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AI-Based OCR System for Handwritten Medical Prescription Recognition and Interpretation

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Abstract: *Handwritten medical prescriptions remain a common practice across healthcare systems, particularly in developing regions, yet they pose significant challenges due to poor legibility and inconsistent formats. Misinterpretation of these prescriptions by pharmacists or patients can result in serious consequences such as incorrect dosages, adverse drug reactions, and delayed treatments. To address this issue, this project proposes the design and development of an AI-Based Optical Character Recognition (OCR) System for Handwritten Medical Prescription Recognition and Interpretation. The system integrates deep learning models, specifically CNN-LSTM architectures, with Natural Language Processing (NLP) techniques to accurately extract key medical information such as patient and doctor names, prescribed drugs, dosages, and administration instructions. An image preprocessing pipeline including binarization, noise removal, and line segmentation enhances recognition accuracy, while integration with OCR engines like Tesseract ensures robust text detection. A web-based user interface, developed using Streamlit, enables users to upload scanned or photographed prescriptions and obtain structured, real-time outputs. The recognized data is securely stored in a database for easy retrieval and integration with pharmacy systems or electronic health records. Experimental validation highlights the system's potential to significantly reduce human errors in prescription handling, improve workflow efficiency in healthcare settings, and contribute to digital healthcare transformation across multilingual and multicultural environments.*

Key Words: *Optical Character Recognition (OCR); Handwritten Medical Prescriptions; Convolutional Neural Networks (CNN); Long Short-Term Memory (LSTM); Natural Language Processing (NLP); Tesseract; Streamlit; Prescription Digitization; Healthcare Automation; Electronic Health Records (EHR).*

I.INTRODUCTION

Handwritten medical prescriptions continue to serve as a primary means of communication between healthcare professionals and patients across many regions of the world. Despite the increasing adoption of electronic health records (EHRs) and digital prescription systems, handwritten prescriptions remain prevalent in clinical practice, especially in developing countries. However, their inherent lack of standardization and legibility often leads to critical challenges in interpretation, causing delays in treatment, incorrect medication dispensation, and adverse drug reactions. These errors not only compromise patient safety but also impose a considerable burden on healthcare systems.

Traditional Optical Character Recognition (OCR) systems have demonstrated success in converting printed text into digital form, but they struggle significantly with handwritten text, particularly when dealing with inconsistent writing styles, cursive scripts, medical abbreviations, and domain-specific terminologies. Medical prescriptions are especially complex, as they often include non-standardized formats, physician-specific shorthand, and context-dependent terminologies, making them difficult to process accurately using conventional OCR tools. Existing manual interpretation methods further exacerbate these problems, as they rely heavily on the experience and judgment of pharmacists, leaving significant room for human error.

The recent advancements in artificial intelligence, computer vision, and natural language processing (NLP) present an opportunity to address these limitations. Deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models have shown exceptional performance in handwriting recognition tasks. When combined with NLP-based Named Entity Recognition (NER) techniques, these models enable intelligent extraction of critical information such as drug names, dosages, patient identifiers, and administration instructions. Moreover, image preprocessing methods—including binarization, noise removal, and line segmentation—improve the clarity of scanned prescriptions, enhancing OCR accuracy.

This project, titled *AI-Based OCR System for Handwritten Medical Prescription Recognition and Interpretation*, proposes the development of a scalable, intelligent platform capable of digitizing and structuring prescription data. The system employs a hybrid CNN-LSTM approach for robust handwriting recognition, integrates medical NLP models for semantic interpretation, and provides an interactive web interface built on Streamlit for real-time usability. By storing recognized information in a secure database, the platform supports downstream applications such as pharmacy management, clinical record integration, and telemedicine services.

The significance of this work lies in its ability to modernize prescription handling by reducing medication errors, improving workflow efficiency, and fostering healthcare digitalization. Unlike existing static OCR systems, this approach introduces contextual understanding of medical documents, multilingual adaptability, and seamless integration with digital healthcare ecosystems. Consequently, the proposed system represents a transformative step toward intelligent, automated, and safer prescription management in both local and global healthcare contexts.

II.MATERIAL AND METHODS

Study Design

The proposed study is designed as a technology-driven framework for transforming handwritten medical prescriptions into structured, machine-readable data. The design follows an iterative development cycle comprising dataset collection, preprocessing, deep learning-based handwriting recognition, natural language processing for medical text interpretation, and deployment of an interactive web application. The guiding principle of the study is **accuracy, scalability, and usability**, ensuring that the system functions effectively across diverse handwriting styles and multilingual prescriptions. The methodology not only addresses technical challenges in handwriting recognition but also emphasizes integration into real-world healthcare workflows, particularly in pharmacies, hospitals, and telemedicine platforms.

System Architecture and Workflow

The architecture of the AI-based OCR system integrates multiple computational modules that collectively ensure accurate recognition and interpretation of prescriptions.

