

# DeepPill : Web Framework for Automatic Pill Recognition and Recommendation System using Deep Learning Techniques

Vishnukirthik R<sup>1</sup>, Manoj Kumar NR<sup>2</sup>, Jayaram M<sup>3</sup>, Dr. A. B. Arockia Christopher<sup>4</sup>

Students<sup>1,2,3</sup> and Associate Professor<sup>4</sup>

Dr. Mahalingam College of Engineering and Technology, Pollachi, India  
18bit100@mcet 18bit078@mcet.in

**Abstract:** Medication safety is a critical issue in daily patient care. In recent reports indicates that medication error is the most preventable medical error. Medication errors represent one of the most important problems in health care, with 'look-alike and sound-alike' (LASA) being the lead error. Accurately recognizing prescription pill images according to their visual appearance helps to ensure patients' safety and facilitate contemporary healthcare system for patients/ old people/blind people. Several research groups have tackled the pill identification problem, with solutions based on content-based image retrieval (CBIR) and image classification. However, accurate pill recognition in daily life is usually hindered by the few-shot learning problem. Existing solutions to prevent LASA still have their limitations. This challenge targets the development of software tools to help users accurately identify known prescription pills from pictures. In this project, we propose an automated classification system for pill images using deep learning. The deep learning algorithm of deep convolutional neural network was adopted for implementation of the proposed system. One of the key steps in building deep learning systems for pill classification and generation is the choice of featurization for the molecules. This model outperformed identification using conventional computer vision solutions, and could assist users in identifying pills or drugs while preventing medication errors. With an accuracy greater than 90%, the results of this project may be applied to the real environment, and may assist patients to identify pills or drugs and prevent medication errors caused by look-alike pills.

**Keywords:** Pills Recommendation

## I. 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 Types of Tablets for Pharmaceutical

There are several types of pharmaceutical tablets, including:

- **Compressed Tablets.** Compressed tablets provide rapid disintegration in gastric fluid after ingestion, allowing for quick absorption of the dosage form. They come coated or uncoated and are formed by compressing powdered, granular, or crystalline materials into the required shape.

- **Coated Tablets.** Coated tablets are compressed tablets that are coated in an additional layer, such as sugar or wax, to increase durability and ease of consumption. Examples include Advil and Diclofenac Potassium tablets.
- **Dispersible Tablets.** Dispersible tablets can be formulated as uncoated or coated tablets and offer uniform dispersion when suspended in water.
- **Effervescent Tablet** Effervescent tablets are uncoated tablets that produce gaseous carbon dioxide when placed in water, causing it to quickly dissolve and produce a suspension of powdered material that is readily absorbed by the body once consumed.
- **Modified Release.** Modified release tablets are coated or uncoated tablets formulated to release medication when a specific condition or desired activity is reached.
- **Enteric-Coated or Gastro- Resistant tablets.** This tablet type is coated with a polymer material that gives it resistance to acidic gastric juices. This coating is used when the drug substance is easily destroyed by gastric fluid or is irritating to the gastric mucosa.
- **Prolonged Release Tablets.** Prolonged release tablets require special excipients and deliver the active ingredient in a controlled manner over a prolonged period.
- **Soluble Tablets.** Soluble tablets are coated or uncoated tablets that must be dissolved in water before administration.
- **Tablets for Mouth Use.** These tablets are designed to release active ingredients when placed in the mouth or buccal area. They are used when a patient has difficulty swallowing or is in need of fast release to the bloodstream. Examples include lozenges, troches, and buccal and sublingual tablets.
- **Fast-dissolving.** Tablets that disintegrate almost immediately, in the mouth, upon contact with saliva.
- **Tamper-resistant.** Some manufacturers have developed formulations that make it extremely difficult to change the final form of a tablet through means such as heat or melting, as in the case of abusers doing so when manipulating opioids.
- **Osmotic pump.** Tablets with a tiny hole laser-drilled into a semi-permeable outer coating. Water within the human body is absorbed through the coating (via osmosis), with the resulting pressure pushing the drug substance through the hole (or holes).
- **Implantable or Other Route Tablets.** These tablets administer medication through areas of the body other than the mouth, such as rectal or vaginal tablets, or through a medical implant. Implantable tablets allow for small dosages and are used to deliver medicines at the site where the drug is needed most.

