Detection and Identification of Pills using Machine Learning Models

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Abstract: Accurate identification of pharmaceuticals is vital in order to minimize medical errors, as it directly effects the well being of patients and prevents major consequences.Drug abuse puts patients at significant risk for problems and possible injury. Healthcare providers are burdened by this problem since they have to manually search pill databases to find prescriptions when patients are unable to supply their prescription details. Because patients typically throw away the containers that hold their medication along with the prescription, this situation occurs regularly. The development of computerized medication systems that use information technology to precisely identify medications and identify possible interactions between them is imperative in order to address these issues. An inventive deep learning-based pill detection system with sophisticated medicinal substance recognition capabilities is shown in this senior project. The MobileNet architecture serves as the underlying model for the system, which was created with the Python programming language. The primary goal of this research is to deliver intelligent drug identification and accurate pill detection from photos. The system is trained using a dataset of 1,268 samples for both training and testing in order to achieve this. The MobileNet architecture is used in the system's training process, which produces remarkable performance metrics. Both training and validation accuracy are said to have been attained at 98.00%. The system's capacity to precisely identify medications and detect pills is validated by its excellent accuracy rates. This deep learning-based pill identification system has a lot to offer the healthcare industry in real-world applications. It reduces human mistake and saves healthcare personnel important time by automating the pill identification procedure. The system also helps patients by allowing them to get detailed information about their prescriptions and confirm that they are what they were prescribed. Thorough testing on a variety of pill images is part of the system's evaluation process to guarantee its robustness, accuracy, and dependability. The study shows how well the proposed system works to achieve precise pill detection and intelligent medicinal medication identification through a great deal of testing and validation.

Keywords: Pill detection, Image classification, Deep learning, Machine learning, Medication identification, Healthcare automation.

INTRODUCTION

Computational models with many processing layers can learn representations of data with different levels of abstraction thanks to deep learning. The state-of-the-art in a variety of fields, including drug discovery and genomics, has been significantly enhanced by these techniques, including speech recognition, visual object recognition, and object detection. By employing the back propagation approach to tell a machine how to alter its internal parameters that are required to compute the representation in each layer from the representation in the previous layer, deep learning finds complex structure in massive data sets. While recurrent nets have shed light on sequential data like text and speech, deep convolutional nets have made significant strides in processing pictures, video, speech, and audio.

Many facets of contemporary life are powered by machine-learning technology, including web searches, social network content filtering, e-commerce website recommendations, and the growing use of this technology in consumer goods like smartphones and cameras. Machine-learning systems are used to recognize objects in photos, convert speech to text, match users' interests with news articles, postings, or products, and choose pertinent search results. These applications are increasingly using a class of methods known as deep learning. Natural data in its unprocessed state was difficult for traditional machine-learning approaches to handle. For many years, building a machine learning or pattern recognition system required a great deal of domain knowledge and careful engineering to create a feature extractor that converted raw data (like an image's pixel values) into an appropriate internal representation or feature vector that the learning subsystem, usually a classifier, could use to identify or categorize patterns in the input. A collection of techniques known as representation learning enables a machine to automatically identify the representations required for detection or classification when it is given raw data. A representation at one level (beginning with the raw input) is transformed into a representation at a higher, slightly more abstract level by each of the simple but non-linear modules that make up deep-learning methods, which are representation-learning techniques with several levels of representation. It is possible to learn extremely complex functions by composing enough of these transformations. Higher layers of representation accentuate certain features of categorization problems.

of the input that suppress unimportant variances and are crucial for discrimination. The learnt features in the first layer of representation, for instance, usually indicate whether or not edges are present at specific orientations and locations in an image, which is represented by an array of pixel values. Usually, the second layer finds motifs by identifying specific edge configurations, even if there are little differences in the edge placements. Subsequent layers would identify items as combinations of the motifs that the third layer assembled into larger combinations that matched portions of recognized objects. Deep learning's main characteristic is that these feature layers are not created by human engineers; rather, they are acquired from data through a general-purpose learning process. Significant progress is being made by deep learning in addressing issues that have long eluded the artificial intelligence community's best efforts. It has proven to be highly effective at identifying complex patterns in high-dimensional data, making it relevant to a wide range of fields in academia, industry, and government. It has outperformed other machine-learning techniques in predicting the activity of possible drug molecules, analyzing particle accelerator data, reconstructing brain circuits, and predicting the effects of mutations in non-coding DNA on gene expression and disease, in addition to breaking records in image and speech recognition.

