

MACHINE LEARNING APPLICATION FOR MEDICINE DISTRIBUTION MANAGEMENT SYSTEM

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Abstract

This research proposes a technique for intelligent medication recognition in vending machines. Because the name of the drug is typically the most visible character recognition in the picture, the identification of the medicinal name in this thesis may wind up being the most prominent character recognition in the image. We choose the most linked region to acquire the medical name after finding the text area using SVM and associated components. Second, we separate the text into two pieces (fragment and link), which are then concatenated based on the parameters stated. This is known as a "fragment link." Character recognition software, such as optical character recognition, may also be used (OCR). According to studies, this technology accurately identifies between medicines.

Keywords: Medicine distribution, machine learning, optical character recognition, AI

1. Introduction

Artificial intelligence helps humans for better life. Vending machines are a more contemporary kind of retail business. The market, on the other hand, features a number of vending machines that sell beverages and snacks [1]. Given that many customers' drug demands are often impulsive, there are frequently numerous hospitals, lengthy queues, or late-night drug usage, this sometimes makes customers feel extremely uncomfortable, and many pharmacies are expensive. Problematically, it is typically not accessible 24 hours a day, which makes purchasing medications difficult. Self-administration creates the necessity for medication checks. Self-administration creates the necessity for medication checks [2].

The microprocessor that generated the picture is located near the pharmacy's exit, where the light level is low, making it difficult to see the barcode. To study the medication, we utilise the technique of pulling the drug's name out of the drug box [3]. Image text extraction and text recognition have grown in popularity since the 1970s. This research proposes an intelligent medication identification system for drug distribution machines based on picture letter recognition. Figure 1 depicts two sections of the model: the Terminal and the Medicine Identification Center (DIC). Both patient and hospital are benefited by this system [4].

The remaining details are as follows:

Approach. The integrated algorithm, as well as the basic premise of the Medicine Identification Center, are extensively addressed.

Experiment. The approach is used to training the data set, and the outcomes of the experiment are then analysed.

Conclusion. We summarise the content and provide suggestions for modifications or new directions.

2. Methodology

A visual region made up of nearby foreground locations and pixels with the same pixel value is known as a linked component. The method of finding and identifying each linked region in a picture is known as related component analysis [5]. The SVM classifier is then used to distinguish between the linked part of text using the Linked Component detection method, which uses the Maximum Stable Extreme Area approach to extract the linked area in the picture as a candidate for the letter region. This technique's goal is to identify the text region with the same grey value. Giving the connecting region the same grey colour as the text area makes it possible to identify the text-related area. As a consequence, the location where the drug's name is needed is the one that is most relevant. This is a quick method of finding any text. Links and fragments will be the two main divisions of the material. A bounding box fragment is a small portion of a word or text box that is shown as an angled rectangle. The link, which indicates the temporal connection between two adjacent fragments and is positioned between them, has a height that is almost equal to the height of the whole word [6]. While linking words are given to different phrases, unrelated words are given to the same

term. The method scans the whole network for connections and fragments, assembling the related fragments into a whole word leaping box. A small camera placed close to the departure of the pharmacy distribution machine takes a photo of the outside of the medicine box when a patient picks up a prescription from it. Figure 1 shows the precise installation layout:

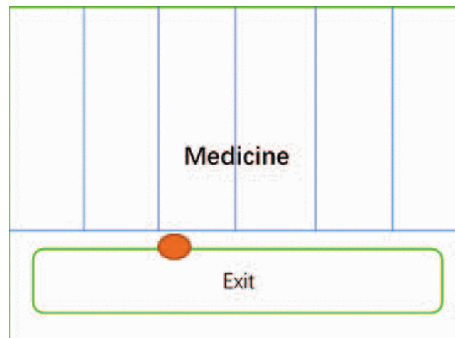


Fig. 1 Pictorial representation of microcontroller

A camera snaps a environment and transmits it to a Medicine detection center, when a medicine is about to be detached Figure 2 shows how the MIC method works.

