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UTILISING MACHINE LEARNING MODELS FOR PILL DETECTION AND IDENTIFICATION

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Abstract : Accurate medication identification is crucial for patient safety, considering factors like pill colour, size, and shape. Environmental influences can lead to medication errors, necessitating quick and efficient pill identification methods. A proposed solution involves a trained system using Keras and TensorFlow for pill identification, employing object detection to interface with a pill database and leveraging pre-trained datasets for detailed information. This approach aims to gather datasets for automated medicine detection technology, validated through experiments. The innovative deep learning-based system, developed with Python and MobileNet architecture, achieves 98.00% accuracy in both training and validation, reducing human error and saving time for healthcare professionals. Patients benefit from reliable medication verification and access to comprehensive drug information. Rigorous testing confirms the system's reliability and effectiveness in preventing medical errors, enhancing patient care in healthcare settings.

***IndexTerms* – Pill, Keras, Tensor Flow, Object detection, Medicine.**

I. INTRODUCTION

Growing concerns over medication errors necessitate improved management. Deep learning offers more accurate pill detection, mitigating risks posed by unidentified pills. The goal of training machine learning models on large datasets of pill images is to automate identification and provide patients with crucial medication information. We used Keras and TensorFlow to train our deep learning models, improving pill detection. Furthermore, the study aims to improve pill recognition and analyze challenging identification problems with deep Convolutional Neural Network (CNN) models. Using MobileNetV2, a convolutional neural network design known for its larger number of layers, which improves accuracy and efficiency. MobileNetV2, which is a convolutional neural network (CNN) optimised for resource-constrained contexts, including mobile and edge devices. The follow-up to the initial MobileNet design aims to strike a compromise between the accuracy of models and computing performance. Researchers at Google launched MobileNetV2 in 2018 as part of the MobileNet series. It is lightweight and excels at image categorization, which makes it suitable for implementation on devices with restricted computational capabilities. Overall, using deep learning techniques has the potential to greatly improve patient safety and efficiency in healthcare globally.

II. EXISTING SYSTEM

Convolution Neural Networks:

CNNs stand out for their deployment of convolutional layers, which execute convolution operations on input data. A CNN's key elements include convolutional layers, pooling layers, fully connected layers, and activation functions. Convolutional layers consist of filters, also known as kernels, which learn spatial feature hierarchies from input data. The typical CNN structure involves alternating convolutional and pooling layers, followed by fully connected layers. MobileNetV2 opts for depth-wise separable convolutions over standard convolutions, resulting in both depth-wise and pointwise convolutions. This approach reduces parameter count and computational load. MobileNetV2 employs inverted residuals, incorporating a lightweight linear bottleneck followed by a non-linear activation function. This arrangement enhances the capture of nonlinearities effectively.

While Convolutional Neural Networks (CNNs) have proven to be remarkably effective in various image-related tasks, they are not without their drawbacks. One significant limitation lies in their sensitivity to hyperparameter choices. Parameters such as learning rates and batch sizes can significantly impact the performance of CNNs, often requiring meticulous tuning to achieve optimal results. Additionally, the design of the network architecture itself plays a crucial role in its performance, making it challenging to find the right balance between complexity and efficiency. Furthermore, CNNs typically require substantial computational resources, both in terms of training time and memory consumption, which can pose challenges for applications with limited computational capabilities or real-time processing requirements.

III. PROPOSED SYSTEM

MobileNetV2:

MobileNetV2 adopts depth-wise separable convolutions in lieu of standard convolutions, resulting in both depth-wise and pointwise convolutions. This approach reduces parameter count and computational requirements. Additionally, MobileNetV2 incorporates inverted residuals, comprising a lightweight linear bottleneck followed by a non-linear activation function, facilitating more effective capture of nonlinearities. Tailored for resource-constrained environments such as mobile and edge devices, MobileNetV2 serves as a follow-up to the original MobileNet, striving to strike a balance between model accuracy and computational efficiency. Introduced by Google researchers in 2018 as part of the MobileNet series, MobileNetV2 is lightweight and well-suited for deployment on devices with limited processing capabilities, making it popular for applications such as image categorization.

MobileNetV2 brings notable advantages in efficiency and lightweight design, making it an attractive choice for various applications, particularly on mobile devices. Its architecture, featuring depth-wise separable convolutions, enhances parallelization capabilities, enabling faster processing and lower computational demands. This design not only facilitates efficient use of computing resources but also enables seamless deployment on devices with limited processing power. As a result, MobileNetV2 stands out for its ability to deliver high performance while maintaining a small memory footprint, making it ideal for applications where speed, efficiency, and scalability are paramount, such as mobile image recognition and real-time object detection.

