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An Efficient Scheme for Automatic Pill Recognition Using Neural Networks

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ABSTRACT

An efficient scheme, capable of extracting key pill features, for an automatic pill recognition is proposed. The devised system involves a number of processes which starts with the thresholding applied to the input query pill image for extraction of the shape feature vector and generation of mask images. The extracted shape feature vector is used for shape recognition through a trained neural network. Information regarding the color and size of the pill is obtained by using the mask images and shape information. For pill imprint extraction, a modified stroke width transform (MSWT) and two-step sampling is applied. The extracted pill query features are compared with the feature values of the created database for recognition of the pill and its purpose. The proposed method is evaluated on a dataset of 2500 images and achieves an accuracy of 98% which shows the supremacy of the proposed method in comparison to the other similar pill recognition systems.

1. Introduction

The pharmaceutical industry is making progress day by day and more effective medicines are being manufactured now-a-days to cure the diseases. With rapid industrial growth, many pharmaceutical industries have emerged and they all are manufacturing their medicines in their unique way. However, with the variety of tablets/pills available in the market, it raises a problem for an average person to distinguish or recognize an unlabeled pill. While pills can be distinguished based on their appearance (physical appearance characteristics), it demands an effective system which can be used to identify/recognize the pills accurately. The Food and Drug Administration (FDA), a federal agency in the US dealing with products related to the food and drugs, enforces all pharmaceutical companies through their regulation code 21CFR206 [1] to make a unique look of every pill in the context of four features. These features are; shape, size, color and imprint of the pill. As every pill has its unique appearance, a system can be devised to extract all these four features accurately to predict the unlabeled pill. Several systems have been developed in recent years to classify and identify an unlabeled pill accurately. These systems can be classified mainly into two main categories; Manual Recognition System and Automatic Recognition System.

1.1 Manual Recognition System

The manual recognition system requires a user to provide manual inputs regarding the features of the pill, e.g., color, shape, an imprint, etc. There are many websites which offer the online pills recognition system. Few of them include WebMD Pill Identification Tool [2], Pillbox [3], RxList Pill Identification Tool [4], Drugs.com [5] and Health-line Pill Identifier [6]. Although, the manual input method is easy to utilize, it is less efficient in comparison to the automatic recognition system. When the database has a large number of pills, the manual input method becomes time-consuming and also requires a human resource to do the inputs. Therefore, for a large number of pills, the automatic pill recognition system is preferred.

1.2 Automatic Recognition System

An automatic pill recognition system is fast and easy to use for a large number of pills as there is no requirement of manually entering the data. A lot of research is being carried out in the area of automatic pill recognition. Recently, Yu and Chen [7] proposed a technique which utilized color, shape and imprint features of the pill for pill recognition and achieved an accuracy of 97.1 %. They created their own pills image database of 2500 pills. Data augmentation was done by randomly changing brightness, contrast, rotation, etc., of each acquired pill image; thereby, making an image dataset of 12,500 pills images in total. Neto et al. [8] proposed a pill feature extractor to classify pills based on used pill shape and color. Feature extractor is evaluated using KNN, SVM and Bayes classifiers. To extract the features, they utilized two datasets (PILL BR and NIH NLM PIR) and achieved an accuracy of 99.85 and 99.82 in 0.01006 and 0.00810 seconds, respectively. Wang et al. [9] introduced highlighted deep learning (HDL) technique for identification of the pill's blister package. Segmentation and descriptive features can be extracted using HDL technique. The technique utilizes CNN to classify correct blister pack type and is rotation and light invariant. They got almost 100% accuracy on the database of 272 types of blister packages.

Palenychka et al. [10] proposed a new set of rotation-invariant image descriptor, which fully discriminates between different medication pills. They used three independent descriptors to form pill descriptor vector. Also, they applied a

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machine learning algorithm to train their database for detection. Their proposed system shows a precision and recall rate of 0.95 and 0.97, respectively. Wong et al. [11] used Deep Convolutional Network (DCN) for automatic pill identification and verification. After the application of Geometric transformation, Saliency-driven pill detection is performed, followed by Deep model training to develop DCN. They used a database of 400 commonly used tablets and capsules. The reported mean accuracy rate of DCN at Top-1 return was 95.35%. Hart [12] proposed object segmentation based mobile computer vision system. Estimators can deliver the parameters (color, shape and size of the pill) of the unknown input pill image, which are used in recognizing the input image by matching these parameters with the database. Nguyen and Huynh [13] worked on tablet imprint recognition. They used polar transform technique and NN to train their system for specific imprint and then recognized the tablet using a trained network. Hu [14] employed edge localization method and the invariant moment technique for imprint extraction. Chen and Kamata [15] technique is based on finding the measurement of similarity between two shapes. The correspondence between two different shape points is found and then an aligning transform is evaluated using the correspondence. The technique shows promising results on different variety of images including handwritten digits, trademarks, silhouettes and the coil data, etc.

