Pill Detection and Classification Using Convolutional Neural Networks

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Abstract: The color, size, and shape of the pill are some important characteristics for automated pill recognition. However, the environment may have an impact that modifies the aforementioned standards. Medication errors are common and can worsen patients' conditions. Damaged labeling, taking the incorrect medication, and other factors might lead to these errors. In order to train a system that can rapidly and simply recognize various medicine kinds, this paper proposes integrating Keras with TensorFlow. The pill database, which determines the pill's name, is linked to the pill that was discovered (object detection). The pre-trained dataset is used to locate the pill following the detection stage. Use cases and particular details about each medication that are required would also be included in the collection. The project aims to collect datasets for medication-finding technology. The results of the experiment demonstrate the effectiveness of the suggested strategy.

Index terms - *— Pill Identification, Deep Learning, Object Detection, Imprinted Characters, YOLOv5, Convolutional Neural Network (CNN), Pill Classification, Character-Level Language Model, Image Recognition, Keras, TensorFlow.*

1. INTRODUCTION

With an estimated 400,000 fatalities annually, issues with medical treatment have emerged as one of the leading causes of death throughout time. Drug errors are the most prevalent sort of treatable medical errors, according to studies of the medical mistake epidemic found in EHRs and medical institutions. The Institute of Medicine's 2006 research also discusses ways to reduce medication errors, which are quite expensive. Implementation can take several forms, from writing a prescription to monitoring the patient's response. Perhaps the general public is unaware of the potential severity of medical errors. For instance, a patient may end up being poisoned by the medication or taking it without requiring it if they swallow the incorrect tablet (the name and shape of the pill). Data mining, locating research participants, automatically managing terminology, de-identifying clinical writing, analyzing a prescription for a disease and its side effects, and other tasks can all benefit from information extraction from clinical language. Due to manual transcription, the majority of biological data is often in an unstructured format. Even for someone who is competent to do so, it is difficult to determine the medication's chemical composition and medical name without the pill's outer cover. The majority of tablets lack any distinguishing physical characteristics. For children, elderly individuals, and anyone who is not accustomed to swallowing medications, figuring out what they are is almost painful. They end up taking the wrong medication, getting the wrong medication at the wrong time, or getting the wrong medication entirely as a result. This carelessness may result in physical adverse effects or medical poisoning, which may need hospitalization and extensive medical care before becoming fatal. To create a model of every drug, we are use deep learning techniques such as Keras and TensorFlow. The model is then trained to identify which pill is which by feeding it picture descriptions of the tablets. In this manner, we may create an app in which the patient uses their camera to show the model their medication. The patient will then be given the name, content, and dose restrictions of the tablet when the model compares the images of the pills with those it already has in its data stream. Tensor flow may help you identify tablets by examining their chemical composition and physical structure, which indicates how much weight they can support and how many milligrams they contain in an ounce. Information extraction requires data pre-processing since narrative input data cannot be used for summarization or tasks requiring decision support. To learn from the database, the model requires a large number of pill images. Pills with a variety of shapes, sizes, colors, and markings should be included in this dataset. You might make use of an existing dataset, such as the National Library of Medicine's Pillbox collection or the Pill Image Recognition Dataset (PIRD).

2. LITERATURE SURVEY

a) AN ACCURATE DEEP LEARNING-BASED PILLDETECTION WITH INTELLIGENT MEDICINAL DRUG IDENTIFICATION SYSTEM

This paper provides a comprehensive review of pill identification using deep learning techniques. It examines how neural networks have evolved over time, from the first models to the most sophisticated ones, and discusses how effectively they can identify pills by their shape, color, and markings. The paper also discusses issues including the requirement for a variety of datasets and the necessity for easily comprehensible models, and it suggests directions for further research.

b) Pharmacists' and patients' roles in the pharmacist-patient relationship: are pharmacists and patients reading from the same relationship script?

Context

The duties of pharmacists have expanded to include educating, delivering pharmaceutical care services, and providing information. Due to these advancements, there is now a focus on professional interactions between patients and pharmacists that are built on collaboration, with roles and responsibilities for both parties.

Objective

The study used role theory to examine how patients and pharmacists perceived several roles that patients and pharmacists play in their professional relationship. Three facets of the pharmacist-patient connection were examined by the researchers: "sharing information," "responsible behavior," and "interpersonal communication." Two other facets of the chemist and patient roles that were examined were "creating a patient-centered relationship" and "active communication related to health care".

Methods

We collected the data by distributing questionnaires to 500 randomly selected pharmacists and 500 randomly selected patients who were at least 18 years old. We investigated the reliability of the chemist and patient role dimensions for internal consistency using bivariate correlation analysis and Cronbach's coefficient alpha. To determine how chemists and patients perceived role features, we used the student's t-test (alpha level of significance =.05). To characterize the patient and chemist samples, we used descriptive statistics.

