COMMUNICATION THROUGH GESTURES

1.1 Introduction

Artificial Intelligence (AI) is the intelligence of machines and the branch of computer science which aims to create it. Artificial Intelligence (AI) is the study of how computer systems can simulate intelligent processes such as learning, reasoning, and understanding symbolic information in context. The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision making and translation between languages.

1.2 Objectives of Research

- Problem Solving
- Machine learning
- Language processing
- Motion and perception
- Social intelligence
- Creativity

1.3 Problem Statement

Touchless hand gesture recognition systems are becoming important in automotive user interfaces as they improve safety and comfort. Various computer vision algorithms have employed color and depth cameras for hand gesture recognition, but robust classification of gestures from different subjects performed under widely varying lighting conditions is still challenging. We propose an algorithm for hand gesture recognition from challenging depth and intensity data using Convolutional Neural Networks.

2. Literature Review

The essential aim of building hand gesture recognition systems is to create a natural interaction between humans and a computer where the recognized gestures can be used for controlling a robot or conveying meaningful information. Human computer interaction (HCI) also named Man-Machine Interaction (MMI) refers to the relation between the human and the computer, or more precisely the machine. There are two main characteristics should be deemed when designing a HCI system: functionality and usability. System functionality refers to the set of functions or services that the system equips to the users, while system usability refers to the level and scope that the system can operate and perform specific user purposes efficiently. The system that attains a suitable balance between these concepts considered as influential performance and powerful system. Gestures can be **static** (posture or certain pose), which requires less computational complexity, or dynamic (sequence of postures), which are more complex but suitable for real time environments. Different methods have been proposed for acquiring information necessary for recognition gestures system. Some methods use additional hardware devices such as data glove devices and color markers to easily extract comprehensive description of gesture features. Other methods are based on the use of the appearance of the hand and the skin color to segment the hand and extract necessary features. Some recent reviews explained gesture recognition system applications and its growing importance in our life especially for Human-Computer Interaction (HCI), Robot control, games, and **surveillance**, using different tools and algorithms. This work demonstrates the advancement of gesture recognition systems, with the discussion of different stages required to build a complete system with fewer errors using a different algorithm.

3. Data Collection

The Data collection process turned out to be the most important step, since finding the right dataset is crucial to the performance and accuracy of the CNN model. After various datasets were tried and tested with, one dataset found on Github.com. This dataset worked out to train the model in the right way to produce the desired results and a good accuracy rate.