Caban et al. [16] introduced a classification technique which automatically identifies the prescription of the tablet using the pill's image. They used a modified shape distribution method and created an invariant descriptor for imprint extraction. Grigorescu and Petkov [17] presented a novel rich local descriptor named distance set which can be found by using an image feature point. Two-dimensional images are used as a distance set where the distance set contains the feature points of the image. By doing so, they resolved object segmentation and shape matching problem by finding the difference between distance set and dissimilarity between sets of distance sets. The use of shape matching/filtering is very useful in traffic sign detection and recognition of handwritten character. Suntronsuk and Ratanotayanon [18] presented an algorithm for an automatic pill recognition system based on the text of the imprint of the pill. Edge-based connected component technique and edge masking technique is utilized to extract the text from the imprint. Then, an optical recognition system (OCR) is applied to different extracted binary imprint area to recognize the pill.

Osada et al. [19] illustrated a method to discriminate 3D shapes. They find a shape measuring function based on the signature of an object as a sampled shape distribution, which defines the global geometric properties of the object. The discrimination method eventually was used as a pre-classifier for a recognition or similarity retrieval system. Experimental results show a 60.9% system accuracy. Lee et al. [20] proposed an automatic pill recognition system based on an imprint of the pill. Feature vector based on edge localization and invariant moments of the tablet was extracted. Experimental results showed 93.02% matching accuracy over 2116 real drug pill images. Belongie et al. [21] introduced the weighted shape context technique, in which, the similarity between two shapes is measured and used for object recognition.

In this paper, an efficient scheme for automatic pill recognition system using Neural Networks (NN) is proposed. In our method, an imprint of the pill is detected by first applying the Modified Stroke Width Transform (MSWT) [22] which is a combination of switch function, accumulated gradient and Stroke Width Transform (SWT). Then, Two-step Sampling Descriptor Set (TSDS) is utilized to refine the imprint section. Thresholding technique is applied for extracting information related to the shape and size of the pill. Color information is extracted by using a pill mask image and averaging three color channels of the image. At the end, a neural network is used for shape and imprint recognition.

2. Proposed Methodology

The proposed method consists of a series of steps which start with the analysis of pill image dataset (available on the US National library of medicine website [3]). Along with the pill images, the information about the disease for which the pill is prescribed is also available. Information of four pill features, i.e., size, shape, color and imprint, is extracted through our devised technique by exploiting the prior knowledge about the format of the available pill images in the dataset. A database of acquired features of each pill is created in the MATLAB. After the database creation, automatic feature extraction of any input query pill image (acquired according to the format and constraints implied in the pill image dataset acquisition) is performed by our proposed system and then compared with the database for matching and identifying the pill. Comparison is done by utilizing distance metric which computes the distance between the extracted feature value of the query pill image and already available feature values of the pills present in the dataset. If the distance is within the threshold value, the search region for the query image in the database will be reduced. The same procedure is performed for all four feature values. Finally, the proposed system gives the resultant pill image and conveys the information regarding the class of query image along with its location in the database.

The information about the class and instant (at which the resultant pill image is present in the database) is utilized to find out the disease for which query pill can be used. However, if the distance between the query pill image features value and the database pill image features value is not within the threshold, the database search range will not be reduced. This will lead to the result that the pill is not present in the database. In our proposed pill recognition system, 2500 pills images are used as a database. Overview of the proposed system is shown in Fig. 1 and detailed description of the steps involved in the devised technique is presented next.

