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PILL DETECTION AND IDENTIFICATION WITH DEEP LEARNING USING CNN

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Abstract: Pill size, shape, and colour are some crucial factors for automated pill recognition. However, environmental influences can have an impact that results in changes to the aforementioned criteria. drug mistakes frequently occur and can lead to issues for patients. Label destruction, mismatches in drug consumption, etc., are the main causes of these errors. This article suggests a trained system for quickly and easily identifying different types of medications, mostly utilising Keras and TensorFlow. The pill database where the pill name is discovered is accessed by the detected pill (object detection). Following the detection phase, the pill is identified using the pretrained dataset. Additionally, the dataset would contain the necessary precise information and use cases for the specific drug. The project entails gathering data for automated medical detection systems. The experimental findings demonstrate the effectiveness of the suggested approach.

Index terms - *Deepfake Audio, CNN, BiLSTM, Mel-Spectrogram, MFCC, Audio Forensics, Voice Synthesis, Speech Authentication, Machine Learning, Temporal Dependencies, Deepfake Detection.*

1. INTRODUCTION

As time has gone on, deficiencies in medical care have supplanted illnesses as a frequent cause of mortality, with an estimated 400,000 or more deaths annually. Medication errors are the main type of curable medical error, according to reports of medical error outbreaks presented by the data from EHRs and medical institutions. Additionally, lowering pharmaceutical errors—which result in significant financial losses—is covered in the Institute of Medicine's 2006 study. From prescribing to tracking the patient's response, implementation can be carried out. It's possible that the general public is unaware of the consequences of medical errors, such as the fact that unlabelled medicines (their name or form) might cause patients to misuse them and become ill with medical poisoning or take unnecessary medications.

Information extraction from clinical language can be used for data mining, research subject identification, automatic terminology management, de-identification of clinical text, study of the illness medication and its adverse effects, and other applications. Due to dictated transcriptions, the majority of biomedical data is usually available in an unstructured format. Without the pill's outer cover, it can be challenging for anybody other than the trained eye to distinguish or even identify the chemical composition and medical name of a given medication. Most tablets don't have any visible marks that would identify their name or content. Elderly folks, kids, and anybody else who is unfamiliar with the pill find it very difficult to identify, which leads to them taking the wrong prescription, receiving the wrong drug at the wrong time, or receiving the wrong medication altogether. When this negligence results in medical poisoning or physical side effects, a patient may need to be admitted to the hospital and require extensive treatment before they pass away. In this study, deep learning techniques such as Keras and Tensor Flow are used to help us build a model of each pill. The model is then trained to identify which pill is which by feeding it data in the form of image descriptions through image sensing. This allows us to create an app where the patient shows the model his medication using his camera, which provides visual sensing that would match one of the thousands of pills fed to the model. The model then compares the picture the patient took with the picture it already has in its data feed to provide the patient with the pill's name, composition, and dosage limits.

The physical structure of the tablets and their chemical component, which shows their weight capacity and ounce mg level, may be used to identify them using Tensor Flow. Data pre-processing is required for information extraction since the narrative form of the input data cannot be used for summarising or jobs requiring decision assistance. In terms of the database, training the model requires a sizable collection of pill pictures. Different kinds of pills with varying sizes, forms, colours, and markings should be included in this dataset. An existing dataset, such the Pill Image Recognition Dataset (PIRD) or the Pillbox database from the National Library of Medicine, might be used.

2. LITERATURE SURVEY

3.1 PILL DETECTION AND IDENTIFICATION: A DEEP LEARNING PERSPECTIVE

https://jespublication.com/uploads/2024-V15I7034.pdf

ABSTRACT: A few of the most important characteristics for automated pill recognition include pill colour, size, and shape. However, the aforementioned parameters may change as a result of environmental impacts. Errors in medication administration are frequent and can cause problems for patients. These mistakes are brought about by deteriorating labels, inconsistencies in medication use, and other factors. This article proposes a trained system that identifies different kinds of drugs mainly using Keras and Tensor Flow. The pill database, which contains the pill name, is accessed by the found pill (object detection). The pill is identified using the pre-trained dataset after detection. Additionally, the dataset would contain the use cases as well as the relevant pill's unique information.

