# Pill Identification with Imprints Using a Neural Network

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**Abstract.** *Since there are more than ten thousand different types of pills commonly used in hospitals in Thailand, they are not easily recognized by an inexperienced pharmacist or even an experienced pharmacist. Thus, our long term goals are to develop a commonly-used pill database in Thailand and to build a system to assist pharmacists to identify unknown pills in real-time. In this paper, we focused only on using imprints to identify pills that are almost identical in color and shape. We proposed a new algorithm to extract the feature vector from the imprints. The extracted feature vector was invariance to image rotation and was fed into the neural network. The neural network was used to identify the type of an unknown pill. Although the number of pill types was limited to six in this work, the results were promising. The percent accuracy was about 94.4%.*

## Keywords:

Pill identification, neural networks, image processing, imprints,

## 1. Introduction

A drug is a chemical substance that is used to treat or prevent disease in living things. A pill is a small, solid, oral dosage form of drug. There are more than ten thousand different types of commonly-used pills in hospitals in Thailand, so it is essentially impossible for a human to recognize all of them. The situation becomes more serious for patients with drug allergy. A pharmacist must identify the drug type that makes patients allergic. This is a very difficult task for an inexperienced pharmacist or even an experienced pharmacist. Pills also need to be verified before being delivered to patients. This task is very tedious and time-consuming. Therefore, in this work, we use a neural network to recognize pill images and assist a pharmacist to identify pills. Our long-term goals are to develop a pill database commonly used in Thailand and to construct a machine that can be installed at hospitals to identify pills from this database.

Over the past few decades, a variety of novel algorithms have been proposed to identify pills. For example, Chantasitiporn [1] studied a feed-forward back-propagation neural network for pill identification and classified pills by using shape, color and internal features.

Lee et al. [2] developed an automatic system, called Pill-ID, to match drug pill images based on several features of the tablet. The color and shape information was encoded as a three-dimensional histogram and invariant moments, respectively. The imprint on the pill was encoded as feature vectors derived from SIFT and MLBP descriptor. Hema and Anna Saro [3] presented a drug identification, registration, detection and matching features of the image with image mining concept to identify the legal and illegal pills. The registration process consisted of two modules, i.e., feature extraction (text, color and shape) and corner detection. Color and shape feature extraction were performed using color histogram and geometrical gradient vector. The average accuracy was 86.9% and the total elapsed time was 4.48 second.

Chen et al. [4] studied an automatic drug image identification system (ADIIS) based on multiple image features (shape, magnitude, color, ratio and texture). These five features were combined with dynamic weight setting of drug identification. The query image was matched with database images of drugs by the weighted Euclidean distance to calculate similarity distance. The system then retrieved ten of the images most similar to the target drug image, allowing the user to correctly identify the drug and obtain information about it. The average recognition accuracy rate was 95.3% in rank 1 of random selection tests using relevance feedback to adjust the answer. Caban et al. [5] used a modified shape distribution technique to examine the shape, color, and imprint of a pill and create an invariant descriptor used to recognize the same drug under different viewing conditions. The proposed technique has shown accuracy percentage of 91.13.

Although many algorithms proposed in the literature have been able to identify pills using a variety of features, the main problem of pill identification is how to extract features using pill imprints. Many pills have the same color and shape. They are almost identical, except imprints. The imprints can help us identify them since the imprints (text or symbols) that are printed on a pill or capsule are unique. Thus, in this paper, we propose a novel algorithm that can extract features using imprints. The radius (r) of the pill is first divided by 5. Then the number of imprint pixels that are inside the circle with the radius of 0.2r, 0.4r, 0.6r and 0.8r is calculated. These extracted features are invariance to image rotation. They are used as an input vector of the

neural network. The experiments were conducted to show the effectiveness of our proposed algorithm.

