KULLIYYAH OF INFORMATION AND COMMUNICATION TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE

FYP PRELIMINARY REPORT

SIGN LANGUAGE RECOGNITION USING DEEP LEARNING

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SUPERVISED BY

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DECLARATION

I hear by declare that this report is the result of my own investigations, except where otherwise stated. I also clear that it has not been previously or currently submitted as a whole for any other degree at IIUM or other institutions.

MHD KHALED MAEN (1523591)

Signature: .... Date: ....

APPROVAL PAGE

I certified that I have supervise can read this study and that in my opinion, confirms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as final year project paper a partial fulfilment for a degree of bachelor of Computer Science (Honours).

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ABSTRACT

Communication is an essential part of our life. Unfortunately, some of us were born in various types of disability such as deaf, since hearing impaired people can't listen they can't learn to speak so they developed a new communication why to interact with other people by using distinct hand gestures, which wasn't enough to overcome this issue, even now with all technologies and tool still challenging problem to solve. For the mentioned reason, the intention of the proposed research is to improve an ordinary model to translate the hand gestures of the sign language into voice. In that, Deep learning is remarkably serviceable for this mission, firstly by identifying the hand in the video frame by using Convolutional neural network algorithm then states the sound that matches the sign.The accuracy achieved for detect hand gesture using initial CNN model 92 % for MNIST dataset and 82% for regular dataset.

ACKNOWLEDGEMENT

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Chapter 1

Introduction

1.1 Background

Communication is a process of sending and receiving data among individuals. People communicate with o with a considerable measure of ways yet the best way is eye to eye correspondence. Numerous individuals trust that the significance of communication is like the importance of breathing. Indeed, communication facilitates the spread of knowledge and structures connections between individuals.

Deep learning added an immense lift to the already rapidly developing field of computer vision. With deep learning, a lot of new utilization of computer vision techniques have been presented and they are currently ending up some portion of our regular day to day existence.

Alongside with the intensity of the present computers, there are now various algorithms that were developed to empower the computers to perform tasks such as object tracking and pattern recognition.

In this study, the attention will be on hand gestures detection and make an interpretation of them into voice.

1.2 Problem Statement

Communication difficulties arising from damage to hearing directly have an effect on the standard of life. Difficulties in communication could end in deviations within the emotional and social development which will have a major impact on the standard of lifetime of every one. It is well recognized that hearing is crucial to speech and language development, communication, and learning. Folks with listening difficulties due to hearing loss or auditory processing problems continue to be an under-identified and under-served population. The earlier the matter is known and intervention began, the less serious the ultimate impact (Frajtag1 & Jelinic2, 2017).

The communication between hearing-impaired and other individuals is a colossal gab need to be filled up. In order to overcome this challenge many researches and products have been developed to solve this problem, but there is a lot to be enhanced.

1.3 Objectives

- To study sign language gestures.
- To develop a new hand gesture into voice algorithm.
- To construct a hand gesture into voice model.

