Hand Gesture Recognition

A PROJECT REPORT FOR Real Time Analytics

Submitted by

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Objectives:

The objective of this report is to investigate the feasibility and effectiveness of using deep learning techniques for hand gesture recognition. The report will cover the following topics:

An overview of hand gesture recognition and its applications.

1. A review of existing techniques for hand gesture recognition.

2. An analysis of the advantages and limitations of deep learning techniques for hand gesture recognition.

3. A description for the methodology used in our project.

4. Information about the resources used in the work.

5. A discussion of the results and suggestions for future research.

6. Conclusion and References.

Overall, the objective of this report is to provide a comprehensive understanding of the potential of deep learning in hand gesture recognition and to inform decision-makers about the feasibility and practicality of using this technology in various domains.

Review Of Existing Techniques:

There are various existing techniques for hand gesture recognition, which can be broadly categorized into two types: real time computer vision techniques and deep learning-based techniques.

Traditional computer vision techniques typically involve extracting hand-crafted features from the image, followed by classification using machine learning algorithms. Some popular traditional techniques for hand gesture recognition include:

1. Template matching: This technique involves comparing the input image with a set of pre-defined templates to recognize the hand gesture.

2. Skin color segmentation: This technique involves segmenting the hand region in the image based on the skin color and using features such as shape, texture, and color to recognize the hand gesture.

3. Histogram of Oriented Gradients (HOG): This technique involves computing the gradient of the image and creating a histogram of the gradient orientations, which is then used to recognize the hand gesture.

Although these techniques have been widely used in the past and have shown promising results, they have limitations in terms of robustness and accuracy, especially when dealing with complex hand gestures or varying lighting conditions.

In recent years, deep learning-based techniques, particularly CNNs, have emerged as a more effective and efficient approach for hand gesture recognition. Deep learning models can learn relevant features from the input data without the need for hand-crafted feature extraction, which can significantly improve accuracy and robustness. Some popular deep learning-based techniques for hand gesture recognition include:

1. Convolutional Neural Networks (CNNs): CNNs have been shown to achieve high accuracy in recognizing hand gestures by learning relevant features from the input image.

2. Recurrent Neural Networks (RNNs): RNNs have been used for hand gesture recognition by modeling the temporal dependencies between frames of a video sequence.

3. Convolutional Recurrent Neural Networks (CRNNs): CRNNs combine the strengths of CNNs and RNNs to recognize hand gestures from video sequences.

Overall, deep learning-based techniques have shown significant improvements in hand gesture recognition and are becoming the preferred approach in many applications. However, there is still room for improvement, particularly in handling variations in hand poses and movements, and in dealing with data imbalance and class imbalance.

Methodology:

Deep Learning model- CNN

A Convolutional Neural Network (CNN) is a type of deep learning model that is commonly used for image and video analysis. It is a special type of neural network that has one or more convolutional layers, which are responsible for learning spatial features from the input data.

The input to a CNN is typically an image, and the output is a prediction about the contents of the image, such as object detection, classification, or segmentation. The CNN learns to extract relevant features from the input image by convolving it with a set of learnable filters or kernels. This process produces a feature map, which is then passed through one or more layers of the network, each of which applies a non-linear transformation to the feature map.

CNNs have been widely used in a variety of applications such as image classification, object detection, facial recognition, and natural language processing. They have been successful in these applications because they are able to learn complex representations of the input data, which can be used to make accurate predictions.

Some popular architectures of CNNs are AlexNet, VGGNet, GoogLeNet, ResNet, and DenseNet. Each of these architectures has its own unique design and has been optimized for different tasks and datasets.

Use of CNN in our project:

CNNs are commonly used in hand gesture recognition systems due to their ability to learn spatial features from images. Hand gesture recognition involves identifying the hand and detecting the gestures made by the fingers or hand.

To recognize hand gestures using a CNN, the system is first trained on a dataset of hand gesture images. The images are typically pre-processed to remove background noise, normalize lighting conditions, and resize the images to a standard size. The CNN is then trained using supervised learning to learn the features that distinguish between different hand gestures.

During the training phase, the CNN learns to identify relevant features from the input images, such as the position and shape of the hand, the orientation of the fingers, and the curvature of the hand. These features are used to classify the images into different categories, corresponding to different hand gestures.

