
# AI-BASED SMART DEAF TRANSLATOR


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**NOVEMBER 2022**


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THIS REPORT IS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE.

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NOVEMBER 2022

# Declaration of Originality

We hereby declare that this project report is based on our original work except for citations and quotations, which had been duly acknowledged. We also declare that it has not been previously and concurrently submitted for any other degree or award at KAU or other institutions.

| NAME: | ID: | DATE | SIGNATURE |
|---|---|---|---|
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## Acknowledgment

we want to thank our supervisor for assisting and helping us during this course he answered every question we asked he even helped us with the resources that we needed, also we want to thank our coordinator for his advices which helped us.

# Abstract

The project subject focuses on using machine learning techniques to build a model that can accurately recognize hand gestures. The model will be trained on a large dataset of images of hand gestures and will be tested on a separate dataset to evaluate its accuracy. The goal of the project is to build a model that can recognize hand gestures with high accuracy, which can have a wide range of applications in fields such as human-computer interaction, gaming, and sign language recognition. The project will utilize various software and tools, such as Kaggle Notebook, Python, Tensorflow, Numpy, Pandas, and Matplotlib, to build and train the model. The project will also implement data augmentation techniques to increase the size and diversity of the training dataset and improve the performance of the model. The project will conclude with a detailed evaluation of the model's accuracy and a discussion of potential future work that can be done to improve the model.

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# CHAPTER 1
# INTRODUCTION AND BACKGROUND OF THE PROJECT

# 1.1 Introduction

The deaf and mute community faces significant barriers to communication, which can negatively impact their ability to fully participate in society. Despite advances in technology, solutions for this population are often limited and not tailored to their specific needs. To address this critical issue, it is crucial to develop innovative solutions that can bridge the communication gap and empower deaf and mute individuals to live more fulfilling lives. This project aims to do just that by utilizing technology and programming languages to create a solution that will help improve the quality of life for the deaf and mute community and provide equal opportunities for engagement and communication with the world around them.

# 1.2 Proposal

## 1.2.1 Problem Statement

After inventing the computers, humans did not stop at that point, they continued working on other things related to computer science such as artificial intelligence which we are going to use to help deaf people communicate with others easily, and we hope to achieve that goal in our project, the problem is when deafs want to communicate with others to enjoy their time or study or learn even if they want to ask for something they face a lot of problems, the other part of the communication cannot understand them since they are not talking using spoken languages, they use their hands to communicate and the problem here also that a few people know the sign language, so no one can understand them only if they talked with someone who knows the sign language.

## 1.2.2 Possible solution

The solution that this project will do to solve this problem is to create a visual interaction system that can take the sign from the deaf one as an input and then translate it into words for the normal one as an output.

# 1.3 Motivation

The deaf and mute community faces unique and challenging obstacles in their daily lives, particularly when it comes to communication. This not only affects their ability to fully participate in society, but also limits their potential for personal and professional growth. Our goal is to empower the deaf and mute community by providing them with a solution that can bridge the communication gap and improve their quality of life. With advancements in technology, we believe that it is possible to create a solution that can be customized to the specific needs of this population and provide equal opportunities for communication and engagement. We are motivated

by the idea of making a positive impact on the lives of the deaf and mute community, and believe that this project has the potential to do just that.

## 1.4 Scope of deliverables

The scope of deliverables for this project includes the following:

**Requirements Analysis:** A comprehensive review of the communication needs and requirements of the deaf and mute community, including an analysis of current solutions and their limitations.

**Solution Design:** A detailed design of the proposed solution, including the technology and programming languages that will be used, and how they will meet the needs of the deaf and mute community.

**Implementation:** The actual development and implementation of the solution, including the programming of the technology and tools needed to support the solution.

**Testing and Validation:** Thorough testing of the solution to ensure its functionality and effectiveness, as well as user acceptance testing to ensure that the solution meets the needs of the deaf and mute community.

**Deployment:** The deployment of the solution to the target audience, including any necessary training and support to ensure that the solution is used effectively.

**Maintenance and Support:** Ongoing maintenance and support to ensure that the solution continues to function effectively and meet the changing needs of the deaf and mute community.

The scope of deliverables is designed to ensure that the solution meets the needs of the deaf and mute community, and is implemented, tested, and supported effectively. This will help to ensure the success of the project and its positive impact on the deaf and mute community.

# CHAPTER 2
# LITERATURE REVIEW

# 2.1 Literature

## 2.1.1 Face Detection and Recognition Using OpenCV

**Introduction**

A face recognition program is a software application for verifying a person and identifying him or her with a video or picture from a source, Some of the earliest findings include experiments on Darwin's feelings for facial expressions. With the open-source platform named Intel called OpenCV.

facial recognition can be done quickly and reliably. One way from a face and an image database is the preferred facial features. It is generally compared to biometrics like fingerprints and eye reconnaissance systems and is used in security systems, thumb recognition systems were also common recognition algorithms. The computer-View library for Intel's open-source makes programming easy to use. This provides advanced capabilities such as facial detection, face tracking, and facial recognition Face algorithms.

**The currently available algorithms are:**

A. Haarcascade_frontalface_default.xml

B. Eigenfaces see createEigenFaceRecognizer()

C. Fisher(Placeholder3)faces see createFisherFaceRecognizer()

D. Local Binary Patterns Histograms

**OpenCV Structure and content**

OpenCV is organized loosely into five main elements, four of which are outlined in Figure. The CV portion includes the main picture processing and lower computer vision algorithms.