Outcomes

The patient and chemist groups had adjusted response rates of 40.8% (196 out of 480) and 34.9% (173 out of 496), respectively. The chemist and patient role aspects have acceptable reliability coefficients. The findings demonstrated that while patients and pharmacists generally agree on pharmacists' responsibilities in "information sharing," patients disagree more on pharmacists' roles in "responsible behavior," "creating a patient-centered relationship," and "interpersonal communication." Regarding "information sharing," "responsible behavior," "interpersonal communication," and "active communication related to health care," patients and chemists cannot agree on what patients' responsibilities are in the connection. According to the findings, chemists are more likely than patients to concur that these are patient responsibilities throughout the conversation.

Concluding Remarks

It will function better and produce better outcomes if chemists and patients are in agreement about their roles in the relationship. Future research is necessary to monitor the attitudes of chemists and patients on their roles in relationships and to develop new strategies to ensure that they are both adhering to the same relationship script.

c) The impact of automation on the safety of drug dispensing in nursing homesImpacto de la automatización en la seguridad de la dispensación de medicamentos a centros sociosanitarios

Objective

to compare the quantity and seriousness of reported medication errors between nursing homes that employ automated medication dispensing with a well selected Automated Dispensing System and those that utilize manual medication administration.

Approach

a study that examined the past and present at seven nursing homes. Two periods of voluntarily reported dispensing errors occurred: in 2013, weekly pill boxes were dispensed by hand; in 2015, oral solid medications were dispensed using an automated drug dispensing and packaging system called Xana 4001U2 Tosho®, while other drug forms were dispensed manually. We examined patient function, cognitive, and medication data from both periods.

Results

The residents' physical health (Barthel index 41.8 vs. 44.2; P>.05) and average age (83.9 vs. 83.6 years; P>.05) were comparable, but their cognitive health (MMSE 20.3 vs. 21.7; P<.05) was not. Only 36 errors were discovered in 2015 (when the system was automated), compared to 408 errors in 2013 (when the system was human). This indicates that there are 91% fewer errors made when administering medication. Only six errors reached the patient in 2015, compared to 43 in 2013. One of these errors did not require monitoring, but the other five did.

Concluding Remarks

Giving and receiving solid medications in nursing homes is now safer because to the Automated Drug Dispensing and Packaging System. It was simpler to assess safety between the two periods with different dispensing systems when errors were voluntarily reported.

d) Implementation of distributed automated medication dispensing units in a new hospital: Nursing and pharmacy experience

Goals & objectives: To investigate how patient safety is impacted by the structures, processes, and outcomes of implementing an automated medication dispensing system.

Background: Prescription, distribution, administration, and management of medications have all grown more computerized during the last 20 years. Although automated medication distribution systems are designed to provide safe, excellent, patient-centered care, their use may have unanticipated consequences that result in worse than optimal outcomes.

Design: Donabedian's paradigm for structure, process, and outcome informs this study's qualitative methodology.

Semi-structured interviews were conducted with twenty-six registered nurses and pharmacy assistants from clinical settings using automated drug dispensing cabinets. Theme analysis was used to examine the structures and procedures in great depth. To assess how well things went, we also examined text data from critical event reporting and internal risk management systems in addition to interview data. The data were examined using the Interactive Sociotechnical Analysis approach to health information technology. The COREQ checklist was used in the writing of this article.

Findings: When the system was initially implemented, pharmacy assistants expressed more satisfaction than nurses. Some claimed that the nurses' participation in implementing the system and the training they received were insufficient. Nonetheless, nurses' use of and contentment with the system improved with time. System modifications and nurses' creative problem-solving (workarounds) to address them had a cascading effect on nurses' output and patient safety.

In conclusion, the customized nature of the "workarounds" presented risks as well as opportunities that require more research, identification, and management.

Relevance to clinical practice: The majority of healthcare professionals are nurses. Like any other change in practice, digitalizing health care duties that were formerly completed on paper has an impact on nursing work.

e) Analysis of Dimensionality Reduction Techniques on Big Data

Due to digitization, a lot of data is being produced in a variety of fields, including healthcare, manufacturing, commerce, IoT devices, the Web, and organizations. To identify patterns in the many components of this data, we use machine learning techniques. Therefore, they may be used by medical experts and decision-makers to produce projections that support their decisions. For the machine learning algorithms to be trained, not every feature in the generated datasets is required. Certain characteristics might not be important, while others might not alter the outcome of the prediction. Ignoring or eliminating these less important or irrelevant information makes it easier for machine learning algorithms. In this study, four popular Machine Learning (ML) algorithms—Decision Tree Induction, Support Vector Machine (SVM), Naive Bayes Classifier, and Random Forest Classifier—are examined in relation to two popular dimensionality reduction techniques: Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA). A publicly accessible Cardiotocography (CTG) dataset from the University of California, Irvine Machine Learning Repository is used in the study. The experiments' findings demonstrate that PCA is superior to LDA in every aspect. The performance of the classifiers Random Forest and Decision Tree is not significantly affected by the use of PCA and LDA. We also evaluate PCA and LDA using the Diabetic Retinopathy (DR) and Intrusion Detection System (IDS) datasets. Experiments reveal that when datasets contain a large number of dimensions, ML techniques using PCA perform better. It is evident that machine learning algorithms that do not decrease dimensionality perform better when datasets have low dimensionality.