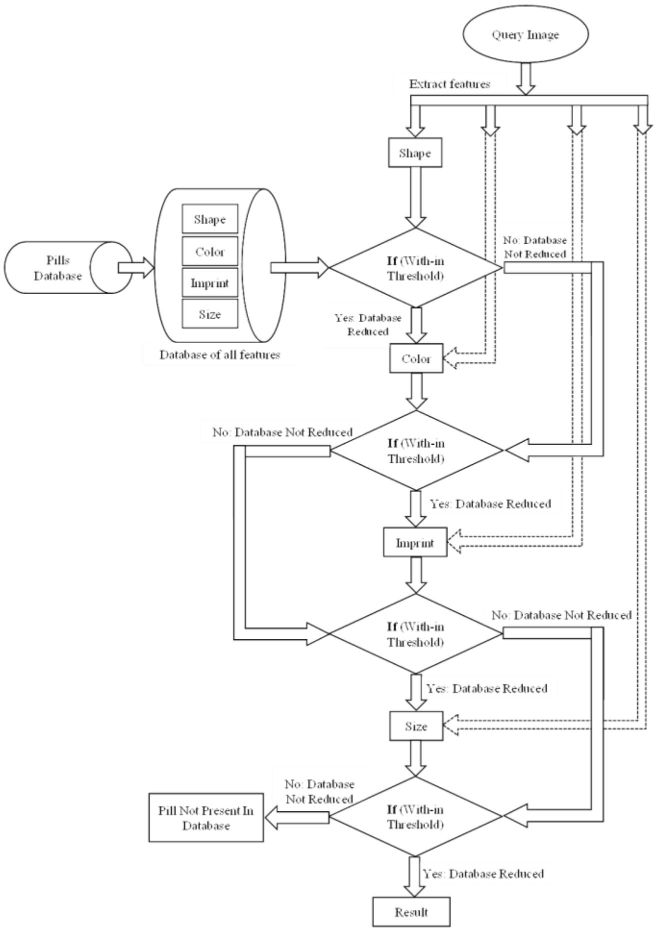

Fig. 1: Block diagram of the proposed pill recognition system.

2.1 *Shape Identification*

The pill image dataset utilized in our proposed pill recognition system is available on the website of the US National library of medicine [3]. In this dataset, every pill image comprises of the front and back side of the pill presented side by side against a uniform grey background, as shown in Fig. 2. For pill shape identification, extraction and recognition of the pill shape from the input query pill image needs to be done. For this purpose, color query pill image is first converted into the grayscale representation. This is carried out through appropriate thresholding by converting each color channel of the input query pill image into the binary form and then taking a union of all three binary channels. The threshold value of 0.67 is found to be sufficient for this purpose for all the pills present in the dataset due to the uniform background. After thresholding, the resulting query pill image will have a pill's shape/geometry represented in the white region (logical 1) and background represented in the black region (logical 0) as shown in Fig. 3.

Fig. 2: Example of a pill image present in the dataset [3].

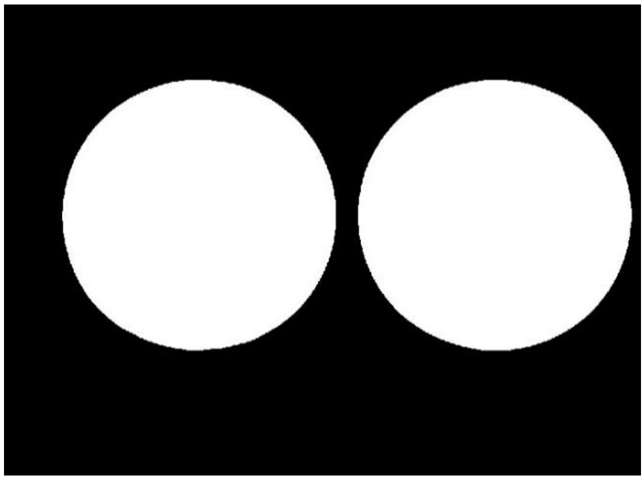

Fig. 3: Binary thresholded image.

Although the shape of the pill is highlighted in the binary thresholded image, the image needs to be cropped from the center to separate front and back side of the pill image to facilitate the training of the recognition system. The prior knowledge about the pill image dataset is exploited for separating the front and back side of the pill. Through close examination of the dataset, it can be seen that the search region for cropping the pill images lies in between 37% to 67% of the image resolution as depicted in Fig. 4.

