Blister Package Classification Using ResNet-101 for Identification of Medication

Narit Hnoohom
Image, Information and Intelligence Laboratory,
Department of Computer Engineering, Faculty of Engineering, Mahidol University
Nakorn Pathom, Thailand
narit.hno@mahidol.ac.th

Nagorn Maitrichit
Image, Information and Intelligence Laboratory,
Department of Computer Engineering, Faculty of Engineering, Mahidol University
Nakorn Pathom, Thailand
nagorn.mat@student.mahidol.ac.th

Pitchaya Chotivatunyu
Image, Information and Intelligence Laboratory,
Department of Computer Engineering, Faculty of Engineering, Mahidol University
Nakorn Pathom, Thailand
pitchaya.cht@student.mahidol.ac.th

Virach Sornlertlamvanich
[1]Asia AI Institute (AAII), Faculty of Data Science, Musashino University, Tokyo, Japan
[2]Faculty of Engineering, Thammasat University, Thailand
Pathumthani, Thailand
virach@gmail.com

Sakorn Mekruksavanich
Department of Computer Engineering, School of Information and Communication Technology, University of Phayao
Phayao, Thailand
sakorn.me@up.ac.th

Anuchit Jitpattanakul
Intelligent and Nonlinear Dynamic Innovations Research Center, Department of Mathematics, Faculty of Applied Science, King Mongkut's University of Technology North Bangkok
Bangkok, Thailand
anuchit.j@sci.kmutnb.ac.th

Abstract—This research aimed to fine-tune image classification with deep learning techniques to verify the dispensing of prescriptions in hospitals. The proposed approach will be able to help pharmacies reduce the errors that lead to patients receiving the wrong medications. The image classification model uses a double-side transformed image dataset with download from Highlighted Deep Learning (HDL) paper. The dataset collected two-hundred seventy-two images for types of medicine blister packs, including 72 images of front-side and backside merged with a horizontal cropped background, which were used for training the model. The blister package image dataset uses a deep learning model with a ResNet-101 pre-trained model from the TensorFlow framework. The experimental results indicated that the TensorFlow framework achieved higher precision, recall, and F1-score than the Caffe framework. A ResNet-101 model with histogram equalization in the front and backside has the highest accuracy at 100 percent.

Keywords—Blister package identification, Deep learning, Dispense

I. Introduction

Generally, a hospital uses multiple drugs to treat patients' illnesses. Drug dispensing statistics from Rajavithi Hospital reveal that the drug dispensing process contains errors at 3.8 percent [1]. During the dispensing process, a pharmacy checks the medication order from the doctor in terms of the type of blister medicine and quality. Due to multiple reasons, pharmacists can be distracted and make errors during this process, which includes the large volume of patients, doctors' handwriting, stress, heavy workload, long hours of work, and a low number of pharmacists. The issue of dispensing the wrong medicine becomes serious especially when it involves children or the elderly. The ultimate objective of this research is to increase the accuracy of the identification for types of blister package to ensure that the brand, quantity, and drugs dispensed in blister package form match the information specified in the prescription exactly.

II. Related Work

In literature, most papers and conferences conduct the identification of pills, tablets, and capsules by using shapes, imprints, and colors as feature extraction, then build machine learning applied to extract relevant features with a trained classifier to achieve tablet or capsule identification. Y. Lee and U. Park [2] proposed an automatic method to match pill images by using imprints appearing on the pills with invariant moments and edge localization features for classification. Their approach showed 76.74 percent matching accuracy. Chen, R.-C, and Chan [3] proposed a neural network with the fuzzy method, and relevant feedback for classifying pill shapes by using five features of drug images including color, shape, ratio, magnitude, texture, and dynamic weight. The dataset downloaded from multiple websites included 2,116 images showing 822 types of drug pills. Their experiment results showed a 92.60 percent matching accuracy. S. Suntronsuk and S. Ratanotayanon [4] proposed extracting the text from pill images with a technique using Imprint Area and Kasar for processing edge masks of the imprint. The experiment results showed that the text imprint extraction method had 56.67 percent accuracy. Charlene Tay [5] proposed using feature extraction on images through Hu Moments and other shape descriptors to build a classification model. The experiment results showed that using a shape classifier with the decision method had 81 percent accuracy. Overall, organizations classify pills, except for Jing-Syuan Wang et al. [6], who proposed the identification of blister packages. Specifically, Highlighted Deep Learning (HDL) uses automatic detection and segmentation to remove the background and process raw blister packages images, then builds a ResNet CNN model to classify the correct blister package types. The dataset used was from an experiment for adult lozenge dispensing at MacKay Memorial Hospital. It consisted of 272 types of blister packages, with 65 images of each type (font and back) for image training and 7 images for validation, with a total of 39,168 images. The experiments