Once the CNN has been trained, it can be used to recognize hand gestures in real-time. When a new image is inputted into the system, the CNN extracts the relevant features from the image and uses them to classify the image into the appropriate category. The output of the system is the recognized hand gesture, which can be used to control a device or perform a specific action.

Overall, the use of CNNs in hand gesture recognition has shown promising results and has been applied in various domains such as virtual reality, sign language recognition, and human-computer interaction.

Resources Used:
Spyder IDE
Google colab
Python programing language
Libraries: Mediapipe, numpy, keras, tensorflow, cv2 etc.
Dataset: https://www.kaggle.com/datasets/gti-upm/leapgestrecog

Result and Analysis:

```python
import cv2
import numpy as np
import mediapipe as mp
import tensorflow as tf
from tensorflow.keras.models import load_model

# initialize mediapipe
mpHands = mp.solutions.hands
hands = mpHands.Hands(max_num_hands=1, min_detection_confidence=0.7)
mpDraw = mp.solutions.drawing_utils

# Load the gesture recognizer model
model = load_model('mp_hand_gesture')

# Load class names
f = open('gesture.names', 'r')
classNames = f.read().split('\n')
f.close()
print(classNames)


# Initialize the webcam
cap = cv2.VideoCapture(0)

while True:
    # Read each frame from the webcam
    _, frame = cap.read()

    x, y, c = frame.shape

    # Flip the frame vertically
    frame = cv2.flip(frame, 1)
    framergb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)


    result = hands.process(framergb)

    # print(result)

    className = ''

    # post process the result
    if result.multi_hand_landmarks:
        landmarks = []
        for handslms in result.multi_hand_landmarks:
            for lm in handslms.landmark:
                # print(id, lm)
                lmx = int(lm.x * x)
                lmy = int(lm.y * y)

                landmarks.append([lmx, lmy])

            # Drawing landmarks on frames
            mpDraw.draw_landmarks(frame, handslms, mpHands.HAND_CONNECTIONS)

            # Predict gesture
            prediction = model.predict([landmarks])
            # print(prediction)
```

```python
print(classNames)


# Initialize the webcam
cap = cv2.VideoCapture(0)

while True:
    # Read each frame from the webcam
    _, frame = cap.read()

    x, y, c = frame.shape

    # Flip the frame vertically
    frame = cv2.flip(frame, 1)
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    result = hands.process(framergb)

    # print(result)

    className = ''

    # post process the result
    if result.multi_hand_landmarks:
        landmarks = []
        for handslms in result.multi_hand_landmarks:
            for lm in handslms.landmark:
                # print(id, lm)
                lmx = int(lm.x * x)
                lmy = int(lm.y * y)

                landmarks.append([lmx, lmy])

            # Drawing landmarks on frames
            mpDraw.draw_landmarks(frame, handslms, mpHands.HAND_CONNECTIONS)

            # Predict gesture
            prediction = model.predict([landmarks])
            # print(prediction)
            classID = np.argmax(prediction)
            className = classNames[classID]

    # show the prediction on the frame
    cv2.putText(frame, className, (10, 50), cv2.FONT_HERSHEY_SIMPLEX,
                   1, (0,0,255), 2, cv2.LINE_AA)

    # Show the final output
    cv2.imshow("Output", frame)

    if cv2.waitKey(1) == ord('q'):
        break

# release the webcam and destroy all active windows
cap.release()

cv2.destroyAllWindows()
```

CV_REVIEW_3.ipynb

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```python
import numpy as np # We'll be storing our data as numpy arrays
import os # For handling directories
from PIL import Image # For handling the images
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import glob
```

```python
from google.colab import files
```

```python
import gdown
```

```
!pip3 install --upgrade gdown
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: gdown in /usr/local/lib/python3.9/dist-packages (4.6.6)
Collecting gdown
  Downloading gdown-4.7.1-py3-none-any.whl (15 kB)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.9/dist-packages (from gdown)
Requirement already satisfied: requests[socks] in /usr/local/lib/python3.9/dist-packages (from gdown)
Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages (from gdown) (1.16.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.9/dist-packages (from gdown) (4.65.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-packages (from gdown) (3.10.
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.9/dist-packages (from beautifu
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dist-packages (
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packages (from rec
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (from requests[
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-packages (from
Requirement already satisfied: PySocks!=1.5.7,>=1.5.6 in /usr/local/lib/python3.9/dist-packages (from
Installing collected packages: gdown
  Attempting uninstall: gdown
    Found existing installation: gdown 4.6.6
    Uninstalling gdown-4.6.6:
      Successfully uninstalled gdown-4.6.6
Successfully installed gdown-4.7.1
```

