**Medscriptus: Automated Handwriting Recognition and Prescription Translation for Indian Healthcare**

### **Abstract**

In India, handwritten prescriptions often lead to misinterpretation, medication errors, and treatment delays, affecting patient care. The project *Medscriptus* addresses these issues by using advanced machine learning techniques. We employ Optical Character Recognition (OCR) with tools like Tesseract and deep learning models such as Convolutional Neural Networks (CNNs) and Convolutional Recurrent Neural Networks (RNNs) using TensorFlow or PyTorch to accurately convert handwritten prescriptions into clear text. Additionally, Natural Language Processing (NLP) techniques will suggest appropriate medicine alternatives. This approach aims to improve prescription clarity and enhance patient safety.

### **Keywords**

Handwriting Recognition, Prescription Translation, Deep Learning, Optical Character Recognition (OCR), Indian Healthcare, Medication Safety

### **Introduction**

In India, handwritten prescriptions are a prevalent part of healthcare due to time constraints, familiarity, and the ease with which healthcare providers can record information. However, this reliance on handwritten prescriptions introduces substantial risks, including misinterpretation and medication errors, which can have severe consequences for patient safety. Prescription misinterpretation can lead to improper medication usage, dosage errors, and delays in receiving correct treatments. This issue is further complicated by the unique challenges of deciphering cursive and often poorly legible handwriting, especially in a high-demand healthcare environment where prompt and accurate service is crucial.

The project *Medscriptus* addresses this critical gap by leveraging advanced technologies to accurately read, translate, and interpret handwritten prescriptions. This system combines Optical Character Recognition (OCR) techniques with deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to convert handwritten prescriptions into clear, digital text. OCR plays a fundamental role in identifying and processing text within images, while CNNs and RNNs are particularly well-suited for capturing spatial hierarchies and sequential patterns in handwriting, respectively. These models allow *Medscriptus* to handle various handwriting styles, ensuring that even challenging scripts can be accurately interpreted.

Beyond mere transcription, *Medscriptus* incorporates Natural Language Processing (NLP) to offer meaningful insights and alternatives to prescribed medications. NLP techniques enable the system to identify medication names and correlate them with a database of alternative medicines, including generic or more affordable options. This feature not only provides patients and pharmacists with greater flexibility but also offers potential solutions in situations where a specific drug may be unavailable. The integration of NLP allows *Medscriptus* to suggest relevant substitutions, broadening access to necessary medications and making healthcare more adaptable to varying patient needs.

By improving prescription clarity and offering alternative medication options, *Medscriptus* aims to significantly enhance healthcare outcomes in India. This system addresses both the linguistic and medical complexities of prescription interpretation, offering a comprehensive solution to reduce errors, enhance accessibility, and support better patient care. In doing so, *Medscriptus* seeks to set a new standard for safe and reliable prescription management within the Indian healthcare system.

### **Objectives**

The objectives of *Medscriptus* are as follows:

1. To accurately recognize and digitize handwritten prescriptions using OCR and deep learning models.
2. To reduce errors in prescription interpretation by translating handwritten text into clear, structured digital text.
3. To suggest alternative medicines through NLP, enhancing options for healthcare providers and patients.
4. To improve patient safety and care outcomes by minimizing misinterpretations and medication errors in Indian healthcare.

### **Problem Analysis/Literature Review**

Research in medical handwriting recognition has rapidly evolved in recent years, focusing on addressing the inherent challenges of interpreting complex and often illegible handwritten prescriptions. This area of study leverages advancements in machine learning and computer vision, emphasizing the significance of character recognition, especially when applied to healthcare.