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built three models consisting of a cropped front view, cropped back view, and signature template (both-side view). When using the signature template approach, the experiments showed an accuracy of nearly 100 percent. W. Chang et al. [7] proposed ST-Med-Box to assist chronic patients to avoid taking the wrong medications based on deep learning techniques. The experiment results showed that accuracy reached 96.6 percent when classifying eight different types of medicine. Although many solutions have been published to help keep patients from taking the wrong medication, those solutions focused on pills, tablets, and capsules; very little focus has been placed on blister packages in zip bags. Y. Han et al. [8] proposed a real-time blister package identification system by using image processing to remove the blister package area from the background, then using YOLO v2, ResNet, and SE-ResNet-101 optimizing deep learning to apply the model into embedded technology. This requires less computation and offers better identification. The experiments showed almost 100 percent accuracy by the signature template approach.

III. Deep Learning Method

Deep learning is has become a popular technique in recent years. It is based on neural network architecture inspired by the structure of the human brain. It can automatically extract the characteristics of images; it is also called "feature learning". The main advantage of deep learning is that its high-accuracy and expandability can be used in multiple ways, such as image classification, pose classification, and sound classification. The deep learning blister package identification model is an important thing to help people to prevent dispensing errors in hospitals and patients to ensure the patient takes the wrong medicine. However, it required minimum error classification in the model. In that case, this research focuses on fine-tuning a model for the identification of a blister package dataset by using the pre-train with the deep learning technique. A method consists of the dataset, pre-processing, and deep learning model as shown in Figure 1.

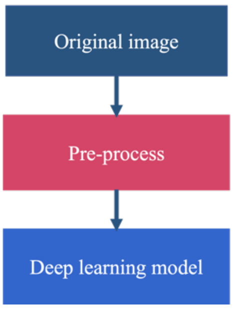

Fig. 1 Fine-tuning a deep learning method

A. Dataset

A dataset downloaded from J. S. Wang et al. [6] consists of 272 types of blister packages, totaling 19,584 double-sided transformed images. Examples are illustrated in Figure 2.

Fig. 2 Double-sided transformed image

The dataset was partitioned as mentioned, and the number of each training set and testing set is as shown in Table I.

TABLE I. HDL Dataset Partition

Dataset	Total	Train	Test
Dataset	19,584	17,680	1904

B. Pre-processing

The purpose of data preprocessing is to improve the accuracy of blister package identification. Specifically, it helps deep learning to solve related problems such as lighting and limited blister package information and improves the accuracy of identification. The pre-processing method shown in Figure 3 is proposed to improve lighting conditions. There are four steps: extract front and back, color space, adaptive histogram equalization, and merge front and back.

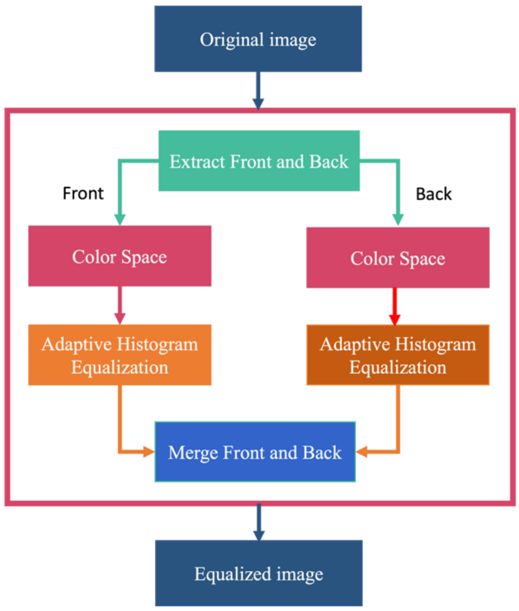

Fig. 3 Pre-process blister package image

1) Extract Front and Back

This step extracts the front and backside of blister packages from images. The double-sided size (448×448 pixels) cropped left side (front) and right side (back) are shown in Figure 4.

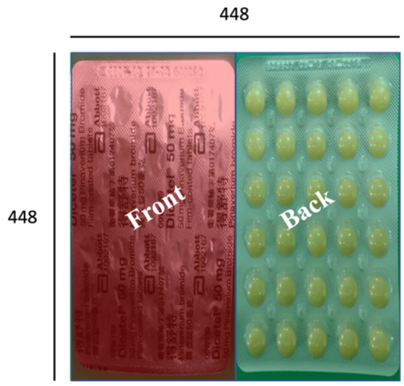

Fig. 4 Cropped front and backside of blister packages

2) Color Space

The original image is a 448×448 pixels image with three channels of RGB to YUV color space, which then processes the Y component using a respective filter. Figure 5 provides a flow chart representation of the proposed approach.