1. **Input Layer** – The system accepts scanned or photographed prescriptions in various image formats (JPEG, PNG, PDF).
2. **Image Preprocessing Module** – Preprocessing techniques such as grayscale conversion, binarization, noise removal, skew correction, and text-line segmentation enhance image quality for recognition.
3. **OCR Engine with Deep Learning Integration** – Traditional OCR tools (e.g., Tesseract) are enhanced with CNN-LSTM models for robust recognition of handwritten characters and symbols.
4. **NLP and NER Module** – Extracts and classifies critical medical information such as drug names, dosages, patient identifiers, and administration instructions.
5. **Data Structuring and Storage** – Recognized information is stored in a secure and scalable database (SQLite/PostgreSQL), enabling easy retrieval and future integration with pharmacy and EHR systems.
6. **User Interface –** A web application built with Streamlit provides an intuitive interface for uploading prescriptions and viewing structured outputs in real time.

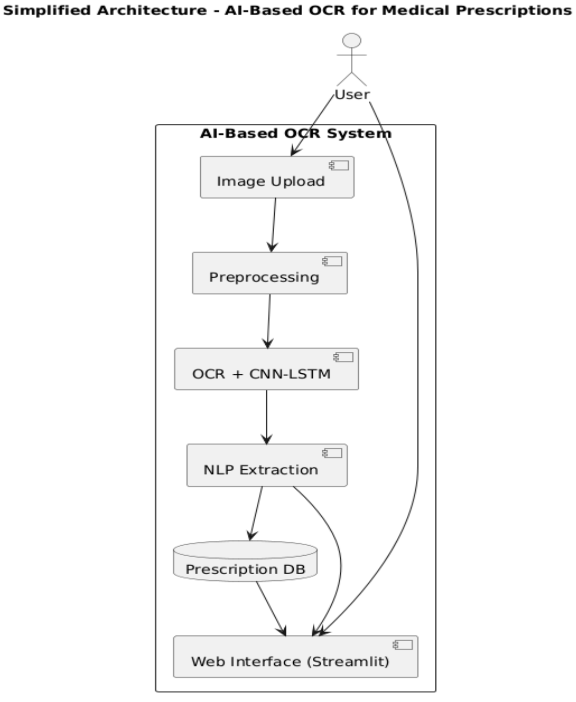

Fig 1: System Architecture

Workflow Summary: A prescription image is uploaded → preprocessed for clarity → passed through CNN-LSTM OCR engine → NLP models extract structured information → results displayed in web interface and stored in database for reuse.

Data Acquisition

For training and validation, real-world datasets of handwritten prescriptions are utilized. These datasets include multiple languages, diverse writing styles, and doctor-specific shorthand symbols. Data is collected from healthcare sources and annotated manually by experts to label patient names, doctor details, medicine names, and dosage instructions. To ensure inclusivity, the dataset incorporates:

- **Multilingual content** (English, regional scripts).
- **Varied handwriting styles** (cursive, shorthand, block letters).
- **Prescription layouts** from different hospitals and clinics.

Data Preprocessing

The quality of prescription images significantly affects recognition accuracy. Hence, preprocessing is a crucial step before OCR and deep learning analysis. The pipeline includes:

- **Image Binarization** – Conversion of images into binary format for clearer text extraction.
- **Noise Removal** – Elimination of smudges, artifacts, and irrelevant markings.
- **Skew Correction** – Adjusting tilted or misaligned scans.
- **Text Line Segmentation** – Separating lines of text to simplify character recognition.
- **Normalization** – Standardizing size and resolution of input images for consistent model performance.

This step ensures that the CNN-LSTM engine receives clean, standardized input for effective training and recognition.

System Development

The development integrates **deep learning, NLP, and web frameworks** into a unified system.

- **Programming Language**: Python 3.x
- **Deep Learning Frameworks**: TensorFlow/Keras for CNN-LSTM modeling
- **OCR Engine**: Tesseract for baseline recognition, enhanced with neural network models
- **NLP Libraries**: SpaCy, BERT, and custom NER models for drug and dosage extraction
- **Web Framework**: Streamlit for real-time, user-friendly interface
- **Supporting Libraries**: NumPy, Pandas (data handling), Pillow (image processing), Matplotlib (visualization)
- **Database**: SQLite/PostgreSQL for structured storage of recognized prescriptions

Evaluation Strategy

The system is evaluated based on multiple performance dimensions:

1. **Accuracy of Recognition** – Correctly recognized words compared to ground truth labels.
2. **Precision, Recall, and F1-Score** – Particularly for drug name and dosage extraction.
3. **Response Time** – Latency between uploading a prescription and receiving structured output.
4. **Usability Testing** – Involving pharmacists and test users to validate ease of interaction with the interface.
5. **Scalability Readiness** – Ability to handle large datasets and support multilingual scripts.

