Identification of Drug-Drug Interactions Using OCR

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Abstract. Text detection and recognition in natural images have recently gained the attention of many researchers. It plays a significant role in different applications such as labels package identifications, and many blind assistance applications. OCR is widely used for this purpose. Precisely, for the drug label identification. It can be used to detect the Drug-Drug Interaction (DDI) which considers as one of the challenging tasks in public health safety. In this research, OCR is used to detect and extract the drug name from the drug boxes. Then the extracted drug name is used as input for the DDI identification process. The results of the proposed system are promising.

Keywords: OCR · Drug-drug interactions · Text detection · Drug label

1 Introduction

Text detection and recognition in natural images have recently gained the attention of many researchers due to their various practical applications. It plays a significant role in different applications such as label package identifications, plate number recognition, and many blind assistance applications [1]. Optical Character Recognition (OCR) is widely used to detect and extract text from documents or images and convert it into a digital data format [2]. Recently, many researchers used OCR to detect and extract the drug label [2, 3].

However, text detection and recognition for drug packages can be beneficial for many applications e.g. drug tracking, dose controlling and drug prescription. Moreover, the drug name is a unique feature that distinguishes each drug from another [3]. It can be used to detect the Drug-Drug Interaction (DDI) which is considered as one of the challenging tasks in public health safety [4]. In this research, OCR is used to detect the drug name from natural drug images. The extracted name then will be used as input for the DDI identification process. Many papers have discussed different text detection issues. However, a few of them have discussed text detection and recognition in natural drug images. This paper is organized as follows. Section 2 present different recent drug recognition systems. Section 3 proposes Drug-Drug interactions identification systems. Experimental Results and Discussion in Sect. 4. Section 5 conclude the finding of the research in addition to future works.

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2 Related Works

2.1 Drug Label Identification Through Image and Text Embedding Model

Liu et al. [2] developed a model called "Drug Label Identification through Image and Text embedding model (DLI-IT)" to detect suspicious drugs. First, they cropped the raw images into sub-images based on the text by training a Connectionist Text Proposal Network (CTPN). Then, they used the Tesseract OCR Engine to independently recognize the sub-images and combined them as one document for each row image. Finally, they transformed these documents into vectors by applying universal sentence embedding. Furthermore, they used the cosine similarity to find the similarity between the reference image and the test image. They showed that their model achieved up to 88% precision in drug label identification.

2.2 ST-Med-Box

Wan-Jung et al. [5] develop an intelligent medicine recognition system named "ST-Med-Box" to help chronic patients in organizing several medications they take to avoid drug interactions. Moreover, it gives users other functionalities related to medication like reminders of time to take medications, and some information about medication, as well as chronic patient information management. Authors need four things to build their system, an intelligent medicine recognition device, an application running on the Android platform, "Google TensorFlow" deep learning framework, and a cloud-based management platform. Their proposed system achieves an accuracy of up to 96.6%, so it is very effective in reducing drug interactions. Figure 1 illustrated their system.

Although the system has achieved high accuracy, it remains limited to chronic patients drugs so, it needs modifications so that it can be used on different types of drugs to discover interactions between them.

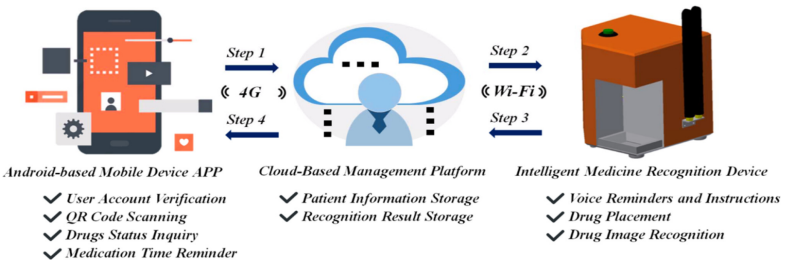


Fig. 1. "ST-Med-Box" system [5]

2.3 LSTM-CRF

Authors in [6] proposed the LSTM-CRF method based on a neural network to achieve the purpose of the Drug-Named Entity Recognition without the need for extra knowledge. This method takes the sequence of word embedding and character-level embedding from a sentence as an input vector and output a label sequence. However, they use two datasets, the DDI2011 and the DDI2013 and achieve precision rate up to 93.26%.

