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Handwritten Medical Prescription Recognition using Deep Learning Technique

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***Abstract*—The difficulty in deciphering doctors' incomprehensible handwriting poses a substantial obstacle for both the general public and pharmacists.This paper addresses the persistent challenge of systematically extracting drug names from medical prescriptions, focusing on mitigating the risks associated with illegible handwritten prescriptions that can lead to medication errors and patient harm. The proposed methodology involves a comprehensive process, starting with the collection and preprocessing of medical prescriptions to ensure data consistency, integration of a Convolutional Neural Network (CNN) for training the model and for making prediction. The trained CNN model is used to evaluate the quality of prescriptions. This process is followed by the application of Optical Character Recognition (OCR) to convert these images into text. This combination facilitates subsequent Named Entity Recognition (NER) techniques, enabling accurate identification of drug names. The drug names identified by the NER system is then integrated with a side effect dataset which enabled the extraction of corresponding side effects associated with the drug. The ongoing work also focuses on integrating all these features in a user friendly mobile application. This tool addresses the challenges posed by illegible prescriptions, providing a significant advancement in drug name extraction for practical healthcare applications.**

***Index Terms*— Convolutional neural network, named entity recognition , optical character recognition, drug side effects, medical prescription.**

I. INTRODUCTION

Accurate information retrieval is crucial in healthcare, especially with the challenges posed by illegible handwriting on prescriptions. Computational solutions have been proposed to address this issue, focusing on improving the quality of prescriptions for better patient care and efficient medication dispensing. A previous study assess the quality of prescriptions written by dental and medical students and practitioners[1] . Similar studies utilized simulation exercises and statistical analysis to compare the quality of prescription writing among different groups[2].The extraction of drug names, specifically isolating them from the entirety of medical prescriptions, represents a pivotal step in streamlining information extraction from the unstructured data. Automated tools are in use now a days for detecting and classifying text regions within the prescription[3][4]. Accurate classification is vital for distinguishing between handwritten and printed text in medical prescriptions. Robust recognition systems are crucial for handling diverse handwriting styles, ensuring precise extraction of medication-related details. This study focuses on enhancing accuracy in interpreting handwritten prescriptions, including deciphering illegible handwriting. Several studies propose machine learning-based systems that utilize

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techniques such as signature verification, pen coordinates, time features, image processing and Convolutional Neural Networks (CNN) for feature extraction[5][6][7]. These systems have demonstrated promising accuracy ranging from 38.5% to 95% and aim to reduce medical errors, enhance patient safety, and improve healthcare efficiency .Signature verification techniques were used previously for recognizing handwritten medical prescriptions[8]. In [9], an online handwritten recognition system was presented for predicting doctors' cursive handwriting and generating digital prescriptions .A system employing bidirectional LSTM and SRP achieves 89.5% accuracy in recognizing doctors' handwritten medical terms, aiming to cut medical errors and costs. Another study presents a method for named entity recognition in offline handwritten documents.[10] . Utilizing features from word images and a neural network classifier, the system achieved an average F1-Measure of 74.59% on historical and modern datasets. Various other groups had conducted similar studies using different image processing and machine learning techniques with matching objectives. In [11], the authors proposed a method for text/image region separation in scanned document images using edge enhancement diffusion and level set methods. This method aims to accurately detect the layout of scanned documents. Additionally, research explores character recognition systems designed for cursive English handwriting, employing techniques including segmentation, feature extraction, and Support Vector Machine (SVM) classification[12]. These systems demonstrated high accuracy for text-line segmentation, word segmentation, and overall recognition.