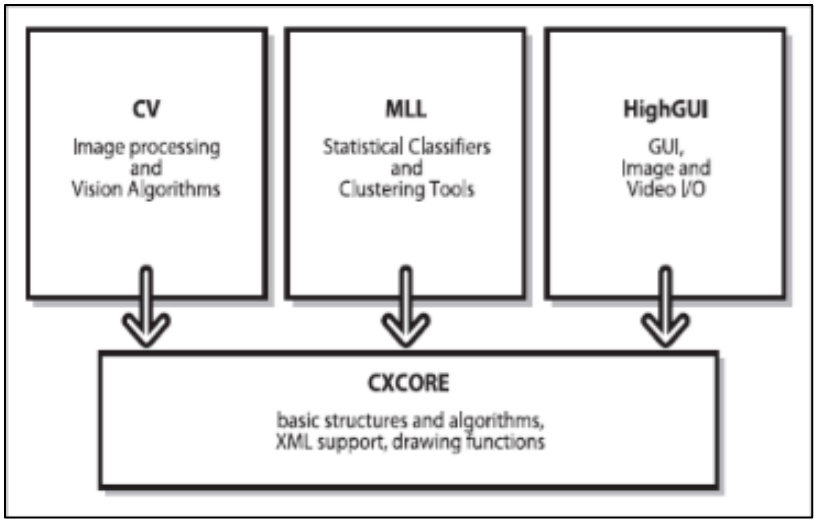


*Figure 1, OpenCV Structure and content*

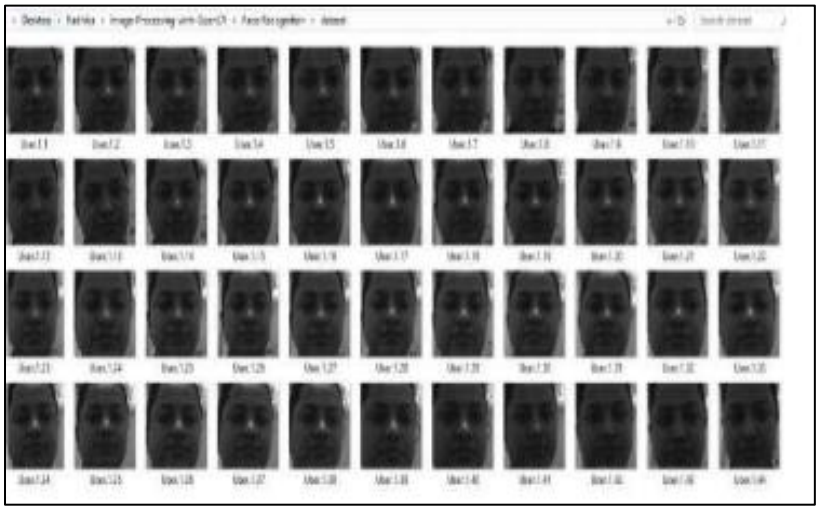

*Figure 2, Facial Recognition using OpenCV*

## Conclusion

In the last 20 years, facial recognition technology has come a long way. Today can check identity information automatically about safe transactions, tracking, security purposes, and building access control. Such systems normally work in controlled environments and algorithms of recognition may manipulate environmental constraints to achieve high accuracy of recognition. Yet face-recognition technologies of the next generation will be commonly used in smart settings where computers and machines are more like supportive helpers.[1]

## Prompt criteria

*Table 1, Prompt criteria For first literature*

| *Table 1* | **Notes** |
|---|---|
| **Presentation** | the presentation was fine the only mistake was some grammar errors which can be ignored because they're not native speakers |
| **Relevance** | The information that I got is important for me because we might use the library, for face detection |
| **objectivity** | because the paper only showed the algorithm that is being used and no more information, and the paper has been written in 2019, some algorithms become old |
| **Method** | there is no data collection |
| **Provenance** | all relevant papers are correctly referenced and provided at the end of the paper |
| **Timelines** | The paper was published in 2019 |

## 2.1.2 Development of a hand pose recognition system on an embedded computer using Artificial Intelligence

**Introduction**

Hand gesture recognition is one of the obvious techniques for building a friendly interface between a machine and ausers hand pose recognition technology would allow for the operation of complex machines and smart devices through only a series of hand postures, hand and finger movement, would eliminate the physical interaction between human and the machine.

In recent years, Convolutional Neural Networks (CNNs) have become the state-of-the-art for object recognition in computer vision Despite the high potential of CNNs in object detection problems and image segmentation tasks.

**METHODOLOGY**

the system worked with image capture from a standard CMOS camera and is executed on embedded computers with low computational resources without GPU support, such as Raspbery , etc. Therefore, the main objectives of the proposed system are as follows: high accuracy rate, fast time response, low power consumption and low computational costs.

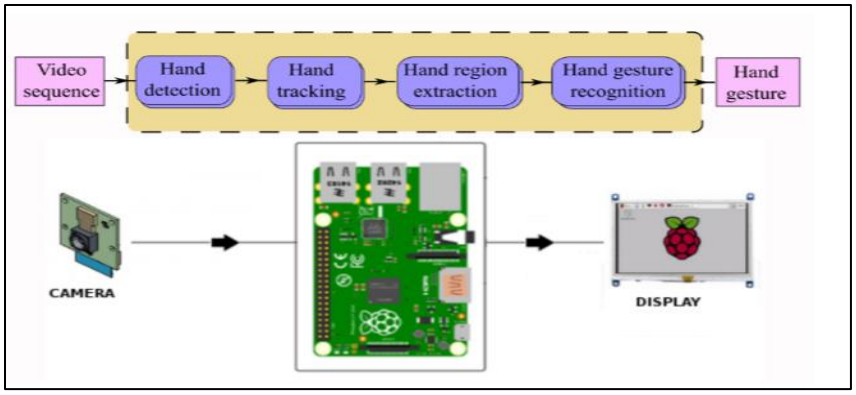


*Figure 3, Steps of the recognition system*

The system is composed of three main steps

- Hand detection
- Hand region tracking
- hand gesture recognition

the Haar cascades classifier detects a basic hand shape in order to have a good hand detection. Then, this hand region is tracked using the MIL (Multiple Instance Learning) tracking algorithms.

Finally, hand gesture recognition is performed based on a trained Convolutional Neural Network.

## EXPERIMENTAL RESULTS

The performance of the CNN of hand poses classification was evaluated using different metrics such as confusion matrix and accuracy. The confusion matrix presents a visualization of the misclassified classes and helps to add more training images in order to improve the model.

The confusion matrix of our model is shown in Fig. 5 and discloses which letters are misclassified. These errors happen because of similarities between the classes. Furthermore, our architecture shows an outstanding accuracy of 94.50%.

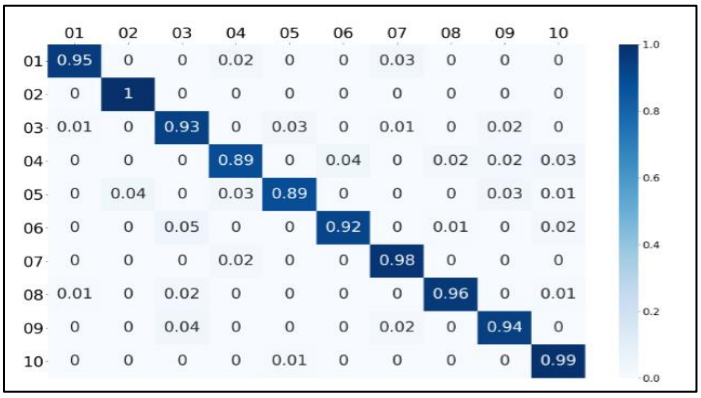


*Figure 4, Confusion Matrix[2]*

The Table I shows some details of CNNs tested on the Raspberry Pi 3 platform. As you can see, the proposed NN achieves the fastest time response, compared with other architectures, by using the lowest power consumption because its simple and efficient design.