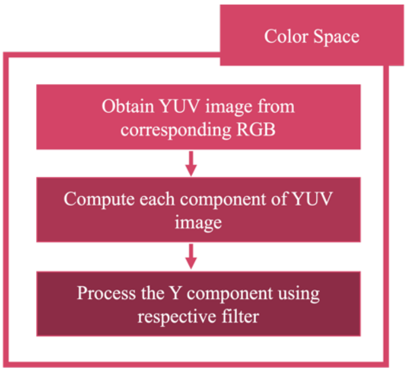

Fig. 5 Flowchart for Color Space

The proposed method algorithm has been experimented with and researched on color images using the OpenCV function. In the example, one color image (PNG format, 448×448×3) was used as the base image. The results of the example are shown in Figures 6 and 7.

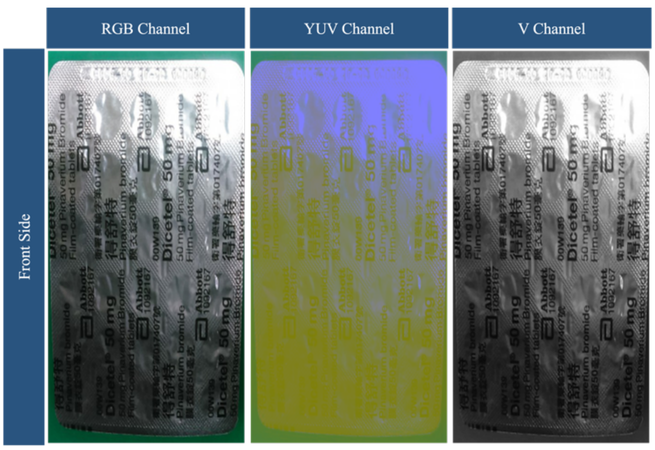

Fig. 6 Example of front-side blister packages

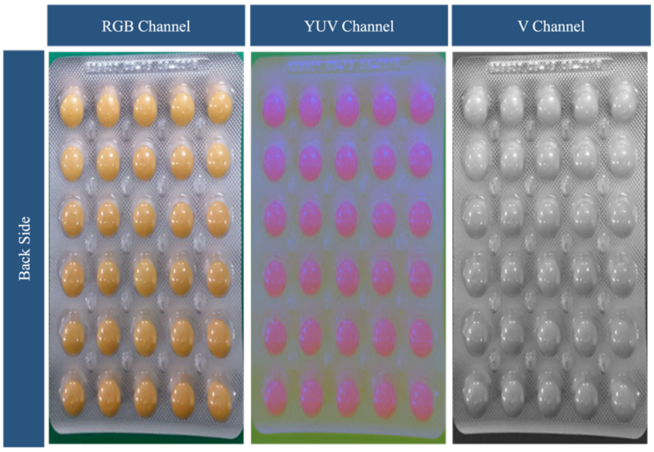

Fig. 7 Example of back-side blister packages

3) Histogram Equalization

Histogram equalization is an aspect of image enhancement that involves the direct manipulation of image pixels in the spatial domain to highlight interesting textures and imprints in images, removing noise from images, and making images more visually appealing. It obtains the histogram equalization of the V component and converts it to the RGB channel, as shown in Figure 8.

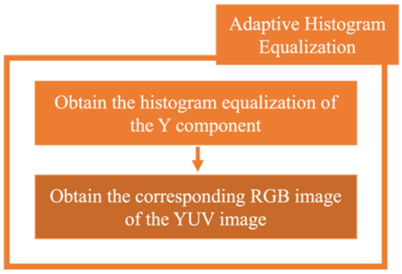

Fig. 8 Flowchart for Adaptive Histogram Equalization

4) Merge Front and Back

This step concatenates the front and backside blister package images in a horizontal line. As shown in Figure 9, the front side is on the left side and the back side is on the right side.

Fig. 9 Example of image processing in the pre-process

C. Deep Learning Model

This research uses the pre-trained model from the Model Zoo by using the TensorFlow framework, which provides a collection of pre-trained models. In this case, the researcher reuses the ResNet-101 model to classify blister packages. All the input images are then resized to 227×227×3 to fit the model input. After that, data is split into train, validation, and test dataset, as shown in Table II.