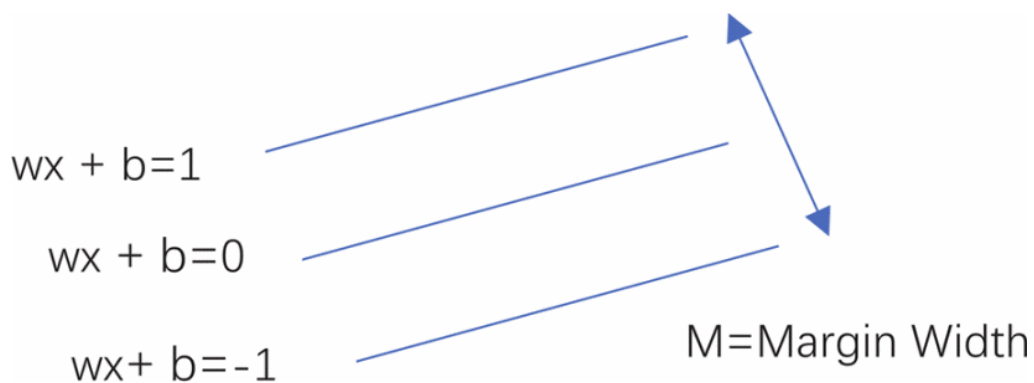


Fig. 2 Interval definition

As a result, we can identify the amount of grey for each pixel in a photograph. After binarizing each pixel in the pixel point matrix, we average each pixel's grey values and compare each pixel to the average. If it is less than or equal to the average, it is 0 (black), and if it is more, it is 255. (white) [7]. The following steps are used for recognising medicine.

Step 1: We greyed and preprocessed the image, making it basic and straightforward to work on.

Step 2: To train the training set of data for classification modelling, the SVM approach is utilised, and the best kernel function C and g penalty factors are chosen. SVM has two subclasses: hard intermission SVM and soft interval SVM. In this example, the soft interval C-SVM is utilised to advance recognition accurateness. The nonlinear classification strategy (Fig. 3) is described as follows:

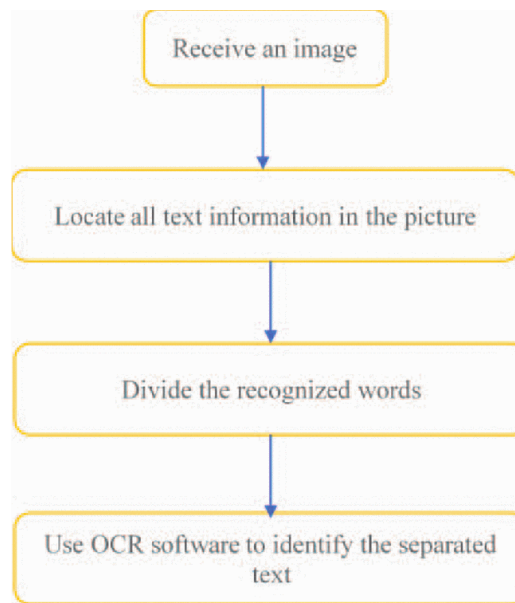


Fig. 3 Flow diagram

The $M=2W.W.$ era is shown in Figure 3. When linear segmentation is used, the optimal function is $\min |2|w|2$. In the case of linear indivisibility with the constraint condition, the soft interval C-SVM is analogous to totalling a penalty function (C is the penalty factor) after the unique optimization function.

Determine the linked region for the linked area acquired in above step—that is, the largest linked region or the linked region that includes the drug title. Because the image's backdrop must be the biggest linked zone, the linked region containing the medicinal name is really the second largest linked region.

Step 4: To discriminate between words and characters, we partition the contents of the linked region into segments and connections. Because both fragment and link are limited, fragment only takes up a tiny proportion of the entire word and just has to be aware of the picture's local properties. Links exist between two linked components, allowing them to be considered local. Fragments and linkages may be tightly identified on any size image to produce words of any distance, allowing for the recognition of long words as well as non-horizontal long words.

