



Smart Pill Detection Using Machine Learning Models

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Abstract

One of the most significant responsibilities of pharmaceutical safety is pill identification. The rapid advancement of technology has produced fresh chances to improve medication compliance, patient safety, and healthcare delivery. This is especially true in the healthcare industry. Pharmacies, including pills, tablets, and capsules, must be identified in order to ensure patient safety and the delivery of healthcare. In the past, this initiatives has primarily depended on manual processes and human judgement, which can be time-consuming and error-prone. Since drug errors can occur and can cause patient difficulties, proper prescription drafting is crucial for patient safety. These errors are mostly caused by label damage, inconsistencies in the way medications are taken, and other problems. This study looks at the use of deep learning and machine learning.

Keywords: Pill Identification. Deep Learning. Drug Errors. Manual Processes. Healthcare Technology.

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1 Introduction

Detecting and identifying pills accurately is crucial in various domains, including healthcare, pharmaceuticals, and law enforcement. Machine learning (ML) models have emerged as powerful tools in this endeavor, offering efficient and reliable solutions to tackle this challenge. This introduction tells the significance of pill detection and identification, and the potential applications and benefits of employing ML models in this domain. Pills serve as a fundamental component of modern healthcare, aiding in the diagnosis, treatment, and management of various medical conditions. However, mis identification or misuse of pills can have serious consequences, including adverse drug reactions, treatment failures, and even fatalities. Moreover, in forensic investigations and law enforcement, accurately identifying pills is essential for detecting illicit drug trafficking and ensuring public safety. Furthermore, the deployment of ML models for pill detection and identification opens up possibilities for innovative applications, such as mobile apps and web platforms that enable users to quickly identify pills using their smartphones or other devices. Such tools can empower their medications and help prevent medication errors and adverse reactions (Jara, Zamora, & Skarmeta, 2014).

Ramya, Suchitra, and Nadesh's (2013) in his paper provides a comprehensive review of deep learning methods for pill recognition. It covers convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants applied to pill image analysis. The survey discusses the performance of different architectures, data set challenges, and future trends in deep learning-based pill recognition systems. Gordon, Hadsall, and Schommer's (2005) focuses on feature extraction methods used in pill identification systems. It reviews traditional techniques such as texture analysis, color histogram, and shaped scriptors, as well as advanced methods like deep feature learning. The paper discusses the strengths and limitations of each approach and provides recommendations for feature selection in pill recognition system. This comparative survey evaluates the performance of various machine learning techniques for pill identification tasks. It compares classification algorithms such as support vector machines (SVM), random forests, and k-nearest neighbors (KNN) on different datasets. Survey by Fung et al.'s (2009) analyzes the accuracy, computational efficiency, and robustness of each method to aid researchers in selecting appropriate models for pill recognition applications.

Konda et al.'s (1990) reviewed the challenges and opportunities in pill identification using machine learning approaches. It addresses issues such as data set size, class imbalance, and real-world deployment constraints. The survey also explores emerging technologies such as mobile health applications and Internet of Things (IoT) devices for improving pill recognition systems. It provides an analysis of data set characteristics such as size, diversity, and annotation quality. The survey by Hartl's (2010) discusses the relevance of benchmark datasets in evaluating the performance of machine learning models and iden-

tifies gaps for future data set collection efforts. Rani et al.'s (2020) explores the role of machine learning in pill identification within the healthcare domain. It discusses applications such as medication adherence monitoring, counterfeit drug detection, and medicine. The paper examines regulatory challenges, privacy concerns, and ethical considerations associated with deploying machine learning-based pill recognition systems in clinical settings .

2 Methodology

Medication identification is a significant problem that helps lower the chance of medical errors. The project aims to create a precise and effective method for detecting drugs and determining any interactions between them by utilizing computerized systems and information technology. Twenty different classes are included in the data set: Amoxicillin 500 MG, Apixaban 2.5 MG, Aprepitant 80 MG, Atomoxetine 25 MG, Benzonatate 100 MG, Calcitriol 0.00025 MG, Duloxetine 30 MG, Eltrombopag 25 MG, Montelukast 10 MG, Mycophenolate Mofetil 250 MG, Oseltamivir 45 MG, Pantoprazole 40 MG, Pitavastatin 1 MG, Prasugrel 10 MG, Ramipril 5 MG, Saxagliptin 5 MG, Sitagliptin 50 MG, and Tadalafil 5 MG. To train the system to identify patterns and attributes linked to various drugs, methods of deep learning will be incorporated into the proposed system. The model, which is based on the MobileNet architecture (see figure 1), will go through a rigorous training process with a dataset made up of different pill images that represent different drugs and their properties. The goal of the training procedure will be to identify pills with high accuracy and robustness.

Furthermore, the suggested system will include a module for identifying possible drug interactions, ensuring patient safety by alerting users to harmful combinations. The system will incorporate a secure database to store pill information and interaction rules, enabling quick access and updates. Creating a user-friendly interface will simplify the process for medical practitioners to upload and analyze pill images, enhancing efficiency. The system will leverage advanced image processing algorithms to ensure high accuracy in identifying pills and matching them to the correct database entries. Once the image is uploaded, the data will be processed rapidly, reducing waiting times and minimizing errors. The web framework for this system is built using Python's Flask, ensuring seamless integration, scalability, and easy deployment across different platforms.

