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# Deep Learning-Based Automated Pill Identification Using Image Preprocessing

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***Abstract –*** **Accurate pill identification is essential for reducing medication dispensing errors and improving patient safety in healthcare environments. The increasing number of prescription and over-the-counter medications has made manual pill identification a challenging and time-consuming task for pharmacists and healthcare professionals. Similarities in pill shape, color, size, and imprint often contribute to medication errors, potentially leading to serious health consequences. This paper presents an intelligent deep learning framework for automated pill identification that integrates Convolutional Neural Networks (CNNs) with image preprocessing techniques to accurately recognize pharmaceutical pills. The proposed framework employs the Pillbox dataset, image augmentation using the Keras Image Data Generator, OpenCV for image preprocessing, HSV-based color segmentation, Paddle OCR for imprint recognition, and feature extraction based on pill shape, color, and imprint characteristics. Two CNN architectures are developed for pill detection and pill classification using ReLU activation and Softmax classification layers. The feature extraction module further enhances recognition accuracy by comparing extracted characteristics with a reference database. Experimental evaluation demonstrates that the proposed CNN model achieves 98.9% training accuracy, 98.9% validation accuracy, and 97.5% testing accuracy, while integrating image preprocessing improves the overall identification accuracy to 97.9%. The proposed framework provides a scalable, accurate, and efficient solution for automated medication identification and has significant potential for deployment in pharmacies, hospitals, and intelligent healthcare systems to minimize medication dispensing errors and improve pharmaceutical safety.**

*Keywords* - **Pill Identification, Deep Learning, Convolutional Neural Network, Image Preprocessing, OpenCV, Paddle OCR, Keras, Computer Vision, Pharmaceutical Image Analysis, Healthcare Automation.**

## I. INTRODUCTION

Medication safety remains one of the most critical concerns in modern healthcare systems. Thousands of prescription and over-the-counter medications are distributed annually, making accurate pill identification increasingly difficult for pharmacists, healthcare professionals, and patients. Medication dispensing errors may occur because of distractions, heavy workloads, similar pill appearances, incorrect storage, and manual verification processes. Such errors can result in incorrect medication administration, adverse drug reactions, delayed treatments, and, in severe cases, life-threatening situations. Consequently, intelligent automated pill identification systems have become an important research area for improving pharmaceutical safety and reducing human error.

Traditional pill identification primarily depends on visual inspection of pill characteristics such as shape, size, color, imprint, and dosage information. Although experienced pharmacists can identify many medications manually, the continuously growing number of pharmaceutical products makes manual identification increasingly difficult and time-consuming. Conventional image processing methods based on handcrafted feature extraction provide limited performance when pills exhibit similar appearances, different lighting conditions, or partially visible imprints. These limitations have encouraged researchers to investigate artificial intelligence and computer vision techniques capable of automatically learning complex visual characteristics from pharmaceutical images.

Recent developments in Deep Learning and Computer Vision have significantly improved automated image recognition systems. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification by automatically extracting hierarchical visual features from large image datasets. Combined with image preprocessing techniques such as color segmentation, feature extraction, and optical character recognition, CNN-based models provide highly accurate pharmaceutical pill identification. Libraries including Keras, TensorFlow, OpenCV, and Paddle OCR offer efficient tools for developing intelligent healthcare applications capable of recognizing pills based on their shape, color, and imprint information.

This paper presents an intelligent deep learning framework for automated pill identification using CNNs and image preprocessing. The proposed system employs the Pillbox dataset, image augmentation through the Keras Image Data Generator, feature extraction using OpenCV, HSV-based color analysis, Paddle OCR for imprint recognition, and CNN-based classification using ReLU and Softmax layers. Experimental evaluation demonstrates that the developed framework achieves 98.9% training accuracy, 98.9% validation accuracy, and 97.5% testing accuracy, while integrating feature extraction increases the overall identification accuracy to 97.9%. These results

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demonstrate the effectiveness of combining deep learning with image preprocessing for intelligent pharmaceutical pill recognition.

## II. RELATED WORK

Automated pill identification has received considerable attention due to the increasing need for reducing medication dispensing errors and improving patient safety. Early pill identification systems primarily relied on conventional image processing techniques involving image segmentation, color analysis, shape recognition, and optical character recognition for identifying pharmaceutical tablets and capsules. Several studies utilized handcrafted feature extraction methods combined with database matching to recognize pills according to their physical characteristics. Although these approaches achieved satisfactory performance for small datasets, their effectiveness decreased considerably when applied to larger pharmaceutical databases containing visually similar medications.

