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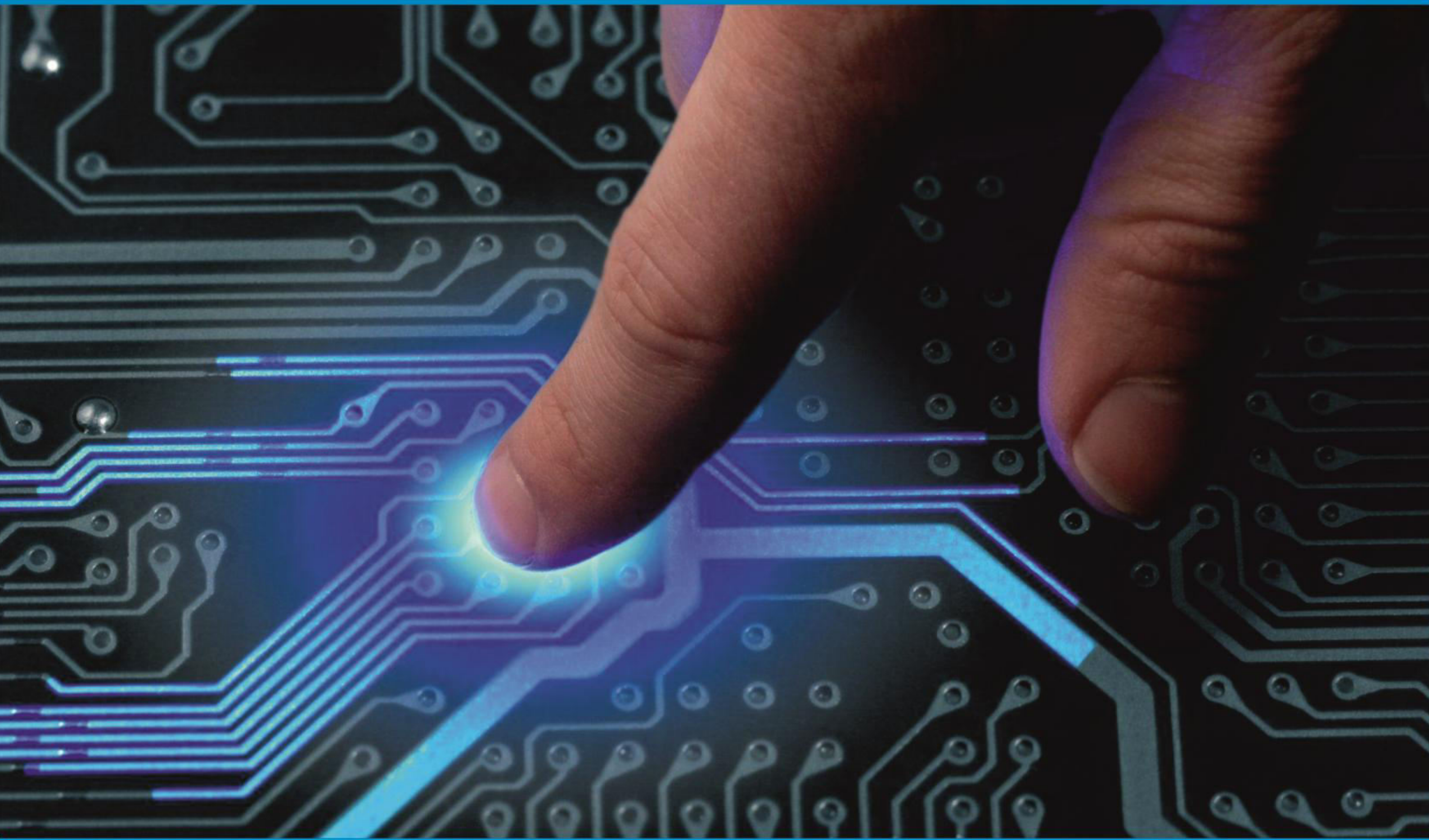

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Image Classification Using Convolution Neural Network

G.Bhuvaneswari [1], **M.Faiz** [1] , **M.Priya Dharshini** [1], **Dr. R. Vijayalakshmi** [2] ,

UG Student, Dept. of CSE, Velammal College of Engineering and Technology, Madurai, Tamilnadu, India [1]

Associate Professor, Dept. of CSE, Velammal College of Engineering and Technology, Madurai, Tamilnadu, India[2]