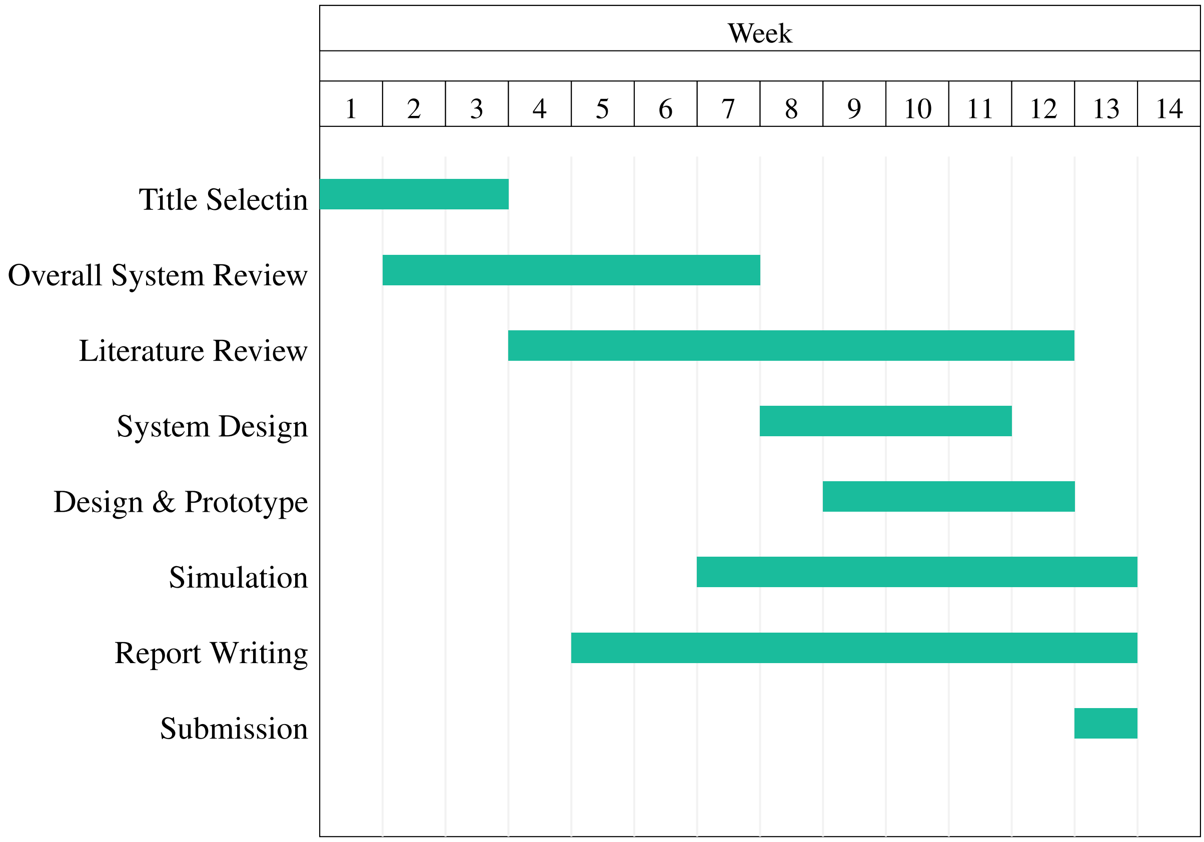
1.4 Scope

This research aims to develop a sign language recognition algorithm, and converting it into voice.

1.5 Significance

Help the hearing-impaired community to communicate with hearing ones, in order to make a strong connected community.

1.6 Timeline



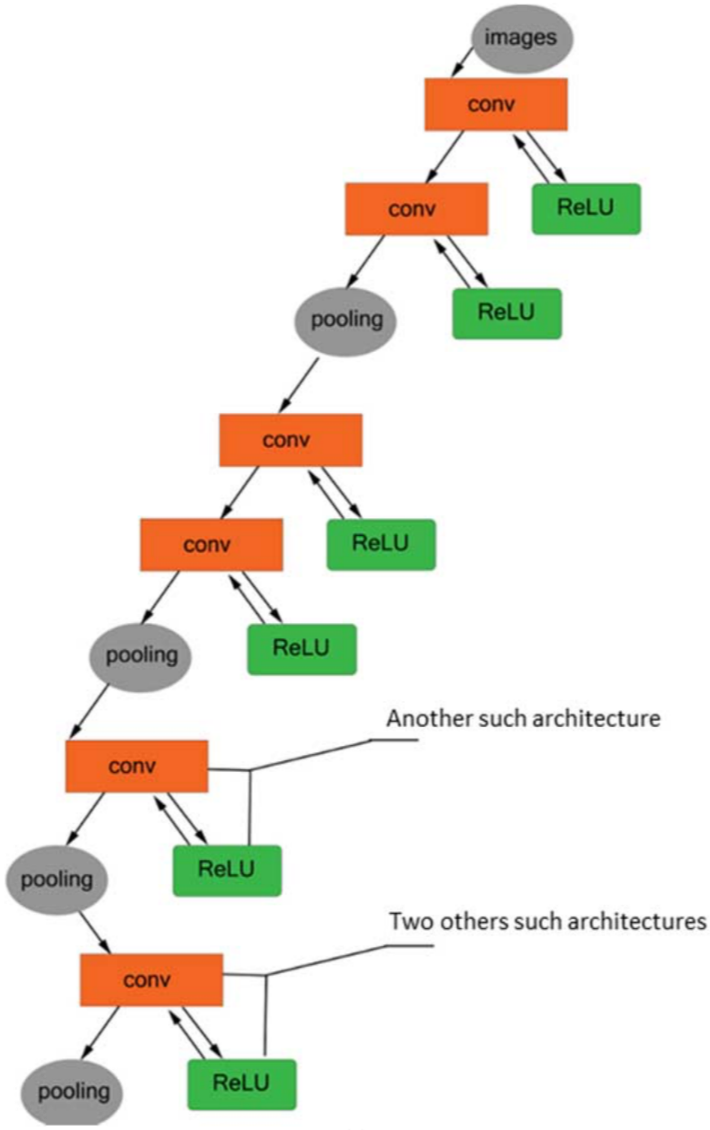
Chapter 2

Literature review

This chapter includes reviews of other previous researcher and their proposed methods they used in implementing deep learning to recognize hand gestures. These researches will help to grasp the knowledge to achieve the project's objectives.