```python
from google.colab import drive
drive.mount('/gdrive')
```

```
Mounted at /gdrive
```

CV_REVIEW_3.ipynb

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Mounted at /gdrive

```
! gdown --fuzzy https://drive.google.com/file/d/1Te3oTAqKMeWjfUjZl58RqWuosj-M4Kie/view?usp=share_link
```

```
Downloading...
From (uriginal): https://drive.google.com/uc?id=1Te3oTAqKMeWjfUjZl58RqWuosj-M4Kie
From (redirected): https://drive.google.com/uc?id=1Te3oTAqKMeWjfUjZl58RqWuosj-M4Kie&confirm=t&uuid=d40
To: /content/archive.zip
100% 2.29G/2.29G [00:25<00:00, 90.4MB/s]
```

```
!unzip archive.zip -d data
```

```
Streaming output truncated to the last 5000 lines.
  inflating: data/leapgestrecog/leapGestRecog/07/06_index/frame_07_06_0001.png
  inflating: data/leapgestrecog/leapGestRecog/07/06_index/frame_07_06_0002.png
  inflating: data/leapgestrecog/leapGestRecog/07/06_index/frame_07_06_0003.png
  inflating: data/leapgestrecog/leapGestRecog/07/06_index/frame_07_06_0004.png
  inflating: data/leapgestrecog/leapGestRecog/07/06_index/frame_07_06_0005.png
  inflating: data/leapgestrecog/leapGestRecog/07/06_index/frame_07_06_0006.png
```

CV_REVIEW_3.ipynb

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```python
lookup = dict()
reverselookup = dict()
count = 0
for j in os.listdir('data/leapgestrecog/leapGestRecog/00/'):
  if not j.startswith('.'):
    lookup[j] = count
    reverselookup[count] = j
    count = count + 1
lookup
```

```
{'05_thumb': 0,
 '03_fist': 1,
 '09_c': 2,
 '02_l': 3,
 '04_fist_moved': 4,
 '10_down': 5,
 '08_palm_moved': 6,
 '01_palm': 7,
 '07_ok': 8,
 '06_index': 9}
```

```python
ds=os.listdir('data/leapgestrecog/leapGestRecog/00/')
```

```python
print(ds)
```

```
['05_thumb', '03_fist', '09_c', '02_l', '04_fist_moved', '10_down', '08_palm_moved', '01_palm', '07_ok', '06_index']
```