3.2 Detection of Broken Pharmaceutical Drugs using Enhanced Feature Extraction Technique

https://enggjournals.com/ijet/docs/IJET13-05-02-260.pdf

ABSTRACT: Medication has become more important in everyone's life; people are affected by many diseases. There are certain diseases which cannot be cured without medication. The production of medicine has increased a lot in recent days. During production there may be damages like breakage, cracks present in the tablets or capsules. Consumption of these damaged tablets may cause some problem in skin, eyes and mouth. Most of the tablets are not advisable to be consumed in broken form. Manual inspection is a very challenging task. Image processing plays a major role in automation of visual inspection. Therefore we propose some ideas to identify the damaged tablets after production. This is a series of process involving image enhancement, segmentation, thresholding, filtration, pixel calculation, subtraction, de-noising and region based statistic to identify the broken tablets. In the case of capsules we propose a feature extraction technique to find the defective blister.

3.3 Computer-Vision based Pharmaceutical Pill Recognition on Mobile Phones

https://www.researchgate.net/publication/228855597_Computer-Vision_based_Pharmaceutical_Pill_Recognition_on_Mobile_Phones

ABSTRACT: In this study, we introduce a mobile computer vision system that makes pharmaceutical pill identification easier. An effective technique for object segmentation on a structured backdrop processes a single input picture of pills on a unique marker-based target. Estimators for the size, shape, and colour of an object provide parameters that can be utilised to query an internet database for an unidentified medication. The Studierstube ES framework is used to construct a prototype application that enables pill detection on commercially available mobile phones. A realistic test set is then used to assess system runtime and retrieval performance using the estimated characteristics. The system's ability to provide mobile pill detection in a practical setting is confirmed by the retrieval performance on the widely used Identa database.

3.4 Analysis of Dimensionality Reduction Techniques on Big Data:

https://ieeexplore.ieee.org/document/9036908

ABSTRACT: Many AI-based audio authentication systems (classifiers) have been proposed since audio has traditionally been a potent biometric authentication resource. To our knowledge, the security of these classifiers has not been fully investigated when they are subjected to sophisticated assaults that use AI-generated deepfake audio, despite the fact that they are successful in recognising authentic human-generated input. Because samples created via adversarial assaults, for example, might trick these classifiers and provide false categorisation, this problem raises severe concerns about the security of these classifiers. We prove the argument in this paper by showing that the most advanced audio deepfake classifiers are susceptible to adversarial assaults. Specifically, we create two adversarial attacks against the Deep4SNet classification model, a state-of-the-art audio-deepfake classifier that detects fake audio samples with 98.5% accuracy. The generative adversarial network architecture is used in the planned adversarial attacks1, which lower the detector's accuracy to almost zero. Specifically, we show that we can lower the accuracy of the state-of-the-art detector from 98.5% to just 0.08% when beginning with random noise under graybox assault scenarios. We provide a highly generalisable, lightweight, easy-to-use, and efficient add-on defence mechanism that can be included into any audio-deepfake detector to lessen the impact of adversarial assaults on these devices. Lastly, we talk about possible avenues for further study.

3.5 Audio Deepfake Approaches:

https://ieeexplore.ieee.org/document/9036908

ABSTRACT: Numerous industries, including healthcare, manufacturing, commerce, IoT devices, the Web, and organisations, are producing enormous amounts of data as a result of digitisation. Patterns among the characteristics of this data are found using machine learning methods. As a result, they may be utilised to forecast outcomes that managers and medical professionals can use to inform their executive choices. Not every feature in the produced datasets is crucial for machine learning algorithm training. Certain features may not have any bearing on the prediction's result, while others may be irrelevant. Machine learning algorithms are less burdened when these unimportant or irrelevant features are ignored or eliminated. Using the publicly available Cardiotocography (CTG) dataset from the University of California and Irvine Machine Learning Repository, this study examines four well-known Machine Learning (ML) algorithms: Decision Tree Induction, Support Vector Machine (SVM), Naive Bayes Classifier, and Random Forest Classifier. Two of the most well-known dimensionality reduction techniques, Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA), are examined. The results of the experiment demonstrate that PCA performs better than LDA across the board. Additionally, applying PCA and LDA had little effect on the performance of the classifiers, Decision Tree, and Random Forest that were studied. The Diabetic Retinopathy (DR) and Intrusion Detection System (IDS) datasets are used in the experiment to further examine the performance of PCA and LDA. Results from experiments show that when the dimensionality of the datasets is high, ML methods using PCA get superior results. It has been shown that ML algorithms without dimensionality reduction perform better when datasets have low dimensionality.