2.1 Previous works

(Bao, Maqueda, del Blanco, & García, 2017), proposed a Deep convolutional neural network algorithm for hand-gesture recognition without hand localisation, since the hands only occupy about 10% of the image. They used a combination of 9 convolution layers, 3 fully connected layers, interlaced with ReLU(Rectified Linear Unit) and dropout layers as shown in figure 2.1. Alongside this architecture the apply some image processing techniques to have sufficient computation efficiency and memory requirement. According to the paper the accuracy achieved was 97.1% in the images with simple backgrounds and 85.3% in the images with complex backgrounds.However, the main disadvantage of of the proposed algorithm is the training set which only includes 7 different gestures, and it tends to have bad accuracy with complex backgrounds.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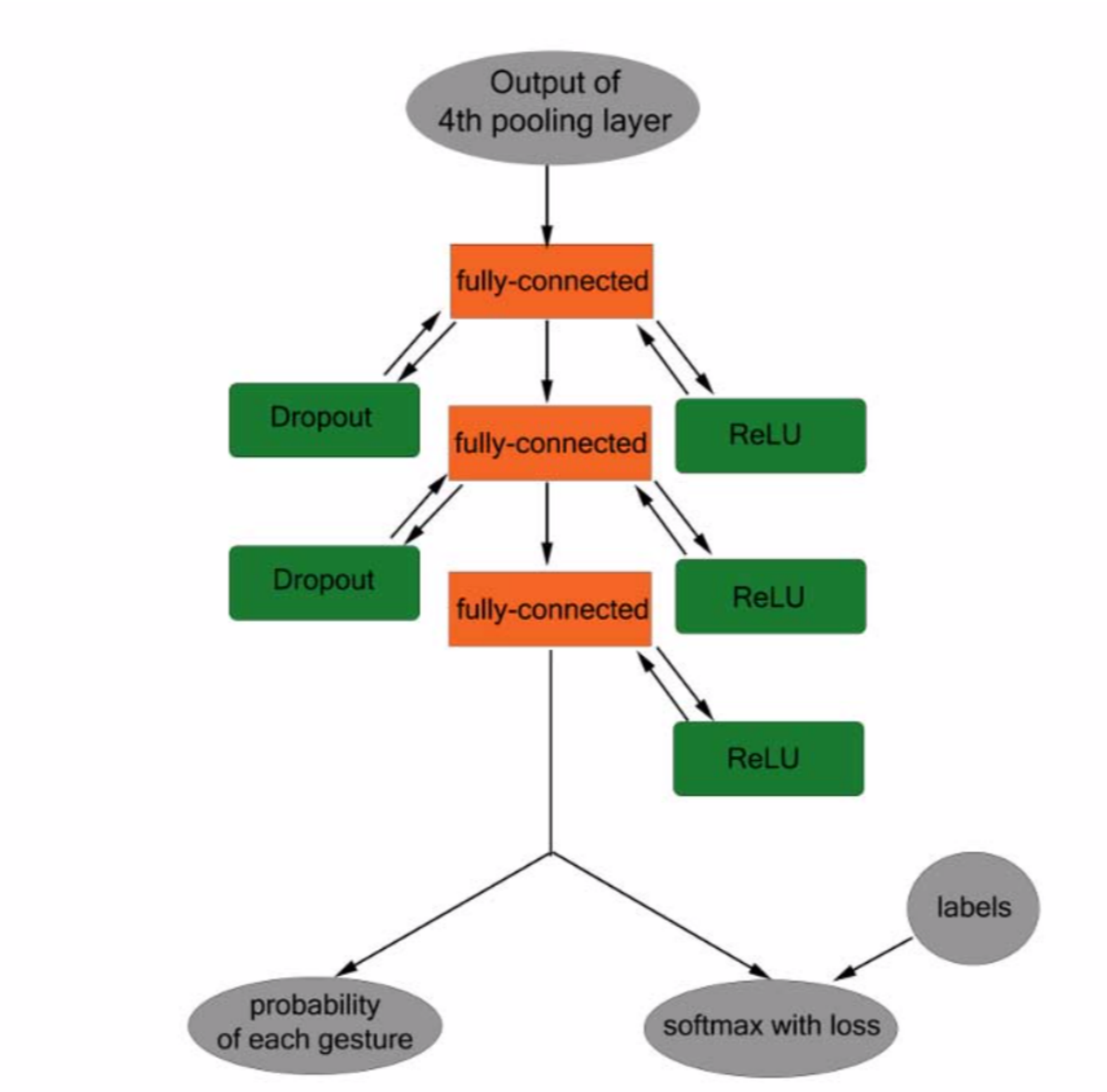
(a)



(b)

Figure 2.1: Architecture of the proposed deep CNN

(Rao, Syamala, Kishore, & Sastry, 2018), proposed a CNN architecture for classifying selfie sign language gestures. The CNN architecture is designed with four convolutional layers. Each convolutional layer with different filtering window sizes as shown in figure 2.2 They had a dataset with five different subjects performing 200 signs in 5 different viewing angles under various background environments. Each sign occupied for 60 frames or images in a video. The proposed model performed training on 3 batches to test the robustness of different training mode using caffe deep learning framework. However, the result accuracy was 92.88% need more training and improvements.