4. Methodology

4.1 Exploratory Data Analysis

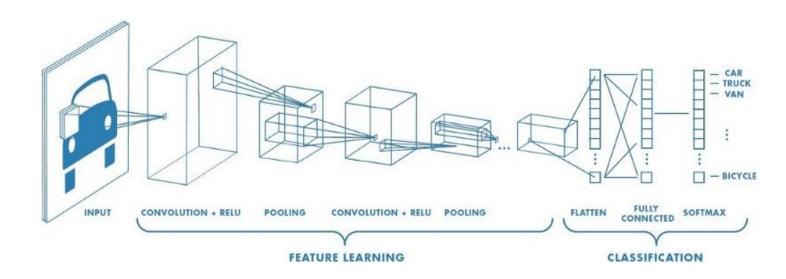
4.1.1 Figures and sample images

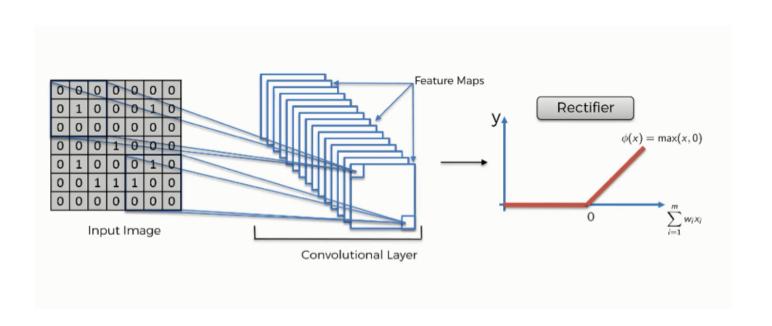




4.2 Data Modelling

Overview of the Convolutional Neural Network Model





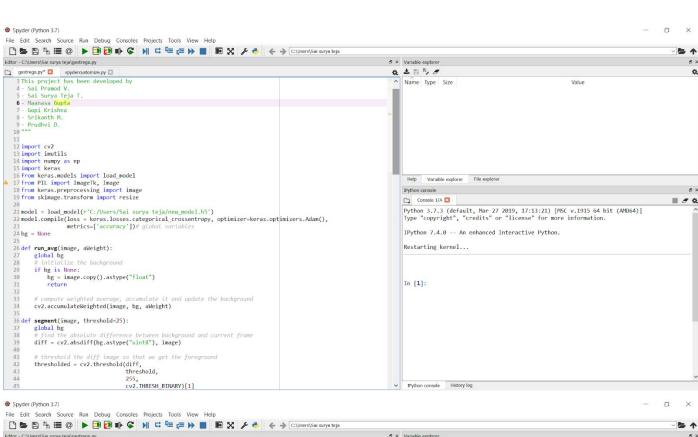
Working CNN Code

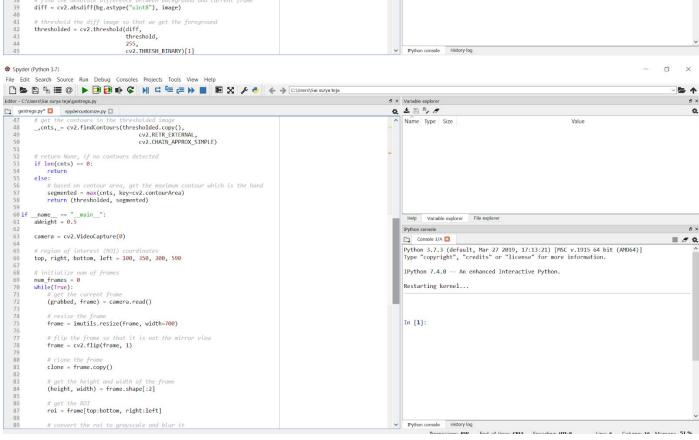
```
In [1]: #Importing the libraries.
                  import numpy as np
                  import pandas as pd
In [2]: import keras
                  from keras.models import Sequential
                  from keras.layers import Dense
                  from keras.layers import Conv2D
                  from keras.layers import MaxPooling2D
                 from keras.layers import Flatten
import tensorflow as tf
                 Using TensorFlow backend.
In [3]: #Initializing the model.
                  model=Sequential()
In [4]: model.add(Conv2D(128,3,3,input_shape=(128,128,3),activation='relu'))
                  #128-no.of feature extraction, for better extraction
                  WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-packages\tensorflow\python\framework\op_def_library.py:263: colocate_
                  with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.
                  Instructions for updating:
                 Colocations handled automatically by placer.
                 C: \PogramData\ Anaconda \ 'ib\ site-packages' ipykernel\_launcher.py: 3: \ User \ Warning: \ Update \ your \ `Conv2D` \ call \ to \ the \ Keras \ 2 \ API: 
                  Conv2D(128, (3, 3), input_shape=(128, 128,..., activation="relu")
                    Conv2D(128, (3, 3), input_shape=(128, 128,..., activation="relu")`
This is separate from the ipykernel package so we can avoid doing imports until
In [5]: #Adding maxpooling layer here.
                   model.add(MaxPooling2D(pool_size=(2,2)))
In [6]: #Adding a Flatten layer to the cnn which converts many dimensions many dimensions into 1-Dimensional.
                   model.add(Flatten())
In [7]: #Hidden Layer of ANN.
                   model.add(Dense(output_dim=128,activation='relu',init='random_uniform'))
                   C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarning: Update your `Dense` call to the Keras 2 API: `
                  Dense(activation="relu", units=128, kernel_initializer="random_uniform")

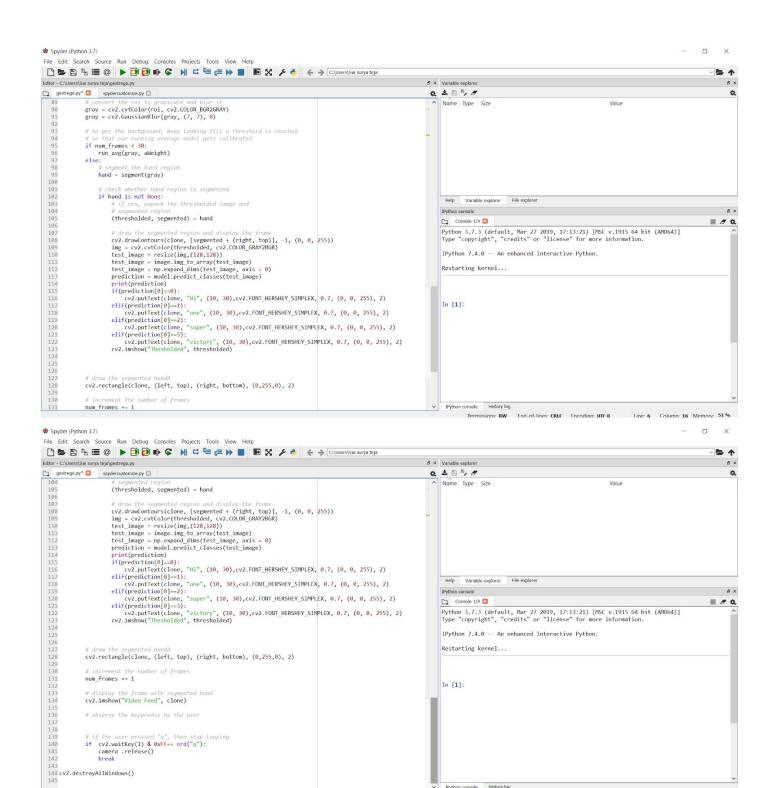
This is separate from the ipykernel package so we can avoid doing imports until
In [8]: #Output Layer of ANN.
                   # As the data is categorical, we use 'softmax' as the activation function.
                   model.add(Dense(output_dim=4,activation='softmax',init='random_uniform'))
                  C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarning: Update your `Dense` call to the Keras 2 API: `Dense(activation="softmax", units=4, kernel_initializer="random_uniform")`
This is separate from the ipykernel package so we can avoid doing imports until
In [9]: #We use 'categorical_crossentropy' as loss.
```

```
In [10]: #Importing libraries.
       from keras.preprocessing.image import ImageDataGenerator
In [11]: #Steps for rescaling the images into the range of 0 to 1.
        train_datagen = ImageDataGenerator(rescale=1./255,shear_range=0.2,zoom_range=0.2,horizontal_flip=True)
       test_datagen = ImageDataGenerator(rescale=1./255)
In [12]: #Splitting the data into x_train and x_test variables for further training and testing of the data.
       x train=train datagen.flow from directory("C:/Users/Sai surva teja/Desktop/last/train set",target size=(128,128),batch size=10,c
       x_test=test_datagen.flow_from_directory("C:/Users/Sai surya teja/Desktop/last/test_set",target_size=(128,128),batch_size=10,clast