Many other studies also integrated research on offline handwritten character recognition, including Tamil character recognition and handwriting prediction[13][14]. The system utilizes OpenCV, TensorFlow, and NIST Special Database[13] for data classification and image processing. Achieving up to 94% accuracy, the system showed potential for recognizing cursive text, supporting multiple languages, and identifying special symbols. [3]introduced an OCR system for Arabic letter recognition. A similar studyintroduced a character recognition system tailored for cursive English handwriting, particularly for medicine names in prescriptions[12]. Employing segmentation, feature extraction, and SVM classification techniques, the system achieved high accuracy rates in recognizing medicine names and supporting diverse applications. To enhance the classification process, the research introduces Convolutional Neural Network (CNN)[15][5]for preprocessing the prescription image. This addition aims to tackle the complexities arising from diverse handwriting layouts, specific annotations used by doctors, and various formatting elements such as lines, tables, and dotted gaps within prescriptions. In[5], a minimal Convolutional neural network was used for handwritten digit recognition on the MNIST dataset. The study offered insights into CNNs' learning process for image recognition tasks.The utilization of Tesseract OCR[11][3]is applied to extract text from the preprocessed images, contributing to the overall systematic approach. Furthermore, other approaches involve deep learning models such as Deep Convolutional Recurrent Neural Networks (CRNN)[16]specifically tailored for recognizing doctors' cursive handwriting and medical terms. These models contributed to generating digital prescriptions, aiming to reduce healthcare costs and improve prescription legibility. Another study presented a handwriting recognition system utilizing a Deep Convolutional Recurrent Neural Network (CRNN) achieving a training accuracy of 76% and validation accuracy of 72%[17]. A hybrid model also achieves a 76% accuracy rate on prescription images, with suggestions for improving recognition algorithm accuracy and providing a comprehensive reference list for future research[12], [14]. Engaging patients in pharmacovigilance efforts and utilizing e-Health tools for adverse drug reaction (ADR) reporting are crucial for identifying and preventing drug-related harm. This contributes significantly to improved drug safety and public health outcomes [13]. By reducing misinterpretation of drug names, many studies involving mobile applications were used to prevent errors in prescriptions, benefiting pharmacists and patients[17]. Those studies used machine learning-based systems with a mobile application designed to recognize handwritten medical prescriptions. A ‘Smart Health Tracking Application’ outlined the creation of an ‘Intelligent Prescription Reader’ system, employing regular expressions to extract medication details from medical prescriptions[19].Our study aims to develop a medication recognition system that accurately identifies medication names and integrates information on potential side effects, enhancing patient safety and healthcare decisions.

II. Design and Methodology

We aim to achieve precise identification of medication names through an innovative prescription scanning process ,including Convolutional Neural Network (CNN) [13]for model training and Tesseract OCR [3]for text extraction. This aligns with the need for accurate medication information extraction using NER.We are utilizing a dataset comprised of handwritten medical prescriptions to facilitate accurate recognition.This study also incorporates a medication recognition system that includes a wide-ranging dataset of medication side effects.This helps in reducing risks to patient safety. Additionally, our ongoing research aims to develop a user-friendly mobile app designed specifically for healthcare professionals. Fig 1 shows the process including Convolutional Neural Network, Optical Character Recognition (OCR), Named Entity Recognition (NER), and integration with a drug side effect dataset. This helps in understanding how the system works and how user-friendly it is.

A . Model Creation using CNN

CNN-based approach was introduced for training the model to effectively identify and classify the prescription to handwritten or printed prescriptions. The classified images are then used to streamline medication information extraction from prescription images. Fig 2 shows the CNN architecture for model creation.

- Input Layer: Convolutional layer with 32 filters of size (3, 3) and ReLU activation function.
- MaxPooling Layer: Pooling layer with a pool size of (2, 2) to down-sample the feature maps.
- Convolutional Layer: Another convolutional layer with 64 filters of size (3, 3) and ReLU activation function.
- MaxPooling Layer: Another pooling layer with a pool size of (2, 2).
- Convolutional Layer: A third convolutional layer with 64 filters of size (3, 3) and ReLU activation function.
- Flatten Layer: Flattens the 3D output to 1D.
- Dense Layer: Fully connected layer with 64 neurons and ReLU activation function.
- Dense Layer: Fully connected layer with 128 neurons and ReLU activation function.
- Output Layer: Dense layer with 1 neuron and sigmoid activation function for binary classification.

The Prescription Dataset from Roboflow Universe provides a diverse array of scanned prescription images. With 2308 images for training and 105 for testing, this dataset is indispensable for assessing the system's drug name extraction proficiency from medical prescriptions. Fig 3 shows sample prescription images that was used to evaluate the performance of our model.