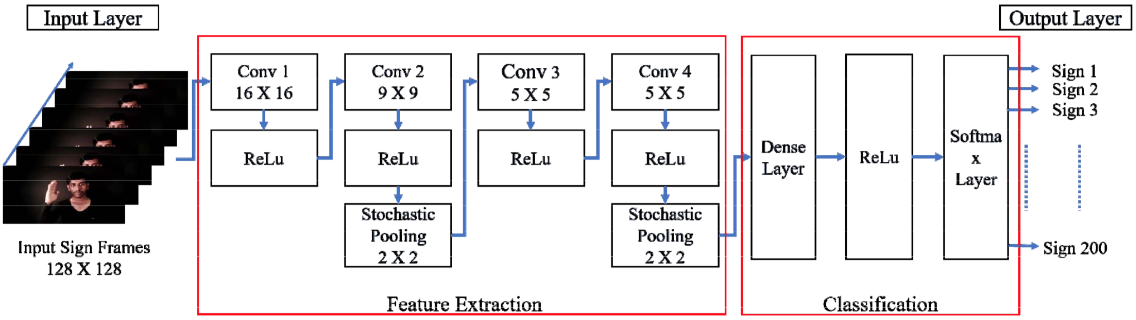


Figure 2.2: Proposed Deep CNN architecture

(Hussain, Saxena, Han, Khan, & Shin, 2017), introduced a CNN based classifier trained through the process of transfer learning over a pretrained convolutional neural network which is trained on a large dataset. We are using VGG16 figure 2.3 as the pretrained model. The According to the paper the accuracy was 93.09%,while using AlexNet figure 2.4 was 76.96%. the same problem here with the other papers which is the small number of sign that begin trained on 7 signs, and the accuracy need to be improved as well.

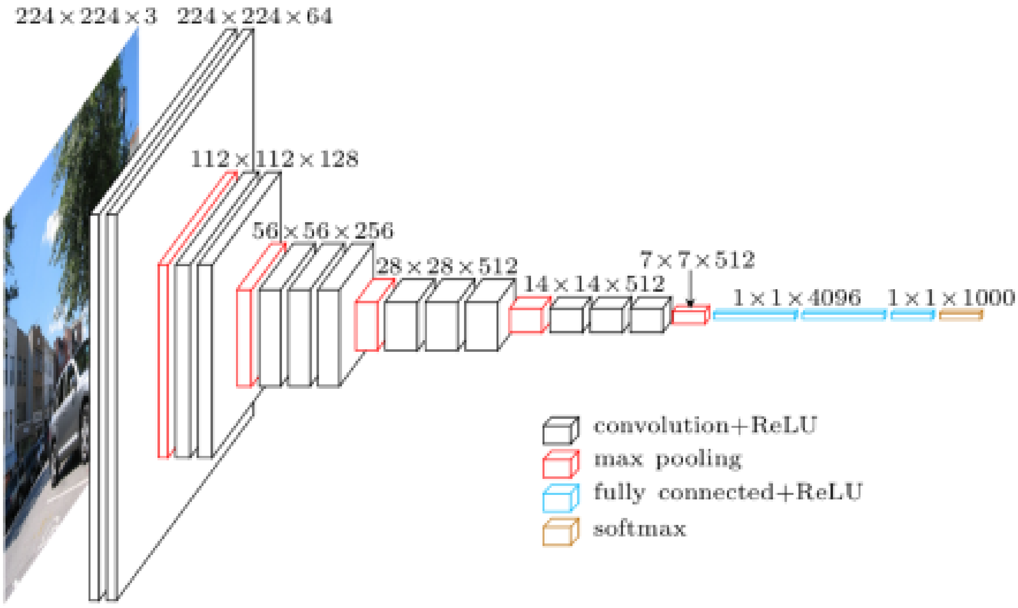


Figure 2.3: VGG16 architecture. Retrieved from www.cs.toronto.edu

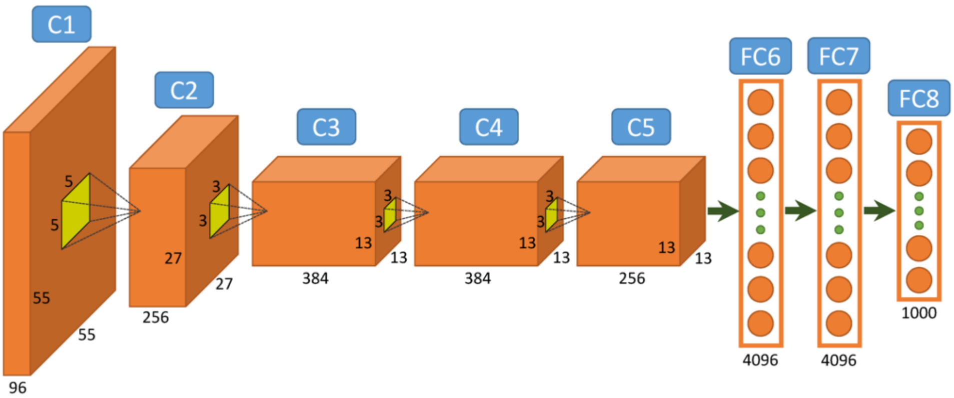


Figure 2.4: AlexNet architecture. Retrieved from www.saagie.com

(Pyo, Ji, You, & Kuc, 2016), introduced a depth-based hand data with convolution neural networks (CNNs).The hand gesture dataset has roughly 6,000 RGB-D images in each of 12 labels. In all, there are approximately 60,000 training images, 1S,000 validation images, and 12,000 training images. each time they were increasing the number of layers and testing the accuracy 2.5. They came with result that more number of layers, does not guarantee the increase of accuracy.