RELATED WORK

The creation and deployment of a deep learning-based pill detection system with sophisticated medicinal medication recognition capabilities is included in the project's scope. By automating the pill recognition and drug classification process, this system seeks to meet the urgent demand for precise medicine identification in healthcare environments. The project uses the MobileNet architecture and the Python programming language to train the model on a dataset of various pill images. High pill detection and drug identification accuracy rates, as evidenced by thorough testing and evaluation, are among the main goals. The scope of the system also includes giving medical practitioners a dependable tool to expedite medication verification procedures, which lowers the possibility of medical errors and saves important time. By giving patients access to thorough pharmacological information and the ability to confirm their given medications, the project also seeks to empower patients. The project's scope must include ethical issues like patient privacy and regulatory compliance to ensure responsible deployment and use in healthcare settings. By integrating state-of-the-art deep learning technology, the initiative aims to improve clinical efficiency, develop drug management practices, and increase patient safety.

In order to greatly enhance medication management procedures in healthcare settings, the main goal of this project is to create a deep learning-based pill detection system with intelligent medicinal drug identification capabilities. The system's goal is to correctly detect pills from photos and categorize them into the appropriate medicinal substances by utilizing the MobileNet architecture and the Python programming language. Achieving high pill detection and drug identification accuracy rates via reliable model training and validation on a variety of datasets is one of the main goals. In order to lower the possibility of medical errors and improve clinical processes, the project aims to automate and simplify the medication verification procedure for medical personnel. By giving patients access to thorough pharmacological information and the ability to confirm their prescribed medications, the system also seeks to empower patients. In order to ensure responsible deployment and usage within healthcare environments, ethical considerations—such as patient privacy and regulatory compliance—are essential to the project's goals. The project's overall goal is to improve patient

A subclass of deep neural networks called convolutional neural networks (CNNs) is made specifically for processing structured grid input, like pictures.

picture classification, object identification, picture generation, and image segmentation are among the computer vision tasks in which they excel. State-of-the-art results in a variety of visual identification tasks have been made possible thanks in large part to CNNs.
safety, enhanced clinical effectiveness, and improvements in drug management techniques by incorporating state-of-the-art deep learning technology.

LITERATURE SURVEY

J. Suchitra, R. K. Nadesh, and S. Ramya, Since numerous diseases impact people, medication has become more significant in everyone's life. There are some illnesses that require medication to be cured. In recent years, there has been a significant increase in the manufacture of medicine. There could be cracks or breaks in the pills or capsules during manufacture. Taking these broken tablets could lead to issues with the lips, eyes, and skin. It is not recommended to take the majority of the tablets broken. The task of manual inspection is extremely difficult. A key component of automating visual examination is image processing. As a result, we offer some suggestions for identifying the faulty pills after manufacturing. To find the broken tablets, a number of procedures are used, including image enhancement, segmentation, thresholding, filtration, pixel calculation, subtraction, de-noising, and region-based statistics. We provide a feature extraction method for identifying the faulty blister in the instance of capsules.

Emergency departments (EDs) have frequently used innovative approaches to drug delivery, particularly beyond regular business hours when hospital pharmacy departments may be closed (O. Gordon, R. S. Hadsall, & J. C. Schommer). Some have chosen to store supplies of frequently prescribed drugs in containers labeled "starter." Pharmaceutical access is addressed by this method, but when therapy beyond the initial supply is required, the clinician must write a second prescription. Nurses usually manage the medication delivered at the emergency department (ED), and they frequently have to choose the appropriate medication, properly label the medication, and educate the patient on top of their regular responsibilities. Getting paid by payers for the drugs that are prescribed may be challenging or impossible.

An outpatient automated dispensing system (ADS) specifically made for emergency departments (EDs) was developed as a result of awareness of these issues and personal experience. The purpose of this point-of-care advertisement is to give patients in emergency departments at hospitals without a 24-hour pharmacy a complete supply of prescription drugs. An emergency medicine doctor spearheaded the system's development after he couldn't find a 24-hour pharmacy one night to complete a prescription for his little kid, who had acute otitis media.

J. Hanson, B. Dalgliesh, M. Wallis, K. Bennett, A. Craswell, to investigate the components, procedures, and results of implementing an automated medication dispensing system and how they affect patient safety. Over the past 20 years, there has been a growing digitization of the prescription, dispensing, administration, and stock management of medications. Although the goal of automated medicine dispensing systems is to deliver safe, excellent, patient-centered care, deployment may have unforeseen repercussions that produce less than ideal results.