*, Response time and power consumption for evaluation of different CNNs on a Raspberry Pi 3 using Caffe.[2]*

| Model | proposed | VGG_F | NIN | AlexNet | GoogleNet |
|---|---|---|---|---|---|
| liars | 9 | 13 | 16 | 11 | 27 |
| power | 0.690 | 0.760 | 0.840 | 0.750 | 0 |
| Time | 0.351 | 0.857 | 0.553 | 1.1803 | 1.175 |

**Conclusion**

In this paper, we introduce the implementation of a hand pose recognition system on a regular embedded computer. We demonstrated that our system is capable to recognize 10 hand gestures with an accuracy of 94.50% on images captured from a single RGB camera, and using low power consumption, about 0.690 W. In addition, the average time to process each 640x480 image on a Raspberry Pi 3 board is 351.2 ms.[2]

**Prompt criteria**

*Table 2, Prompt criteria for second literature*

| | **Notes** |
|---|---|
| **Presentation** | the presentation was good, they follow a nice approach during the writing they start with the basic going to the deep step by step ending up with good result |
| **Relevance** | I got some information like even though that they don't use GPU and big computer to get their result so we as group we might get better result' cause we use a computer they use embedded computer |
| **objectivity** | - |
| **Method** | has been mentioned in the methodology used |
| **Provenance** | all relevant papers correctly referenced and provided at the end of the paper |
| **Timelines** | The paper was published in 2019 |

## 2.1.3 Deep Learning-based Hand Pose Estimation from 2D Image

**Introduction**

The human hand pose is a type of communication that can be used to interact with a computer. It can be used in various ways, such as virtual reality and touch-free communication.

Due to the increasing number of studies on the development of artificial hand poses, researchers have started to focus on the efficiency of performing effective work. However, performing this task is still challenging due to the various factors that affect its accuracies, such as the complexity of the hand and the multiple perspectives involved.[3][4]

**Proposed Approach**

The following steps are considered for 3D hand pose estimation: hand localization, hand image frames, and tracking of joints and fingers The first step is to find the area of the hand from an image to crop. We, then proceed to create a heatmap-Figure 6 of the hand key points to identify the 2D joints, Finally, 3D joints are estimated from 2D joints. However, this system uses tracking methods for continuous image frames to create smooth hand pose estimation.

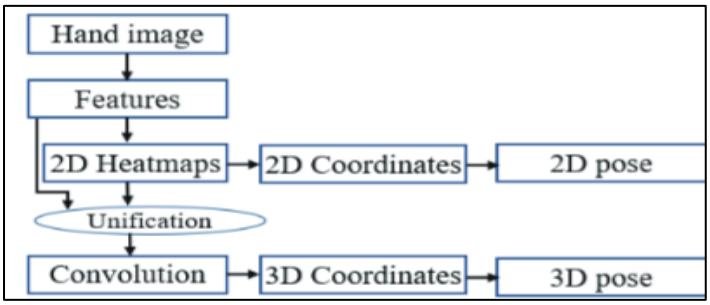


*Figure 5, The estimation process of the 3D pose.[4]*

**Experimental Results and Evaluation**

A-Dataset For the training and testing of our proposed model, we used Synthhand's Benchmark dataset The data set of 4000 images was randomly selected for validation, and 1500 images for testing, and the rest of the images for training.

The image size was 128 x 128 pixels. We trained our model for both 2D and 3D locations.[6]

**Result and evaluation**

The evaluation of 3D hand pose estimation is considered through vector representation using the predictive method, However, the model was trained with heatmaps and the locations of the key points were estimated. The range of the key points' locations was between 0 and 1 for both (x, y) coordinates which made an average error of 3% for key points joints. Figure 8 shows the example of the performance of 2D and 3D hand pose from the benchmark dataset.

The performance became better when the hand image was a normal appearance and the key points were visible. Figure 9 shows the model performance based on the validation sets. However, some images were similar in viewpoints and difficult to separate from the dataset. Therefore, these types of images were considered in both the training and the validation process. For this, the model showed high efficiency in validation datasets. [7]

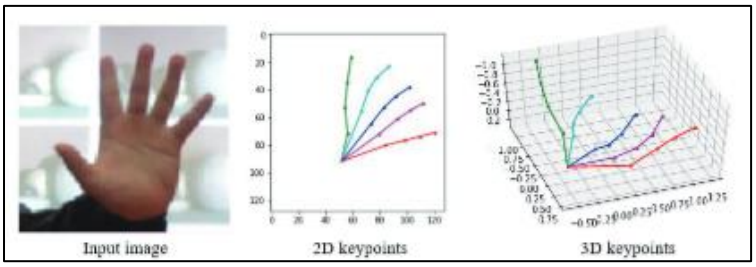


*Figure 6, An example of the input image of 2D and 3D key points.[7]*

VALIDATION PERFORMANCE OF PROPOSED MODEL

| Dataset | Before trained | | After trained | |
|---|---|---|---|---|
| | 2D | 3D | 2D | 3D |
| Non-augmented | 0.030 | 0.23 | 0.09 | 0.19 |
| Augmented | 0.21 | 0.70 | 0.06 | 0.26 |

*Figure 7, model performance based on the validation sets[5]*

This paper estimated 3D hand poses from 2D images. We considered hand images from benchmark datasets. The proposed CNN model created a 2D heatmap and image features. The convolution was then applied to obtain the normalized 3D hand pose. We trained and evaluated the proposed method for 2D and 3D estimations of heatmap and vector representation poses. The results show that the key points error of the model performance was about 3% for normalized 3D hand poses.[6][7]

## Prompt Criteria

*Table 2, Prompt criteria for third Literature search*

| | **Notes** |
|---|---|
| **Presentation** | the presentation was fine there a lot of repeating information The diagrams are understandable |
| **Relevance** | not a lot of information due to the published year although I get used of their database and I might use it in our project |
| **objectivity** | Due to database date they get around 4% improvement compared to previous work |
| **Method** | they use data collections and previous work and clear data |
| **Provenance** | all relevant papers are correctly referenced and provided at the end of the paper |
| **Timelines** | The paper was published in 2017,m and meets some of our requirements. |

## 2.1.4 Sign Language Recognition Application Systems for Deaf-Mute People: A Review Based on Input-Process-Output

**Introduction**

This paper aims to discuss the Sign Language Recognition Systems that are being used by researchers. In this paper, we will discuss the Sign Language Recognition form application point of view. This paper will talk about the device used in getting the data, data acquisition, such as data from early research or self-made data, the recognition method that are recently used by researchers, and the output of some previous research.