        Found 3100 images belonging to 4 classes.
       Found 900 images belonging to 4 classes.
In [13]: #classes in the dataset.
       print(x train.class indices)
       {'hello': 0, 'one': 1, 'three': 2, 'victory': 3}
In [14]: #Training the model.
       model.fit generator(x train, samples per epoch = 3100, epochs = 10, validation data = x test, nb val samples = 900)
       model.fit_generator(x_train, samples_per_epoch = 3100, epochs = 10, validation_data = x_test, nb_val_samples = 900)
       WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from tenso
       rflow.python.ops.math_ops) is deprecated and will be removed in a future version.
       Instructions for updating:
       Use tf.cast instead.
       C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: UserWarning: The semantics of the Keras 2 argument `steps_p
       er_epoch' is not the same as the Keras 1 argument `samples_per_epoch'. `steps_per_epoch` is the number of batches to draw from the generator at each epoch. Basically steps_per_epoch = samples_per_epoch/batch_size. Similarly `nb_val_samples`->`validation_
       steps` and `val_samples`->`steps` arguments have changed. Update your method calls accordingly.
"""Entry point for launching an IPython kernel.
       C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: UserWarning: Update your `fit_generator` call to the Keras
       2 API: `fit_generator(<keras_pre..., epochs=10, validation_data=<keras_pre..., steps_per_epoch=310, validation_steps=900)
         """Entry point for launching an IPython kernel.
       Epoch 1/10
       310/310 [===
                  Fpoch 2/10
       310/310 [==:
                        Epoch 3/10
       310/310 [====
                        =========] - 469s 2s/step - loss: 0.0442 - acc: 0.9868 - val_loss: 0.5288 - val_acc: 0.8600
       Epoch 4/10
                         =========] - 749s 2s/step - loss: 0.0361 - acc: 0.9874 - val loss: 0.5622 - val acc: 0.8700
       310/310 [==
       Epoch 5/10
       310/310 [==:
                         Epoch 6/10
       310/310 [==
                         =========] - 1297s 4s/step - loss: 0.0171 - acc: 0.9952 - val_loss: 0.6673 - val_acc: 0.8489
       Epoch 7/10
       310/310 [==:
                        =========1 - 579s 2s/step - loss: 0.0128 - acc: 0.9961 - val loss: 0.3202 - val acc: 0.9178
       Epoch 8/10
       310/310 [====
                      Entry point for launching an IPython kernel.
       C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: UserWarning: Update your `fit_generator` call to the Keras
       2 API: 'fit_generator(<keras_pre..., epochs-le, """Entry point for launching an IPython kernel.
             fit_generator(<keras_pre..., epochs=10, validation_data=<keras_pre..., steps_per_epoch=310, validation_steps=900)
       Epoch 1/10
       Epoch 2/10
       310/310 [===
                 Epoch 3/10
       310/310 [===
                         ==========] - 469s 2s/step - loss: 0.0442 - acc: 0.9868 - val_loss: 0.5288 - val_acc: 0.8600
       Epoch 4/10
       310/310 [===
                         ==========] - 749s 2s/step - loss: 0.0361 - acc: 0.9874 - val_loss: 0.5622 - val_acc: 0.8700
       Epoch 5/10
       310/310 [==
                           =========] - 738s 2s/step - loss: 0.0345 - acc: 0.9871 - val_loss: 0.3871 - val_acc: 0.8789
       Epoch 6/10
                        310/310 [===
       Epoch 7/10
       310/310 [===
                     Epoch 8/10
       Epoch 9/10
       Epoch 10/10
       Out[14]: <keras.callbacks.History at 0x21b5aaa0748>
In [16]: #Saving the model.
      model.save('new model.h5')
```