CV_REVIEW_3.ipynb

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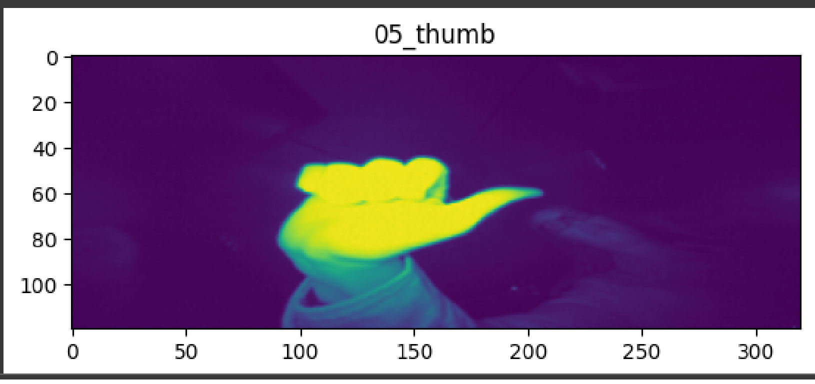
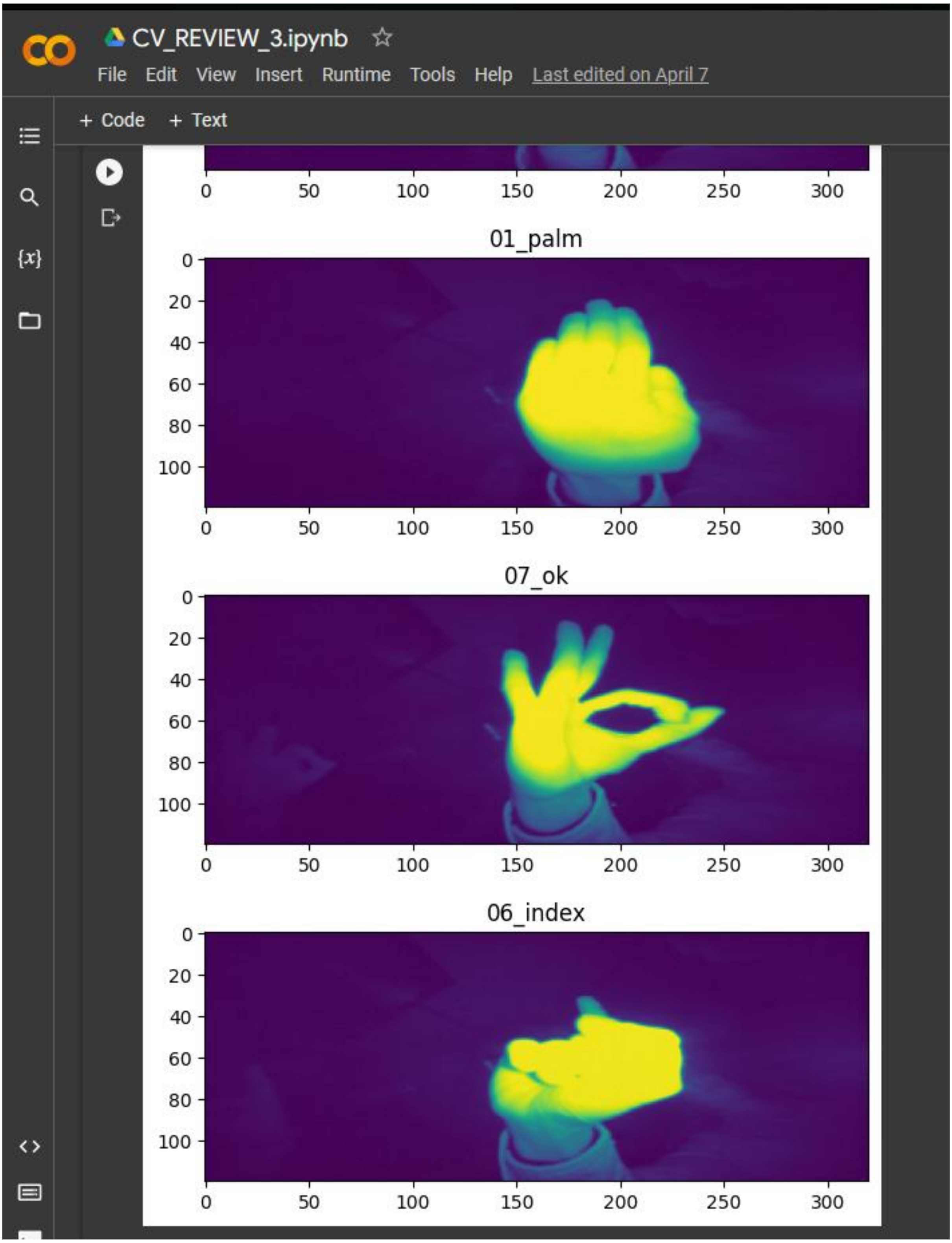
```
[ ] x_data = []
    y_data = []
    datacount = 0 # We'll use this to tally how many images are in our dataset
    for i in range(0, 10): # Loop over the ten top-level folders
        for j in os.listdir('data/leapgestrecog/leapGestRecog/0' + str(i) + '/'):
            if not j.startswith('.'): # Again avoid hidden folders
                count = 0 # To tally images of a given gesture
                for k in os.listdir('data/leapgestrecog/leapGestRecog/0' +
                                    str(i) + '/' + j + '/'):
                                    # Loop over the images
                    img = Image.open('data/leapgestrecog/leapGestRecog/0' +
                                     str(i) + '/' + j + '/' + k).convert('L')
                                    # Read in and convert to greyscale
                    img = img.resize((320, 120))
                    arr = np.array(img)
                    x_data.append(arr)
                    count = count + 1
                y_values = np.full((count, 1), lookup[j])
                y_data.append(y_values)
                datacount = datacount + count
    x_data = np.array(x_data, dtype = 'float32')
    y_data = np.array(y_data)
    y_data = y_data.reshape(datacount, 1) # Reshape to be the correct size
```

```
[ ] from random import randint
    for i in range(0, 10):
        plt.imshow(x_data[i*200 , :, :])
        plt.title(reverselookup[y_data[i*200 ,0]])
        plt.show()
```