3. METHODOLOGY

i) Proposed Work:

For pill identification, our approach takes into account the imprinted characters on tablets as essential information. Convolutional networks and a character-level language model were used to identify other aspects, such as shape, colour, and form. To increase generalisability and, consequently, the discovery of novel medicines, we also separated the kinds of pills in the training and assessment data sets.

By creating a system that concentrates on imprinted characters, we were able to overcome the shortcomings of the current pill search methods. A trained system that mostly uses Keras and TensorFlow is suggested for the simple and rapid detection of different kinds of medications. Furthermore, in order to learn the imprinted characters on tablets in alphabet and number units, we took inspiration from the field of natural language processing and took into account the characteristics of pills as context. Features are described as the pill's shape, colour, and form; features and the imprinted characters are referred to as characteristics overall.

ii) System Architecture:

The suggested pill detection system uses an organised methodology that combines image processing and deep learning methods. From data collection and preprocessing to model training, assessment, and deployment, the technique is divided into many phases.

Gathering a dataset of pill photos is the initial stage in the data gathering and preparation procedure. These pictures show pills with different imprints, colours, and forms. Data augmentation methods including rotation, contrast modification, and scaling are used to enhance model generalisation. This guarantees that the model is resilient in real-world situations by learning from a variety of pill picture permutations.

Convolutional Neural Networks (CNNs) in Keras with TensorFlow as the backend are then used to create the deep learning model. Using the preprocessed dataset, the CNN model is trained to identify the form, colour, and imprinted text of pills. To improve accuracy and cut down on training time, pre-trained models such as MobileNet or ResNet can be adjusted.

Following training, the model is used to feature extraction and picture categorisation. When a user uploads a picture of a pill, the system analyses it, pulls important information, and uses patterns it has learnt to categorise the pill. The name, dose, and manufacturer of the pill are among the pertinent details that are obtained when the categorisation output is compared to a pill database that is stored in SQLite.

Performance optimisation and assessment are carried out to guarantee the model's efficacy. Metrics like confusion matrices and loss functions are used to gauge the model's accuracy. To avoid overfitting and enhance generalisation, strategies including dropout layers and hyperparameter adjustment are used.

Lastly, Django is used to deploy the system, incorporating the learnt model into an online application. Users can provide photos for real-time pill identification, which is handled by the Django framework. After processing the input image and sending it to the CNN model, the backend extracts the pill details from the database and displays the data in an easy-to-understand manner.

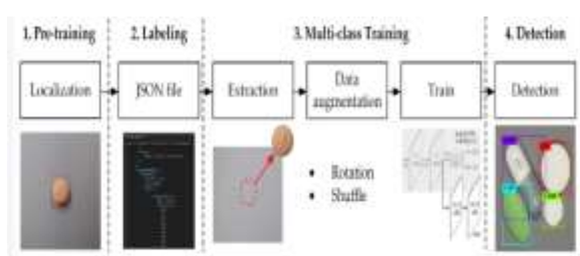

Fig.1 System architecture

iii) MODULES:

a) Admin Action

The Admin Action function processes login requests by verifying credentials. If the entered username and password match 'Admin' and 'Admin', access is granted, and the admin is redirected to the home page. If authentication fails, an error message is displayed, and the user is returned to the login page. This function ensures only authorized users can manage the system. Proper validation and session management enhance security.

b) Upload Dataset

The Upload Dataset function allows the system to load training and testing datasets. It defines global variables for dataset paths, ensuring accessibility throughout the system. Once the dataset paths are set, a success message is passed to confirm the upload. This function is crucial for maintaining an organized data pipeline. Proper dataset management ensures efficient model training and evaluation.

c) Preprocessing

The Data Generate function applies preprocessing using Keras' ImageDataGenerator. It augments images, resizes them to 48x48 pixels, and prepares them for categorical classification. This step ensures better generalization and model performance. It loads images from the training and testing datasets for further processing. A success message confirms successful preprocessing.

d) Generate CNN Model

The Generate CNN function checks for an existing trained model before proceeding. If a pre-trained model is found, it loads the model, restores its weights, and visualizes training history graphs. If no model exists, a new CNN model is created, trained for 50 epochs, and saved for future use. The function then displays final accuracy and performance graphs. This step ensures efficient model utilization and training management.