Semi-structured interviews were conducted with 26 registered nurses and pharmacy assistants who worked in clinical settings with automated medicine dispensing cabinets. The structures and procedures were thoroughly examined using thematic analysis. To assess results, content analysis of text data produced by critical incident reporting and internal risk management systems was done in addition to interview data. The results were examined in the context of health information technology using the Interactive Sociotechnical Analysis method. This article was prepared using the COREQ checklist.

Hartl, A. In this study, we introduce a mobile computer vision system that makes recognizing prescription medications easier. An effective method for object segmentation on structured background is used to process a single input image of pills on a specific marker-based target. Parameters that can be utilized to query an online database about an unknown pill are provided via estimators for the object characteristics size, shape, and color. The Studierstube ES framework is used to build 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 support mobile pill detection in a practical setting is confirmed by the retrieval performance on the widely used Identa database.

Rani, G.E., Rajini, N., Siengchin, S., Murugeswari, R., In order to demonstrate quantifiable connections between the mechanical properties of particle reinforced polymer composites (PRPC) and the particle/cluster size distribution, an automated image analysis method is created in this work.In order to process and examine the microstructural images of the polymer-based composite materials, an automated image analysis tool was created using Python computer tools. For the analysis, a poly-propylene carbonate (PPC) polymer composite reinforced with spent coffee bean powder (SCBP) and varying weight percentages of filler is chosen. In addition to the most frequently reported "clustering of particles," a detailed statistical analysis of the microstructural pictures shows that there is also "clustering of clusters" and a bimodal distribution of particle/clusters. An effective volume fraction for the filler material is suggested in light of these findings in order to primarily capture the agglomeration effect. The typical rule-of-mixture model accurately depicts the experimentally determined modulus and tensile strength as a function of filler weight percentage with this effective volume fraction. Additionally, it is examined whether this effective volume percentage may be applied to other theoretical models. Compared to the traditional qualitative association of microstructural features with qualities and failure processes, the comprehensive statistical analysis of the microstructure and the suggested effective volume fraction contributes to a richer quantitative understanding of the PRPC.

PROPOSED WORK

Convolutional neural network (CNN) architecture MobileNetV2 is made to perform well on edge devices, mobile devices, and other settings with limited resources. It is an improvement on the original MobileNet architecture with the goal of striking a good balance between computing performance and model correctness.

As part of the MobileNet series, Google researchers unveiled MobileNetV2 in 2018. Since then, it has been well-known for its ability to perform well on tasks like picture categorization while being portable and appropriate for deployment on devices with constrained processing power.

The goal of this project is to transform medication management in healthcare settings by creating an advanced deep learning-based pill detection system with intelligent medicinal drug recognition capabilities. The system will be trained on a large dataset of various pill images using the MobileNet architecture and the Python programming language in order to correctly detect pills and categorize them into the appropriate therapeutic medications. In order to lower the possibility of medical errors and improve patient safety, the system's primary function is to automate the formerly manual and error-prone medication identification procedure. Because the technology offers quick and precise medication verification, healthcare personnel will experience improved efficiency and streamlined workflows. The ability to acquire thorough drug information and validate their prescription medications would empower patients as well. Thorough testing and validation processes will guarantee the accuracy, robustness, and dependability of the system in a variety of real-world situations. Patient privacy and regulatory compliance are only two examples of the ethical issues that will be crucial during the project's development and implementation stages. Ultimately, this research seeks to make major steps in expanding drug management techniques, ultimately contributing to improved patient outcomes and healthcare quality.

Modules Name: In the first module of Detection and Identification of Pills, we developed the system to get the input dataset. Data collection process is the first real step towards the real development of a machine learning model, collecting data. This is a critical step that will cascade in how good the model will be, the more and better data that we get; the better our model will perform. There are several techniques to collect the data, like web scraping, manual interventions. Our dataset is placed in the project and it's located in the model folder. The dataset is referred from the popular standard dataset repository kaggle where all the researchers refer it. The dataset consists of 1,268 pills images. The following is the URL for the dataset referred from kaggle.

Importing the necessary libraries: We will be using Python language for this. First we will import the necessary libraries such as keras for building the main model, sklearn for splitting the training and test data, PIL for converting the images into array of numbers and other libraries such as pandas, numpy, matplotlib and tensorflow.

