitoring, and model improvements based on user feedback and newly collected prescription data.

VIII IMPLEMENTATION

- **Data Annotation:** Prescription images are manually labeled using LabelImg, generatingbounding boxes around medicine names to create supervised training data.
- **Model Training:** The YOLOv5 model is trained iteratively on the annotated data, refiningdetection accuracy with hyperparameter tuning and validation tests.
- **Text Recognition Model**: Parallelly, a deep learning model is trained on a handwritten textdataset, enabling it to decode varied handwriting styles encountered in prescriptions.
- **Image Preprocessing:** Scripts are implemented to preprocess images for both training and real-time inference, including techniques such as grayscale conversion, denoising, and normalization.
- **Web Development:** The Flask backend is coded to serve API endpoints for image upload and result retrieval. The frontend is designed for ease of use, allowing users to upload prescriptions, view extracted data, and search pharmaceutical information.
- **Integration:** The object detection and text recognition modules are integrated into the backend, enabling end-to-end prescription processing.

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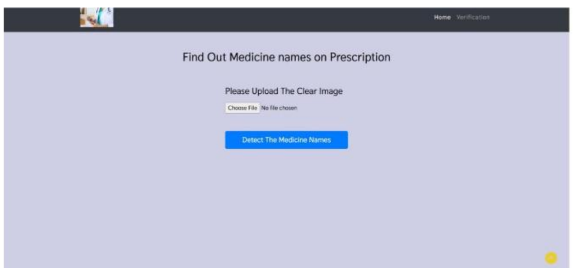
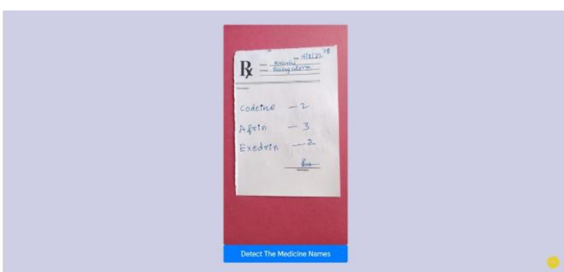
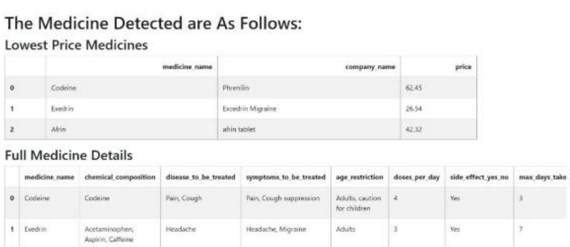
IX RESULTS







The Medicine Detected are As Follows:

Lowest Price Medicines

	medicine_name	company_name	price
0	Codeine	Phrenilin	62.45
1	Exedrin	Excedrin Migraine	26.54
2	Afrin	afrin tablet	42.32

Full Medicine Details

	medicine_name	chemical_composition	disease_to_be_treated	symptoms_to_be_treated	age_restriction	doses_per_day	side_effect_yes_no	max_days_take
0	Codeine	Codeine	Pain, Cough	Pain, Cough suppression	Adults, caution for children	4	Yes	3
1	Exedrin	Acetaminophen, Aspirin, Caffeine	Headache	Headache, Migraine	Adults	3	Yes	7

X CONCLUSION

develop an intelligent system capable of accurately detecting and recognizing medicine names from handwritten medical prescriptions using state-of-the-art deep learning methods. By integrating the YOLOv5 object detection framework with a powerful handwritten text recognition model, the system delivers a seamless pipeline—from image upload to structured text output.

The development process addressed several practical challenges, including inconsistencies in handwriting, diverse prescription formats, and varying image quality. Implemented in Python with support from the PyTorch library, the solution was deployed through a Flask-based web interface to ensure ease of use for end users. Extensive testing on a wide range of real-world prescription samples confirmed the system's effectiveness. The detection and recognition modules consistently achieved high accuracy, demonstrating the system's capability to assist pharmacists and medical professionals by minimizing interpretation errors, accelerating prescription handling, and improving workflow efficiency. Ultimately, this project represents a meaningful contribution to the digital transformation of healthcare. By automating the extraction of handwritten prescription data, it not only enhances operational efficiency but also supports safer, more informed medical practices.

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