**Data Acquisition**

The main device used as an input process in Sign Language Recognition (SLR) is the camera. The SLR input data is in the form of gesture images that can be easily captured by the camera. Some researchers still use simple cameras to capture the image. Some researchers argue that they use cameras and no gloves to prevent difficulties when using sensory gloves 4 . Usually, cameras support many video formats, so that we need to specify the default format and the format we want to use by using digitizer configuration format (DCF) file 5. Some researchers also use higher specification cameras because the web camera's image is blurred.

There is also another device named Microsoft Kinect, which is used to capture images. Nowadays, Kinect is widely used by researchers because of its feature. Kinect can provide color video stream and depth video streaming simultaneously. With depth data, background segmentation can be done easily, and uses Kinect for Sign Language Recognition. A sample of the Kinect video stream is shown in Fig 10.

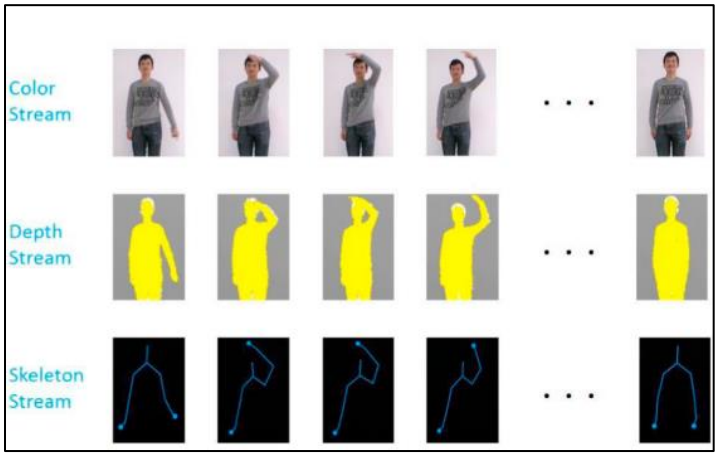


*Figure 8, Example of Kinect color and depth video stream[8]*

**Processing methods**

One of the processing methods widely used in SLR is the Hidden Markov Model (HMM) Firstly, they use a fuzzy K-means algorithm to do the Hand Shape Classifier. The hand shapes are classified into clusters for the right hand and 7 clusters for the left hand (based on the algorithm testing). And then, the orientation classifier is done by classifying the direction in which the palm is facing.

Due to the large variety of SLR gestures, the classification is done by classifying the onset and offset of hand orientation, as it is relatively consistent when the same sign is done repeatedly. Lastly, they do the movement classifier by using HMM. The HMM they use is Multi-Stream HMM (MSHMM). It is based on two standard single-stream HMM. The ACC and sEMG data feature sets are used to train the stream via the Baum-Welch algorithm. The other method of HMM is which is called Light-HMM. They select the keyframes through low-rank approximation and adaptively determine the hidden states in HMM. By using such a method, the keyframes can be reduced and the estimation of hidden states can be more precise. The basic idea is that the frames with linearly independent features will be selected as key frames and the others will be discarded. There is also an HMM approach that is called TD-HMM. This method uses a method similar to continuous HMM (CHMM), with the amount of computation reduced by tying similar Gaussian mixture components.

**Conclusion**

Sign Language Recognition System has been developed from classifying only static signs and alphabets, to a system that can successfully recognize dynamic movements that comes in continuous sequences of images. Researchers nowadays are paying more attention to make a large vocabulary for sign language recognition systems. Many researchers are developing their Sign Language Recognition System by using small vocabulary and self-made databases. A large database built for Sign Language Recognition System is still not available for some of the countries that are involved in developing the Sign Language Recognition System. Especially the Kinect-based data.[8]

**Prompt criteria**

*Table 3, Prompt criteria for the fourth Literature search*

| | **Notes** |
|---|---|
| **Presentation** | Very clear and understandable. |
| **Relevance** | A lot of information that might be helpful |
| **objectivity** | Direct explanation and comparisons between the methods |
| **Method** | They explained a lot of methods to the users of these methods |
| **Provenance** | all relevant papers are correctly referenced and provided at the end of the paper |
| **Timelines** | published in 2017 and meet some of our requirements. |

## 2.2 Comparison between the literature

The table below shows the types of literature and the differences between them:

*Table 4, Literature comparison*

| Literature Title | Methodology | Outcome |
|---|---|---|
| Face Detection and Recognition Using OpenCV. [1] | Showing different algorithms And the way that how OpenCV Works. | Having an idea about OpenCV and some algorithms. |
| Development of a hand pose recognition system on an embedded computer using Artificial Intelligence.[2] | Processing hand pose recognition and showing the steps of the recognition. | Learning how the computer can recognize the hand pose. |
| Deep Learning-based Hand Pose Estimation from 2D Image.[3] | data collection techniques, previous work, and clear data. | How to collect the data and how previous researchers deal with it. |
| Sign Language Recognition Application Systems for Deaf-Mute People: A Review Based on Input-Process-Output.[4] | Direct explanation and comparisons between previous researchers' methods. | Different ways of working on sign language recognition, their failures, and success. |

# CHAPTER 3
# METHODOLOGY

## 3.1 Methodology

The Waterfall Methodology will be employed in this project, as it is well-suited for projects with well-defined requirements and a fixed scope. The sequential nature of this methodology ensures that each stage must be completed before proceeding to the next, reducing the risk of deviation from the project's goals.

The phases involved in this methodology are as follows:

**Requirements Analysis:** In this phase, the requirements for the solution will be determined and documented.

**Design:** The design of the solution will be developed taking into account the requirements and the specific needs of the deaf and mute community.