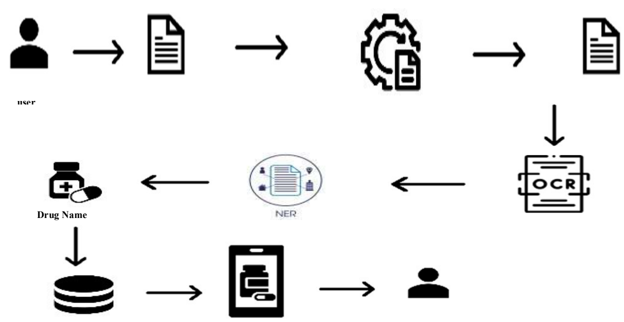


Fig. 1. System Design **:**Users can upload prescription images, and then does the preprocessing, Optical Character Recognition (OCR) for text extraction from the prescription. Named Entity Recognition (NER) is then used for extracting drug names which are then integrated with drug side effect dataset, for retrieving medication name and drug safety information

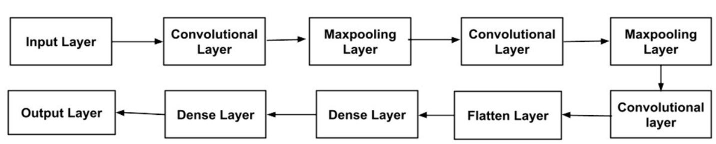
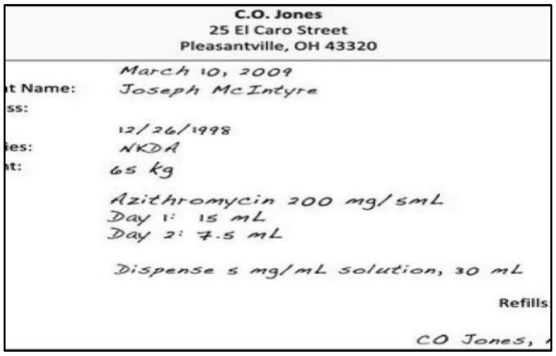


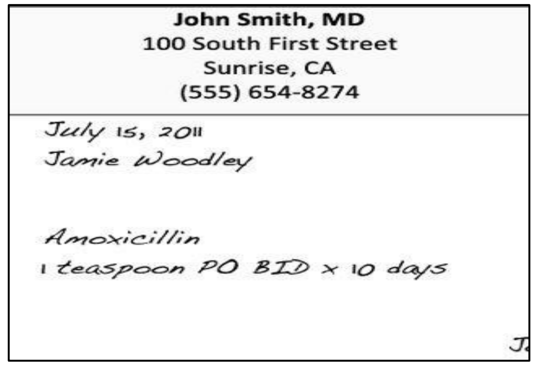
Fig .2. CNN architecture

B. OCR and NER

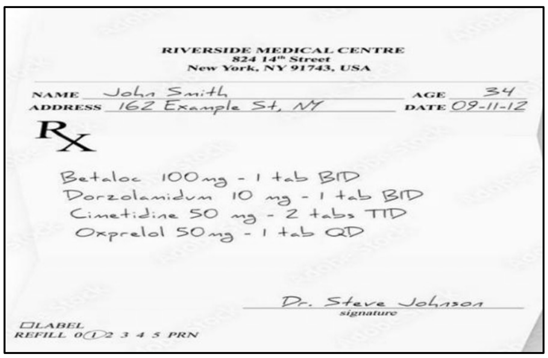
Handwritten prescription images first underwent pre-processing like gray scale conversion, applied Gaussian blur to remove noise, performed adaptive thresholding to binarize the image, and then resized it to improve the accuracy. The image was then fed into the OCR system, which converts the text in the images into machine-readable format. The extracted text went through Named Entity Recognition (NER) to identify entities such as people, places, organizations, and drug names. From this list, only the drug names were selected with the help of specific libraries. To harness its potential in the medical domain, specialized libraries like spaCy with tailored biomedical entity recognition models or domain-specific NER models such as en_ner_bc5cdr_md are used .These libraries often come pre-trained on vast medical datasets, enabling them to recognize common medical entities.



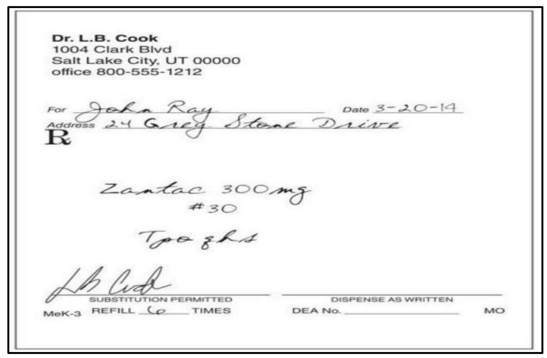
(A)Sample 1



(B) Sample 2



(C) Sample 3



(D) Sample 4

Fig. 3. Handwritten Prescription images used to evaluate the model performance

C. Drug Side Effect Integration

The drug names identified by the NER system can be integrated with a side effect dataset. This integration enables the extraction of corresponding side effects associated with the retrieved drug names. This dataset offers comprehensive data on over 248,000 medical drugs worldwide covering details like drug names, side effects, and substitutes (https://www.kaggle.com/datasets/shudhanshusingh/250k-medicines-usage-sideeffects-and-substitutes). It serves as a valuable resource for medical researchers, healthcare professionals, and drug manufacturers.