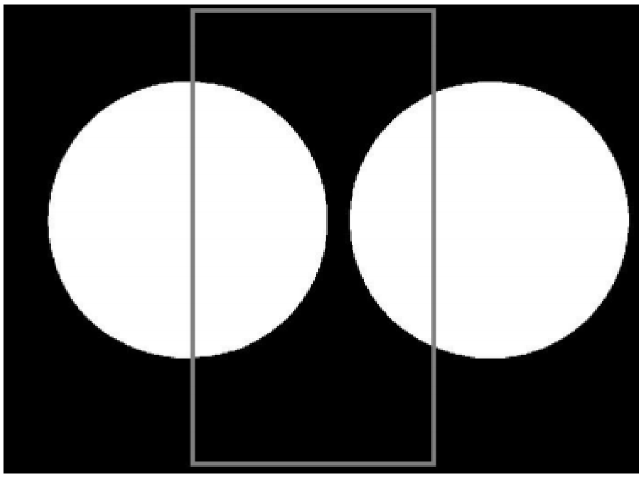

Fig. 4: Search region for cropping pill image.

The location for cropping is identified by moving horizontally a vertical line (equal to the height of the image) pixel by pixel in the search region and then finding the number of connected components at each location. For vertically presented side by side pill images, the same process is followed with a virtual horizontal line (equal to the width of the image) moved in the vertical direction. Pixel locations, where connected component value is 1, indicates that there is no boundary (shape) present in that location. All such pixel locations are identified and an average of these pixel locations is computed to find a suitable location for cropping the binary image without cutting the front or back side of the query pill. The cropped front and back side binary query pill images are utilized as mask images in color identification process. The shape of the query pill is recognized through a trained neural network.

2.2 Size Identification

The size information of the pill images available on the US National library of medicine website is present within the image in the form of a graph scale (in mm) as shown in Fig. 5. The need is to devise a mechanism to extract this information from the query pill mage automatically.

Fig. 5: Size information of the pill [3].

In order to find the size of the query pill, a binary thresholded image is first generated to represent graph scales in white color (logical 1) and the rest of the image in black (logical 0). As graph scales are already present in the white color in the dataset pill images, a high threshold value of 0.90 is found to do the needful. The thresholded binary image is then utilized to find the height and width of the pill by calculating connected components. For this purpose, a vertical line equal to the height of the image is swept from left to right. When the value of the connected component is other than 1, it indicates the overlapping of the virtual line and vertical graph scales. In this case, the value of the connected components gives the height of the pill under consideration. The same process is repeated for calculating the width of the pill in which virtual horizontal line is swept from the bottom to the top. Finally, the computed width or height is divided by two based on the orientation of the query pills (as shown in Fig. 6) in the image to get the size information of the single pill.

The size information of the pill is stored in the form of area. The computed height and width information along with the shape information extracted in the shape identification stage is utilized to compute the area of the query pill.

Fig. 6: (a) Side by side position, (b) Up and down position [3].

2.3 Color Identification

To find out the color of the input query pill image, mask images obtained from the shape identification step are utilized. After cropping the input query pill image in a similar fashion as done before, the binary mask image is multiplied with the colored front and back side of the pill image. As the value of the mask is 1 for the pill shape area and zero otherwise, the resulting values after multiplication will give the pill color values of each R, G and B color channel. The average of each color channel is computed to give three color values of each channel to be used for color identification purpose.

2.4 Imprint Identification

To detect and identify imprint on the pill, pre-processing is first applied to enhance the contrast of the pill image. Then, the modified stroke width transform (MSWT) [22] is applied on each color channel separately to get a rough area where pill imprint exists. Result of application of MSWT on one channel is shown in Fig. 7.

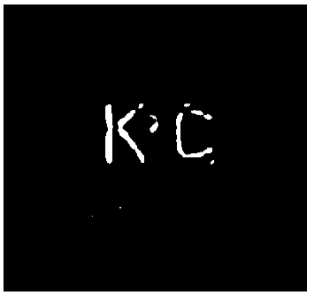

Fig. 7: Pill imprint after the application of MSWT.

Maximally Stable Extremal Region (MSER) algorithm [23] is applied to all these three color channel images by setting its region area and threshold equal to 0.1 to get the maximum output region, as shown in Fig. 8.

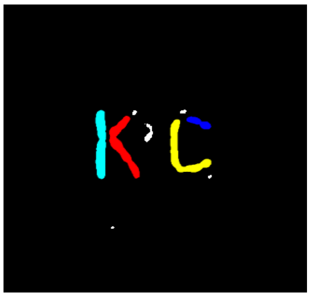

Fig. 8: Imprint results after the application of MSER algorithm.

