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Medicine Identification for Blind People by Deep Learning Techniques

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ABSTRACT

Giving blind people with great accessibility to their environment is of great demand. People with visual impairments experience a lot of problem in using the modern assistive device that limits their daily basic activities. The level of assistance provided of these special aids does not meet the consumer requirements and not affordable by the every section of the society. To overcome the some of the limitations of the existing visual aids, in this paper we present the work that helps the visually impaired person with smart glasses to identify the medicine. The name of the medicine can be read by the smart glass system that provides audio signal through the ear phones. The smart glass system reads the medicine name using Convolutional neural network.
Keywords : Convolutional Neural Network, LeNet, Alex Net, Image Processing Techniques and Python.

I. INTRODUCTION

Various statistics shows an increase of visually impaired people are in higher. Worldwide around 285 million people are estimated to be visually impaired as reported by WHO. The development of the assistive technology is not affordable to the all the section of the society and cost effective devices are provided with single or the limited function. This inadequacy of the assistive aids has limited the accommodation of visually impaired in schools and other jobs making their life more dispirited. Wearable devices for helping blind people are found to be the most effective because they require minimum use of hands.

Giving blind people with great accessibility to their environment is of great demand. People with visual impairments experience a lot of problem in using the modern assistive device that limits their daily basic activities

II.RELATED WORK

Real Time Image Processing on Single Board Computer

This paper focus on real time image processing. Industrial image processing is a very important branch of scientific image processing and it is because of the rapid development of computer industry production and computer intelligence, as well as the corresponding developments in computer-aided image analysis . Image edge detection on single board computer is discussed in this paper. The application (GUI) Graphical User Interface was designed using Qt and Linux gcc Integrated Development Environment (IDE) for implementing image processing algorithm using Open Source Computer Vision Library (OpeCV). This developed software integrated in mobiles by the cross compilation of Qt and the OpeCV software for Linux Operating system.

Learning to localize objects with structured output regression

Sliding window classifiers are among the most successful and widely applied techniques for object localization. However, training is typically done in a way that is not specific to the localization task. First a binary classifier is trained using a sample of positive and negative examples, and this classifier is subsequently applied to multiple regions within test images. We propose instead to treat object localization in a principled way by posing it as a problem of predicting structured data: we model the problem not as binary classification, but as the prediction of the bounding box of objects located in images. The use of a joint-kernel framework allows us to formulate the training procedure as a generalization of an SVM, which can be solved efficiently. We further improve computational efficiency by using a branch-and-bound strategy for localization during both training and testing. Experimental evaluation on the PASCAL VOC and TU Darmstadt datasets show that the structured training procedure improves performance over binary training as well as the best previously published scores.

Body part detectors trained using 3D human pose annotations

We address the classic problems of detection, segmentation and pose estimation of people in images with a novel definition of a part, a poselet. We postulate two criteria . It should be easy to find a poselet given an input image it should be easy to localize the 3D configuration of the person conditioned on the detection of a poselet. To permit this we have built a new dataset, H3D, of annotations of humans in 2D photographs with 3D joint information, inferred using anthropometric constraints. This enables us to implement a data-driven search procedure for finding poselets that are tightly clustered in both 3D joint configuration space as well as 2D image appearance. The algorithm discovers poselets that correspond to frontal and profile faces, pedestrians, head and shoulder views, among others.

Automatically Structured Neural Networks for Handwritten Character and Word Recognition

Highly structured neural networks like the Time-Delay Neural Network (TDNN) can achieve very high recognition accuracies in real world applications like on-line handwritten character and speech recognition systems. Achieving the best possible performance greatly depends on the optimization of all structural parameters for the given task and amount of training data. We propose an Automatic Structure Optimization (ASO) algorithm that avoids time-consuming manual optimization and apply it to Multi State Time-Delay Neural Networks (MSTDNNs), a recent extension of the TDNN. We show that MSTDNNs are a very powerful approach to on-line handwritten character and word recognition and that the ASO algorithm can automatically structure this type of architecture efficiently in a single training run.