D. Visualization

In the ongoing study, a mobile application is under development that displays medication names along with their associated side effects. This app includes a translation feature, allowing the medication names and side effects extracted from handwritten prescriptions to be converted into the user's native language, making it easier for illiterate individuals to understand. Additionally, the app offers a voice translation option, which aids elderly users or those with low vision in comprehending the medication information.

III. Result and Discussion

We employed CNN for both model development and prediction of prescription classes for which the model attained an accuracy rate of 80% (Fig.4(A)).The rows and columns are labeled "printed" and "handwritten", suggesting that this classify handwritten and printed labels. The diagonal cells show the number of correctly classified labels. The off-diagonal cells show the number of mis-classified labels. The rows of the matrix represent the actual classes of the data, and the columns represent the classes that the model predicted. Fig 4(B) shows the receiver operating characteristic (ROC) curve. ROC curves are used to evaluate the performance of binary classification models. The ROC curve plots the true positive rate (TPR) on the y-axis against the false positive rate (FPR) on the x-axis. The TPR is the proportion of positive cases that were correctly identified by the model, and the FPR is the proportion of negative cases that were incorrectly identified as positive by the model. The area under the ROC curve (AUC) is a measure of how well the model can distinguish between positive and negative cases. Fig 4(C) and Fig 4(D) shows the precision and recall curve respectively.

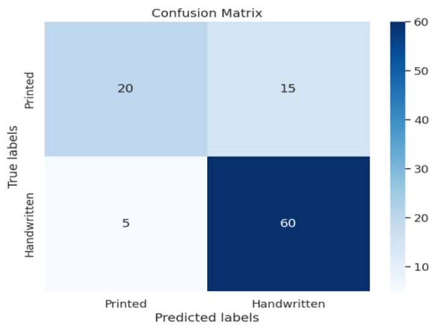


Fig.4 (A).Confusion Matrix

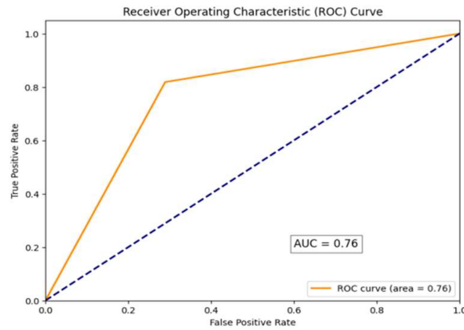


Fig .4 (B). ROC curve

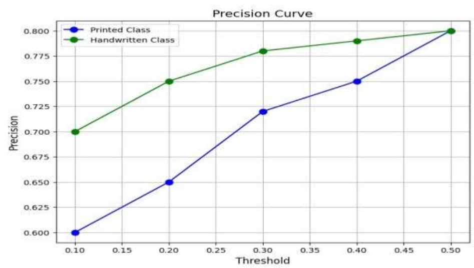


Fig.4 (C).Precision Curve

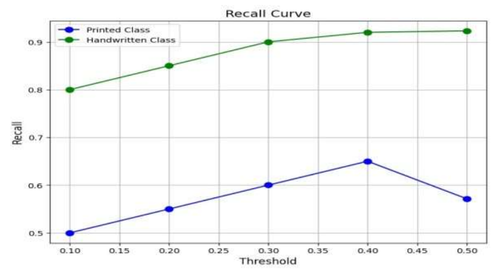
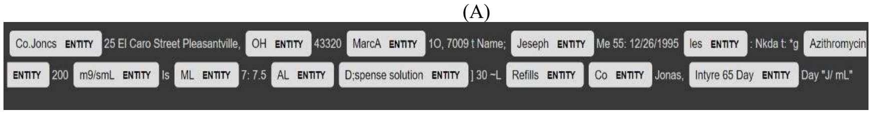