In parallel, the thresholding method is also performed on the front and back side cropped image of the query pill. A suitable threshold is estimated as an average of all pixel values present in the image. Then, the image is converted into binary form. While converting into binary, the background is intentionally kept equal to logical 0 (black) and the imprint is generally mapped to logical 1 (white) as shown in Fig. 9.

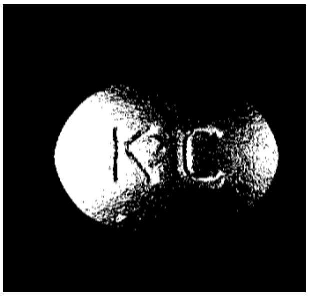

Fig. 9: Imprint results after the application of thresholding.

To get the final imprint image, a union of the image after thresholding and MSER algorithm is taken to get more reliable imprint image as shown in Fig. 10.

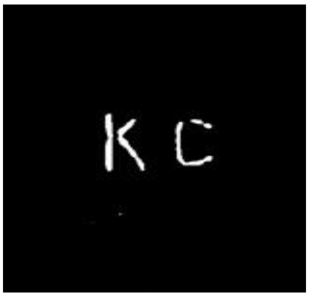

Fig. 10: Final extracted imprint result.

The dataset of the pills that is used in this research has broad pills diversity in terms of color, shape, size and imprint. Also, the contrast and brightness of the pills in the dataset have a large variation, so the imprint algorithm gives the intermediate results. Some imprint extraction results are very accurate like the above-shown example and some results are just satisfactory. Therefore, a NN is employed to identify the extracted pill imprint correctly.

3. Experiments and Results

The proposed method is evaluated on a dataset of 2500 pill images [3]. After extracting all the features, Neural Network (NN) is used for shape and imprint recognition. As there are in total of nine different shapes of the pills, as shown in Fig. 11, the database is categorized into nine different classes. These nine shape classes are as follows:

a. Circular	*b. Square*	*c. Rectangular*
d. Capsule	e. Tear	f. Elliptical
g. Star	h. Diamond	i. Triangular

Fig. 11 Nine shapes of pills (a: Circular, b: Square, c: Rectangular, d: Capsule, e: Tear, f: Elliptical, g: Star, h: Diamond, i: Triangular) [3].

Table 1: Neural network parameters and settings.

Input Images	2500
Input Layers	Equal to Input Sample Size
Hidden Layers	10
Output Layers	Equal to Output Values
Activation Function	Logsin
Training Function	Traingdx
Cost Function	MSE
Iterations / Epochs	8000

NN for pill shape recognition in the proposed system is created with an input layer having nodes equal to the dimension of the shape feature vector. While the output layer has nine nodes with each representing nine shape classes, intermediate hidden layer nodes are equal to 10. For creating an input shape feature vector, the binary thresholded pill image from the shape recognition stage is first down-sampled to 512 x 512 resolution. Then, a column shape feature vector of 2601 x 1 dimension is created which contains average values of every 10 pixels present in the row and column of the image. Finally, the feature vector is normalized to get the binary values. The activation function for all layers is “logsin”, and MSE is used as a cost function. These parameters are presented in Table 1. The trained network is used to identify the shape of the input query pill image by classifying it into one of the 9 classes. Same parameters and a similar procedure is also used for imprint recognition. However, as each pill imprint is unique, the very large number of required output layer nodes due to the pill image dataset size makes the usage of NN very complex. To cater this problem, set of all images with similar shape pills like circle, square, capsule, etc., is created. Then, for each set (which now contains less number of pill images), NN is trained on the corresponding final extracted imprint images obtained from the imprint identification stage. The selection of trained NN for imprint extraction of input query pill image is made based on the shape recognized in the earlier process.

Once the classifier is trained, then during the test phase, a query pill image (as a test image, as shown in Fig. 12a) is given as an input to the proposed pill recognition system. The system first extracts the features as explained in the methodology section and then tends to match these extracted features value with the created pill database in MATLAB. If a match is found, a resultant matched image is displayed as shown in Fig. 12b. The system will also present the class and instance of the input image in the form of text message such as "*The pill is present in DB. Class =3 and Instance =5. The pill is used for cold and fever*". On the other hand, if the input query pill image is not present in the database or no match of the input query image is found, a text message "*The pill is not present in the image*" will be shown.