Step 5: The data received in Step 4 is recognised using OCR package to determine the title of the medicine.

3. Result and Discussion

The project used a database that it had created. The sole source of picture data was the medication vending machine. It contains eleven medicines. For a total of 100 photos, each drug was represented by ten photographs. Each picture has a resolution of $450300=135000$ after processing, indicating that it is an RGB tricolour image. The first seven data sets from

each drug were used as training sets, and the final three as training sets. The training set has 30 samples while the training set contains 70 samples.

determining the image's genre The figure shows the total number of categories. The sample training set consists of the first seven images of each medication in the training set. By integrating the final three photos with the training set, the training sample set was formed. Matlab's image cutting tool was used to convert the medical picture to 256*256 format. Figure 4 depicts the result of greying and binarizing the image. After using the MSER technique to identify the area inside the text with the same grey value, the matching region in the picture was obtained as the text applicant region.



Fig. 4. Images of the drug

The biggest linked region of the text was then found using SVM to discriminate between the linked area of the text and non-text. As a result, as illustrated in Fig. 6, the extreme linked text area in Fig. 5 may be attained. The fragment link will anticipate every fragment and connection on an image of size I.



Fig. 5. Images of drug after binarization

Scar Clinic™ Thin
Osicent™ 80

Fig. 6. Text region identified by the system

Scar Clinic™ Thin
Scar Clinic™ Thin
Scar Clinic™ Thin
Osicent™ 80
Osicent™ 80
Osicent™ 80

Fig. 7. Link diagram

The detected fragment is merged with the given link to provide the finding result for the entire term. The rectangular box will provide a visual representation of the detection result for the whole word, including its centre, length, and breadth.

A yellow boundary signifies a fragment in Fig. 7, and a green line connecting two pieces is shown between adjacent yellow borders. After all of the bits are joined, the whole word may be recognised. After the detection data has been linked from the linked area segment, the pharmaceutical name is detected using OCR software. Figure 8 depicts the findings. The outcome is then decided by the technique that only examines the linked region, as illustrated in Figure 9, and the anticipated method is compared with the approach that only analyses the linked region.

```
D:\python_install\python.exe E:/py_resource/SVM/SklearnSimple.py  
Scar Clinic™ Thin  
D:\python_install\python.exe E:/py_resource/SVM/SklearnSimple.py  
Osicent' 80
```

Fig. 8. Python execution path

```
D:\python_install\python.exe "E:/py_resource/SVM/Connected Component.py"  
ScarClinic- Thin  
D:\python_install\python.exe "E:/py_resource/SVM/Connected Component.py"  
Osicent' "80
```

Fig. 9 linked components are recognised by the system

The identification findings in Fig. 8 demonstrate that the approach's accuracy has improved. size variations The findings of our investigation are still extremely useful since even tiny font differences, such as the spot in the grey binarization method impact, may cause mistakes in

training identification. Nonetheless, little terms like superscript information seldom alter medical knowledge. It may be able to solve both the pressure on hospital infrastructure and the issue of patients taking their own medicine wrongly in an efficient manner.

Conclusion

A vending machine smart drug recognition system is described in this study. SVM was utilised to identify the text area and associated region, as well as to determine the medical name. The text had to be broken into bits before OCR could recognise it using the fragment link approach. The findings of the research indicate that the strategy is more accurate in recognising drug names. However, owing to the microscopic amount of pixel points left next binarization, it is not feasible to get a more precise outcome for small typefaces. This region still has potential for improvement. The language in the medication package reviewed for this thesis does not address the challenge of binarizing colour text to 255 due to time restrictions (white). Investigating the adaptive threshold of the primary colour picture and trying to discover a solution as quickly as feasible would be difficult. The usefulness of our proposed technique will be shown by comparing its results to those of SVM and DNN.

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