## 2. Neural Networks for Object Identification

Numerous advances have been made in developing intelligent systems, some inspired by biological neural network. Researchers from many scientific disciplines are designing artificial neural networks (ANNs) to solve a variety of problems in pattern recognition, prediction, optimization, associative memory and control [6]. The ANN can be represented by a geometric model consisting of a set of points (called nodes) along with a set of directed line segments (called links) between them, see Fig. 1. Thus, an ANN is a parallel distributed information processing structure in the form of a directed graph. The nodes of the graph are called processing units.
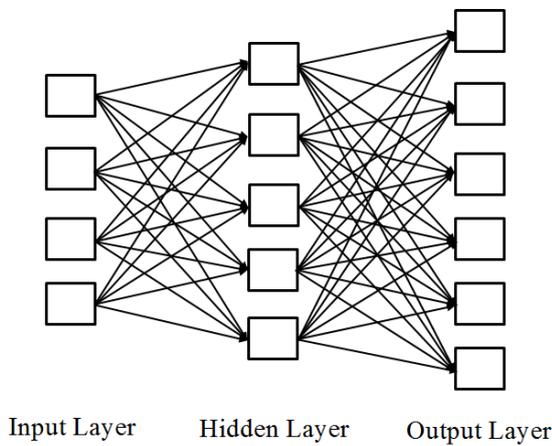


**Fig. 1**   Artificial neural network model

A structure (network) is composed of a number of interconnected units (artificial neurons). Each unit or neuron has an input/output (I/O) characteristic and implements a local computation or function. The output of any units is determined by its I/O characteristics, its connections to other units and the external inputs. It develops an overall function through one or more form of training. The net or overall function achieved is determined by the network topology, individual characteristics, learning or training strategy and training data.

### 2.1 Neuron

The model is based on the biological neuron found in the brain. The biological neuron works in the following way: the neuron's output is either on or off. The output depends only on the inputs. A certain number of inputs must be on at any one time in order to make the neuron fire. Each input has a weight, see Fig. 2. A larger weight means that the signal is more important in determining the output. A basic neuron adds its weighted inputs and compares the sum to an internal threshold level. If the threshold is exceeded, the neuron will turn on. This system is known as a feed forward [7].

Formally, this can be expressed as

$$t = w_1 x_1 + w_2 x_2 + ... + w_n x_n \tag{1}$$

Where $w$ is weight, $x$ is input, $t$ is total input and $n$ is the number of inputs. The output $y$ is defined as $y = f_h[t + b_i]$ where $b_i$ is target output and $f_h(x)$ is the activation function defined as follows:

$$f_h(x) = 1, \quad x > 0$$
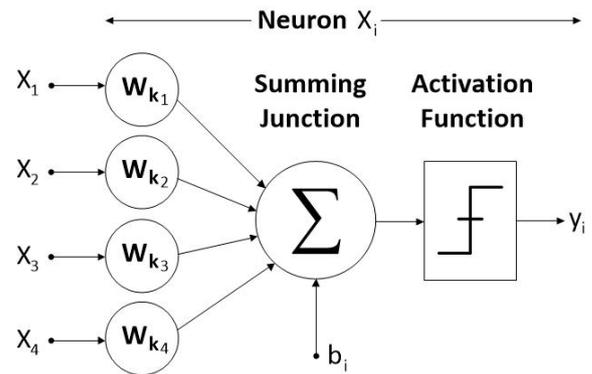$$f_h(x) = 0, \quad x < 0 \tag{2}$$



**Fig. 2**   Schematic diagram for neurons

### 2.2 Learning Rules

A learning rule modifies the weights and biases of a network. It is applied to train the network to perform some particular task. It falls into two broad categories: supervised learning, and unsupervised learning [8]. In supervised learning, the learning rule is provided with a set of examples (the training set) of proper network behaviors where an input to the network leads to the corresponding correct (target) output. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets. In unsupervised learning, the weights and biases are modified in response to network inputs only. There are no target outputs available.

## 3. Pill Identification

We developed an image recognition system for the identification of drug pills. The algorithm consisted of three main stages. In the first stage, images were preprocessed by removing noise in background. Then, the pill image was cropped with a bounding box. Next, the raw RGB image was converted into the grayscale image. The median filtering and contrast enhancement operations were then performed. After that, the grayscale image was converted into the binary image using a proper thresholding value. Finally, the opening operation was used to eliminate noise in the binary pill image. In the second stage, imprint

features were extracted and they were used as the input vector in the last stage, i.e., the pill was identified by a Levenberg-Marquardt backpropagation neural network.