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3conv 1fully	100.00%	99.47%	97.87%	100.00%	99.47%	98.40%	99.47%	54.79%	89.42%	99.04%	97.12%	96.15%	94.27%
3conv 2fully	100.00%	100.00%	95.21%	100.00%	100.00%	97.87%	99.47%	64.89%	97.12%	98.08%	100.00%	94.23%	95.57%
3conv 3fully	100.00%	100.00%	97.87%	100.00%	100.00%	97.87%	98.94%	62.23%	90.38%	97.12%	99.04%	91.35%	94.57%
4conv 1fully	100.00%	92.55%	93.62%	98.94%	99.47%	98.40%	97.87%	55.32%	95.19%	98.08%	98.08%	100.00%	93.96%
4conv 2fully	100.00%	96.81%	99.47%	100.00%	100.00%	98.40%	99.47%	64.36%	91.35%	98.08%	100.00%	91.35%	94.94%
4conv 3fully	100.00%	95.21%	98.94%	98.94%	99.47%	96.28%	97.87%	60.64%	92.31%	96.15%	99.04%	95.19%	94.17%
5conv 1fully	99.47%	92.55%	96.81%	97.87%	99.47%	97.87%	97.87%	58.51%	94.23%	97.12%	98.08%	94.23%	93.67%
5conv 2fully	100.00%	97.87%	98.94%	100.00%	100.00%	98.40%	97.34%	53.19%	88.46%	97.12%	99.04%	94.23%	93.72%
5conv 3fully	99.47%	94.68%	96.28%	99.47%	98.94%	98.40%	97.34%	52.66%	93.27%	95.19%	97.12%	91.35%	92.85%
6conv 1fully	99.47%	94.68%	98.40%	97.34%	98.94%	97.34%	98.40%	55.32%	84.62%	98.08%	98.08%	95.19%	92.99%
6conv 2fully	100.00%	97.34%	96.81%	97.87%	98.40%	97.87%	98.40%	53.72%	92.31%	95.19%	98.08%	94.23%	93.35%
6conv 3fully	98.40%	43.09%	89.36%	97.34%	94.68%	93.09%	96.81%	47.87%	73.08%	88.46%	99.04%	93.27%	84.54%

Figure 2.5: Classification results of modifiednetworks

(?, ?), introduced a 3D hand gesture recognition approach based on a deep learning model using Convolutional Neural Network (CNN). The proposed model only uses hand-skeletal data and no depth image. The model produced by multi-channel convolutional neural network with two feature extraction modules and a residual branch per channel 2.6. The achieved accuracy was a 91.28% classification accuracy for the 14 gesture classes case and an 84.35% classification accuracy for the 28 gesture classes case.

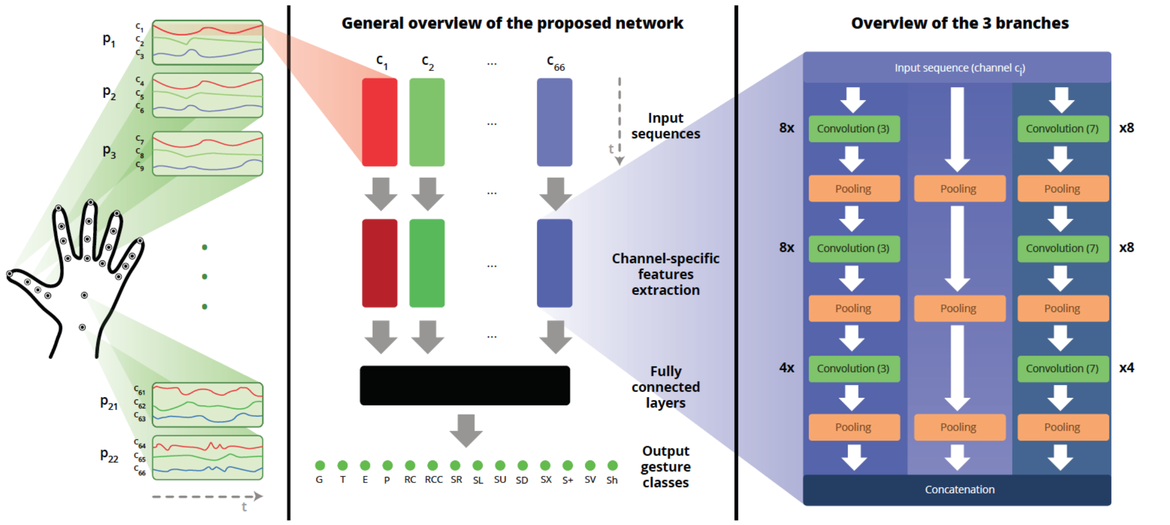

Figure 2.6: parallel convolutional neural network

2.2 Summary

This chapter illustrated some works have been done previously on hand gesture and sign language recognition using deep learning. Table 2.1 the Summary of the literature review.