ABSTRACT: This paper presents evaluation of the performance of famous convolutional neural networks (CNNs) for classifying objects in real time video. The most famous convolution neural networks for object detection and object class classification from images are Nets, GoogLeNet and ResNet50. A variety of image data sets are available to analyse the performance of different types of CNN's. The generally found datasets for evaluating the performance of a convolutional neural network are an ImageNet dataset, and CIFAR10, CIFAR100 and MNIST object image data sets. We have taken three most famous data sets ImageNet, CIFAR10 and CIFAR100 for our study, though, analysing the performance of a network on a single data set does not reveal its true ability and limitations. It must be acclaimed that videos are not used as a training dataset, but they are used as testing datasets. Our analysis displays that GoogLeNet and ResNet50 are able to recognize objects. Moreover, the performance of trained CNN's differs substantially among different categories of objects , and we therefore, will examine the possible reasons for it.

KEYWORDS: Convolutional neural networks (CNNs), Deep Learning, Image classification, Image detection.

I. INTRODUCTION

Right now, internet is filled with plenty of images and videos, which is cheering the development of search applications and algorithms. There has been major progress in image labelling, object detection, scene classification, areas reported by different researchers across the world. This leads to making it feasible to formulate different approaches concerning object detection and scene classification problems. Since convolution neural networks have shown a performance progress in the area of object detection and scene classification, this work focuses sharp on identifying the best for this purpose. Feature extraction is an essential of such algorithms. Feature extraction from images involves extracting an least set of features containing ahigh amount of object, therefore, capturing the difference among the object groups involved. CNN has been presenting an effective class of models for better understanding of contents present in object image, hence resulting in better image recognition, segmentation, detectionand retrieval. CNN's are efficiently and effectively used in numerous pattern and image recognition applications, for example, face recognition, object classification and creating scene descriptions. The successful combination of all the applications is due to advances and development in learning algorithms for deep network construction and relatively to the open-source large labelled data set available for experimentation reason, for example, ImageNet, CIFAR 100, etc. CNN has familiar trained networks that uses these datasets available in open source networks and increases its potency of classification after getting trained over millions of images contained in the datasets of CIFAR-10 and Image-Nets. The datasets used are composed of millions of minute images. Therefore, they can simplify well and precise and hence successfully categorize the classes' out-of-sample examples. It is important to note that neural network classification and prediction accuracy and error values are all most comparable to that of humans when such comparisons are made on a variety data set vailable in such as Image-Net, CIFAR-10 etc. This work aims at analyzing the ability of convolutional neural networks to categorize the scene in videos on the basis of recognized objects. A variety of image classes are included in CIFAR-100, CIFAR 10 and ImageNet datasets for training the CNN. The test datasets are videos of diverse categories. The contradiction branches out because of the feature extraction abilities of diverse CNN.

The main contribution of our work is to present object detection methods using convolution neural networks where current up-to-date models show diverse performance rates for test images or videos when contrasted to trained images. After training this network for various object classes presented as input in the form of object images, and then testing for the more specific real-time video feed, we can better understand what is being learned and conferred by these models.Therefore, we can suggest that an image representation on the basis of objects detected in it would be remarkably useful for high-level visual recognition. These networks are trained on datasets containing millions of

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minute images. We suggest that the concept of object detection can be used as an assign for scene representation. These networks used for our study are built using existing neural networks and each of these networks have various layers, therefore their performance differs considerably. Using complex real-world scenes the object observation accuracy of the network can be checked. This paper is set out as follows. We start by presenting literature survey, following with the proposed system for comparing the networks chosen for the study, including Architecture and flowchart diagram. We then present a comprehensive analysis of results acquired on various datasets.

II. LITERATURE SURVEY

1. Hasbi Ash Shiddieqy, FarkhadIhsanHariadi, Trio Adiono "Implementation of Deep-Learning based Image Classification on Single Board Computer",2014 In this paper, a deep-learning algorithm on convolutional neural-network is applied using python and tflearn for image classification, in which two dissimilar structures of CNN are used, namely with 2 and 5 layers and It infers that the CNN with higher layer executes classification process with much greater accuracy.