**Development:** The solution will be built through coding and programming in this stage.

**Testing:** The solution will undergo thorough testing to verify its functionality, security, and reliability.

**Deployment:** The solution will be deployed and made available for use by the deaf and mute community.

**Maintenance:** Ongoing maintenance and improvement of the solution will be conducted to ensure its continued effectiveness.

By utilizing the Waterfall Methodology, we aim to create a solution that addresses the needs of the deaf and mute community in a structured and systematic manner. The methodology will help ensure the project stays on track and is delivered on time and within budget.

### 3.1.1 Requirements Analysis

The Requirements Analysis phase is a crucial part of the project, where we identified and evaluated the necessary specifications for the solution. During this phase, we considered various requirements including Functional Requirements, Non-Functional Requirements, Data Requirements, Hardware Requirements, and Software Requirements.

As we delved deeper into the project, our understanding of the requirements evolved, and we made adjustments accordingly. This was especially true after gaining more insights into the practical aspects of the solution, such as the software and hardware requirements. For instance, we had to switch to a different software due to the need for a better GPU. This highlights the importance of continuously re-evaluating and updating the requirements to ensure the solution is feasible and meets the needs of the deaf and mute community.

### 3.1.2 Design

In the Design phase, we used various diagrams to gain a comprehensive understanding of the system's architecture and requirements. This helped us to visualize the system's structure and interactions.

One of the diagrams we created was a High-level Architecture View, which provides an overview of the system's components and their relationships. This diagram helped us to understand the overall structure of the solution and identify any potential design challenges.

Additionally, we also created a Use Case diagram, which depicts the interactions between the system and its users. This diagram helped us to understand the system's lifecycle and the various scenarios in which it would be used. By using these diagrams, we were able to design a solution that was both effective and practical for the deaf and mute community.

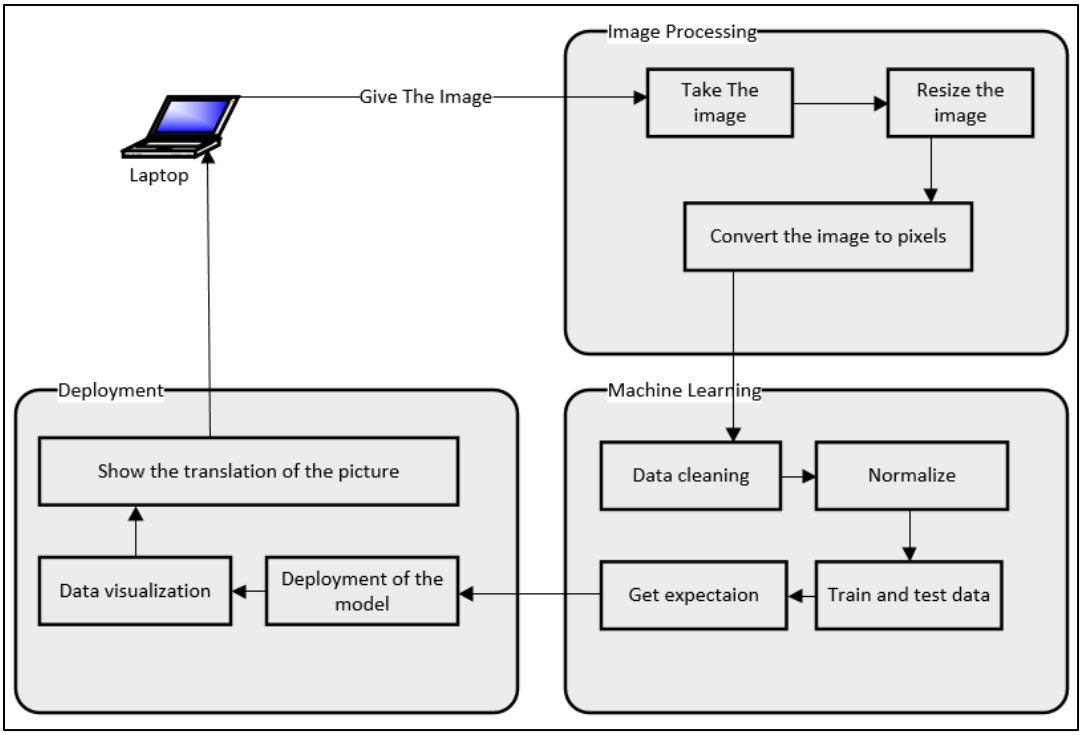


*Figure 9, High architecture view*

## 3.1.3 Implementation:

The Implementation phase is the process of bringing the designed solution to life. In this phase, we divided the work into three stages:

**Data Preprocessing:** In this stage, we prepared the dataset by removing corrupted images and adjusting their sizes to meet the model requirements. This step is crucial in ensuring the quality of the data and reducing errors in the model.

**Model Development:** Here, we divided the dataset into 80% training data and 20% testing data. We then trained the model on the training data and evaluated its performance on the testing data. This stage is the foundation for the overall accuracy of the solution.

**Model Testing:** After the model was developed, we evaluated its performance using several metrics such as Accuracy, Precision, Recall, F-Measure, ROC Area, and Confusion Matrix. To further validate the model, we used techniques such as Cross Validation and Train/Validate/Test split. These testing methods helped us to assess the model's performance and fine-tune it before deploying the solution.

Overall, the Implementation phase is a critical step in the development of the solution, and by following a structured approach, we were able to create a high-performing model that met the needs of the deaf and mute community.

### 3.1.4 Integration:

In this stage, we will integrate all the code developed during the previous stages into the main system to create the final solution.

### 3.1.5 Testing:

We will test our solution using two different models and compare the results to determine the best one.

### 3.1.6 Maintenance:

We will incorporate feedback from our supervisor and make any necessary improvements to the model. Any errors or malfunctions discovered after testing will also be addressed during this phase to ensure optimal functioning of the solution.

### 3.1.7 Deployment:

Once we have completed the testing and maintenance phase, we will deploy the final solution in a suitable environment that meets the hardware and software requirements, and make it available to the end-users. We will also ensure that the system is secure and has proper backup and recovery mechanisms in place. The system will be monitored regularly to ensure its smooth functioning and to make any necessary updates or improvements.