IV. TECHNIQUE USED OR ALGORITHM USED

EXISTING TECHNIQUE:

Convolutional Neural Networks (CNNs) are deep neural networks that handle structured grid data, including pictures. They excel in computer vision tasks including picture categorization, object recognition, image production, and segmentation. CNNs have significantly improved performance in visual recognition tasks. CNNs employ convolutional layers to process incoming data. CNN architecture comprises convolutional layers, pooling layers, fully linked layers, and activation functions. Convolutional layers use filters, sometimes known as kernels, to learn spatial feature hierarchies from input data. A CNN's design generally consists of convolutional and pooling layers, followed by fully linked layers.

PROPOSED TECHNIQUE OR ALGORITHM:

MobileNetV2 uses depth wise separable convolutions, which divide the convolution into depth wise and pointwise layers. This decreases the number of parameters and computations. MobileNetV2 uses inverted residuals, with a lightweight linear bottleneck followed by a non-linear activation function. This structure allows for more effective capturing of nonlinearities. MobileNetV2 presents advantages like increased efficiency and decreased size, while also enabling better parallel processing and deployment. This is achieved through its architecture, which incorporates depth-wise separable convolutions, allowing for more effective parallelization of computations.

V. METHODOLOGY

Importing the necessary libraries:

We will be employing Python for this. To begin, we'll import the essential libraries, including Keras for the primary model, sklearn for dividing data used for training and testing, PIL for converting pictures to numerals, and pandas, NumPy, Matplotlib, and TensorFlow.

Retrieving the images:

This module involves retrieving photos from the data set and converting them into a format suitable for both testing and training models. This process comprises reading, resizing, and normalising pictures. We'll collect the photographs and labels. We will get the photographs and labels. Resize the images to (224, 224) to ensure consistent identification. Convert the photos into a NumPy array.

Dataset Splitting:

This module will divide the picture dataset into two sets: training and testing. Separate the dataset into Training and Testing. 80% train data, 20% test data. The model will be trained on a certain amount of data, validated, and tested on unseen data for correctness. Divide the dataset into two parts: training and testing. The data consists of 80% training and 20% testing.

Model Building:

Convolutional neural networks are very effective in recognising images. CNN differs from classic neural networks primarily through its convolution process. CNN scans a picture many times to identify certain characteristics. This scanning (convolution) has two key parameters: stride and padding type. The initial convolution process generates new frames, which are represented in the second column (layer). Each frame offers information about an individual element and its inclusion in the scanned image. The resulting frame will have higher values when a feature is apparent and fewer ones where there are few or no such characteristics. Following that, the procedure continues for each of the collected frames for a certain number of times. In this research, I used the standard Mobile Net model, which has just two convolution layers. The higher-level characteristics are sought for in the last layer of convolving. It functions similarly to perception in humans. For example, the image below is quite detailed and has traits that are searched on multiple You may wonder how the model determines which traits to search. If you build the CNN from scratch, the searched characteristics are random. Then, throughout the training procedure, the connections between neurons are modified, and CNN gradually begins to identify features that allow it to accomplish a predetermined objective, namely, effectively recognise pictures in the training set.

VI. IMPLEMENTATION AND RESULT

The project's goal was to implement Machine Learning Algorithms to create a system to detect and identify any sort of pill. Using a predefined dataset with consolidated collection of data while it consists of distinct pieces of information, its primary purpose lies in training algorithms to uncover predictable patterns across the entire dataset. Quality datasets are paramount for AI progress, often outweighing algorithmic advancements. In fact, improvements in datasets can accelerate AI breakthroughs sixfold compared to algorithmic enhancements. By leveraging TensorFlow and Keras in this project with helps in Object detection which is a fundamental task within this project as a pill technically is an object, encompassing not only the identification of objects in images but also precise localization and classification. This research focuses on detecting and recognizing pills of various sizes, shapes, and colors for further analysis. As deep learning and computer vision technologies progress, object detection capabilities are poised to play an increasingly vital role in fostering innovation and addressing complex challenges across various industries. Implementing MobileNetV2 in this project which is a Convolutional Neural Network (CNN), A Convolutional Neural Network (CNN) represents a specialized type of deep learning algorithm well-suited for image recognition and processing tasks. Comprising multiple layers, including Convolutional, Pooling, and Fully Connected layers, CNNs excel in extracting features like edges, textures, and shapes from input images, facilitating accurate predictions or image classification.

Figure 1 Result

VII. FUTURE SCOPE

In the years to come, this proactive technique may help patients prevent negative side effects and improve their prescription regimens. In addition, integrating methods from NLP may enable the programme to gather and evaluate medication data from unorganised material including electronic health records or medicines labels, resulting in a greater awareness of the patient's medical history and treatment plan. Furthermore, integrating a medication detection system with EHR systems, or electronic health records, can improve information exchange and support for decisions by allowing medical professionals to access prescription information from current procedures.

VIII. CONCLUSION

The needed results for the thorough investigation of pill detections have satisfied the requirements for identifying a pill based on its physical structure and chemical makeup. As the pill is detected by the camera, the image is instantly transferred to the dataset where a comparable image is searched for. Once the detection

is successful, the previously learned data is taken according to the tablet. Thus, the pill is recognised by getting data from the dataset and cross-checking it against the scanned pill.

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