2 . Rui Wang, Wei Li and JinZhong Wu "Blur Image Classification on Deep Learning",2012 In this paper, a convolution neural network (CNN) of Simplified-Fast-Alexnet (SFA) based on the learning attributes is proposed for handling the sorting matter of defocus blur, Gaussian blur, haze blur and motion blur four blur type images. The experiment results support that the performance of sorting accuracy of SFA, which is 96.98% for simulated blur dataset and 92.74% for natural blur dataset, is equivalent to Alexnet and excellent to other classification methods.

3. Sameer Khan and Suet-Peng "A Deep Learning Architecture for Classifying Medical Image of Anatomy Object",2017 In such paper, a modified CNN architecture that associates multiple convolution and pooling layers for extraordinary feature learning is proposed. In this, medical image classification has been carried out and it exhibits that the proposed CNN feature representation outperforms the three architectures for categorizing medical image anatomies.

4. Ye Tao, Ming , Mark Parsons "Deep Learning in Photovoltaic Penetration Classification", 2013 this paper proposed a deep learning based algorithm to differentiate photovoltaic incident from other grid events, and it achieves that a deep convolutional neural network can conclude better classification accuracy than a fully connected model.

5 C. A. Ronao and Cho, "Human activities identification and classification with new phone sensors using DL convolution neural networks,". Appl., vol. 62, pp. 235_234, Oct. 2016. Convolutional networks comprised of various convolutional and pooling layers followed by one or more fully-connected layers, have earned popularity due to their ability to sense unique representations from images or speeches, taking local dependency and distortion invariance.

Proposed System :

The steps of proposed approach are as follows:
Steps 1: Creating teaching training and testing dataset: The super classes object images used for training is altered [224,244] pixels for AlexNet and [227,227] pixels GoogLeNet and ResNet50, and the dataset is isolated into two categories i.e. training and validating some data sets.

Steps 2 : Modifying CNNs network: Substitute the last three layers of the network with fully connected layer, a SoftMax layer, and a classification output layer. Lay the final fully connected layer to have the equal size as the number of classes in the training data set. Increase the learning rate elements of the completely connected layer to train network faster.

Steps 3: Train network: Place the training options, including learning rate, mini-batch size, and authenticate data according to GPU requirement of the system. Train the network using the training particular data.

Steps 4: Test the accuracy of network: Categorize the validation images using the fine-tuned network, and calculate the classification accuracy rate. Correspondingly testing the fine tune network on real time video feeds for precise results.

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III. METHODOLOGY

Convolutional Neural Network:

The CNN was first introduced in 1989 and proved effective for digit recognition. Following this success, the interest for CNNs increased, and they have been shown to perform incredibly well in more challenging image recognition tasks, and have outperformed other ML models. The success of CNNs can be contributed to the availability of larger datasets, increased computational power and improved regularisation techniques. The underlying idea of the CNN is based on previous work in visual pattern recognition, where it has been demonstrated useful to extract and combine local features to more abstract higher-order features . The first layer of a CNN is a convolutional layer, which consists of one or multiple filters convolving over the original input image. As each filter convolves over the original image, element wise multiplication of the pixel values of the filter and the sub-part of the original image (receptive field) is performed and the result is summarised. This will result in one or more feature maps of the original image, where every unit in the resulting feature map is a result of the operations on the neighbourhood of the real image.