# CHAPTER 4
# IMPLEMENTATION DETAILS

# 4.1 Implementation

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import PIL

import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing import image
%matplotlib inline
from sklearn.metrics import confusion_matrix,plot_confusion_matrix, plot_roc_curve
from sklearn.metrics import classification_report
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

*Figure 10, Libraries*

In our project, we utilized TensorFlow for preprocessing the images, as our project involves images. We also employed the ResNet 50 model, which is imported via TensorFlow. It is a pre-trained model, meaning it was created and trained by others on a large dataset to address a similar problem. The ResNet stands for Residual Network, and it is a type of Convolutional Neural Network (CNN). The CNN is commonly used for computer vision applications and was introduced in the 2015 paper "Deep Residual Learning for Image Recognition". The model uses the Adam optimization algorithm, which is an extension of Stochastic Gradient Descent and is increasingly popular for deep learning applications in computer vision and natural language processing. The name "Adam" stands for Adaptive Moment Estimation.

```
import os
num_skipped = 0
for folder_name in ("0","1","2","3","4","5","6","7","8","9","a","b","c","d","e","f","g","h","i","j","k","l","m","n","o"
                    ,"p","q","r","s","t","u","v","w","x","y","z"):
    folder_path = os.path.join(data_dir, folder_name)
    for fname in os.listdir(folder_path):
        fpath = os.path.join(folder_path, fname)
        try:
            fobj = open(fpath, "rb")
            is_jfif = tf.compat.as_bytes("JFIF") in fobj.peek(10)
        finally:
            fobj.close()
        if not is_jfif:
            num_skipped += 1
            # Delete corrupted image
            os.remove(fpath)
print("Deleted %d images" % num_skipped)
```

```
Deleted 0 images
```

*Figure 11, Deleting corrupted images*

In this step, we are checking each file and image in the dataset by specifying the file names and providing the path to the stored dataset in the "data_dir" and "folder_name". We are searching for any "JFIF" images, which indicates corrupted images, and removing them from the dataset. At the end of this process, there were no corrupted images present.

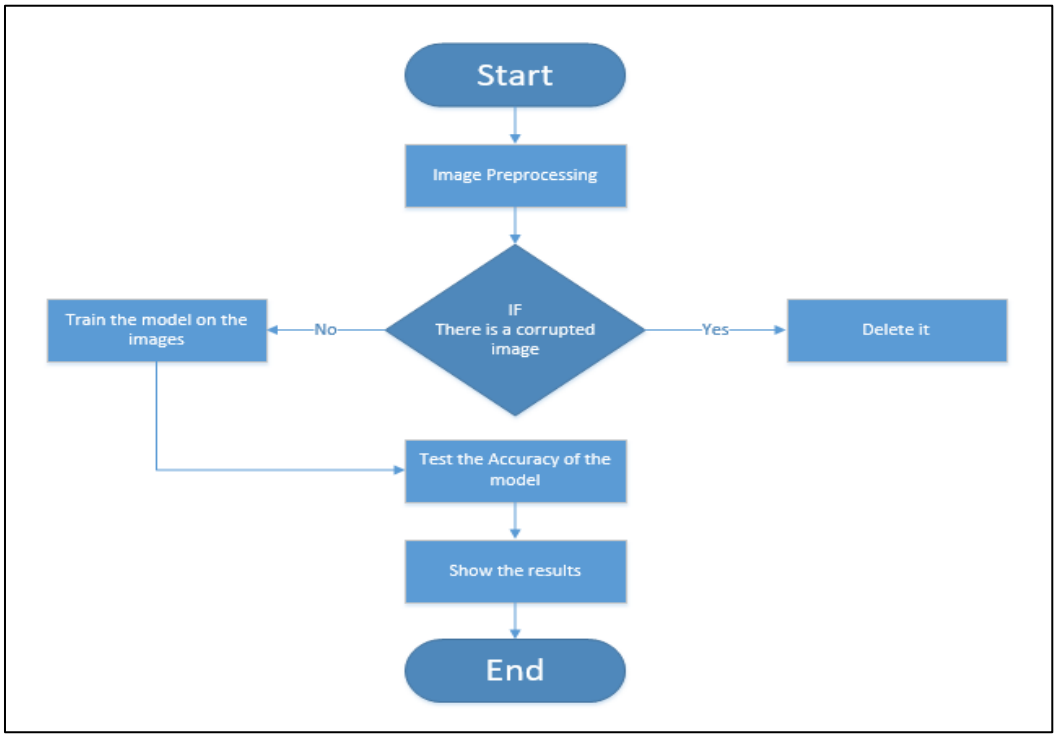


*Figure 12, Flowchart*

```
datagen = ImageDataGenerator(
          rescale = 1./255,
          rotation_range = 40,
          width_shift_range = 0.2,
          height_shift_range = 0.2,
          shear_range = 0.2,
          zoom_range = 0.2,
          horizontal_flip = True,
          fill_mode = 'nearest',
          validation_split = 0.2)
```

*Figure 13, Generating images*

In this stage of the project, we are utilizing data augmentation through the use of a data generator. This generator creates various copies of the images within the dataset, altering the size of the images. This allows for more efficient training of the model. The testing split is set to 20% of the total data.

```
height = 228
width = 228
channels = 3
batch_size = 32
img_shape = (height, width, channels)
img_size = (height, width)
```

*Figure 14, specifeing the image size*

In our project, we utilized the ResNet50 model for image recognition. This model requires images with a size of 228x228, with the channels and batch size set to specific values to avoid overloading the model.

By setting the batch size to 32, we ensured that the model trains on 32 images at a time, resulting in efficient and effective training.

```
pre_trained = ResNet50(weights='imagenet', include_top=False, input_shape=img_shape, pooling='avg')

for layer in pre_trained.layers:
    layer.trainable = False
```

*Figure 15, making the model ready*

Our pre-trained model utilized in the project is ResNet50, which stands for Residual Network. This type of neural network was first introduced in the 2015 research paper, "Deep Residual Learning for Image Recognition" by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun and is based on imagenet.

We set the "include_top" parameter to false, which means that the fully connected layers at the top of the model are not included. This allows us to exclude the top layer and add our own.

The pooling parameter was set to average, which determines the type of pooling used when the model acts as a feature extractor. The default value is max pooling, but we chose to use average pooling instead.

```
x = pre_trained.output
x = BatchNormalization()(x)
x = Dense(1024, activation='relu')(x)
x = Dropout(0.2)(x)
predictions = Dense(num_classes, activation='softmax')(x)

model = Model(inputs = pre_trained.input, outputs = predictions)
model.compile(optimizer = Adam(learning_rate=0.001), loss='categorical_crossentropy', metrics=['accuracy'])
```

*Figure 16, Activision methods*

Here we have employed ReLU and softmax activation functions in our model. ReLU, short for Rectified Linear Unit, is a commonly used activation function in CNNs and multilayer perceptrons, known for its ability to help the model learn faster and produce better results.