Retrieving the images: In this module we will retrieve the images from the dataset and convert them into a format that can be used for training and testing the model. This involves reading the images, resizing them,

and normalizing the pixel values. We will retrieve the images and their labels. We will retrieve the images and their labels. Then resize the images to (224, 224) as all images should have same size for recognition. Then convert the images into numpy array.

Splitting the dataset: In this module, the image dataset will be divided into training and testing sets. Split the dataset into Train and Test. 80% train data and 20% test data. This will be done to train the model on a subset of the data, validate the model's performance, and test the model on unseen data to evaluate its accuracy. Split the dataset into train and test. 80% train data and 20% test data.

Building the model: The concept of convolutional neural networks is very successful in image recognition. The key part to understand, which distinguishes CNN from traditional neural networks, is the convolution operation. Having an image at the input, CNN scans it many times to look for certain features. This scanning (convolution) can be set with 2 main parameters: stride and padding type. As we see on below picture, process of the first convolution gives us a set of new frames, shown here in the second column (layer). Each frame contains an information about one feature and its presence in scanned image. Resulting frame will have larger values in places where a feature is strongly visible and lower values where there are no or little such features. Afterwards, the process is repeated for each of obtained frames for a chosen number of times. In this project I chose a classic Mobile Net model which contains only two convolution layers. The latter layer we are convolving, the more high-level features are being searched. It works similarly to human perception. To give an example, below is a very descriptive picture with features which are searched on different CNN layers. As you can see, the application of this model is face recognition. You may ask how the model knows which features to seek. If you construct the CNN from the beginning, searched features are random. Then, during training process, weights between neurons are being adjusted and slowly CNN starts to find such features which enable to meet predefined goal, i.e. to recognize successfully images from the training set. Between described layers there are also pooling (sub-sampling) operations which reduce dimensions of resulted frames. Furthermore, after each convolution we apply a non-linear function (called **ReLU**) to the resulted frame to introduce non-linearity to the model.

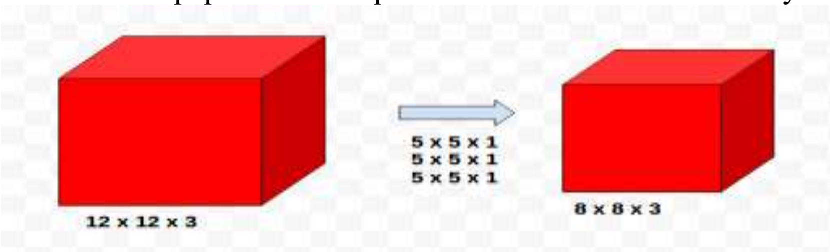
Eventually, there are also fully connected layers at the end of the network. The last set of frames obtained from convolution operations is flattened to get a one-dimensional vector of neurons. From this point we put a standard, fully-connected neural network. At the very end, for classification problems, there is a softmax layer. It transforms results of the model to probabilities of a correct guess of each class

MobileNet | CNN model

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications paper from Google. They developed a class of efficient models called MobileNets which mainly focuses on mobile and embedded vision applications. In one word the main focus of their model was to increase the efficiency of the network by decreasing the number of parameters by not compromising on performance.

1. *Depthwise Separable Convolution*

This is the core basis of MobileNet paper. It is a depthwise convolution followed by a pointwise convolution.



Before getting to depthwise convolution and pointwise convolution, let us understand how normal convolution works.

How normal convolution is done?

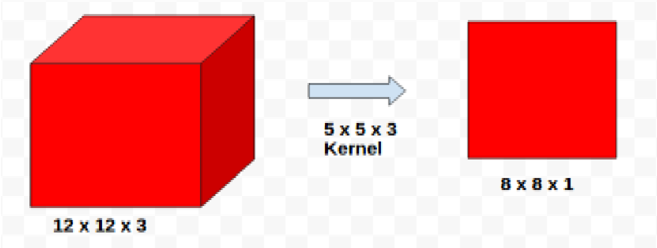


Fig 1. Normal convolution.

Here we have an input image size of 12x12x3. If we do convolution using a 5x5x3 kernel with stride=1, we will get an output size of 8x8x1. Usually, during convolution operations, we specify we need N number of channels in output. During that time what happens is the same operation is repeated N times with different kernels. Suppose N = 10. Then the total computational cost become **8 x 8 x 5 x 5 x 3 x 10 = 48000**

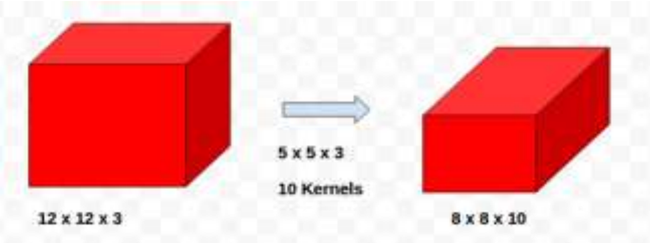


Fig 2.Normal convolution.