## II. LITERATURE SURVEY

### **Colour Compensation Based on Colour Background Shadow for Pill Identification**

**Author: Somchart Chokchaitam**

**Year: 2020**

**CrossRef: <https://ieeexplore.ieee.org/document/9611998>**

### **ePillID Dataset: A Low-Shot Fine-Grained Benchmark for Pill Identification**

**Author: Naoto Usuyama; Natalia Larios Delgado**

**Year: 2019**

**CrossRef: <https://ieeexplore.ieee.org/document/9150727>**

#### **Objective**

The main contribution of this paper is introducing ePillID, a new pill identification benchmark with a real-world low-shot recognition setting.

#### **Methodology**

This is a low-shot fine-grained challenge because (1) for most of the appearance classes there exist only one image and (2) many pills have extremely similar appearances. Furthermore, empirically evaluate various approaches with the benchmark to serve as baselines. The baseline models include standard image classification approaches and metric learning-based approaches. Finally, present error analysis to motivate future research.

#### Dataset

ePillID dataset includes 3728 consumer images for 1920 appearance classes (two sides for 960 pill types) and 8192 reference images (two sides for 4092 pill types). This requires a fine-grained low-shot setup, where models have access to one reference image for all the 8192 appearance classes.

#### Findings

The multi-head metric learning approach performed remarkably well; however, our error analysis suggests that these models still cannot distinguish confusing pill types reliably.

#### **IoMT based Pill Dispensing system**

**Author:** Ujjwal Singh

**Year:** 2019

**CrossRef:** <https://ieeexplore.ieee.org/document/8944886>

#### **Objective**

This project focuses on providing cost effective, time bounded and low power prototype. Most importantly the data is secure and can only be viewed by authorised personnel as the data may be used in critical applications, although the challenges in security have not been challenged in depth in the past and this fact inspires us to propose the desired system. This paper tries to reduce misjudgement of data as it involves the direct consultation of a doctor and only upon his/her approval will the data be considered validated.

#### Methodology

The healthcare model proposed in this paper has a multilayer architecture (3 layer) as shown in Fig. 1. The architecture consists of 3 layers: sensor network, dispenser, public display. The pill dispenser dispenses pills as per the requirements of the patient. These requirements are pre adjusted and can be modified as per the personal need. The pill dispenser works in synchronization with a real time clock that keeps a record of the day date and time.

#### Dataset

As a proof-of-concept demonstration, 1, 7SS images were taken using a normal CMOS camera of four common pill types. The images of acetaminophen, acetylsalicylic acid and ibuprofen were taken using various backgrounds, image angles, and lighting conditions.

#### Findings

The sensors used may produce results that may vary overtime, hence they either need to be replaced or calibrated in order to produce the most accurate results even after usage over a long period of time. As the process involves the consultation of a doctor the whole process can be delayed due to human interaction. The different sensors involve different delay times to be used in order to display the readings, the prolonged display of continuous real time readings cause an error in the parsing of data. Continuous use of hardware may cause heating of the equipment and may lead to temporary shutdown.

#### **IoMT based Pill Dispensing system**

**Author:** Seungtae Kang

**Year:** 2018

**CrossRef:** <https://ieeexplore.ieee.org/document/8552143>

#### **Objective**

This paper proposes a novel method for the compensation of the illumination variations. Applied the shading compensation to the pill images, and obtained improved surface images.