The softmax activation function is utilized in multi-class classification models, typically deployed in the output layer of the neural network. Softmax provides a differentiable approximation of the non-differentiable max function, which is crucial for optimizing machine learning models as differentiability is a requirement.

We have set the learning rate to 0.001, which is the default value for our model and is also considered low to avoid overloading the model.

```
STEP_SIZE_TRAIN = train_data.n // train_data.batch_size
STEP_SIZE_VALID = val_data.n // val_data.batch_size

history = model.fit_generator(train_data,
                  steps_per_epoch = STEP_SIZE_TRAIN,
                  validation_data = val_data,
                  validation_steps = STEP_SIZE_VALID,
                  epochs = 100,
                  verbose = 1)
```

*Figure 17, training and testing*

In this stage, we began training and testing our model. We set the number of training iterations, known as epochs, to 100. This means the model will be trained 100 times on the same data, which allows the model to learn and improve with each iteration. The purpose of setting the number of epochs is to determine how many times the model should be exposed to the training data before being evaluated on the test data. This is an important step in fine-tuning the model and improving its accuracy.

```
Epoch 94/100
62/62 [==============================] - 34s 556ms/step - loss: 1.1461 - accuracy: 0.5995 - val_loss: 1.2722 - val_accuracy: 0.5583
Epoch 95/100
62/62 [==============================] - 35s 559ms/step - loss: 1.1438 - accuracy: 0.6146 - val_loss: 1.1941 - val_accuracy: 0.5958
Epoch 96/100
62/62 [==============================] - 35s 562ms/step - loss: 1.1596 - accuracy: 0.5904 - val_loss: 1.1590 - val_accuracy: 0.6042
Epoch 97/100
62/62 [==============================] - 35s 561ms/step - loss: 1.1197 - accuracy: 0.6010 - val_loss: 1.1785 - val_accuracy: 0.5938
Epoch 98/100
62/62 [==============================] - 34s 557ms/step - loss: 1.1366 - accuracy: 0.6106 - val_loss: 1.1704 - val_accuracy: 0.5979
Epoch 99/100
62/62 [==============================] - 35s 561ms/step - loss: 1.1156 - accuracy: 0.6071 - val_loss: 1.1939 - val_accuracy: 0.5958
Epoch 100/100
62/62 [==============================] - 34s 557ms/step - loss: 1.0946 - accuracy: 0.6192 - val_loss: 1.1037 - val_accuracy: 0.6062
```

*Figure 18, Testing results*

In this section, we report the accuracy of our model after 100 epochs. Unfortunately, the accuracy results were not as high as we had hoped. The accuracy score was recorded at 0.6192 and the validation accuracy was 0.6062, which is considered low. We attempted to improve the accuracy by increasing the number of epochs to 150, but this approach did not yield any significant improvement. Additionally, adjusting the batch size and learning rate did not produce better results and the accuracy remained low.