2.4 Syntax Convolutional Neural Network (SCNN)

Authors in [7] describe "syntax convolutional neural network (SCNN)" based DDI extraction approach. They also used word embedding (both syntax word embedding and novel word embedding) to declare the syntactic information of a sentence after that by using POS features, they recognize the POS data and the position. Experimental results of the proposed method achieve an F-score of 0.686.

However, the two related methods mentioned above are used a neural network to recognize drug name not interactions, but in the same field.

2.5 Position-Aware Deep Multi-task Learning Approach for Extracting DDIs from Biomedical Texts

Authors in [8] proposed a "position-aware deep multi-task learning approach for extracting DDIs from biomedical texts" to predict if two drugs will interact with each other or not. They also focus their approach on word and position embeddings. Also, they used (BiLSTM) network to encode every sentence. The proposed approach was applied to the "DDIExtraction challenge 2013 corpus" and achieves an F-score of 72.99%, so it considers an effective approach.

2.6 Recognition Medicine Name from Doctor's Prescription

Dhande et al. [9] proposed a method for recognition medicine name from doctor's prescription, this prescription is cursive English handwriting. The authors collected the data by scanning the document or taking a photo. The recognition achieved by three techniques, horizontal projection for text-line segmentation while vertical projection histogram for word segmentation. Lastly, SVM is applied for classification. The system produced fine results with total accuracy of 85%.

2.7 DDIs from Structured Product Labels

Tran et al. [10] proposed a method for detecting DDIs from structured product labels with linkage to standard terminologies by applying Deep learning architecture. Additionally, this framework detects the outcome of the interaction. Despite, there were 22 drug labels, 22 drug labels were used for training, additional 180 annotated drug labels have been utilized. Two test sets have been used they achieve 21.59% and 23.55% on relation extraction respectively. The result is not satisfactory enough the method need to be tested more to ensure its accuracy.

2.8 The Automated Drug Detection and Location Identification

Roy et al. [11] proposed a system aimed at serving blind people to identify and locate the drugs around them, whether it is mentioned in a picture or real-time video, via voice commands. To identify the name of the drug, they initially used Aspose optical character recognition tool but the error rate in it was high, around 37.2, so they moved to try the Google Tesseract tool and they obtained good results from it, the error rate did not

exceed 25.4, so it was adopted in their proposed system. Moreover, for taking a frame from the video to extract characters and identify the name the proposed system used a Kinect sensor which worked effectively. Figure 2 below shows the block diagram for the system.

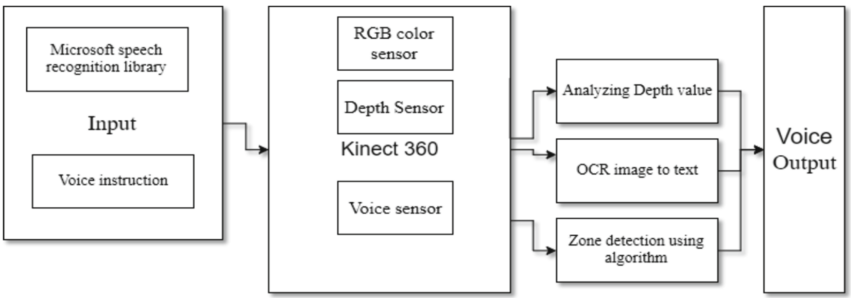


Fig. 2. The automated drug detection and location identification for visually impaired using image processing and voice commands system [11]

2.9 Drug-Drug Interaction Extraction

Demner-Fushman et al. [12] review the Text Analysis Conference (TAC 2018) Drug-Drug Interaction Extraction. Where the teams participating in the conference were given a pre-defined group of drug-drug interactions on a dataset contains 325 Product Labels and they were asked to fulfill four conditions: extracting drug interactions at the level of sentences, then identifying the substances interacting with each other, dividing these interactions and defining the group of distinct interactions in all given drugs. The teams' results were not sufficiently accurate and satisfactory, so more research was encouraged in the field of drug-drug interaction.