#### Methodology

Propose an algorithm for eliminating the effects of lighting, which is suitable for pre-processing of pill and tablet recognition. Since the portion of the background of the captured pill images is very large, we use the class activation map

(CAM), which is a weakly supervised localization method to find the position of the pills by approximating the direction of the illumination using the value as a weight. The illumination variation is approximated by linear regression, and the backlighting is corrected.

#### Dataset

The data used in this project were images captured by two different types of smartphones in indoors and outdoors. 200 different types of pills are collected and their photos were taken at least 10 photos per pill.

#### Findings

As the resulting image shows, the shading variations are removed from the surface of the pills, and the letters on the surface became much clearer than the input images.

CoforDes: An Invariant Feature Extractor for the Drug Pill Identification

**Author:** Mateus A

**Year:** 2018

**CrossRef:** <https://ieeexplore.ieee.org/document/8417208>

#### Objective

The author proposes a pill feature extractor to classify them based on shape and color (CoforDes).

#### Methodology

In this work, the author proposes an extractor for identification of pill images, invariant to rotation, based on shape and color (CoforDes). The proposed approach begins with the pill segmentation step from the conversion of the input image. Shape attributes extraction is performed after pill contour segmentation and detection. The color attribute calculation uses the contour found in the segmentation process. Then, using invariant moments, calculate the contour centre point of the segmented pill using Hu.

#### Dataset

The PILL BR dataset is a public dataset comprised of 1000 pill images in 100 different pills labels. Another feature of this dataset is that all 100 pill labels were produced in Brazil. These images were captured using a partially controlled environment. In obtaining the images, there was variation of rotation, translation, background and illumination. The images have a resolution of 480X400;

#### Findings

Based on this analysis, we can prove that CoforDes has an efficiency higher than all the analysed extractors for identification of pill images. Regarding the extraction time analysis, the CoforDes extractor obtained the best results and the Zernike Moments obtained the worst results, in both datasets. Adding Texture to CoforDes: the initial proposal although having an excellent accuracy can still be improved, one of the best possibilities would be the addition of texture features

### **III. PROPOSED SYSTEM**

#### **3.1 System Analysis**

##### **A. Existing System**

##### **Non-computer vision-based approach**

Various online platforms are now available to serve as an aid in identifying pills, for example, the 'Pillbox' by the United States National Library of Medicine, 'Pill Identifier' by Medscape, and 'Pill Identification tool' by WebMD. These online platforms share a similar user interface, whereby users are required to manually input or select from the drop-down menus a series of features pertaining to the pill in a query, such as its shape, its colour, as well as the presence or absence of imprints and scorings.

#### **Drawback**

- First, the choices provided in the dropdown menu may not encapsulate the features queried. This is particularly prominent for the choices of colour as, being a continuum feature, it is impossible to literally describe each colour and their tones.
- Second, manual inputting of the information is susceptible to the subjectivity of users, for example on the interpretation of colours.
- Third, the requirement of manual inputting could be very time-consuming, especially when there are multiple pills that need to be identified.
- Computer vision-based approach Feature based
- Colour features are usually based on hue, saturation, value (HSV) colour profile due to its robustness to illumination variation.
- Feature based approach Scale Invariant Feature Transform (SIFT) and Multi-scale Local Binary Pattern (MLBP).

#### **Classification Algorithms**

- **Back Propagation (BP) neural network:** BP algorithm, a kind of supervised training method, is used to adjust and optimize weight parameters extracted in the pre-training stage. The classification results were obtained by logistic or SoftMax regression algorithm.
- **Support vector machines (SVMs)** It is an algorithm that can also be used for classification. The major stands out feature is that it extracts features from an image and then segregate them into classes with hyperplanes. Then the model will select the hyperplane with the best classifier to decide which hyperplane has the lowest classification error and least match. In other words, it segregates the classes and chooses the most accurate hyperplane.
- **k-Nearest neighbours (kNN)** (Guo & Wang, 2003): It is an algorithm that can be used for classification. The idea behind the method is that it assumes that similar things exist in close proximity. The method takes into consideration the data points of each image in the dataset using Euclidean distance in other to group them together. So, when an image is applied to the model, the input image will be converted to a feature vector. Thereafter, the image will be used to construct a colour histogram to classifier the colour of the pills and then stored under a class label extracted from the image path.
- Sparse Denoising Auto-Encoder (SDAE).