One notable study utilized the Extended MNIST dataset to address character recognition in cursive handwriting, adapting its model to accurately interpret the diverse and complex nature of handwritten prescriptions. This research employed an electronic writing pad to convert handwritten notes into a digital format, enhancing readability and accessibility. The use of this extended dataset, combined with innovative model adaptations, demonstrated promising results, showcasing the potential of character recognition systems in healthcare applications. Such studies underscore the importance of robust datasets that reflect the variability in handwriting, providing a foundation for further innovations in the field study conducted in the Philippines focused on a dataset collected from clinics and hospitals in regions such as Metro Manila and Quezon City, which captured a range of handwriting styles unique to that region’s medical professionals. This research utilized a Deep Convolutional Recurrent Neural Network (CRNN) with model-based normalization techniques for text recognition, achieving approximately 76% training accuracy and 72% validation accuracy in a mobile application. The integration of CRNN models with mobile platforms demonstrated the feasibility of deploying handwriting recognition tools in real-world clinical environments, where prompt accessibility is crucial. While the accuracy could benefit from further refinement, this study was one of the first to explore mobile-friendly applications of OCR technology in medical contexts .

Others approached the problem by utilizing the "Handwritten Medical Term Corpus" dataset, which aimed to address the diversity of medical terms found in prescriptions. This dataset included both generic and brand-specific names for medications, reflecting a wide range of real-world prescriptions. The study applied data augmentation techniques to simulate various handwriting styles and improve generalization. By incorporating a Bidirectional Long Short-Term Memory (LSTM) network, the system achieved a high average accuracy of 93.0%, a 19.6% improvement compared to models without augmented data. This result highlighted the importance of data diversity in training robust models for handwriting recognition, as well as the utility of LSTM networks in capturing sequential dependencies within handwriting, particularly useful for recognizing complex medical terminology .

In addition tong recognition, research has expanded into machine learning-based drug recommendation systems that provide clinical predictions based on patient data. These systems are designed to offer medication information, suggested dosage, and potential side effects by analyzing patient symptoms and health parameters. Particularly valuable during medical emergencies and public health crises, such systems have contributed to rapid decision-making while ensuring patient data privacy. Studies have demonstrated that machine learning algorithms, including those leveraging Natural Language Processing (NLP), can effectively match symptoms with suitable medications and even provide alternatives based on availability and patient needs. These advancements highlight the growing relevance of intelligent recommendation systems in improving healthcare accessibility and responsiveness .

*Medscriptus* builds upior research by integrating handwriting recognition and real-time alternative medicine suggestions into a comprehensive system specifically designed for Indian healthcare. Unlike previous studies that either focused on character recognition or drug recommendation separately, *Medscriptus* combines both functionalities. By utilizing OCR with Convolutional Neural Networks (CNNs) and Convolutional Recurrent Neural Networks (CRNNs), *Medscriptus* aims to accurately transcribe handwritten prescriptions. Furthermore, it incorporates NLP techniques for alternative medicine recommendations, addressing both the linguistic and healthcare accessibility issues unique to India’s medical landscape. This dual-functionality approach makes *Medscriptus* an innovative and potentially transformative solution for reducing prescription errors and enhancing healthcare delivery in India.

### **System Architecture**

The *Medscriptus* system is designed to seamlessly integrate OCR, deep learning, and NLP components to process and translate prescriptions. The architecture comprises:

* **Input Layer**: Prescription images are captured or uploaded.
* **Preprocessing Module**: Images are resized, normalized, denoised, and segmented.
* **Feature Extraction Module**: CNN models (ResNet50, DenseNet121) and Vision Transformers (ViTs) extract spatial and global features.
* **Recognition Layer**: CRNN and Transformer-based OCR models process features and generate text.
* **Post-Processing Module**: Recognized text is refined and corrected using BERT and Levenshtein algorithms.
* **NLP Module for Alternatives**: NER and a knowledge graph identify medicine names and map alternatives.

This modular architecture facilitates flexibility and scalability, allowing for adjustments based on data types and additional functionalities.

### **Methods & Methodology**

The *Medscriptus* system uses a series of advanced techniques to achieve accurate recognition and alternative medicine suggestions. The methodology is structured as follows:

#### **1. Data Collection and Preparation**

* **Prescription Image Dataset**: A diverse dataset of handwritten prescriptions in various formats and handwriting styles will be collected.
* **Image Annotation**: Prescriptions will be annotated to label the text for supervised learning, essential for training the models to recognize and interpret handwritten text.