## 3.1 Preprocessing

We performed the following preprocessing step:

1) After the RGB pill image was acquired, we eliminated background noise by using the following thresholding technique for each color channel:

$$g_{r,g,b}(x,y) = \begin{cases} 0 & f_{r,g,b}(x,y) < T_1 \\ f_{r,g,b}(x,y) & T_2 < f_{r,g,b}(x,y) < T_1 \\ 255 & f_{r,g,b}(x,y) > T_2 \end{cases} \quad (3)$$

where $T_1$, $T_2$ are preset threshold values. In this work, we used 50 and 190 for $T_1$, $T_2$, respectively. These two values highly depend on the experimental setup. $g_{r,g,b}(x,y)$ is a denoised RGB image, $f_{r,g,b}(x,y)$ is an original RGB image, and $(x,y)$ is a coordinate of each pixel.

2) The pill image was cropped using the bounding box.

3) The RGB pill image was converted into the grayscale image.

4) The median filtering and contrast enhancement operations were performed.

5) The grayscale image was converted into the binary image using the proper thresholding value. In this work, it was 170. However, the adaptive thresholding value will be our future research study.

6) The opening operation was used to eliminate noise in the binary pill image.
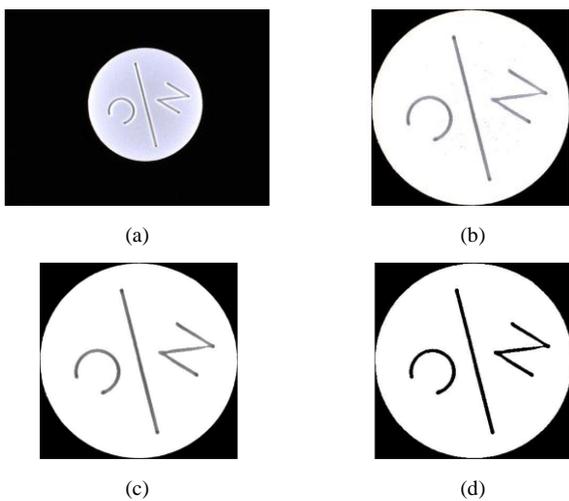


**Fig. 3** An example of the preprocessing step of pill identification: (a) the original pill image, (b) the denoised, cropped image, (c) the enhanced grayscale image, (d) the final binary image with imprint

As an example, Fig. 3(a) shows the original pill image, whereas Fig. 3(b) shows the resulting image after the background noise was removed and the pill image was cropped. After the image was converted into the grayscale image and the median filtering and contrast enhancement operations were performed, we obtained the resulting image as shown in Fig. 3(c). Then, the grayscale image was converted into the binary image and the opening operation was used. The final resulting image is shown in Fig. 3(d).

## 3.2 Feature Extraction

After preprocessing was conducted, the imprint was revealed as shown in Fig. 4(a). The imprint is very important for pill identification since it is unique. To extract the features from this imprint, we first divided the radius (r) of the pill by 5. Then the number of imprint pixels inside the circle with the radius of 0.2r, 0.4r, 0.6r and 0.8r was calculated, see Figs. 4(b) – 4(e), respectively. Note that these extracted features were invariance to image rotation.
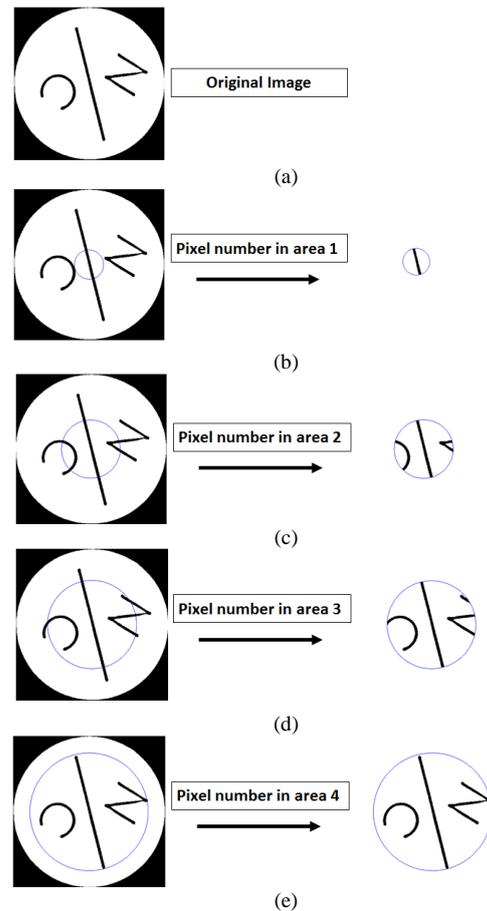