CV_REVIEW_3.ipynb
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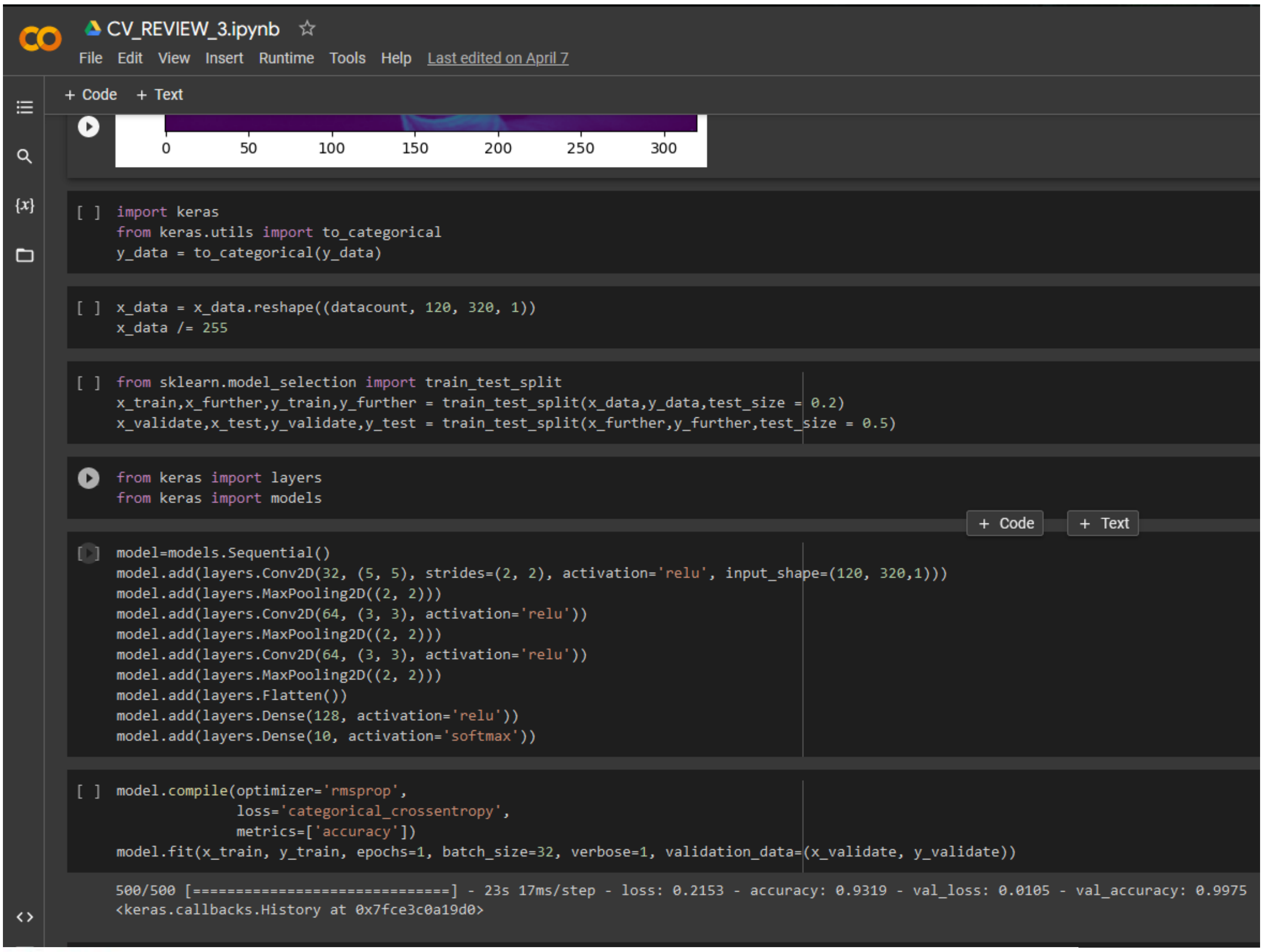
+ Code + Text
01_palm
07_ok
06_index