Several researchers have investigated machine learning techniques for automated pill classification. Earlier studies employed Support Vector Machines (SVMs), Multilayer Perceptrons (MLPs), feature extraction algorithms, and edge detection techniques to classify pills based on color, texture, and geometric properties. Other investigations focused on developing mobile applications capable of identifying medications using smartphone cameras combined with image processing algorithms. While these systems demonstrated promising results, they often required carefully controlled imaging conditions and experienced reduced performance under variations in illumination, camera orientation, and background complexity.

Recent advances in deep learning have significantly enhanced pharmaceutical image recognition. Convolutional Neural Networks (CNNs) automatically learn discriminative visual features directly from training images, eliminating the dependence on manually designed feature descriptors. Furthermore, image preprocessing techniques using OpenCV, HSV color segmentation, Paddle OCR, and image augmentation improve recognition robustness by enhancing image quality and extracting informative features such as pill shape, color, and imprint text. Previous research has also compared real-time object detection algorithms including RetinaNet, SSD, and YOLOv3 for medication recognition, demonstrating the growing importance of deep learning in intelligent healthcare applications.

Motivated by these developments, the present study proposes an intelligent deep learning framework that integrates CNN-based classification, image preprocessing, OpenCV, Paddle OCR, and feature extraction for automated pill identification. The proposed system utilizes image augmentation, CNN training, shape analysis, HSV-based color extraction, imprint recognition, and database comparison to accurately identify pharmaceutical pills while reducing medication dispensing errors. Experimental evaluation confirms that combining CNNs with feature extraction significantly improves pill recognition accuracy and provides an efficient solution for intelligent medication identification.

## III. PROPOSED METHODOLOGY

The proposed methodology presents an intelligent framework for automated pill identification by integrating deep learning, image preprocessing, and feature extraction techniques. Initially, pill images are collected from the Pillbox dataset, which contains thousands of pharmaceutical tablets and capsules. Since each pill originally contains only a limited number of images, the dataset is expanded using the Keras Image Data Generator, which performs augmentation operations including rotation, brightness adjustment, rescaling, zooming, horizontal flipping, width shifting, height shifting, and whitening. This augmentation process generates a large and diverse training dataset that improves CNN generalization while reducing overfitting during model training.

Following dataset preparation, the augmented images undergo image preprocessing using OpenCV to improve feature extraction. The preprocessing stage performs background segmentation, contour extraction, and HSV color-space conversion to isolate the pill from its surrounding environment. Shape extraction identifies geometric characteristics such as circular, oval, or oblong pill structures, while color analysis calculates the average HSV values for each segmented pill. Simultaneously, Paddle OCR extracts the imprint text engraved on the pill surface, providing additional discriminative information for accurate identification.

The processed images are then supplied to two Convolutional Neural Network (CNN) models developed using TensorFlow and Keras. The first CNN performs pill detection to determine whether a valid pill exists within the input image, while the second CNN performs multi-class pill classification using ReLU activation functions and a Softmax output layer. During training, the CNN automatically learns hierarchical visual features representing pill shape, texture, color, and imprint characteristics. The extracted features generated through preprocessing further support the CNN by reducing background interference and improving classification robustness.

Finally, the identified pill characteristics—including shape, color, imprint, and CNN classification output—are compared against a reference pharmaceutical database to determine the most probable medication. When all extracted characteristics satisfy the predefined similarity criteria, the corresponding pill information is retrieved and displayed to the user. Experimental evaluation demonstrates that the proposed framework achieves 98.9% training accuracy, 98.9% validation accuracy, 97.5% testing accuracy, and 97.9% overall accuracy when image preprocessing is integrated with CNN classification. These results confirm the effectiveness of combining deep learning with computer vision techniques for intelligent pharmaceutical pill identification.