**Fig. 4** An example of the feature extracted from the imprint: (a) the pre-processed image, (b) – (e) the imprint pixels inside the circle with the radius of 0.2r, 0.4r, 0.6r and 0.8r, respectively, where r is the radius of the pill

## 3.3 Classification with a Neural Network

The features extracted by using the method given in Subsection 3.2 were used as an input vector of the feedforward neural network with supervised learning. Our neural network consisted of three layers with a four-neuron input layer, a five-neuron hidden layer and a six-neuron output layer (six classes). The transfer function of the hidden layer was hyperbolic tangent sigmoid transfer function, while the transfer function of the output layer was linear transfer function. A backpropagation learning algorithm used to train the neural network to perform such a task was based on a Levenberg-Marquardt algorithm.

## 4. Experimental Results

In our experiments, digital images of drug pills were acquired using a digital CCD camera (Basler ACE acA2500-14gc) with a frame rate of 14 fps at resolution of 2590×1942 pixels. To avoid interference of environmental light, four light bars were placed in square shape above the pill samples as shown in Fig. 5. The black background was chosen since the color of pill samples was lighter. The camera was mounted 12 cm above the base.
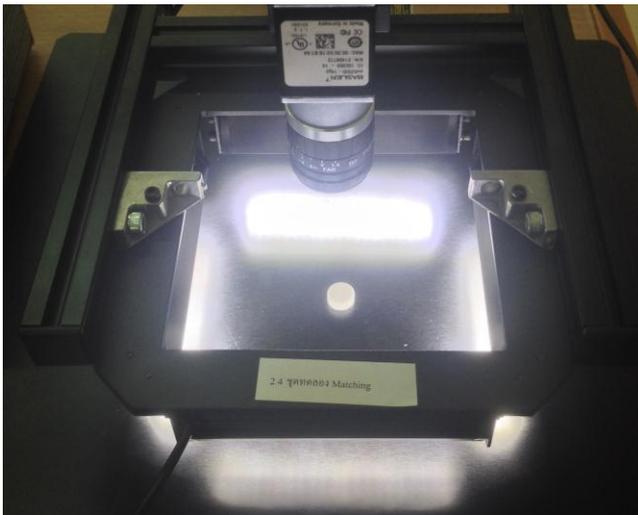


**Fig. 5** Experimental setup using a digital camera to capture the pill image

In this paper, we addressed the problem of pill identification in the case that color and shape of the different pill types were almost identical. The main difference among these pill types was the imprint. Thus, in the experiment, the following 6 pill types were chosen:

- Type 1 : Paracetamol 500 mg. (Cemol)
- Type 2 : Antacid Antiflatulent 325 mg. (Kremil-S)
- Type 3 : Paracetamol 500 mg. (Mypara)
- Type 4 : Paracetamol 450 mg. (Norgesic)
- Type 5 : Paracetamol 500 mg. (Panadol)
- Type 6 : Paracetamol 500 mg. (Sara)