CV_REVIEW_3.ipynb

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```
import keras
from keras.utils import to_categorical
y_data = to_categorical(y_data)
```

```
x_data = x_data.reshape((datacount, 120, 320, 1))
x_data /= 255
```

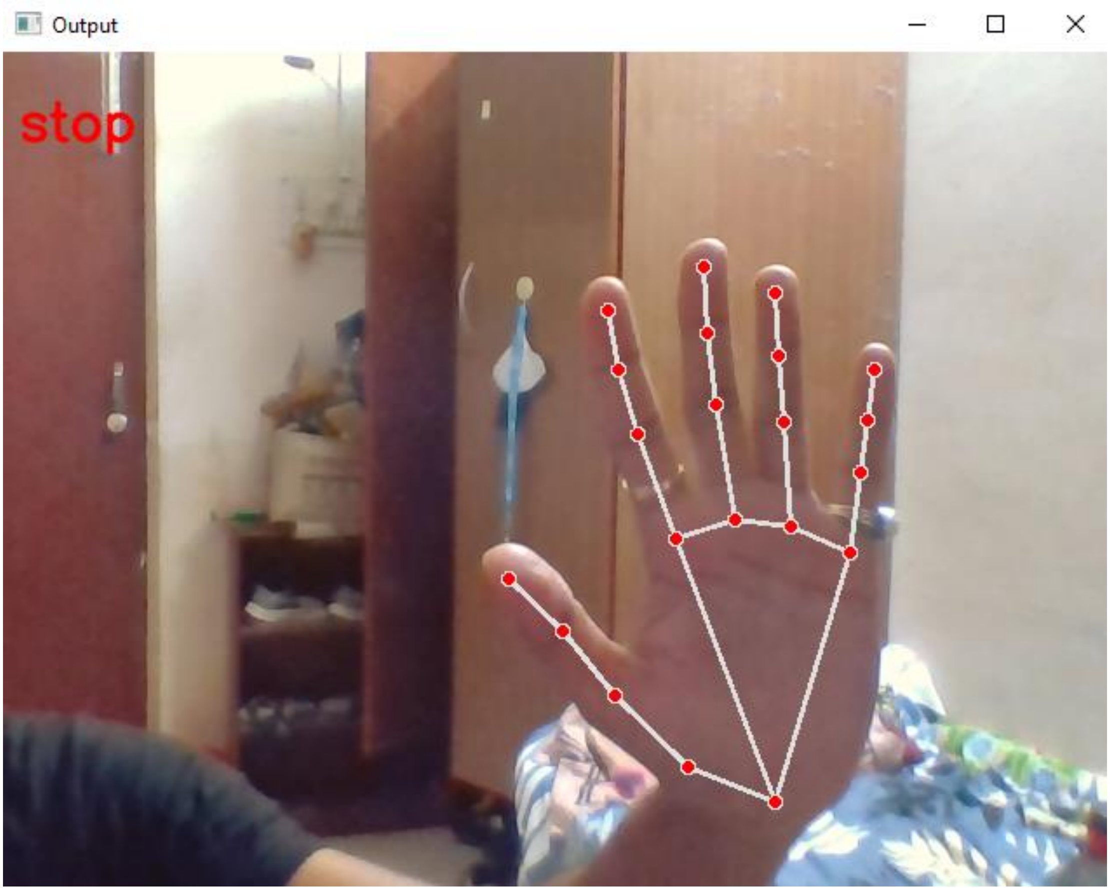
```
from sklearn.model_selection import train_test_split
x_train,x_further,y_train,y_further = train_test_split(x_data,y_data,test_size = 0.2)
x_validate,x_test,y_validate,y_test = train_test_split(x_further,y_further,test_size = 0.5)