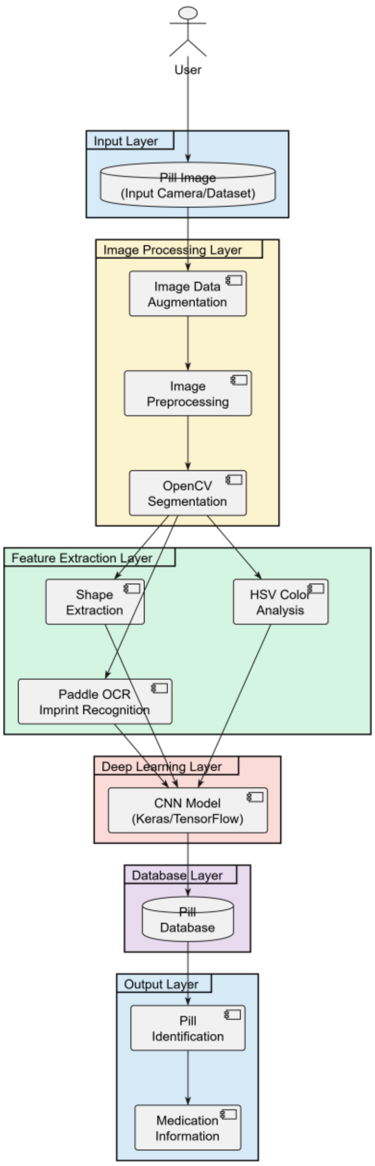


Fig. 1. Proposed System Architecture for Automated Pill Identification

## IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed automated pill identification framework was experimentally evaluated to analyze the effectiveness of integrating Convolutional Neural Networks (CNNs) with image preprocessing techniques for pharmaceutical pill recognition. The experiments were conducted using the Pillbox dataset, which contains thousands of prescription medication images. To improve model generalization, the dataset was augmented using the Keras Image Data Generator, generating multiple transformed versions of each pill image through rotation, brightness adjustment, rescaling, zooming, horizontal flipping, width shifting, and height shifting. The final dataset consisted of approximately 20 pill classes, each containing nearly 320 training images, together with separate validation and testing datasets for performance evaluation.

Initially, two CNN architectures were developed using TensorFlow and Keras. The first CNN model was designed for pill detection using a sigmoid activation function to determine whether a pill was present within the input image. Although this model successfully detected pills, its performance decreased when larger datasets containing multiple pill categories were introduced. To overcome this limitation, a second CNN architecture employing ReLU activation functions and a Softmax output layer was developed for multi-class pill classification. The improved model demonstrated better convergence, reduced overfitting, and higher classification accuracy across multiple pharmaceutical categories.

To further improve recognition performance, the proposed framework integrates image preprocessing with CNN-based classification. Using OpenCV, pill images undergo segmentation to isolate the foreground object from the background before feature extraction. Shape analysis identifies the geometric structure of the pill, while HSV color analysis extracts average color information for comparison with reference records. In addition, Paddle OCR recognizes engraved imprint characters appearing on pill surfaces. These extracted characteristics are combined with CNN predictions to improve identification accuracy and reduce false classifications caused by visually similar medications. Experimental analysis confirms that feature extraction significantly improves the robustness of the recognition process under varying imaging conditions.

Performance evaluation demonstrates that the proposed CNN model achieves excellent classification capability. The developed network obtains 98.9% training accuracy, 98.9% validation accuracy, and 97.5% testing accuracy on the 20-pill dataset. When image preprocessing and feature extraction are integrated with CNN classification, the overall pill identification accuracy increases to 97.9%. The slight improvement illustrates that combining deep learning with traditional image analysis techniques effectively reduces segmentation errors while improving recognition reliability. These results validate the effectiveness of the proposed framework for intelligent pharmaceutical pill identification.

Experimental observations further indicate that pills containing distinctive shape, color, and imprint text are identified with very high accuracy, while pills with similar appearances benefit significantly from the additional

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preprocessing and OCR-based feature extraction stages. The combination of CNN classification and database comparison enables accurate recognition even when one feature becomes ambiguous. This integrated approach minimizes medication dispensing errors while supporting faster and more reliable pharmaceutical verification in healthcare environments.

## VI. CNN MODEL TRAINING AND FEATURE EXTRACTION

The proposed pill identification framework employs a Convolutional Neural Network (CNN) to automatically learn discriminative visual features from pharmaceutical images. Prior to training, pill images are augmented using the Keras Image Data Generator, which performs transformations such as rotation, brightness adjustment, zooming, horizontal flipping, width shifting, height shifting, and rescaling. These augmentation techniques increase dataset diversity, reduce overfitting, and improve the generalization capability of the CNN model. The augmented dataset enables the network to learn robust visual representations despite variations in image orientation and illumination.