Table 2.1: Summary of the literature review

Title	Year	Accuracy	Software
Tiny Hand Gesture Recognition without Localization via a Deep Convolutional Network	2017	97.1%	CNN
Deep Convolutional Neural Networks for Sign Language Recognition	2018	92.88%	CNN
Hand Gesture Recognition Using Deep Learning	2017	93.09%	CNN VGG16
Depth-based Hand Gesture Recognition using Convolutional Neural Networks	2016	95.57%	CNN
Deep Learning for Hand Gesture Recognition on Skeletal Data	2018	91.28%	MC-DCNN

Chapter 3

Methodology

Image recognition, voice producing, system design block diagram figure 3.1 and the flowchart of the research is presented in details alongside with the tools and algorithms in this chapter.

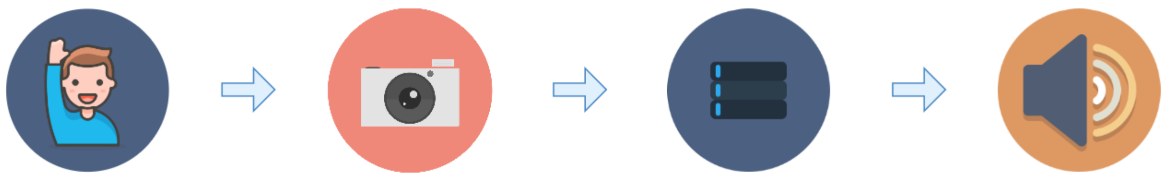

Figure 3.1: System block diagram

3.1 Image recognition

The ancient approach of developing machine learning and vision based algorithm is performing handcrafted features extraction algorithms such as histogram of oriented gradients

(HOG) on an image and convert it into a vectors of values then classify it using a machine learning algorithm such as support vector machine (SVM). In another way, deep learning is a subfield of machine learning, which is subfield of artificial intelligence (AI) totally different approach by stacking layers on top of each others that automatically more complicated, abstract and discriminating features. Figure 3.2 shows the hierarchy of AI.

Figure 3.2: AI hierarchy

3.2 Hand detection

The problem of hand recognition that hand occupied usually less than 25 percent of the image. To overcome this issue the model should be provided with high accurate detection algorithm, Right now there are so many good algorithms for object detection which can be utilize to detect a human hand We are going to concentrate on the most three famous (Faster R-CNN, SSD and YOLO)

3.2.1 Faster R-CNN

The Faster Region-based Convolutional Network (Faster R-CNN) is a mixture among the Region Proposal Network(RPN)[1] and the Fast R-CNN[2] model.

- A CNN produces feature map form the input images.
- A 3x3 sliding window moves through feature map and and maps it into lower dimension.
- Every sliding window, produces multiple regions based on fixed ration (anchor boxes).
- Each region contain an objectness score and it's bounding box coordinates.

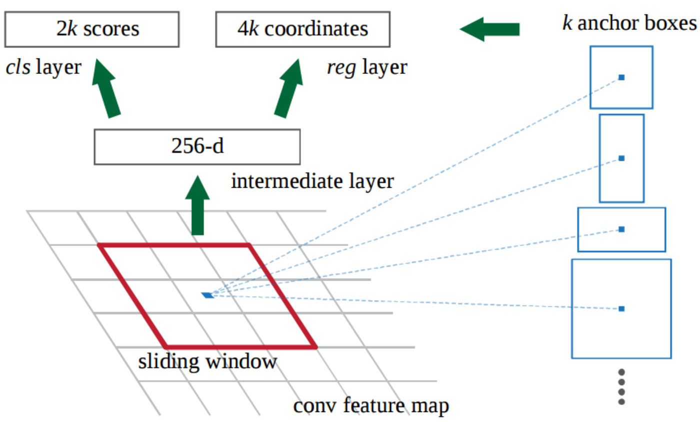

Figure 3.3: One sliding window location. Retrieved from https://towardsdatascience.com

The 2k scores represent the softmax probability of each of the k bounding boxes being on "object." If an anchor box has an "objectness" score above a certain threshold, that box's coor-

[1] algorithm to output bounding boxes to all objects in an image.