2.10 A Label Propagation Method with Linear Neighborhood Information

Zhang et al. [13] proposed a method called "a label propagation method with linear neighborhood information (LPLNI)" based on machine learning to predict drug-target interaction with linear neighborhood information. They evaluated and experimented with the method on four benchmark datasets produced by Yamanishi et al. [14] with pre-defined interaction and then try to predicate unknown ones. To ensure the correctness of predicted drug interactions, they check with the "SuperTarget" which is a database consisting of many drug interactions, they conclude that the proposed method can predict new interactions effectively and with high accuracy.

Table 1 summarizes the related works. Our main requirement is to reflect drug-drug interactions effectively using OCR. The overview represented above on the field of research showed that different types of proposed methods and systems can achieve high precision in drug label identification, but none of them applied OCR to identify drug-drug interaction which leads us to applied it to our proposed system due to its simplicity and fast scanning.

Table 1. Related works summary

Ref	Data used	Techniques	Accuracy
Liu et al. [2]	Samples from Daily-Med website	Partial Levenshtein Distance (PLD) and Tesseract OCR Engine	Up-to 88%
Wan-Jung et al. [5]	chronic patients drugs	"Google TensorFlow", and a cloud-based management platform	Up to 96.6%
Zeng et al. [6]	Two datasets, the DDI2011 and the DDI2013	LSTM-CRF method based on a neural network	Up to 93.26%
Zhao et al. [7]	-	Word embedding using POS features	Achieve an F-score of 0.686
Miao et al. [8]	The proposed approach was applied to the "DDI Extraction challenge 2013 corpus"	Word and position embeddings using (BiLSTM) network	Achieves an F-score of 72.99%
Dhande et al. [9]	Data collected by scanning the document or taking a photo	Horizontal projection, vertical projection histogram and SVM	Up to 85%
Tran et al. [10]	Two different test sets	Deep learning architecture	21.59% and 23.55%
Roy et al. [11]	Frames from real-time video	Google Tesseract tool and Kinect sensor	Error rate up to 25.4
Demner-Fushman et al. [12]	Dataset given by (TAC 2018) Conference	-	Results were not accurate
Zhang et al. [13]	Dataset produced by Yamanishi et al. [14]	(LPLNI) method based on machine learning	High accuracy

3 Methodology

Text detection and recognition using OCR has been used by many researchers for different purpose. In this research, we used OCR to detect and extract text from natural drugs images. This research proposed a system that utilizes OCR tool to detect and recognize drugs names from natural pictures taken by the authors. The following sections describe the dataset that used in this research and the proposed system.

3.1 Dataset

This section presents the dataset that utilized in this research. The dataset consists of 27 drug images collected from different websites based on the active ingredients of each drug. The interactions between the drugs is identified based on the data collected from 'Pharmacy Time' [15] as shown below:

- Fluoxetine interacts with Phenelzine
- Digoxin interacts with Quinidine
- Sildenafil interacts with Isosorbide Mononitrate
- Clonidine interacts with Propranolol
- Warfarin interacts with Diflunisal
- Theophylline interacts with Ciprofloxacin
- Methotrexate interacts with Probenecid
- Bromocriptine interacts with Pseudoephedrine

The interaction between drugs is identified based on this list. When a drug name is extracted and recognized by OCR, the system will search for a match. Precisely, each drug has different brand names. Thus, the system will search for the active ingredient or the brand name. For this reason, we linked each active ingredients with the corresponding brand names as shown in Table 2. The brand names of different drugs were taken from National Library of Medicine (NLM) website [16].

Table 2. Some of the active ingredients with their brand names.

Active ingredient	Brand name	Active ingredient	Brand name
Fluoxetine	Prozac, Rapiflux, Selfemra, Prozac Weekly, Sarafem	Phenelzine	Nardil
Digoxin	Cardoxin, Digitek, Lanoxicaps, Lanoxin	Quinidine	Cardioquin, CinQuin, Duraquin, Quinact,Quinaglute, Quinalan, Quinatime,
Sildenafil	Revatio, Viagra	Isosorbide Mononitrate	BiDil
Clonidine	Catapres, Jenloga, Kapvay	Propranolol	Inderal, InnoPran, Pronol
Warfarin	Coumadin, Jantoven	Diflunisal	Dolobid

3.2 The Proposed System

As the system need an image search, it used a simple technique with a ready function code for text recognition by optical character recognition (OCR). We used a function from Computer Vision Toolbox at MATLAB R2021a. The proposed model works as follows:

First, different preprocessing steps were applied on the images to increase the accuracy of the detection process, such as maximizing the image size and dealing with the drug name as a block instead of single characters [17]. After that, the drug image is input into the OCR code to extract the drug name. This OCR code is from then the extracted drug name goes through the DDI detection step. In the DDI detection step, a MATLAB

code is used to search for a match between the extracted drug name and the drug names stored in the system. It ignored the case of the letters at drug name. If a match is found, drug interaction information will be displayed to the user. Otherwise, the system will display "no interaction is found!" as shown in Fig. 3. Figures 4 and 5 show the proposed system.

```
if (contains([ocrResults.Text],"Fluoxetine", 'IgnoreCase', true)||contains([ocrResults.Text],"Prozac", 'IgnoreCase',true))
 disp("Drug interaction: Phenelzine or Nardil ") ;
elseif (contains([ocrResults.Text],"Phenelzine",'IgnoreCase', true)||contains([ocrResults.Text],"Nardil",'IgnoreCase', true))
    disp("Drug interaction: Fluoxetine or Prozac") ;

 elseif (contains([ocrResults.Text], "Digoxin",'IgnoreCase', true) ||contains([ocrResults.Text],"Cardoxin",'IgnoreCase', true))
 disp("Drug interaction: Quinidine ") ;
elseif (contains([ocrResults.Text],"Quinidine",'IgnoreCase', true))
   disp("Drug interaction: Digoxin or Nardil ");

  elseif (contains([ocrResults.Text],"Sildenafil",'IgnoreCase', true) || contains([ocrResults.Text],"Revatio",'IgnoreCase', true))
 disp("Drug interaction: Isosorbide Mononitrate or BiDil") ;
elseif (contains([ocrResults.Text], "Isosorbide Mononitrate",'IgnoreCase', true )|| contains([ocrResults.Text],"BiDil",'IgnoreCase', true))
    disp("Drug interaction: Sildenafil or Revatio ") ;

elseif (contains([ocrResults.Text], "Clonidine",'IgnoreCase', true) || contains([ocrResults.Text], "Catapres",'IgnoreCase', true))
 disp("Drug interaction: Propranolol or Inderal") ;
elseif (contains([ocrResults.Text], "Propranolol",'IgnoreCase', true) ||contains([ocrResults.Text]," Inderal",'IgnoreCase', true))
    disp("Drug interaction: Clonidine or Catapres") ;

elseif (contains([ocrResults.Text], "Warfarin",'IgnoreCase', true )|| contains([ocrResults.Text]," Coumadin",'IgnoreCase', true))
 disp("Drug interaction: Diflunisal or Dolobid") ;
elseif (contains([ocrResults.Text],"Diflunisal",'IgnoreCase', true )|| contains([ocrResults.Text],"Dolobid",'IgnoreCase', true))
    disp("Drug interaction: Warfarin or Coumadin") ;

elseif (contains([ocrResults.Text],"Theophylline",'IgnoreCase',true))
 disp("Drug interaction: Ciprofloxacin") ;
elseif (contains([ocrResults.Text],"Ciprofloxacin",'IgnoreCase',true))
    disp("Drug interaction: Theophylline") ;

elseif (contains([ocrResults.Text],"Methotrexate",'IgnoreCase',true))
 disp("Drug interaction: Probenecid") ;
elseif(contains([ocrResults.Text],"Probenecid",'IgnoreCase',true))
    disp("Drug interaction: Methotrexate") ;

elseif (contains([ocrResults.Text],"Bromocriptine",'IgnoreCase',true))
 disp("Drug interaction: Pseudoephedrine") ;
elseif (contains([ocrResults.Text],"Pseudoephedrine",'IgnoreCase',true))
    disp("Drug interaction: Bromocriptine") ;


% If no interactions is found
else
   disp("No Drug interaction is Found") ;
end
```