We can say that a standard convolution layer input takes input as a **Df x Df x M** feature map and produce the **Df x Df x N** output feature map where Df is the spatial width and height of the square input feature map. M is the number of input channels and N is the number of output channels. The standard convolutional layer is parameterized by convolution kernel K having the size of Dk x Dk x M x N. So the total computational cost becomes **Dk x Dk x M x N x Df x Df.**

$$D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F$$

Depthwise Separable Convolution

What if we will be able to divide this convolution procedure based on depth. Depth wise separable convolution consists of 2 parts:

1. Depthwise convolution
2. Pointwise convolution

Depthwise convolution

Here we have 3 channels for input. consider we have 3 5 x 5 x 1 kernels.Here what happens is 5x5x1 kernel iterates over the first channel of the input image to produce 8x8x1 output. Each 5 x 5x 1 kernel do the operation to the corresponding channel in the input image. Now we stack all three such outputs to get 8 x 8 x 3 output. This is how depth wise convolution works.

The next one is the **pointwise convolution**. We will do a convolution using a 1 x 1 x 3 kernel on an 8 x 8 x 3 image obtained. This will produce a feature map. We will repeat this using 10 different 1 x 1 x 3 kernels to produce 10 feature maps and we will stack them together.

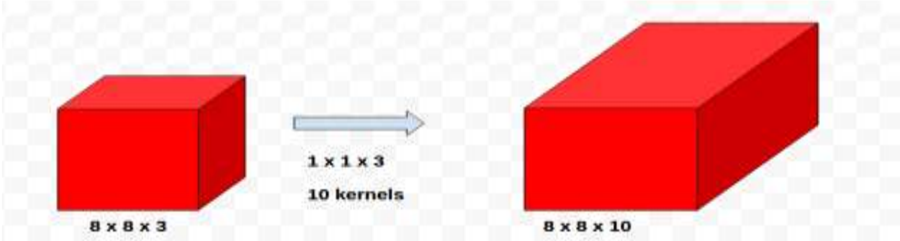


Fig 3. pointwise convolution.

Here the total number of computations is 8 **x 8x 5 x 5 x 3 + 8 x 8 x 10 x 3= 4800 + 1920 = 6720**
Total computational cost is computational cost depth separable convolution

$$D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F$$

Thus the computational reduction is

$$\frac{D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F}{D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F}$$
$$= \frac{1}{N} + \frac{1}{D_K^2}$$

Note: By using 3x3 kernel about 7 to 8 times less computational reduction can be achieved(4*8000/6720 =~ 7.14*).

2. *Network Architecture*

Type / Stride	Filter Shape	Input Size
Conv / s2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1	3 × 3 × 32 dw	112 × 112 × 32
Conv / s1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw / s2	3 × 3 × 64 dw	112 × 112 × 64
Conv / s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw / s2	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 512	14 × 14 × 256
5× Conv dw / s1	3 × 3 × 512 dw	14 × 14 × 512
5× Conv / s1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw / s2	3 × 3 × 512 dw	14 × 14 × 512
Conv / s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw / s2	3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1	Pool 7 × 7	7 × 7 × 1024
FC / s1	1024 × 1000	1 × 1 × 1024
Softmax / s1	Classifier	1 × 1 × 1000

Table 1. Parameters of the architecture.

The network consists of 28 convolutional layers and 1 fully connected layer followed by a softmax layer. It is noted that batch normalization and ReLU is applied after convolution

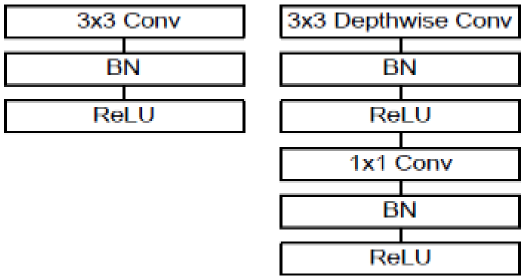


Fig 4. Softmax layer.