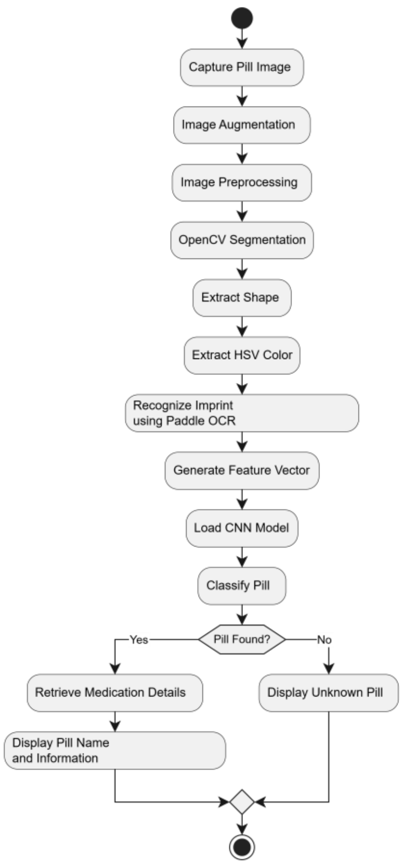


Fig. 2. Activity Diagram for Automated Pill Identification

The CNN architecture consists of multiple convolutional, ReLU activation, max-pooling, dropout, flatten, and fully connected layers, followed by a Softmax classifier for multi-class pill recognition. During training, convolutional layers automatically extract hierarchical image features, while pooling layers reduce feature dimensionality and computational complexity. Dropout layers minimize overfitting by randomly disabling neurons during training, thereby improving model robustness. The Softmax output layer assigns probability values to all pill categories, and the class with the highest probability is selected as the predicted medication.

In addition to CNN classification, the proposed framework incorporates feature extraction techniques to improve identification accuracy. OpenCV is utilized to segment the pill from the background, while HSV color analysis identifies the dominant pill color. Shape extraction determines geometric characteristics, and Paddle OCR recognizes engraved imprint characters on the pill surface. These extracted features are compared with reference database records, providing an additional verification mechanism that complements CNN predictions and reduces false classifications caused by visually similar pills.

## VIII. SYSTEM IMPLEMENTATION AND PERFORMANCE EVALUATION

The proposed automated pill identification system is implemented using Python, TensorFlow, Keras, OpenCV, and Paddle OCR. The complete framework consists of dataset preparation, image augmentation, preprocessing, CNN-based classification, feature extraction, and database comparison. Pill images are first preprocessed to remove background noise and isolate the foreground object before undergoing CNN classification. Simultaneously, feature extraction obtains the pill's shape, color, and imprint information for additional verification against the pharmaceutical database.

Experimental evaluation demonstrates the effectiveness of the proposed framework. The CNN model achieves 98.9% training accuracy, 98.9% validation accuracy, and 97.5% testing accuracy. When combined with image preprocessing and feature extraction, the overall pill identification accuracy improves to 97.9%. Comparative analysis indicates that integrating traditional image processing with deep learning provides better recognition performance than relying solely on CNN classification, particularly for pills exhibiting similar visual characteristics.

The developed framework provides an efficient and scalable solution for pharmaceutical pill recognition and can support various healthcare applications, including hospital pharmacies, retail pharmacies, medication dispensing systems, and clinical decision-support platforms. Its modular architecture also enables future integration with cloud-based healthcare systems, mobile applications, and intelligent pharmacy automation, making

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it suitable for next-generation medication management solutions.

## VIII. CONCLUSION

Accurate pill identification is essential for improving medication safety and reducing dispensing errors in healthcare environments. Conventional manual identification methods are often time-consuming and susceptible to errors because many pharmaceutical products exhibit similar physical characteristics such as shape, color, and imprint. To address these challenges, this study presented an intelligent deep learning framework for automated pill identification by integrating Convolutional Neural Networks (CNNs) with advanced image preprocessing techniques. The proposed framework combines image augmentation, feature extraction, and deep learning-based classification to provide an efficient and reliable solution for pharmaceutical pill recognition.
The developed system utilizes the Pillbox dataset, Keras Image Data Generator, OpenCV, HSV-based color analysis, Paddle OCR, and CNN models implemented using TensorFlow and Keras. Image preprocessing extracts important pill characteristics such as shape, color, and imprint text, while the CNN automatically learns discriminative visual features for multi-class pill classification. Experimental evaluation demonstrates that the proposed framework achieves 98.9% training accuracy, 98.9% validation accuracy, 97.5% testing accuracy, and 97.9% overall identification accuracy when feature extraction is integrated with CNN classification. These results confirm that combining deep learning with computer vision techniques significantly improves recognition performance while reducing segmentation errors and false classifications.

The proposed framework further demonstrates the advantages of integrating image preprocessing with deep learning for intelligent healthcare applications. Shape extraction, HSV color segmentation, and OCR-based imprint recognition provide complementary information that enhances the robustness of CNN predictions, particularly for visually similar medications. The automated identification process reduces pharmacist workload, minimizes medication dispensing errors, and improves the efficiency of pharmaceutical verification in hospitals, pharmacies, and clinical environments.

Overall, the proposed automated pill identification system provides an accurate, scalable, and practical solution for intelligent medication recognition. The combination of deep learning, feature extraction, and image preprocessing offers significant potential for deployment in real-world healthcare systems. Future enhancements involving larger pharmaceutical datasets, real-time object detection models, mobile applications, cloud-based healthcare integration, and edge AI deployment can further improve recognition accuracy, processing speed, and accessibility, making the system highly suitable for next-generation intelligent pharmaceutical management systems.

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