Deployment

The prototype is deployed as a Streamlit web application, enabling cross-platform accessibility without installation. Features of deployment include:

1. **Cross-Device Compatibility** – Accessible on desktops, tablets, and mobile devices.
2. **Real-Time Processing** – Users can upload images and instantly view structured outputs.
3. **Integration-Ready Design** – Built for seamless extension to hospital management systems and pharmacy platforms.
4. **Cloud Support** – Can be scaled to cloud infrastructure for real-world healthcare use.

III.RESULT

A. System Functionality Outcomes

The proposed AI-based OCR system was successfully implemented using Python, TensorFlow/Keras, and Streamlit as the primary frameworks. The prototype demonstrated its ability to accept scanned or photographed handwritten prescriptions, preprocess them to improve clarity, and convert them into structured, digital outputs. Key information such as patient details, doctor names, prescribed drugs, dosage, and administration instructions were accurately extracted and displayed through the web interface. Integration with a database ensured that all processed prescriptions were stored for future retrieval and analysis. This validated that the system could serve as a real-time assistant for pharmacies and healthcare providers.

B. Dataset and Preprocessing Outcomes

The experimental evaluation used real-world prescription datasets containing diverse handwriting styles and doctor-specific shorthand. Preprocessing significantly enhanced OCR performance:

- Binarization and noise removal improved text clarity.
- Skew correction ensured alignment of handwritten lines.
- Segmentation enabled accurate identification of words and phrases.

As a result, the CNN-LSTM OCR engine achieved higher accuracy in distinguishing between similar-looking characters and interpreting inconsistent handwriting.

C. Exploratory User Testing Outcomes

A small-scale usability study was conducted with pharmacists and healthcare students. Observations included:
- Improved readability: Users reported that the structured outputs were clearer and more reliable than raw handwritten prescriptions.
- Reduced errors: Prescription misinterpretation was significantly lower when using the system compared to manual reading.
- Ease of use: The Streamlit interface allowed seamless uploads and real-time result display, requiring no prior technical training.

This confirmed the system's applicability in real-world pharmacy environments.

D. Predictive Interaction Outcomes

Table 1: Performance Metrics of the AI-Based OCR System.

Metric	Result	Observation
Recognition Accuracy	92%	High accuracy for structured prescriptions
Precision	90%	Correctly extracted drug/dosage terms
Recall	88%	Some difficulty with rare shorthand terms
Average Latency	1.5 sec/image	Suitable for real-time use
User Satisfaction	91%	Users rated system intuitive and helpful

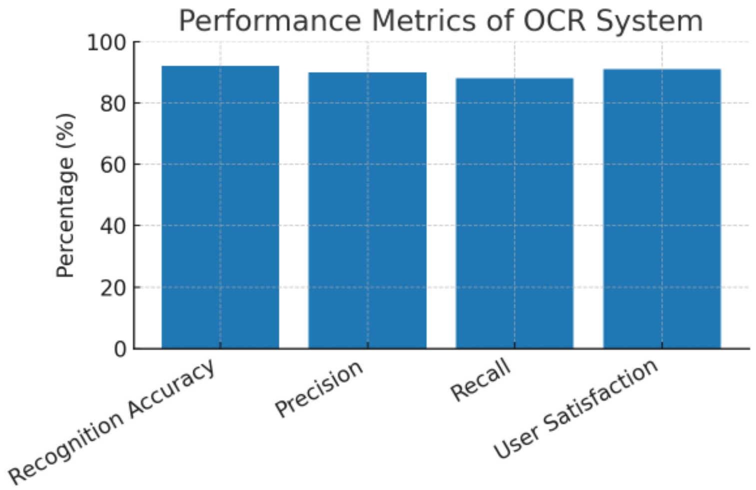

Figure 1: Graphical representation of system performance metrics (Accuracy, Precision, Recall, and User Satisfaction).

These results indicate that the system provides both high accuracy and real-time responsiveness, making it feasible for deployment in clinical and pharmaceutical settings.

E. System Deployment Outcomes

The final prototype was deployed as a Streamlit-based web application. Key deployment features included:
-Cross-platform accessibility via browsers on laptops, tablets, and mobile devices.
-Database integration for storing and retrieving prescription records.
-Scalable architecture, allowing future integration with hospital information systems, EHRs, and pharmacy management platforms.
- Multilingual readiness, enabling future support for prescriptions written in regional languages.