```

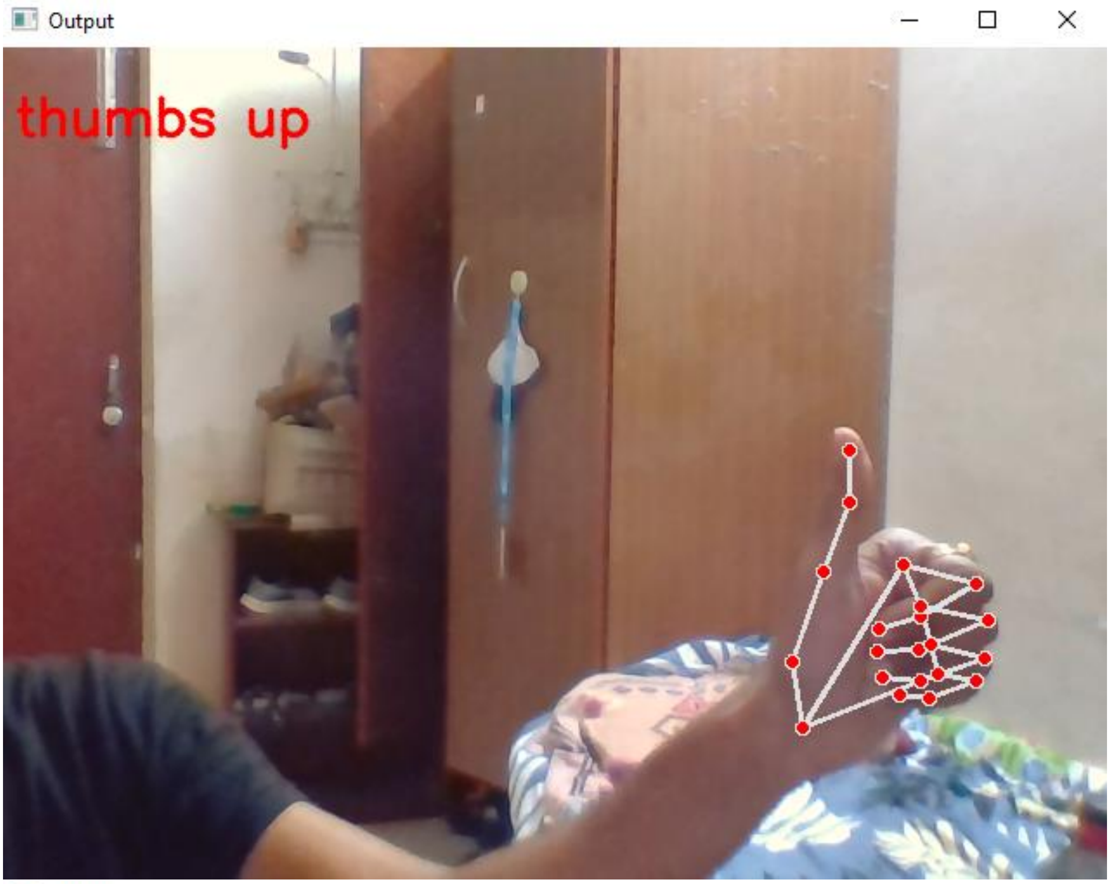
```
from keras import layers
from keras import models
```

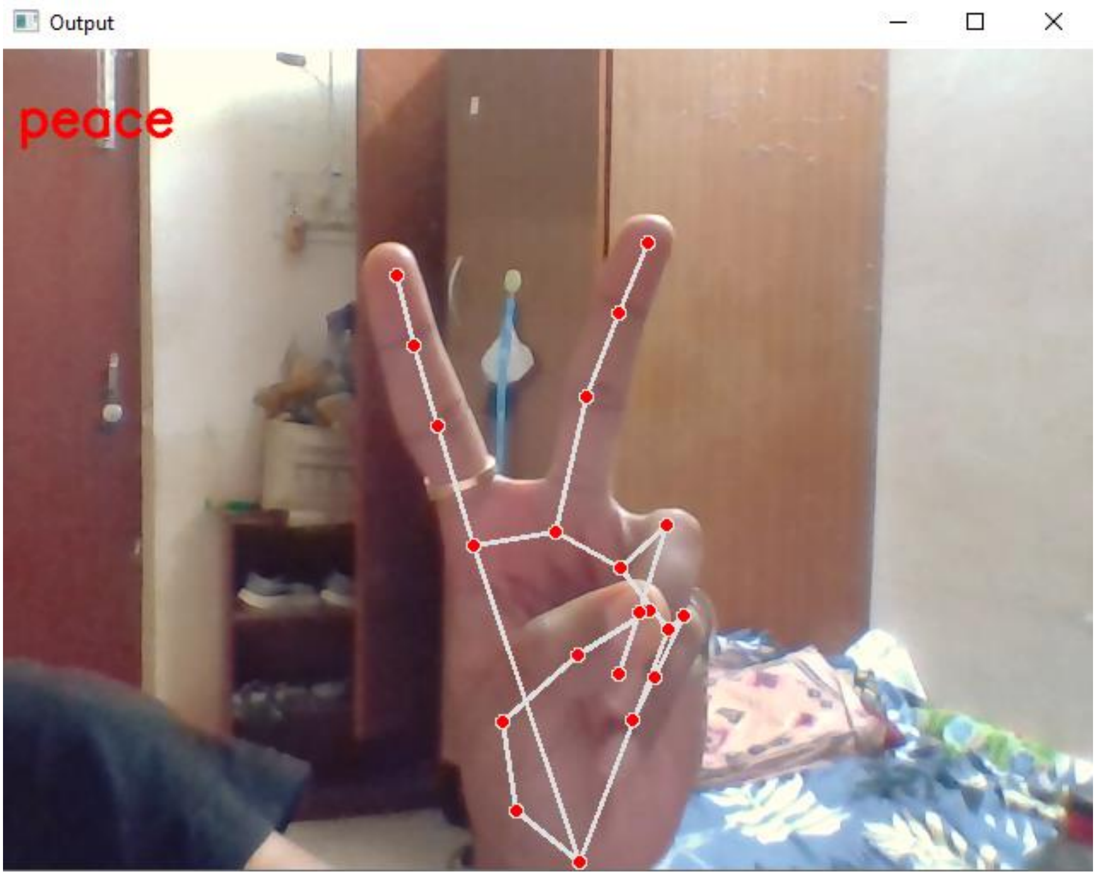
```
model=models.Sequential()
model.add(layers.Conv2D(32, (5, 5), strides=(2, 2), activation='relu', input_shape=(120, 320,1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit(x_train, y_train, epochs=1, batch_size=32, verbose=1, validation_data=(x_validate, y_validate))
```