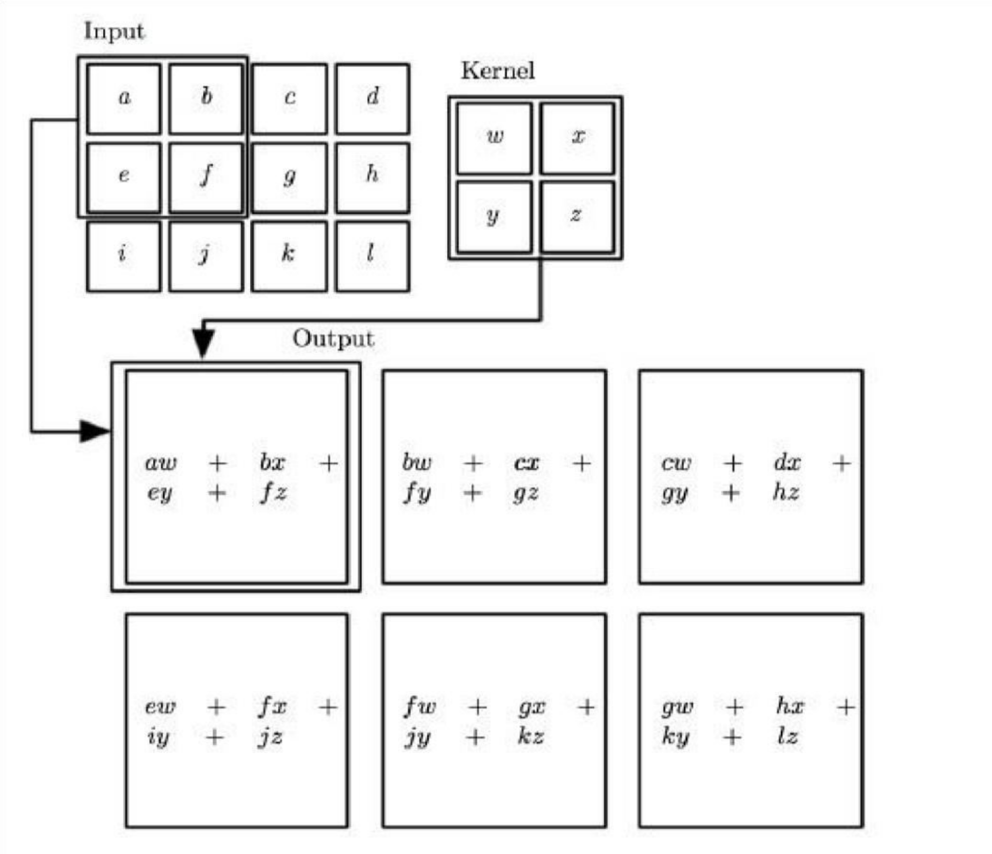

Figure 1 : 2-D CNN Convolution . The figure displays how the sub-part of the original input is multiplied element wise with the filter values to construct new output.

Examine and build an input dataset:

Teachable Machine is a web device that makes it fast and easy to build machine learning models for your projects Train a computer to recognize your loaded images.

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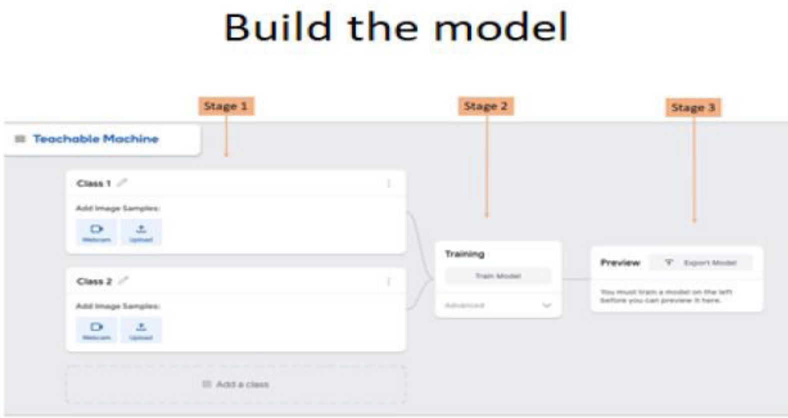

Figure 2: Build the model

Training sample image:

Image dataset of CIFAR- 100 which has 100 classes of images with each class having six hundred images each. These 600 images are divided into five hundred training images and a hundred testing images for each class, therefore, making a total of 60,000 various images. These 100 classes are combined into 20 super classes. Every image in the dataset arrives with a “fine” label (depicting the class to which it belongs) and a “coarse” label (superclass to the “fine” label noticed).

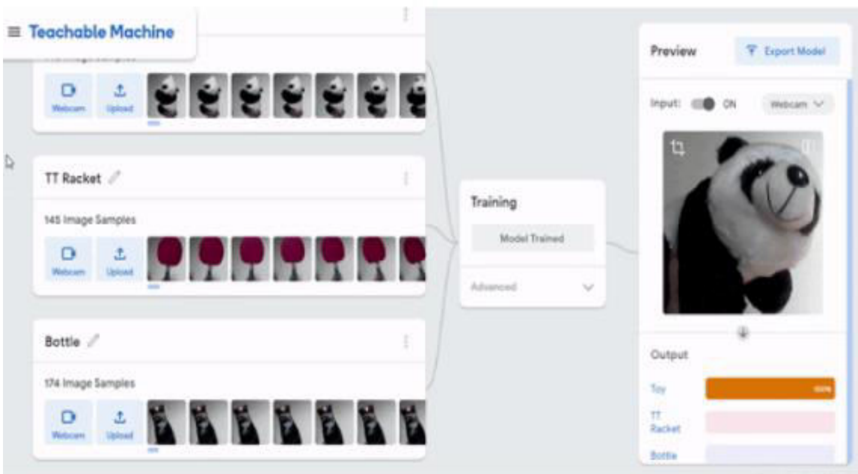

Figure 3: Training datasets with Label.