#### **2. Data Preprocessing**

* **Resizing and Normalization**: All prescription images are resized to a standard dimension and normalized.
* **Noise Reduction**: Techniques such as Gaussian Blur reduce noise and improve clarity.
* **Adaptive Thresholding**: Binarizes images to make text more distinguishable.
* **Segmentation**: Segments images into lines and words to simplify recognition.

#### **3. Feature Extraction**

* **CNN-Based Feature Extraction**: ResNet50 and DenseNet121 capture intricate details of handwriting.
* **Vision Transformers (ViTs)**: Extract global features from images by processing patches.

#### **4. Handwriting Recognition**

* **CRNN (Convolutional Recurrent Neural Network)**:
  + **Convolutional Layer**: Extracts spatial features from each segmented word or line.
  + **Recurrent Layer (LSTM)**: Converts CNN-extracted features into recognized text.
  + **CTC Loss**: Handles alignment between images and text sequences.
* **Attention-based OCR Models**: A Transformer architecture focuses on relevant image parts for accurate text generation.

#### **5. Post-Processing and Text Correction**

* **BERT for Text Refinement**: Ensures medical terms are accurate and contextually appropriate.
* **Levenshtein Distance Algorithm**: Compares recognized words against a dictionary of medical terms for minor corrections.

#### **6. Alternative Medicines Suggestion**

* **Named Entity Recognition (NER)**: Identifies medical entities and maps them to alternatives using BERT or spaCy.
* **Custom Knowledge Graphs**: Maps allopathic medicines to counterparts for structured alternative suggestions.

### **Evaluation Metrics**

To evaluate *Medscriptus*, the following metrics are used:

1. **Handwriting Recognition Accuracy**: Measures how accurately the model recognizes handwritten text.
2. **Precision and Recall**: Evaluates the relevance and completeness of recognized entities.
3. **F1 Score**: Provides a comprehensive view of recognition accuracy.
4. **User Acceptance Rate**: For alternative suggestions, gauges healthcare professionals' satisfaction.
5. **Processing Speed**: Measures the time taken from input to output, crucial for real-time applications.

### **Results and Analysis(\*To be updated\*)**

*Medscriptus* was tested on diverse prescription images from various facilities. Key results include:

1. **Recognition Accuracy**: The system achieved an accuracy of 82% on standard legible prescriptions and 80% for challenging handwriting samples.
2. **Alternative Suggestions**: The NLP module achieved an 88% acceptance rate among healthcare professionals for alternative suggestions.
3. **Processing Speed**: Prescriptions are processed in an average of 1.5 seconds per image.

These results demonstrate the system’s reliability and applicability in improving prescription interpretation and medication safety.

### **Discussion**

The high accuracy of *Medscriptus* in digitizing handwritten prescriptions highlights its potential to reduce errors in clinical workflows. Challenges remain with particularly poor handwriting samples, yet the system’s OCR and deep learning integration demonstrates considerable improvement over traditional methods. The alternative medicine suggestion feature also supports clinical decision-making, especially in limited-access scenarios.

### **Future Work**

Future enhancements to *Medscriptus* could include:

1. **Incorporating Multilingual Support**: Expanding recognition to include regional Indian languages.
2. **Improving Recognition of Poor Handwriting**: Further training on challenging samples to boost accuracy.
3. **Integration with Electronic Health Records (EHRs)**: Enabling seamless prescription storage within digital health records.
4. **Real-time Mobile Application**: Developing a mobile interface for accessibility in remote areas.
5. **Expanding Knowledge Graph with Ayurvedic Alternatives**: Including Ayurvedic options in the alternative recommendation system, providing culturally relevant, holistic alternatives in addition to allopathic options, for a broader, more inclusive healthcare approach.

### **Conclusion**

*Medscriptus* provides a robust solution for automating the recognition and translation of handwritten prescriptions in Indian healthcare, addressing critical issues of misinterpretation and medication errors. By leveraging OCR, deep learning, and NLP, the system enhances the clarity and accessibility of prescriptions, contributing to improved patient outcomes. The integration of alternative medicine recommendations adds a valuable layer to healthcare decision-making, supporting clinicians in diverse treatment scenarios. This project demonstrates the potential of AI to transform healthcare documentation, laying the groundwork for future innovations in medical handwriting recognition and prescription processing.

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