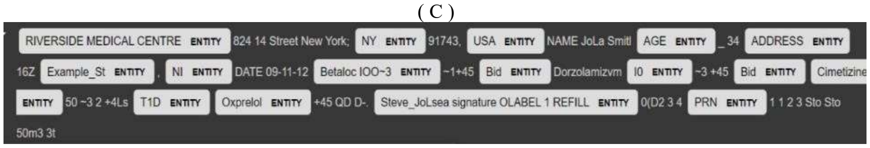
Fig.4 (D).Recall Curve

(A)



(B)

(C)



(D)

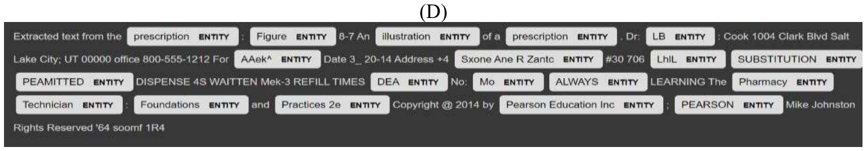


Fig .5 Named Entity Recognition of Prescription Images - (A) NER extracted from prescription Sample 1 in Fig 3 -A. (B) NER extracted from prescription Sample 2 in Fig 3 B. (C) NER extracted from prescription Sample 3 in Fig 3-C . (D) NER extracted from prescription Sample 4 in Fig 3 -D

After enhancing the image quality through preprocessing, the scanned prescription images are input into the OCR (Optical Character Recognition) system,which was used to extract text from images or scanned prescriptions. Fig 5 shows the NER results of the sample prescriptions given. The drug names identified by the NER system is then integrated with a side effect dataset which enabled the extraction of corresponding side effects associated with the drug. TABLE I shows the extracted medication details from the prescriptions in Fig. 3 and its associated side effects.

IV. CONCLUSION

The current study uses Convolutional Neural Networks (CNN) for model training and for making prescription classification. Optical Character Recognition (OCR), like Tesseract, helps to extract text from the images, while Named Entity Recognition (NER) identifies drug names from the extracted text. This combination makes analyzing prescriptions easier and more accurate. This includes information on medication side effects, making it safer for healthcare providers. It allows them to access drug information quickly, helping them make better decisions and reducing the risk of harmful reactions. The study can be extended further by creating a user friendly mobile application that helps healthcare providers, pharmacists, and patients communicate better. This fits with the ongoing digital changes in healthcare, setting a new standard for accuracy, efficiency, and patient safety in managing medications.

TABLE I .SIDE EFFECTS EXTRACTED FROM THE PRESCRIPTIONS

Sl No:	OCR text extracted	Medicine Name	Side effect
1	Co.Jones 25 El Caro Street Pleasantville, OH 43320 March1O,2009	Azithromycin	Med Name: Azithromycin Side Effects: Nausea Abdominal pain
	t Name;JesephMcIntr 55: 12/26/1995 Nkda Azithromycin 200 mg/smL Is ML 7.5 ML D;spense solution 30 ~L Refills Co Jonas,		Diarrhea
2	John Smith, MD 100 South First Street Sunrise, CA (555) 654-8274 15, 2011 Jamie Woodley Amoxicillin teaspoon P0 BID x 10 days July	Amoxicillin	Med Name: Amoxicillin Side Effects: Vomiting Nausea Diarrhea
3	RIVERSIDE MEDICAL CENTRE 824 14" Street New York; NY 91743, USA NAME JoLaSmitl AGE _ 34 ADDRESS 16Z Example_St, NI DATE 09-11-12 Betaloc IOO~3 ~1+45 Bid Dorzolamizvm I0 ~3 +45 Bid Cimetidine 50 ~3 2 +4Ls T1D Oxprelol +45 QD D-. Steve_JoLasea signature OLABEL 1 REFILL 0(D2 3 4 PRN 1 1 2 3 StoSto 50m3 3t #	Betaloc Cimetidine Oxprelol	Med Name: Betaloc Side Effects: dizziness light-headedness drowsiness Med Name: Cimetidine Side Effects: headache ,diarrhea Med Name: Oxprelol Side Effects: Drymouth constipation
4	Dr: LB: Cook 1004 Clark Blvd Salt Lake City; UT 00000 office 800- 555-1212 For AAek^ Date 3_ 20-14 Address 24 Sxone Ane Zantac 300mg LhlL SUBSTITUTION PEAMITTED DISPENSE 4S WAITTEN Mek-3 REFILL TIMES DEA No: Mo	Zantac	Med Name: Zantac Side Effects: Coughing up mucus. Dark urine. Easy bruising or bleeding. Irregular heartbeat.

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