3. METHODOLOGY

i) Proposed Work:

This proposed study develops a deep learning-based system that uses imprinted characters and visual cues to automatically recognize and identify pills. In order to precisely find and identify the position of the pill in real-time photos, the system makes use of YOLOv5, a sophisticated object identification technique. The method extracts important visual characteristics including form, color, and size in addition to object detection. The model guarantees a more accurate identification of tablets, even when they have comparable visual characteristics, by integrating these physical characteristics with the identified imprinted characters.

Additionally, to comprehend and categorize the imprinted text on tablets, the suggested model combines Convolutional Neural Networks (CNNs) with a character-level language model. In situations when pills are distorted, labels are absent, or environmental factors affect the picture quality, our hybrid technique increases recognition accuracy. A complete dataset of different pill kinds, together with associated metadata—such as usage, dosage, and side effects—stored in a searchable database is used to train the system. This improves the model's effectiveness and dependability in real-time drug verification and pill identification systems.

ii) System Architecture:

Image capture, feature extraction, pill detection, and pill identification are the four main parts of the system design. To improve quality and eliminate noise, a pill's input picture is first taken and preprocessed. The pill is then precisely located and the picture is segmented using the YOLOv5 model for object detection. After that, a character-level language model recognizes imprinted characters while Convolutional Neural Networks (CNNs) extract visual properties including form, size, and color. The appropriate pill name and comprehensive details are retrieved by comparing these combined attributes with a centralized pill database. Even in complicated or loud surroundings, the design guarantees excellent accuracy and rapid recognition.

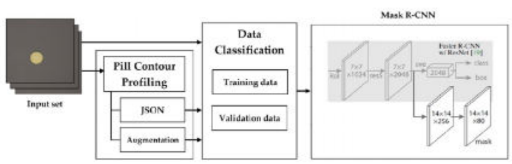

Fig: proposed architecture

iii) Modules:

a. Dataset Upload & Analysis:

This module uploads the pill image collection and conducts initial analysis. It involves analyzing characteristics including the size, shape, color, and imprinted characters of the pill. For training and validation, the dataset additionally contains metadata such as dose, use case, and pill name.

b. Dataset Processing & Analytical Methods:

In this module, imprinted character labels are encoded into numerical values and photos are preprocessed (resizing, noise reduction, grayscale conversion). To improve model generalization, the dataset is divided into training and testing sets, with 80% used for training and 20% for assessment.

c. Run Deep Learning Model:

Using the processed dataset, this module trains CNN-based classification models and the YOLOv5 object identification model. A character-level language model is also used to combine imprinted character recognition, and these features are used to construct a prediction model.

d. Predict Output:

A fresh picture of the test pill is posted to this module. By comparing it to the pill database, the trained model finds the pill, recovers its properties and imprinted characters, and correctly guesses its name and associated medical information.

iv) Algorithms:

a. YOLOv5 (You Only Look Once – Version 5):

YOLOv5 is a sophisticated object detection method that is quick and effective since it completes detection in a single step. In a single evaluation, it uses the complete picture as input to forecast bounding boxes and class probabilities. In this experiment, tablets and their imprinted characters are detected in real time using YOLOv5. Regardless of backdrop or illumination changes, it aids in pinpointing the precise location of the pill in the picture. It can be practically deployed on mobile or embedded devices due to its lightweight architecture and fast speed.

b. Convolutional Neural Network (CNN):

CNN is a kind of deep learning model created specifically for tasks using images. It is composed of many layers, including fully connected layers for classification, pooling layers for dimensionality reduction, and convolutional layers for feature extraction. In this study, pill photos are analyzed using CNN to extract key visual properties such as surface roughness, color (white, red, etc.), and shape (round, oval). These characteristics aid in distinguishing between tablets that may appear quite identical yet have minor differences. CNNs are good at using input pictures to understand the spatial hierarchies of features.