Multi-column deep neural networks for image classification

Traditional methods of computer vision and machine learning cannot match human performance on tasks such as the recognition of handwritten digits or traffic signs. Our biologically plausible, wide and deep artificial neural network architectures can. Small (often minimal) receptive fields of convolutional winner-take-all neurons yield large network depth, resulting in roughly as many sparsely connected neural layers as found in mammals between retina and visual cortex. Only winner neurons are trained. Several deep neural columns become experts on inputs preprocessed in different ways; their predictions are averaged. Graphics cards allow for fast training. On the very competitive MNIST handwriting benchmark, our method is the first to achieve near-human performance. On a traffic sign recognition benchmark it outperforms humans by a factor of two. We also improve the state-of-the-art on a plethora of common image classification benchmarks.

Development of an augmented reality vehicle for driver performance evaluation

Observing drivers' behaviors by reproducing traffic accidents and conflict situations is important for developing advanced driver assistance systems. For this purpose, driving simulators are frequently used to evaluate the effectiveness of driver assistance systems during product development. However, motion (simulator) sickness can be a serious practical problem with driving simulators. Therefore, an instrumented vehicle, the JARI-ARV (Japan Automobile Research Institute-Augmented Reality Vehicle), was developed to reproduce realistic traffic accident and conflict scenarios without endangering the driver. In this study, we examined level of control in the following cases: a right turn and encounter with a pedestrian by comparing the JARI-ARV with a standard (unaltered) same model vehicle. Results of the experiment indicated that drivers tend to react to virtual traffic participants in the same way as driving a standard vehicle. The study indicates that the JARI-ARV can play a useful role in human factors research.

III.PROPOSED SYSTEM

The objects present in an image or in a video sequence are detected and identified using the Object recognition techniques like Convolutional neural network, LeNet, Alex Net

Advantages:

- In the proposed system Wee have using Deep learning leaning algorithm namely CNN.
- Building CNN was quite simple and Fast
- The algorithm gives Accurate predictions

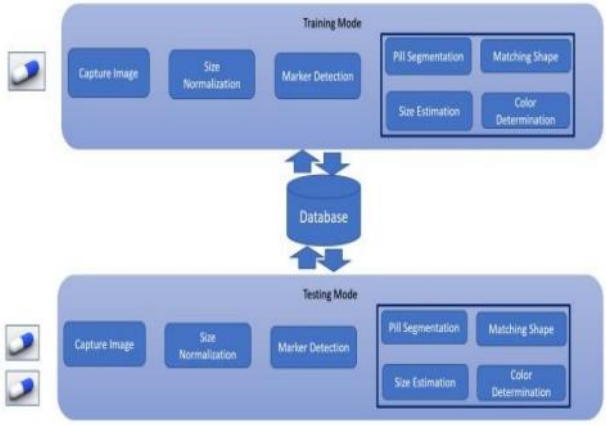

Fig 1: Proposed Workflow

3.1 CNN APPROACH

Convolutional Neural Network (ConvNet or CNN) well known neural network for specially image recognition and classification. CNN is highly excellent in extracting complex features for classifications. CNN consist of neurons where weight and bias can be learned. Each neuron receives some input; weighted sum is taken then given to the activation function. CNN uses successive convolution layer and nonlinear ReLU function to extract valuable feature with specific dimension [7] [8] [11]. Maxpooling layer is used to downsize the feature map. In Fully connected layer, each neuron is connected to every other neuron of previous dense layer. Back- propagation and gradient descent are used while training the network. Softmax function is probability distribution to limit all class output value between 0 and 1. CNN provides feature maps which helps neural network to learn small features of the image depending on the depth of hidden layers. Proposed architecture is as shown in Figure 2.

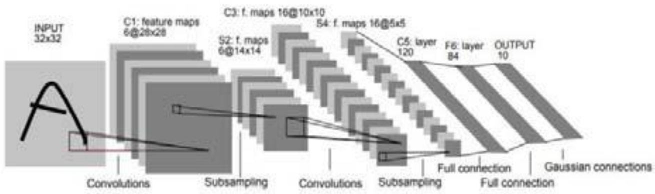

Fig 2: CNN Architecture

IV. RESULTS AND DISCUSSION

```
from PIL import Image
import pandas as pd
import numpy as np
import os
import tensorflow as tf
import keras
import warnings
warnings.filterwarnings("ignore")
```

```
import keras
```

```
def cnn_model(path_loc):
    import tensorflow as tf
    import keras
    from keras.models import Sequential
    from keras.layers import Convolution2D
    from keras.layers import MaxPool2D
    from keras.layers import Flatten
    from keras.layers import Dense

    # Initializing CNN

    classifier = Sequential()