e) Log Action

The Log Action function authenticates users by verifying credentials against records in the pilldetection.db database. If authentication succeeds, a session is created, and the user is redirected to the home page. If credentials are incorrect, an error message is displayed, and access is denied. This function ensures secure and controlled user access. Proper session handling improves security and user experience

f) Model Graphs

The ModelGraphs function visualizes the training progress of the CNN model. It loads the training history, generates accuracy and loss graphs, and converts them into Base64-encoded images. These graphs are then sent to UserApp/ModelGraph.html for user-friendly visualization. This helps in analyzing model performance over time. Proper visualization aids in refining model training strategies.

g) Upload Pill Image

The Upload function renders the UserApp/UploadImage.html template for users to upload pill images. The imageAction function handles the uploaded image using FileSystemStorage, retrieves its URL, and loads it with OpenCV. The image is displayed for verification before processing. This feature ensures user-friendly interaction. A success message is shown upon successful upload.

h) Detect Pill

The Test function processes the uploaded image to identify pills. It preprocesses the image and feeds it into the CNN model for classification. The predicted label is displayed on the image using OpenCV, providing visual confirmation. Additionally, relevant details are fetched from an Excel dataset. This function enhances automation in pill identification. The prediction results improve medication safety and management.

iv) ALGORITHMS:

a) Convolutional Neural Networks (CNN)

A Convolutional Neural Network (CNN) is a deep learning model specialized for image classification and feature extraction. In the context of a pill detection system, CNNs effectively analyze pill images to classify and identify them accurately based on their shape, color, and texture. CNNs outperform traditional machine learning algorithms in image-related tasks due to their ability to automatically learn spatial hierarchies of features.

4. EXPERIMENTAL RESULTS

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

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

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

Test Accuracy: 0.9895

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

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

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

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

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

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

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

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 7.5 Upload Dataset

Fig 7.6 Preprocess Dataset

Fig 7.7 Model Accuracy Graph

Fig 7.8 Model Loss Graph

Fig 7.9 User Login Page

Fig 7.10 User Home Page

Fig 7.11 User View Profile Page

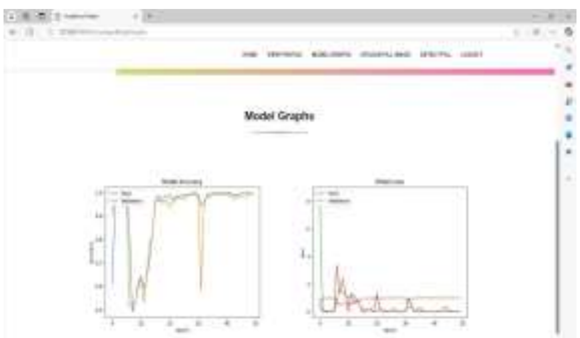

Fig 7.12 Model Graph

Fig 7.13 Upload Pill Image

Fig 7.14 Recheck Pill Image

Fig 7.15 Uploaded Sucessfully

Fig 7.16 Pill Name

Fig 7.17 Pill Description

5. CONCLUSION

In conclusion, the literature survey provides a comprehensive overview of the application of deep learning techniques in the detection of pills, showcasing a paradigm shift in pharmaceutical image analysis. The reviewed studies collectively demonstrate the potential of deep learning models in automating the identification and classification of pills, offering a range of benefits to the healthcare industry.

The evolution from traditional image processing methods to sophisticated deep learning architectures highlights the capacity of neural networks to learn intricate features from pill images. Convolutional Neural Networks (CNNs) and other deep learning models have shown remarkable success in accurately detecting pills based on visual characteristics such as shape, color, and imprints.

6. FUTURE SCOPE

Future research should focus on addressing existing challenges to further improve the accuracy and generalizability of deep learning-based pill detection systems. One crucial area is the expansion and standardization of datasets, as creating large, diverse, and publicly available datasets can enhance model robustness and enable fair benchmarking of different approaches. Additionally, improving model interpretability through explainable AI techniques will be essential to build trust and transparency in medical applications. Another key direction is the seamless integration of these systems into healthcare workflows, ensuring practical deployment in pharmacies, hospitals, and telemedicine platforms. Furthermore, strengthening security and privacy measures through advanced data encryption and anonymization techniques is necessary to protect sensitive patient information. Lastly, real-world testing and validation through clinical trials and case studies will be vital in assessing the effectiveness of these technologies in practical healthcare environments. By addressing these aspects, researchers and developers can work towards creating more efficient, scalable, and trustworthy pill detection solutions, ultimately benefiting the healthcare industry and improving patient outcomes.

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