They were used in our experiment since they were commonly used in hospitals and they were very similar in color and shape but different in imprint as seen in Fig. 6.
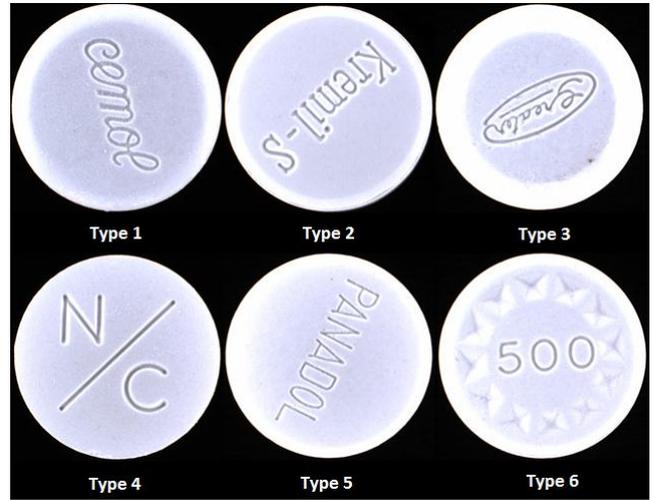


**Fig. 6** Six types of commonly-used pills in hospitals, identified by a number

As mentioned previously in Section 3, our algorithm was composed of three stages. After the preprocessing stage was performed, the imprint features were extracted (as described in Subsection 3.2). As an example, Table 1 shows the results of the imprint features of one pill sample.

| Feature | Value (pixels) |
|---|---|
| Pixel number in area 1 | 8503 |
| Pixel number in area 2 | 18295 |
| Pixel number in area 3 | 28610 |
| Pixel number in area 4 | 34287 |

**Table 1** An example of imprint features extracted from one pill sample

We extracted imprint features from 60 images of each pill type, resulting in 360 images in total. They were equally divided into a training set and a test set. After the neural network was trained, the test set was fed into the neural network to evaluate the effectiveness of our algorithm. The results showed that the identification accuracy was 94.4%, as shown in Table 2.

| Class | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1 | 56 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 59 | 0 | 0 | 0 | 2 |
| 3 | 0 | 0 | 60 | 1 | 3 | 0 |
| 4 | 0 | 0 | 0 | 59 | 1 | 0 |
| 5 | 4 | 1 | 0 | 0 | 56 | 8 |
| 6 | 0 | 0 | 0 | 0 | 0 | 50 |
| Sum | 93.3 | 98.3 | 100 | 98.3 | 93.3 | 83.3 |
| Average | 94.4 | | | | | |

**Table 2** Test results on 6 pill types using our algorithm

Fig. 7 shows an example of the pill that was correctly identified by our proposed algorithm. The original image is shown in Fig. 7(a), while the preprocessed one is shown in Fig. 7(b). The classification result using the neural network

is shown in Fig. 7(c), where the pill was correctly identified.
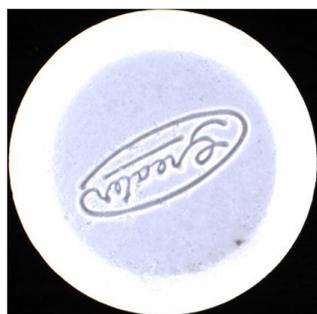


**Pill type no.3**

(a)



(b)

The pill sample is classified to Pill type no. 3

(c)

**Fig. 7**   An example of correct pill identification: (a) the original pill image, (b) the preprocessed version of (a), and (c) the classification result

Fig. 8(a) shows the original pill image that was incorrectly identified. Fig. 8(b) shows the preprocessing result, while Fig. 8(c) shows the classification result using the neural network. The main cause of the error was that some parts of the imprint disappeared after being preprocessed. This made its imprint features similar to those of other pill types.

## 5.   Conclusions and Future work

In this paper, image processing followed by a neural network was used to identify pills. The imprint features were extracted from pill image and used as an input vector of the neural network. After our algorithm was evaluated, the results showed that the accuracy of the pill identification was about 94.4%. To increase the accuracy, we will develop a new preprocessing method that can preserve as many imprints as possible and investigate a method that can extract more features from the imprints. More pill types will be used to evaluate our methods. In addition, since this work concerns a critical safety system, some backup mechanisms will be provided as a final verification scheme.



**Pill type no.6**

(a)



(b)

The pill sample is classified to Pill type no. 5

(c)

**Fig. 8**   An example of incorrect pill identification: (a) the original pill image, (b) the preprocessing result, and (c) the classification result

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