```

Fig 3. Result Screenshot

```
Found 261 images belonging to 2 classes.
Found 261 images belonging to 2 classes.
Epoch 1/15
12/12 [==============================] - 6s 476ms/step - loss: 0.7128 - accuracy: 0.5390 - val_loss: 0.7225 - val_accuracy: 0.5
250
Epoch 2/15
12/12 [==============================] - 3s 254ms/step - loss: 0.7038 - accuracy: 0.4792 - val_loss: 0.6945 - val_accuracy: 0.4
667
Epoch 3/15
12/12 [==============================] - 2s 178ms/step - loss: 0.6911 - accuracy: 0.5106 - val_loss: 0.6897 - val_accuracy: 0.5
083
Epoch 4/15
12/12 [==============================] - 2s 167ms/step - loss: 0.6958 - accuracy: 0.5390 - val_loss: 0.6820 - val_accuracy: 0.5
917
Epoch 5/15
12/12 [==============================] - 2s 181ms/step - loss: 0.6888 - accuracy: 0.6028 - val_loss: 0.6827 - val_accuracy: 0.6
500
Epoch 6/15
12/12 [==============================] - 2s 193ms/step - loss: 0.6835 - accuracy: 0.5957 - val_loss: 0.6738 - val_accuracy: 0.5
750
Epoch 7/15
12/12 [==============================] - 2s 189ms/step - loss: 0.6760 - accuracy: 0.5674 - val_loss: 0.6824 - val_accuracy: 0.5
333
Epoch 8/15
12/12 [==============================] - 2s 175ms/step - loss: 0.6664 - accuracy: 0.5816 - val_loss: 0.6534 - val_accuracy: 0.6
750
Epoch 9/15
12/12 [==============================] - 2s 181ms/step - loss: 0.6484 - accuracy: 0.6250 - val_loss: 0.6722 - val_accuracy: 0.5
```

Fig 4. Result Screenshot

```
import numpy as np
from keras.preprocessing import image
```

```
%matplotlib inline
test_image = image.load_img('F:/NIT/2020-New_projects/Medical_medicins/Cetirizine images/2Q__.jpg', target_size = (128, 128)
test_image.show()
```

```
test_image = image.img_to_array(test_image)
test_image
np.shape(test_image)
```

```
(128, 128, 3)
```

```
test_image = np.expand_dims(test_image, axis = 0)
test_image
np.shape(test_image)
```

```
(1, 128, 128, 3)
```

```
test = training_set.class_indices
```

Fig 5. Result Screenshot

```
test = training_set.class_indices
```

```
result = classifier.predict_classes(test_image)
result
result = result[0]
result
```

```
WARNING:tensorflow:From <ipython-input-14-eac782b4a532>:1: Sequential.predict_classes (from tensorflow.python.keras.engine.sequ
ential) is deprecated and will be removed after 2021-01-01.
Instructions for updating:
Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi-class classification   (e.g. if it uses
a `softmax` last-layer activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does binary classification
(e.g. if it uses a `sigmoid` last-layer activation).

0
```

```
for key, value in test.items():
        if value == result:
            print("The Predected image is", key)
```

```
The Predected image is Cetirizine images
```

Fig 6. Result Screenshot

```
In [15]:
for key, value in test.items():
        if value == result:
            print("The Predected image is", key)

The Predected image is Cetirizine images
```

Fig 7. Result Screenshot

V. CONCLUSION

Recognition of visual objects and the reading the text from an image is an important, yet challenging vision task. However, it is still an open problem due to the complexity and limitation of computational resources. Using the concept of deep learning, a CNN architecture for recognizing the medicine name was studied and analyzed with dataset containing 6290 images. The presented algorithm can be embedded in the Raspberry pi fixed in the smart glass. The camera fixed in the glass captures the image of the medicine and the name is identified and given as audio output to the visually impaired.

VI. FUTURE WORK

Smart Phone can be replaced by any other device if available. Need to use better algorithm so low light image also can recognize. Better algorithm for text recognition so any front style can accept.

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