#### **Drawback**

- Manually designed features work well in a controlled environment but would yield poor performance in unconstrained settings such as with images captured by mobile devices.
- Susceptible to misidentification.
- Effective binary and multi-class classification performance on a spectrum sample set of small size.

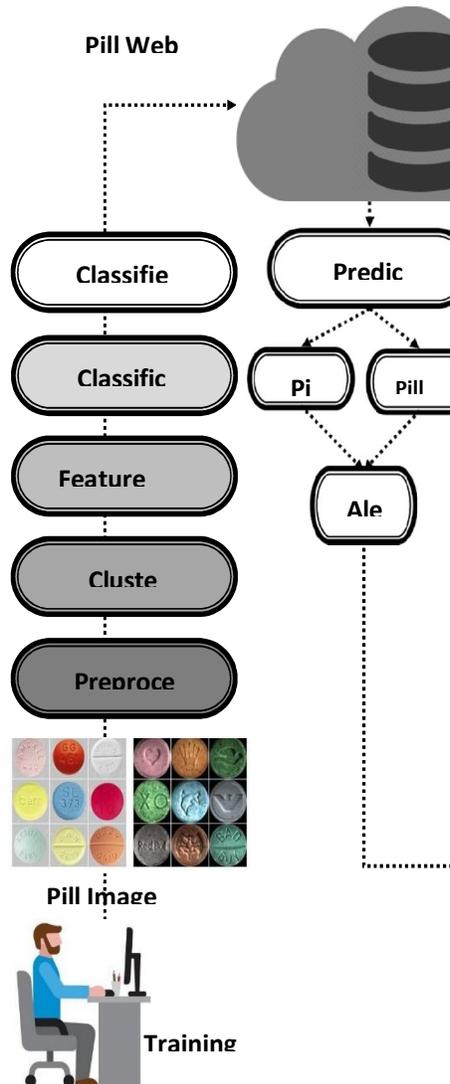
### **3.2 Proposed System**

This project proposes novel algorithms in both pill extraction and description process to achieve automatic and accurate pill recognition, comparing favourable to the state of the art.

A Deep Convolutional Neural Network (DCNN) for the identification of oral pills is proposed. Deep learning approaches typically consist of three steps, once given the image, (i) it finds the pill(s) in an image, (ii) crops the pill(s) and then (iii) classifies the cropped image. We will utilize RPN an object detection model to find the pills in an image and an CNN image classifier to classify the images. The most basic component of CNNs is the neuron model. Two layers of neurons constitute the perceptron model, which can achieve the logical operation and weight learning of a complex task. Adding a hidden layer between the input and output layers to form a multilayer functional neuron model can solve multiclassification problems. CNN is an artificial neural network based on deep learning theory. The core part of CNNs is the hidden layer, which is composed of convolution, pooling, and fully connected layers. The convolution layer extracts the main features of the input image data and contains multiple convolution kernels, which are similar to the feed forward

neural network neurons in the convolutional layer. The convolution kernel in the convolutional layer can extract deep information from the data and local features of the image. The activation function is essential after the convolution operation. The activation function adds nonlinear factors to the neural network to solve complex problems. In recent years, ReLU has been widely used as an activation unit of CNNs. Compared with the common activation functions, sigmoid and tanh, ReLU offers advantages, such as a low calculation cost. ReLU sets the output value of certain neurons to zero, thereby resulting in the sparseness of the network and reduction in the interdependence of parameters; as such, the problem of overfitting is alleviated.