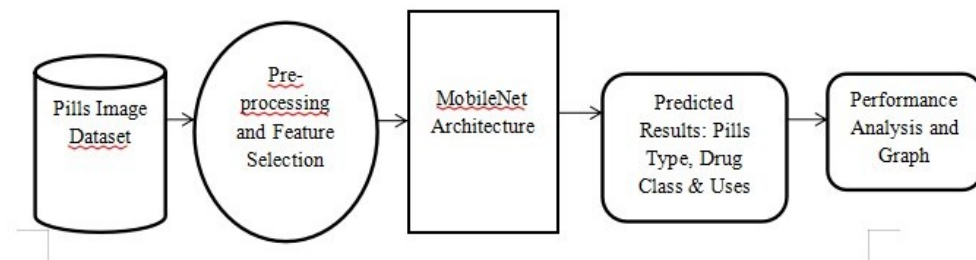


Figure 1. Architecture

1. Data Collection and Preparation Figure 2 depicts the flow of the data in form of a diagram.

- Dataset Acquisition
- Public datasets: Explore publicly available datasets of pill images with labels (e.g., NIH <https://www.ncbi.nlm.nih.gov/datasets> or Kaggle).
- Capturing your own data: If a suitable public dataset isn't available, consider capturing high-quality images of various pills with consistent lighting and background.
- Data Labeling: Label each image with the corresponding pill name and any relevant attributes (e.g., color, shape, imprint). This labeling can be done manually or through crowd sourcing platforms.
- Data Reprocessing: Pre process the images to ensure consistency and improve model performance. This might involve: Re-sizing images to a standard size Cropping images to focus on the pill Normalizing pixel values Converting images to grayscale (if color is not a crucial feature)

2. Model Selection and Training:

- Deep Learning Approach: Convolutional Neural Networks (CNNs) are a popular choice for image recognition tasks like pill identification. Popular pre-trained models like VGG16 or ResNet50 can be fine-tuned for this specific task.
- Training and Validation Split: Divide your labeled data into training and validation sets. The training set is used to train the model, and the validation set is used to evaluate its performance and prevent overfitting.
- Training Process: Train the model on the training data. This involves feeding the images and their corresponding labels to the model and adjusting its internal pa-

rameters to minimize prediction errors. You can use frameworks like TensorFlow or PyTorch to facilitate the training process.

3. Detection and Identification:

- **Object Detection:** Once trained, the model can be used to detect pills in new images. Techniques like YOLO (You Only Look Once) or SSD (Single Shot MultiBox Detector) can be implemented within the CNN architecture for object detection.
- **Classification:** After detecting pill locations, the model classifies each pill by comparing its features to the learned representations in the training data. The model outputs the most likely pill name based on the extracted features.

4. Evaluation and Refinement:

- **Performance Metrics:** Evaluate the model's performance on the validation data using metrics like accuracy, precision, recall, and F1-score for each pill class. For instance, if the model correctly classifies 80 out of 100 pills, the accuracy would be 80%. However, accuracy can be misleading when dealing with imbalanced datasets, where one class dominates significantly over the others, potentially hiding the model's inability to correctly predict minority classes.
- **Hyperparameter tuning** is the process of adjusting key settings of the model, such as the learning rate, batch size, or the number of training epochs, to improve its performance. Hyperparameters are not learned from the data but need to be set before the training process begins. For example, the learning rate determines how quickly the model adjusts its weights during training. A very high learning rate might cause the model to converge too quickly, missing the optimal solution, while a very low learning rate can make training slow and prone to getting stuck in local minima.
- **Tuning:** If needed, adjust hyperparameters (e.g., learning rate, number of training epochs) of the model to improve its performance.
- **Data Augmentation:** Consider data augmentation techniques like random rotations, flips, or color jittering to artificially increase the dataset size and improve model generalizability.