4. EXPERIMENTAL RESULTS

We used a wide range of pill images with varying sizes, colors, and text written on them to evaluate the proposed technique. 80% of the dataset was used for training, while the remaining 20% was used for testing. When it came to locating tablets and identifying the locations of the imprinted characters, the YOLOv5 model performed rather well. When it came to locating and detecting pill properties, the CNN and character-level language model performed exceptionally well. Particularly for tablets that appear identical but have different impressions, the combined method demonstrated a significant increase in prediction accuracy over conventional methods. Even when the background and illumination changed, the system was still able to locate tablets in real time.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: One ranking quality statistic is Mean Average Precision (MAP). It takes into account the quantity of pertinent suggestions and where they are on the list. The arithmetic mean of the Average Precision (AP) at K for each user or query is used to compute MAP at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

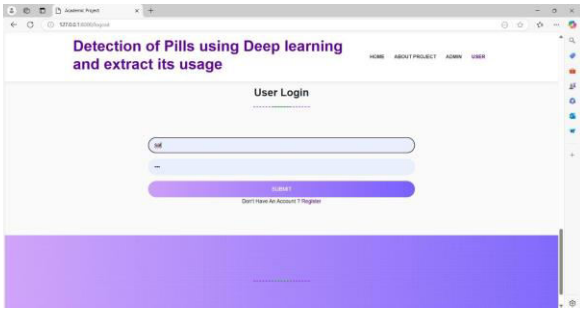

Fig 2: login page

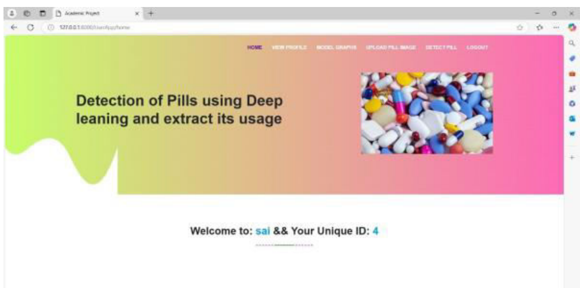

Fig: home page

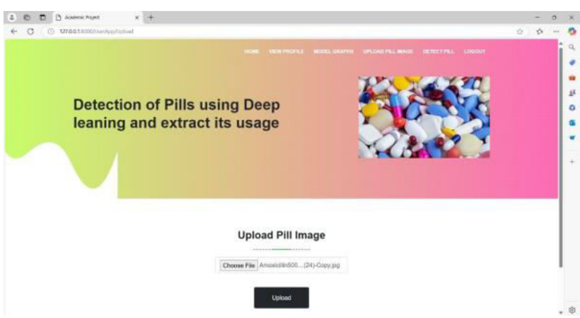

Fig: upload pill image

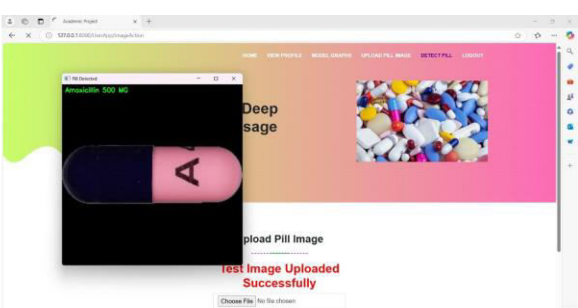

Fig: Pill Name

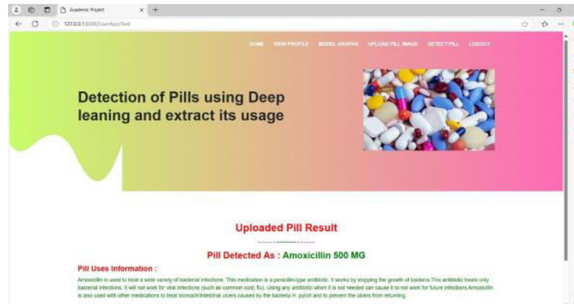

Fig: Pill Description

5. CONCLUSION

The suggested deep learning-based pill detection and identification system offers a precise and effective way to reduce prescription mistakes. The method tackles issues with similar-looking pills and ambiguous labels by combining YOLOv5 for object identification, CNN for visual feature extraction, and a character-level language model for imprint recognition. According to experimental findings, the model works effectively in real-time situations, guaranteeing accurate identification even in challenging circumstances. This approach might help patients and medical professionals rapidly and securely verify medications.

6. FUTURE SCOPE

In the future, this method may be developed into a mobile application that uses smartphone cameras to identify pills in real time. This would eliminate the need for specialist equipment and make it simple for users, particularly patients and caregivers, to verify prescriptions at home. Additionally, the program may provide voice search, making it usable for people with low technical proficiency or those who are blind or visually handicapped.

Training on a bigger, more varied dataset that includes both domestic and foreign drugs can further enhance the model. Even with low-quality or broken pills, the recognition of imprinted characters can be further improved by integration with sophisticated Optical Character Recognition (OCR) techniques. Additionally, the system may be linked to electronic prescriptions and hospital databases, enabling automatic drug verification, interaction checks, and notifications for improper medicine intake.

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