The CNN structure used in the experiment comprised four convolution and pooling layers, followed by fully connected hidden and SoftMax layers. The size of the convolution kernel of the first two layers was 55, and that of the latter two layers was 33. Maximum pooling was used, and the excitation function was ReLU. The experiments were implemented using the TensorFlow toolbox. In the training process of the RACNN model, the k-fold cross validation method was used to evaluate the model, and k was set to 10. All capsule image datasets were randomly divided into 10; nine of them were trained each time, and the remaining one was used for testing (i.e., 1413 and 157 samples were trained and validated, respectively). The process was repeated 10 times, and the image datasets used for testing each time were different. The specific implementation process was completed by calling the k-fold function in the sklearn. model selection module in the Scikit-learn library.



The sample images acquired from the producing spot were input into the DCNN network. Each sample image was pre-processed into a 100x100 pixel image as the input dataset by using the resize function in the Skimage library. The size of the convolution core in the first layer was 5x5, and the convolution layer C1 obtained 32 feature images with 100x100 pixels. The down sampling coefficient was 2, that is, the step length of the pooling layer P2 was 2. The pooling layer P2 obtained 32 feature images with 50x50 pixels. As the last layer of RACNN, the SoftMax layer classified the data and outputted a vector of 10x1. Each vector value represented the probability that each sample belonged to a class. Cross entropy was used as the loss function, which increased as the predicted probability diverged from the actual label. Thus, the model aimed to minimize cross entropy. After establishing the DCNN network as described above, training data were used to train the network and fix the trained DCNN network. Finally, the test data were identified and classified by the trained DCNN network.

#### **Advantages**

- CNNs performs better in the low data regimes due to its hard inductive bias.
- DCN achieved superior results compared to existing methods in pill identification.
- Cost-effective solution that allows us to conveniently identify and verify pills.
- Higher reliability.
- Fast and accurate.
- Ability to learn complex features

#### **IV. RESULT**

The important points involved with the performance metrics are discussed based on the context of this project:

True Positive (TP): There is a pill, and the algorithms detect pill name.

False Positive (FP): There is no pill, but the algorithms detect as pill and display pill name.

False Negative (FN): There is a pill, but the algorithms do not detect pill and name.

True Negative (TN): There is no pill, and nothing is being detected.

#### **Accuracy**

Accuracy is a measure that tells whether a model/algorithm is being trained correctly and how it performs. In the context of this thesis, accuracy tells how well it is performing in detecting humans in underwater environment. Accuracy is calculated using the following formula.

$$\text{Accuracy} = (T P + T N) / (T P + T N + F P + F N)$$

#### **Precision**

It denotes the ratio of positively predicted cases that are actually positive. In the context of this thesis, precision measures the fraction of objects that are predicted to be humans and are actually humans present in underwater environment. Precision is calculated using the following formula.

$$\text{Precision} = T P / (T P + F P)$$

#### **V. CONCLUSION**

Our goal was to illustrate how ‘look-alike’ error can be captured and explained by a convolution-based deep learning network whose working mechanism is in much similarity to the human visionary recognition capability. Subsequently, appropriate solution to extract more detailed nuance differences can be utilized in distinguishing look-alike objects. With an accuracy greater than 90%, the results of this study may be applied to the real environment, and may assist pharmacists to identify drugs and prevent medication errors caused by look-alike blister packages. The superior performance of DCN underscores the potential of Deep Learning model in the application of pill identification and verification

#### **VI. FUTURE WORKS**

In future there are many kinds of drug packages that need to be identified: pills; blister packaging; clip chain bags; powder bags; foil packaging bags; transparent bags; paper packages; bottle packaging, etc.

**REFERENCES**

- [1]. Computer Science and Engineering, University of New South Wales, Sydney 2052, Australia, 2018, [www.elsevier.com](http://www.elsevier.com).
- [2]. Pooja Sharma and RupaliBhartiya " Implementation of choice tree Algorithm to examination of execution" International Journal of Advanced Research in Computer and Communication Engineering", Vol. 1, Issue 10, December 2012, ISSN : 2278-1021.