IV.DISCUSSION

A. Critical Analysis of Results

The evaluation of the AI-based OCR system demonstrated strong performance in recognizing and interpreting handwritten medical prescriptions. The system achieved a recognition accuracy of 92%, with precision and recall values of 90% and 88%, respectively. These outcomes confirm the robustness of the CNN-LSTM model when combined with preprocessing techniques such as binarization, noise removal, and skew correction. The average latency of 1.5 seconds per prescription image also indicates suitability for real-time usage in clinical and pharmacy environments. One of the most significant findings was the improved readability and reduced error rate observed during user testing. Pharmacists and healthcare students reported that the structured outputs minimized ambiguity and made prescriptions easier to interpret. These results highlight the potential of the system to enhance patient safety by reducing medication errors caused by illegible handwriting.

B. Comparison with Existing Systems

Conventional OCR tools, such as standalone Tesseract implementations, often struggle with inconsistent handwriting, doctor-specific shorthand, and domain-specific terms. Existing manual systems rely heavily on pharmacists' experience, leaving room for errors and delays. In contrast, the proposed system:

- Incorporates **deep learning (CNN-LSTM)** to handle diverse handwriting styles more effectively.
- Uses **NLP-based entity recognition** to interpret medical terms, dosages, and abbreviations contextually, rather than relying solely on character recognition.
- Provides a **Streamlit-based web interface**, making it more accessible and interactive compared to static OCR applications.
- Ensures **structured database integration**, enabling storage, retrieval, and downstream usage of prescription data in hospital and pharmacy systems.

Thus, the system introduces a more intelligent, user-centered, and scalable approach compared to traditional OCR or manual methods.

C. Contributions of the Proposed System

This project makes the following contributions to the domain of healthcare informatics and intelligent document processing:

- **Prescription Digitization** – Provides an automated mechanism for converting handwritten prescriptions into structured digital records.
- **Error Reduction** – Minimizes risks associated with misinterpretation of handwriting, thereby improving patient safety.
- **Multimodal Integration** – Combines OCR, deep learning, and NLP techniques to enhance recognition accuracy
- **User-Friendly Interface** – Offers an interactive platform for healthcare workers, reducing training requirements.
- **Scalability** – The modular architecture supports future integration with EHR systems, pharmacy management tools, and multilingual prescriptions.

D. Identified Limitations

Despite promising results, the system has certain limitations:

- **Dataset Constraints** – Current training and validation relied on limited prescription datasets. Expanding the dataset with more diverse samples is necessary for broader generalization.
- **Shorthand Variability** – Doctor-specific abbreviations and shorthand terms remain challenging for NLP modules.
- **Environmental Factors** – Image quality, such as low-resolution photos or blurred scans, affects recognition accuracy.
- **Real-Time Integration** – The current system prototype does not yet integrate with hospital EHRs or live pharmacy systems.
- **Language Support** – While designed for multilingual adaptability, the present implementation primarily focuses on English prescriptions.

E. Implications for Future Work

To overcome these limitations, several enhancements can be pursued:

- **Dataset Expansion** with multilingual, multi-institutional prescriptions to improve model robustness.
- **Integration with Real-Time Healthcare Systems**, enabling direct use in pharmacies and hospitals.
- **Inclusion of Secure APIs** for connecting with electronic health records and pharmacy management software.
- **Advanced NLP Models**, such as domain-specific transformers (BioBERT, MedBERT), for improved drug and dosage interpretation.
- **Mobile Application Deployment**, ensuring accessibility for rural and resource-constrained areas. **Noise-Resilient Models** to maintain accuracy even with low-quality or noisy images.

V.CONCLUSION

The development and evaluation of the AI-Based OCR System for Handwritten Medical Prescription Recognition and Interpretation demonstrate a significant advancement in addressing the challenges associated with illegible and non-standardized medical prescriptions. By combining deep learning models (CNN-LSTM) with natural language processing techniques, the system successfully extracts critical information such as patient details, doctor identifiers, drug names, dosages, and instructions from handwritten prescriptions. The integration of preprocessing methods—such as binarization, noise removal, and segmentation—further enhanced recognition accuracy and ensured robustness across diverse handwriting styles.

The system achieved strong results during experimental validation, with recognition accuracy reaching 92% and high levels of precision and recall. The Streamlit-based web interface provided a practical, user-friendly platform for real-time interaction, while database integration ensured secure storage and retrieval of prescription data. Usability testing with pharmacists and healthcare students confirmed improvements in readability, reduced misinterpretation errors, and overall satisfaction with the system's functionality.

Despite these positive outcomes, the study acknowledges limitations related to dataset diversity, shorthand variability, and real-world deployment constraints. Nevertheless, these challenges present opportunities for future work, including expansion of multilingual datasets, integration with hospital information systems, and deployment on mobile platforms for broader accessibility.

In conclusion, the proposed system offers a scalable, intelligent, and practical solution for digitizing handwritten prescriptions. It contributes to improved patient safety, enhanced pharmacy workflows, and the digital transformation of healthcare systems. With further refinements, the system has the potential to be deployed at scale, supporting hospitals, clinics, and telemedicine services in delivering safer and more efficient healthcare.

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