[2] A main CNN with multiple convolutional layers is taking the entire image as input instead of using a CNN for each region proposals (R-CNN).

dinates (4k coordinates) get passed forward as a region proposal. Then the region proposals are being fed into a Fast R-CNN, followed by a pooling layer, several fully-connected layers and softmax classification layer with bounding box regoessor. Faster R-CNN uses RPN to avoid the selective search method [3], it accelerates the training and testing processes, and improve the performances. (Ren, He, Girshick, & Sun, 2017)

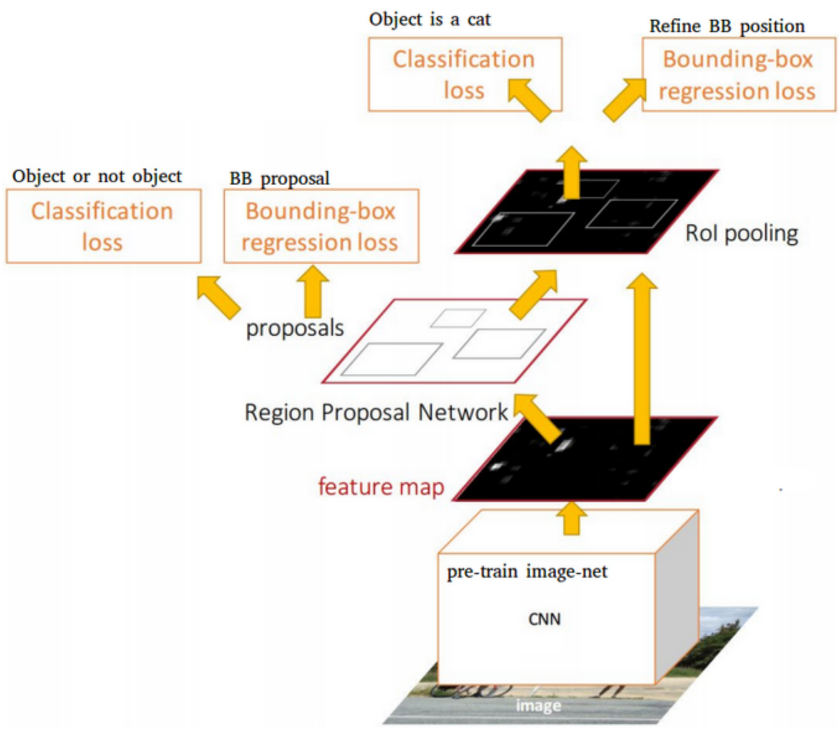

Figure 3.4: Faster R-CNN. Retrieved from https://towardsdatascience.com

3.2.2 Single-Shot Detector (SSD)

Unlike Faster R-CNN which perform regional proposals and region classifications in two steps. SSD does the two in a ”single shot” jointly predict the bounding box and the class while it processes the image.

how it’s work?

[3] Region Proposal algorithm based on grouping of similar region based on color, size, texture and shape compatibility.

- Generate a set of feature maps with different scales by passing the image through sequence of convolutional layers (10x10, 6x6, 3x3 ...).

- Use a 3*3 convolutional filter to evaluate bounding boxes for each location of the feature maps.

- predict bounding box of set and the class probability all together.

- The best predicted box called as "positive" label, alongside with the boxes that have IoU [4] value > 0.5

Sense SSD skip filtering step, it generates multiple bounding box with multiple shapes and most of them are negative example.

To fix this issue, SSD does two extra methods. First, non-maximum suppression:[5] to group overlapping boxes into one box by keeping the highest confidence Then,hard negative mining: to balance classes during the training process; subset the negative examples with the highest training loss with a 3:1 ratio of negatives for positives.(Liu et al., 2016)

3.2.3 You Only Look Once (YOLO)

Like SSD, YOLO directly predicts bounding boxes and class probabilities with a single evaluation. The simpleness of YOLO allows real time prediction.

- The model divide the input image into SxS grid.

- Each cell of the grid predict B bounding boxes with a confidence score.

[4] Intersection over Union

[5] Object detection methods often output multiple detections which fully or partly cover the same object in an image.