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Integration architecture for tensor flow lite:

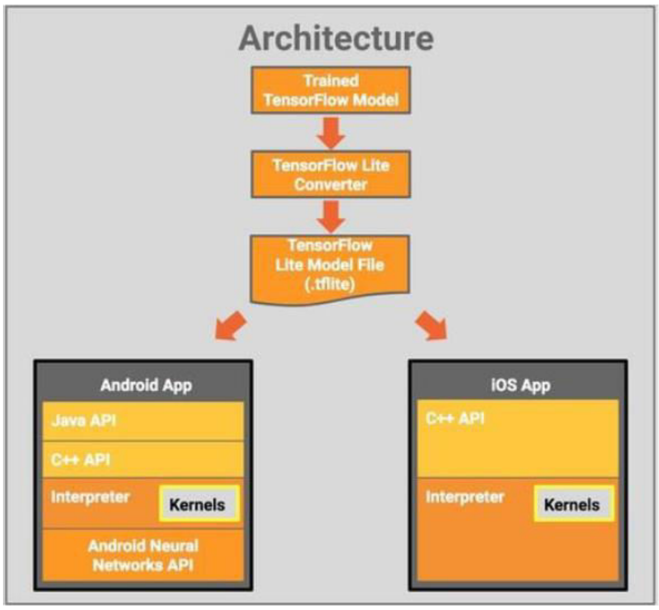

Figure 4: Integration architecture for tensor flow lite

IV. RESULTS

Finally,At the end of the project we have in-depth understanding of CNN and its application for object image classification.

Designed different models for differentiate and performance estimation.
Successfully uploaded the dataset into training and designed a model for forecasting the class of a new test image.
Valuated the performance of model under two dissimilar activation functionsand achieved 92% accuracy and 31% accuracy, undoubtedly stating the impactof activation function on the performance of a model.
Also, designed a model for all 101 classes of the dataset and attained 81% accuracy rate.

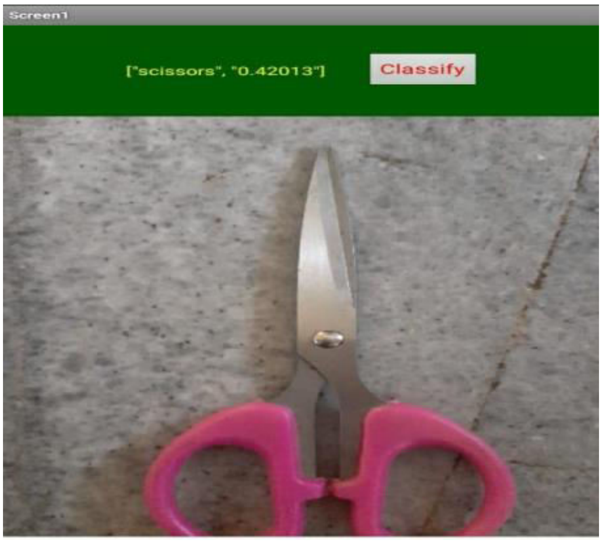

Figure 5: Image classification using convolution neural network

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V. CONCLUSION AND FUTURE WORK

Deep learning is a learning methodology for data analysis and predictions, now-a-days it also becomes a very popular for image classification problems. In this paper, we have a deep learning convolutional neural network based on keras and tensor flow is deployed using python for binary image classification. In this study, we have compared four different structures of CNN on CPU system, with different combinations of classifier and activation function. With the help of the experiments, we obtained results for each combination and observed that for binary image classification, Relu activation function and Sigmoid classifier combination gives better classification accuracy (90.54%) than any other combination of activation function and classifier. So, we finalized that the CPU system, Relu activation function and Sigmoid classifier gives better classification accuracy for binary image classification. , we evaluate the viability of using deep learning models for object detection in real-time video on mobile devices in terms of object detection performance and inference delay as either an end-to-end system or else feature extractor.

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