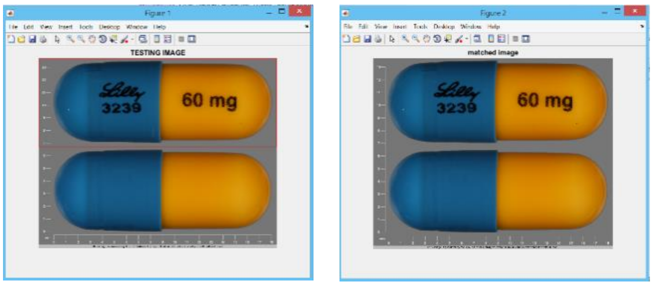

Fig. 12: (a) Test image [3], (b) Resulting matched image.

The accuracy of the system can be checked by computing FRR (False Rejection Rate) and FAR (False Acceptance Rate). To compute the FAR and FRR, a threshold must be defined first. During retrieval, when a pill query image is given as an input for recognition, then our proposed method checks the query image with the existing database and gives the output result in the form of probability, i.e., how much percentage the query image is matched with the existing database. For example, if an image is matched with 90% accuracy and a threshold value for the system is equal to 85%, then the system will recognize it. On the other hand, if an image match is 80%, the system will discard the image and will not recognize it (this falls in the FRR category). If the threshold value is set high, then FRR will increase and if the threshold is set too low then FAR will increase. The threshold of the proposed system is set to EER (Equal Error Rate) by hit and trial method. EER is the point where FAR is equal to FRR as shown in Fig. 13 [24].

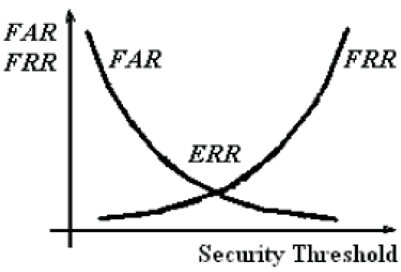

Fig. 13: FAR-FRR Rate [24].

To check the accuracy of the proposed pill recognition system, 200 query pill images are tested. Of these tested images, 100 images exist in the dataset referred to as true images. The rest 100 images are false images, which do not exist in the dataset. The proposed system gives 98 true acceptances and 2 false rejections for true images.

$$FRR = \frac{Number\ of\ false\ rejection}{Total\ identification\ attempts} = \frac{2}{100} = 2\% \qquad (1)$$

For false images (which does not exist in the dataset), the proposed system shows 98 true rejections and 2 false acceptances.

$$FAR = \frac{Number\ of\ false\ acceptance}{Total\ identification\ attempts} = \frac{2}{100} = 2\% \qquad (2)$$

Table 2: Accuracy comparison with other existing systems.

Method	Image Database	Image Complexity	Pixel Size of Images	Total No. of Images	Accuracy
Osada et al.[19]	Available online	High	-	133	60.9%
Lee et al. [20]	Available online	Low	1550x2088	2116	93.02%
Belongie et al. [21]	Available online	Medium	416x448	1400	94.2%
Yu and Chen [7]	Own Database	Low	200x200	2500	97.1%
Proposed Method	Available online	High	768x1024	2500	98%

Total error of proposed pill recognition system is:

$$Total\ Error = FRR + FAR = 4\% \qquad (3)$$

Where, total error is 4% for 200 tested images. The accuracy of the proposed system is calculated as:

$$Accuracy = 100\% - \frac{Total\ Error}{Total\ Number\ of\ attempts}$$
$$= 100\% - \frac{4}{200} = 98\% \qquad (4)$$

Pill recognition results of our system in comparison with other systems are shown in Table 2. It can be observed that our proposed system and devised techniques for feature extraction are more accurate and reliable. This can be seen as our system has the highest accuracy of 98 % in comparison to the other similar methods. Further, our pill recognition system is also more accurate than Yu and Chen method [7] who have utilized the same dataset as ours.

4. Conclusions

An automatic pill recognition system is proposed which can be used in the pharmaceutical factories as a quality inspection where mass production of the pills is happening. Four pill features are extracted automatically and then compared with the database for classification and recognition of the pill. The proposed system achieves high accuracy of 98% showing its potential for marking unlabeled pills. In future work, the pill recognition system will be tested on a very large pill dataset. Further, an effort will be made to build the proposed system as an online system by developing its App, so that the user can interact with the system easily.

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