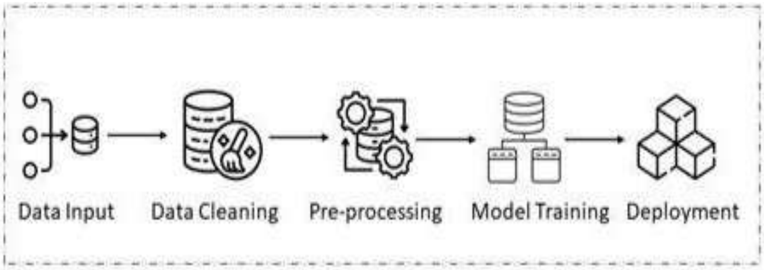


Fig 5. Architecture of the work.

3. *Width Multiplier*

A width multiplier alpha α is introduced to further reduce computational cost. So M becomes αM. So depth wise separable computational cost becomes computational cost with width multiplier.

$$D_K \cdot D_K \cdot \alpha M \cdot D_F \cdot D_F + \alpha M \cdot \alpha N \cdot D_F \cdot D_F$$

where α is between 0 to 1.Typically values of α are 1,0.75,0.5 and 0.25. When α = 1 we have baseline MobileNet.

Width Multiplier	ImageNet Accuracy	Million Mult-Adds	Million Parameter
1.0 MobileNet-224	70.6%	569	4.2
0.75 MobileNet-224	68.4%	325	2.6
0.5 MobileNet-224	63.7%	149	1.3
0.25 MobileNet-224	50.6%	41	0.5

Table 2. performance with different α values

4. *Resolution Multiplier*

Resolution Multiplier ρ is introduced to control the image resolution of the network. With ρ computational cost becomes computational cost with resolution multiplier

$$D_K \cdot D_K \cdot \alpha M \cdot \rho D_F \cdot \rho D_F + \alpha M \cdot \alpha N \cdot \rho D_F \cdot \rho D_F$$

where ρ is between 0 to 1. The corresponding resolutions are 224, 192, 160, and 128. When ρ=1, it is the baseline MobileNet.

Resolution	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
1.0 MobileNet-192	69.1%	418	4.2
1.0 MobileNet-160	67.2%	290	4.2
1.0 MobileNet-128	64.4%	186	4.2

Table 3. MobileNet resolution.

5. *Performance Comparison*

MobileNet-224 outperforms GoogLeNet (Winner of ILSVRC 2014) and VGGNet (1st Runner Up of ILSVRC 2014) and also parameters were lower.

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	1550	6.8
VGG 16	71.5%	15300	138

Table 4. MobileNet comparision to popular models.

When smaller MobileNet (**0.50 MobileNet-160**) is used, it outperforms AlexNet and Squeezenet with fewer Adds and parameters.

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
0.50 MobileNet-160	60.2%	76	1.32
Squeezenet	57.5%	1700	1.25
AlexNet	57.2%	720	60

Table 5. Smaller MobileNet comparison to popular models.

For object detection tasks using the mobile net as the backbone, performance is as follows

Apply the model and plot the graphs for accuracy and loss:

Once the model is built, it will be applied to the validation set to evaluate its accuracy and loss. The accuracy and loss will be plotted as a function of the number of epochs to visualize the performance of the model. We will compile the model and apply it using fit function. The batch size will be 1. Then we will plot the graphs for accuracy and loss. We got average training accuracy of 98.00%.

Accuracy on test set: After training and evaluating the model on the validation set, the accuracy of the model will be assessed on the test set. The accuracy on the test set will be an important metric for evaluating the model's performance. We got an accuracy of 98.00% on test set.

Saving the Trained Model: Once you’re confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5 or .pkl file using a library like pickle.

CONCLUSION

The required results for the comprehensive study of pill detections have met the works satisfaction of detecting a pill on the basis of its physics structure and chemical composition. As the pill is shown to the camera [by object detection], the pill image is immediately taken to the dataset Authorized licensed use limited to: Florida Institute of Technology where the similar image is searched for. Once the detection becomes successful, the data that is already trained is taken according to the pill. Thus, the pill is identified by retrieving the data from the dataset and upon checking with the scanned pill.

In the future, This proactive approach can help prevent adverse events and optimize medication regimens for patients. Furthermore, incorporating natural language processing (NLP) techniques could enable the system to extract and analyze medication information from unstructured text, such as electronic health records or medication labels, providing a more comprehensive understanding of a patient's medication history and treatment plan. Additionally, integrating the pill detection system with electronic health record (EHR) systems can facilitate seamless information exchange and decision support, allowing healthcare providers to access medication data directly within their existing workflows.

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