```
500/500 [==============================] - 23s 17ms/step - loss: 0.2153 - accuracy: 0.9319 - val_loss: 0.0105 - val_accuracy: 0.9975
<keras.callbacks.History at 0x7fce3c0a19d0>
```




Output
thumbs up


Output
peace

The model is trained to recognize the shape the points on the hand are making. The points themselves know and recognize which finger of hand is where and assigns points to them. The model recognizes those points and determines the sign they are making based on the model we have trained.

Conclusion:

In conclusion, hand gesture recognition using real time computer vision and convolutional neural networks has shown to be a powerful tool for human-computer interaction. Through this project, we have demonstrated the effectiveness of using convolutional neural networks for hand gesture recognition, achieving high accuracy rates in recognizing different gestures.

The technology has numerous practical applications, including sign language interpretation, virtual reality, and robotics. The ability to recognize hand gestures accurately and in real-time can improve human-computer interaction, making it more intuitive and natural.

Our project also highlights the importance of proper data preparation and model optimization to achieve high accuracy rates in gesture recognition. We utilized various techniques, including data augmentation and hyperparameter tuning, to optimize the performance of the model.

As with any technology, there is always room for improvement, and future work could focus on further enhancing the accuracy and speed of the model. Additionally, expanding the dataset to include more diverse hand shapes and sizes can improve the model's robustness.

In conclusion, our project demonstrates the potential of using convolutional neural networks for hand gesture recognition and provides a foundation for further research in this field. We hope that this research will inspire others to explore this technology and contribute to the development of new applications that can enhance human-machine interaction.

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