TABLE II. HDL DATASET IN DEEP LEARNING MODEL

Dataset	Train	Validation	Test
Dataset	14,144	3,530	1,904

IV. EXPERIMENTAL RESULTS

To demonstrate the proposed method between the Caffe and TensorFlow framework for the blister package identification task, the deep learning method is implemented using TensorFlow 2.3 framework and executed on a desktop PC with NVIDIA RTX 2080 Ti GPU on Ubuntu 20.1 operating system. In the experiment, two sets of experiments have been conducted. In the 1A-3A experiment, A pre-train model was constructed by using the TensorFlow framework with comparable accuracy to the Caffe framework in ResNet architecture. In the next experiment, a pre-process is a key factor to improve accuracy by using a pre-trained model with ResNet architecture

A. Framework

In this experiment, the researchers used the TensorFlow framework to classify 272 types of blister packages to compare the accuracy of the Caffe framework in the HDL paper by using the ResNet-101 architecture.

1) Experiment 1A: Cropped Front View

Table III shows the results of the text classification models. The accuracy of the models is improved by using the TensorFlow framework with the ResNet architecture used in Experiment 1A. From the results, the proposed method performed better in terms of Precision (98.91 percent), Recall (98.69 percent), and F1-score (98.68 percent) compared to using the Caffe framework, which improves Precision (6.23 percent), Recall (11.97 percent), and F1-score (12.00 percent).

TABLE III. EXPERIMENT RESULTS OF FRONT VIEW

Trained model (ResNet-101)	***Proposed Method (TensorFlow)***	***J. S. Wang et al. [6] (Caffe)***
Epochs	71	71
Precision	98.91%	92.68%
Recall	98.69%	86.78%
F1-score	98.68%	86.68%

2) Experiment 2A: Cropped Back View

In this experiment, the results show the proposed method performed slightly better in terms of Precision (92.90 percent), Recall (91.07 percent), and F1-score (90.89 percent) compared to using the Caffe framework, which improves Precision (1.27 percent), Recall (5.65 percent), and F1-score (5.64 percent), as shown in Table IV.

TABLE IV. EXPERIMENT RESULTS OF A BACK VIEW

Trained model (ResNet-101)	***Proposed Method (TensorFlow)***	***J. S. Wang et al. [6] (Caffe)***
Epochs	56	56
Precision	92.90%	91.63%
Recall	91.07%	85.42%
F1-score	90.89%	85.25%

3) Experiment 3A: Double Side View

In this experiment, the results show the proposed method performed slightly reduced Precision (98.81 percent), Recall (98.58 percent), and F1-score (98.52 percent) compared to using the Caffe framework, as shown in Table V.

TABLE V. EXPERIMENT RESULTS OF SIGNATURE TEMPLATE

Trained model (ResNet-101)	***Proposed Method (Signature Template Histogram Equalization)***	***J. S. Wang et al. [6]***
Epochs	39	39
Precision	98.81%	99.84%
Recall	98.58%	99.83%
F1-score	98.52%	99.79%

B. Pre-process (Histogram Equalization)

In this experiment, the researchers used the pre-process by applying histogram equalization on a signature template and extracting front and back.

1) Experiment 1B: Double Side View apply Histogram Equalization

In this experiment, the results show the proposed method performed Precision (96.95 percent), Recall (97.58 percent), and F1-score (96.89 percent) slightly lower than without applying histogram equalization on the TensorFlow and Caffe frameworks, as shown in Table VI.

TABLE VI. EXPERIMENT RESULTS OF HISTOGRAM EQUALIZATION DOUBLE-SIDED IMAGE

Trained model (ResNet-101)	***Proposed Method (Preprocess)***	***J. S. Wang et al. [6]***
Epochs	39	39
Precision	96.95%	99.84%
Recall	97.58%	99.83%
F1-score	96.89%	99.79%

2) Experiment 2B: Double-Sided View apply Histogram Equalization on Each Side

In this experiment, the results show the proposed method performed Precision, Recall, and F1-score at 100.00%. This further confirms the effectiveness of the approach when applying histogram equalization by the split front and backside of blister packages.

TABLE VII. EXPERIMENT RESULTS OF HISTOGRAM EQUALIZATION SPLIT SIDE IMAGE

Trained model (ResNet-101)	***Proposed Method (Pre-process)***	***J. S. Wang et al. [6]***
Epochs	39	39
Precision	100.00%	99.84%
Recall	100.00%	99.83%
F1-score	100.00%	99.79%

V. CONCLUSION

In this paper, the researchers proposed a fine-tuning deep learning model by applying an image processing technique and a pre-train model by using the TensorFlow framework. The experiment confirmed that using a histogram equalization to classify 272 types of blister packages, totaling 19,584 images split into training, validation, and test. The overall precision, recall, and F1-score in the test dataset attained 100 percent. It is feasible and effective, especially for adjusting the brightness of blister packages. In future work, researchers should explore the use of deploying a model for embedded boards.

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