Fig. 3. MATLAB code

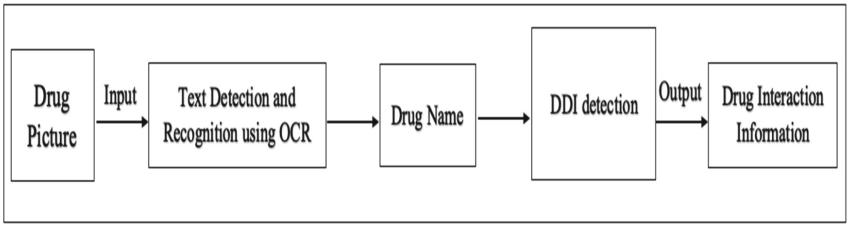


Fig. 4. The General architecture of the proposed system

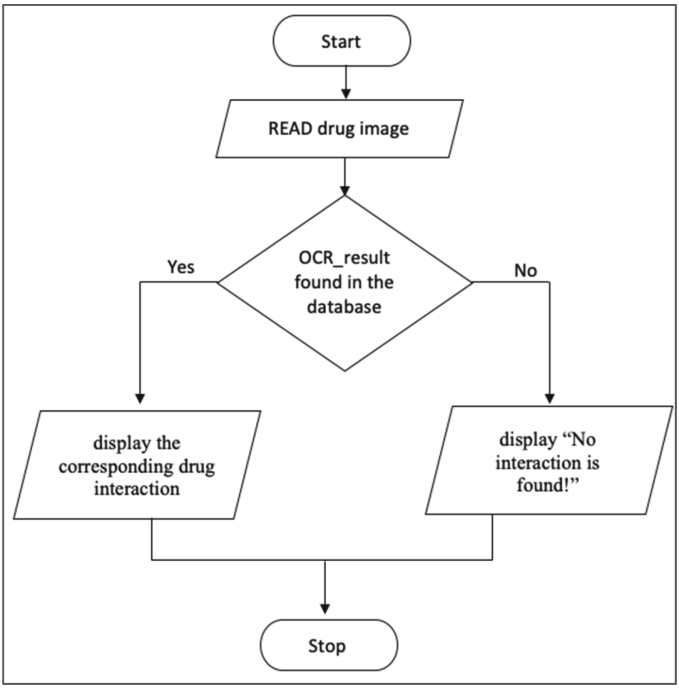


Fig. 5. Flowchart of the proposed system

4 Results and Discussion

The proposed system was tested on 27 drug images. We performed the proposed system on two different datasets. The first datasets consist of raw images without any preprocessing. For the second dataset, we performed different preprocessing steps on the images such as maximizing the image size and dealing with the drug name as a block instead of single characters [17].

However, the system failed to identify ten images when was tested for the first dataset. This false detection is due to different reasons such as font text type, the drug box shape (cylinder drug box is harder to detect) and inappropriate lighting (reflection of the light on the drug image) as shown in Table 3. The accuracy of the proposed system was 63%, while the second part the identification of drug-drug interactions was correctly identified all the drugs. Table 4 shows some of the results.

Table 3. False detection results of the proposed system

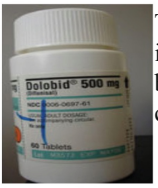
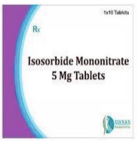
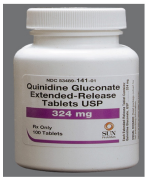
Drug	Preprocessing	OCR Results	Reasons
	Increase the image size	|NDERAI.'	Font text type
	Increase the length of the image	Jflunisal	Drug box shape is cylinder.
	Treat the text in the image as a single block of text and increase the image size	Dolol	Drug box shape is cylinder
	Increase the image size	Not recognized	Reflection of the light on the drug image
	Treats the text in the image as a single block of text	ugnldine Gluconate	Drug box shape is cylinder

Table 4. Some results of the proposed system

Drug	OCR Results	Drug-Interaction
	Ciprofloxacin	Theophylline
	PROZAC	Phenelzine or Nardil
	Probenecid	Methotrexate
	Bromocriptine	Pseudoephedrine
	Wartafm	Failed
	COUMHDiN	Failed

5 Conclusion

Nowadays, there are a lot of people around the world who suffer from different diseases and have to take several drugs together at the same time. In this research, a simple approach of DDI identification based on OCR is presented. In this approach drug pictures are taken as an input then the drug interaction information will display as the output. In the future, we aim to perform more training on the OCR using deep learning techniques

to increase the accuracy. Also, we hope to develop our system so that it includes an audio reading to help the blind to identify their medications.

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