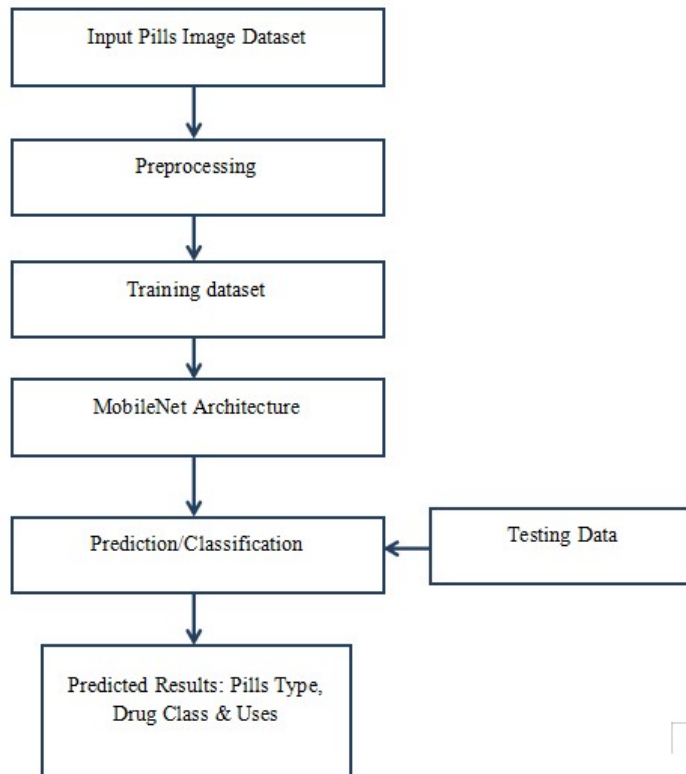


Figure 2. Data Flow Diagram

3 Results

By creating an accurate drug detection device that utilizes deep learning with smart medicinal drug recognition features, this has effectively addressed the significant problem of medicine identification and recognition. The study has demonstrated the effectiveness and promise of utilizing deep learning approaches, such as the MobileNet architecture, to increase the accuracy and efficiency of medicine recognition. High pill recognition and identification accuracy rates have been attained by the created system after rigorous training on a variety of pill picture data sets. Healthcare workers save a great deal of time and money with this method, which also lowers the possibility of human error by streamlining the process and decreasing the need for manual searches. Figures 3, 4, 5 and 6 showcase different pages like login, upload and result page.



Figure 3. Login Page

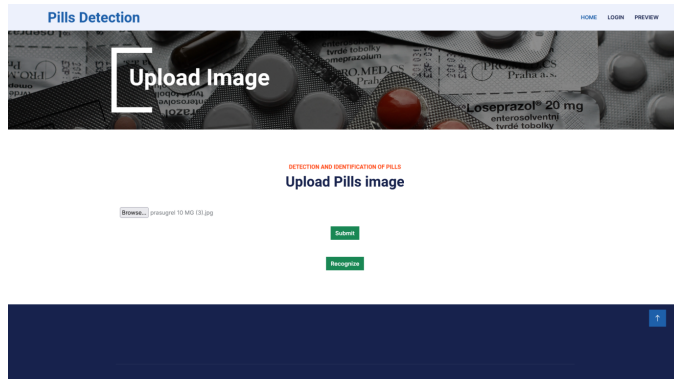


Figure 4. Upload Image

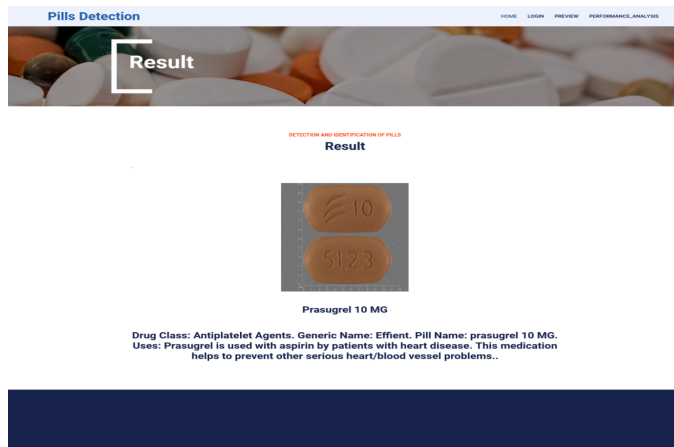


Figure 5. Result page

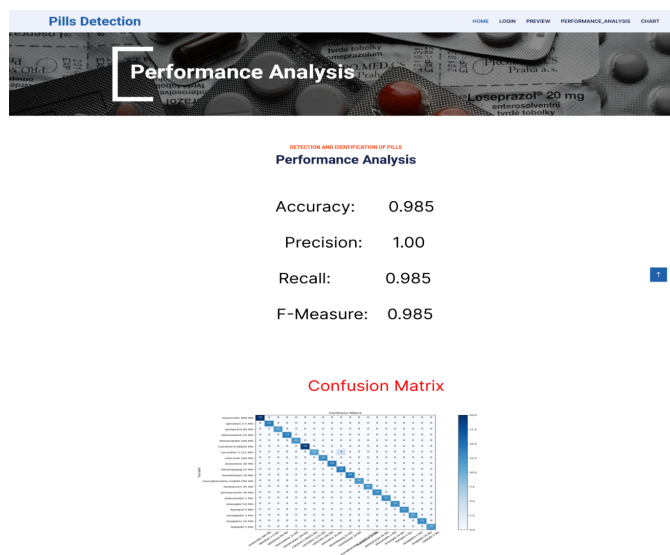


Figure 6. Performance Analysis

4 Conclusion

In order to improve the security of medications and patient care, the system may offer thorough drug information and notify medical personnel of any possible interactions. All things considered, this initiative has established the groundwork for a sophisticated computerized system that might completely transform the process of identifying medications in medical settings. In order to protect patients and lower the possibility of medication errors, it is essential to identify drugs accurately and quickly. Going ahead, the system that has been established can function as a foundation for additional upgrades and developments. This initiative uses cutting-edge technologies to support continuous efforts in the healthcare sector to improve drug management and patient care.

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