model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])







History log Fnd-of-lines CRLF Fncoding: UTI-8 line: 6 Column: 16 Memory: 51%

5. Findings and Suggestions

The following sources have been used for reference and guidance throughout this project.

- Kaggle.com
- Github.com
- towardsdatascience.com

This project can be further enhanced and upgraded to create a real-time gesture recognition software that interacts with humans and acts in response to the gestures recognized by the algorithm. This algorithm can then be embedded into an interactive robot that assists human beings in day-to-day activities.

This algorithm can also be updated to play the audio of the intended gesture, thus rendering it very helpful in assisting people with speech and hearing disabilities.

6. Conclusion

CNNs showcase the incredible levels of control over performance that can be achieved by making effective use of theoretical and mathematical insights. Many real world problems are being efficiently tackled using CNNs, and MNIST represents a simple, "Hello World"-type use-case of this technique. More complex problems such as object and image recognition require the use of Deep Neural Networks with millions of parameters to obtain state-of-the-art results.

Furthermore, applications are not limited to computer vision. The win of Google's AlphaGo Project over Lee Sedol in the Go game series in 2017 relied on a CNN at its core. The self-driving cars which, in the coming years, will arguably become a regular sight on our streets, rely on CNNs for steering. Google even held an art-show for imagery created by its DeepDream project that showcased beautiful works of art created by visualizing the transformations of the network!

Thus a Machine Learning researcher or engineer in today's world can rejoice at the technological melange of techniques at her disposal, among which an in-depth understanding of CNNs is both indispensable and empowering.