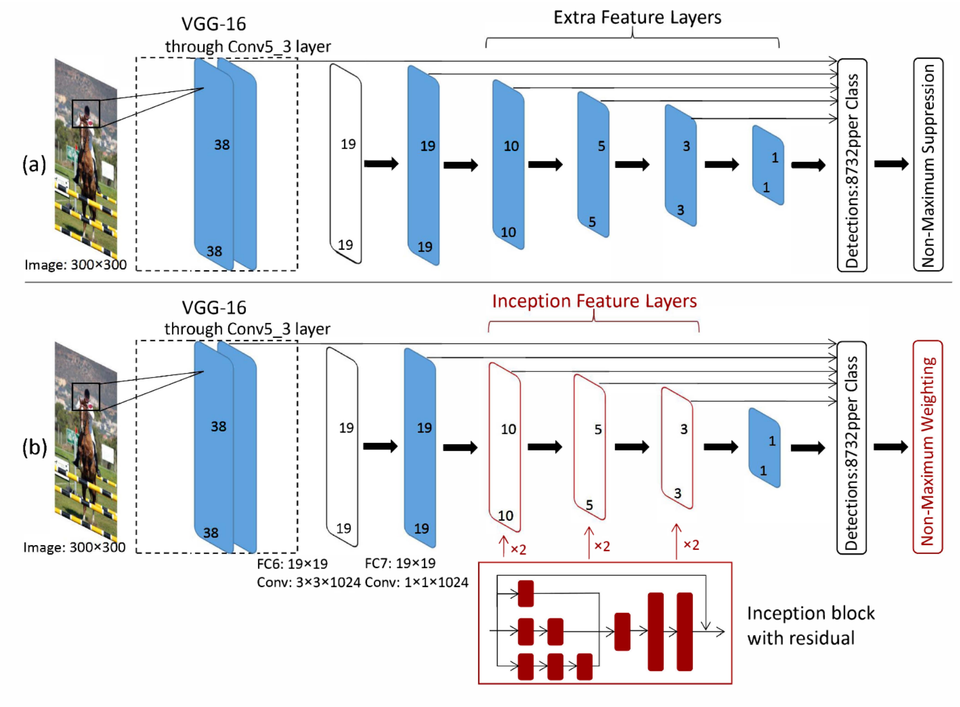

Figure 3.5: SSD. Retrieved from https://www.semanticscholar.org

- The score confidence is the probability of detected object multiply by the IoU between the prediction and the truth boxes.

The CNN has 24 convolutional layers followed by 2 connected layers. Reduction layers with 1x1 filters followed by 3x3 convolutional layers replace the initial inception modules.

The Fast YOLO model comes with 9 convolutional layers and less number of filters. The final layer outputs a S*S*(C+B*5) tensor corresponding to the predictions for each cell of the grid. C is the number of estimated probabilities for each class.

Similar to SSD, YOLO predicts so many bounding boxes without any object, So it applies non-maximum suppression method at the end of the network, to merge high overlapping bounding boxes of the same boxes into a single one. The author noticed that still some false positive detected.(Redmon, Divvala, Girshick, & Farhadi, 2016)

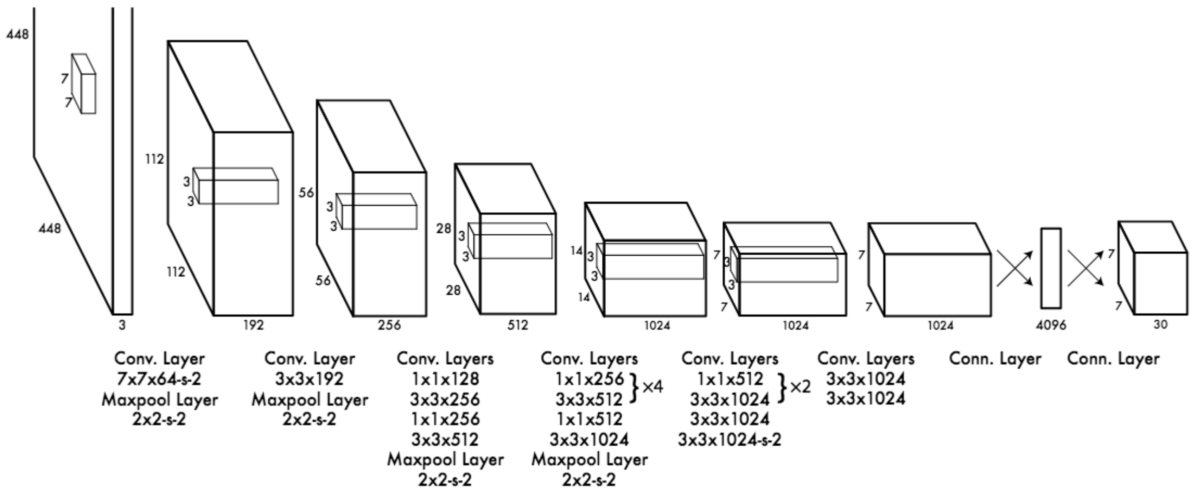

Figure 3.6: YOLO. Retrieved from https://medium.com/

3.3 Voice producing

After processing the image the CNN algorithm classify the gesture that presented in the image, the corresponding text (word, char, number) will be generated as voice that Simulate the human voice.

3.4 Tools

The programming language in use is Python[6] along side with many libraries such as TesorFlow[7], Keras[8], OpenCV[9], NumPy[10], Pandas[11] and Matplotlib[12]. The model is being trained by using Google Cloud Computing[13] service with Ubuntu as operating system.

[6]Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991. https://www.python.org/

[7]TensorFlow is an open-source software library for dataflow programming across a range of tasks. https://www.tensorflow.org/

[8]Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. https://keras.io/

[9]OpenCV (Open Source Computer Vision Library) is released under a BSD license and hence it's free for both academic and commercial use. https://opencv.org/

[10]NumPy is the fundamental package for scientific computing with Python. http://www.numpy.org/

[11]Pandas is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language. https://pandas.pydata.org/

[12]Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. https://matplotlib.org/

[13]Google Compute Engine delivers virtual machines running in Google's innovative data centers and worldwide fiber network. https://cloud.google.com/

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