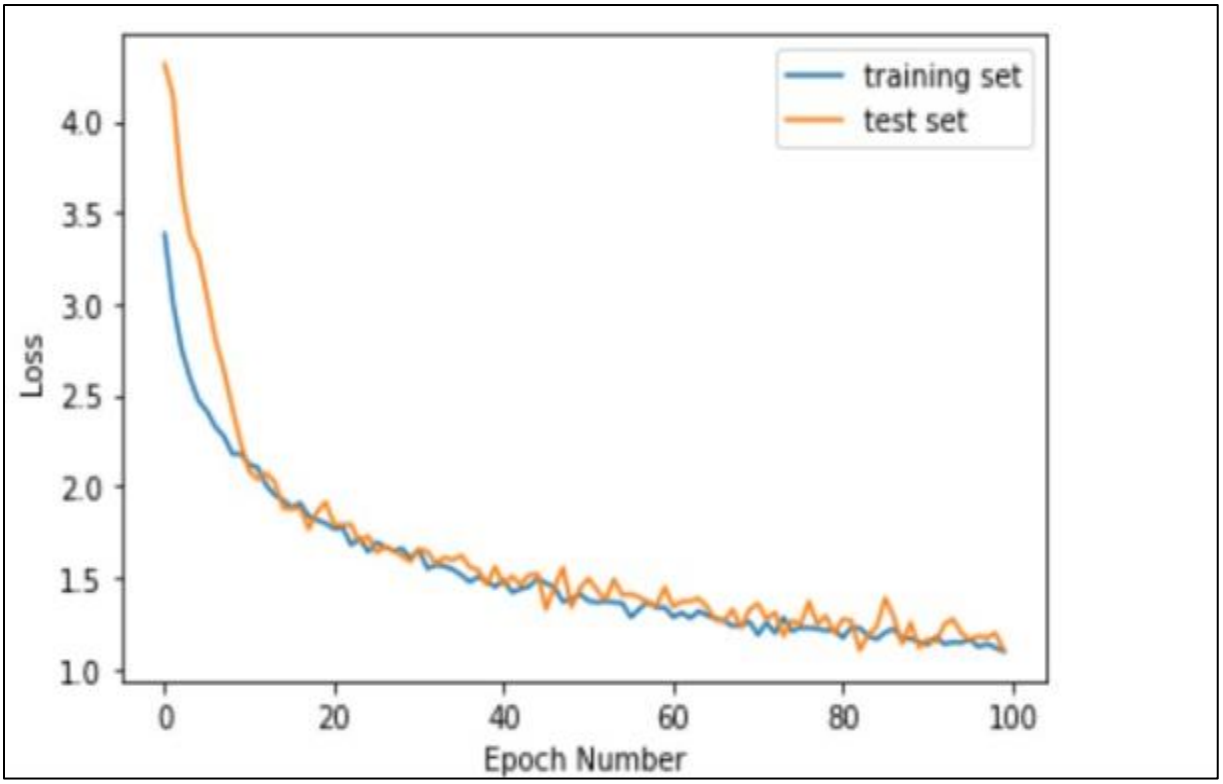


*Figure 19, Loss to Epoch diagram*

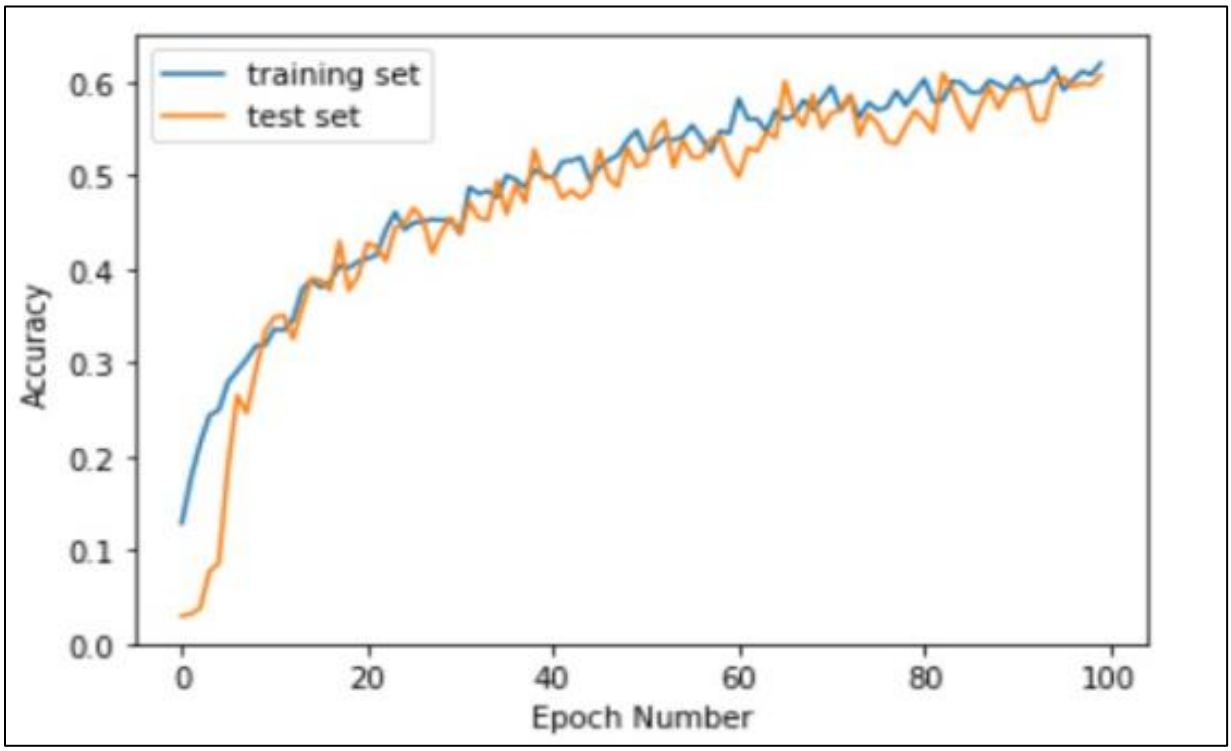


*Figure 20 Accuracy to Epoch diagram*

```
def predict_image(filename, model):
    img_ = image.load_img(filename, target_size=(228, 228))
    img_array = image.img_to_array(img_)
    img_processed = np.expand_dims(img_array, axis=0)
    img_processed /= 255.

    prediction = model.predict(img_processed)

    index = np.argmax(prediction)

    plt.title("Prediction - {}".format(str(classes[index]).title()), size=18, color='red')
    plt.imshow(img_array)
```

```
predict_image('/kaggle/input/asl-dataset/asl_dataset/0/hand1_0_bot_seg_5_cropped.jpeg', model)
```

*Figure 21, testing the model predictions*

In this function, we are testing the model's ability to predict the translation of an image by inputting a "0" sign image of size 228x228, which is the default size used by our model. The model successfully gives the correct prediction. However, the accuracy is still low, and we need to find ways to improve it. We will try various methods and adopt the one that yields the highest accuracy.

## 4.1 Improving Model Accuracy

The previous accuracy of our model, 0.6192 for training and 0.6062 for validation, was not up to par and needed improvement. To boost performance, we attempted to increase the learning rate and the number of epochs, but with little success. As a result, we decided to switch to using "InceptionV3" as our model. Inception v3 has a proven track record, having achieved over 78.1% accuracy on the ImageNet dataset, and it too is a pre-trained model. Additionally, it differs from ResNet50 in that it requires images of 299x299, while ResNet50 requires 228x228. To accommodate this change, we altered the image sizes in the preprocessing step.

```
height = 299
width = 299
channels = 3
batch_size = 32
img_shape = (height, width, channels)
img_size = (height, width)
```

*Figure 22, Image size in InceptionV3*

Additionally, we decided to adjust the pooling method. Our dataset consists solely of hand pose photos, so it was deemed unnecessary to extract partial images. As a result, we switched from using average pooling to using max pooling. This change ensured that the model was using the entire image rather than just a portion of it. We felt that this adjustment would result in a more accurate prediction, as the model would have access to all of the relevant information contained within the image. By making this change, we hoped to see an improvement in the overall accuracy of the model and bring us closer to our goal of achieving a higher level of accuracy.

```
pre_trained = InceptionV3(weights='imagenet', include_top=False, input_shape=img_shape, pooling='max')

for layer in pre_trained.layers:
    layer.trainable = False
```

*Figure 23,Pooling to max*

```
Epoch 94/100
62/62 [==============================] - 56s 905ms/step - loss: 0.2381 - accuracy: 0.9212 - val_loss: 0.8823 - val_accuracy: 0.8292
Epoch 95/100
62/62 [==============================] - 55s 897ms/step - loss: 0.2195 - accuracy: 0.9359 - val_loss: 0.9005 - val_accuracy: 0.7792
Epoch 96/100
62/62 [==============================] - 55s 890ms/step - loss: 0.2764 - accuracy: 0.9197 - val_loss: 1.1301 - val_accuracy: 0.7792
Epoch 97/100
62/62 [==============================] - 55s 888ms/step - loss: 0.2926 - accuracy: 0.9096 - val_loss: 0.7830 - val_accuracy: 0.8146
Epoch 98/100
62/62 [==============================] - 55s 882ms/step - loss: 0.2725 - accuracy: 0.9192 - val_loss: 0.8647 - val_accuracy: 0.8083
Epoch 99/100
62/62 [==============================] - 55s 892ms/step - loss: 0.2243 - accuracy: 0.9348 - val_loss: 0.7892 - val_accuracy: 0.8188
Epoch 100/100
62/62 [==============================] - 55s 890ms/step - loss: 0.2956 - accuracy: 0.9141 - val_loss: 0.8203 - val_accuracy: 0.7854
```

*Figure 24, Model Accuracy after improvements*

Our recent changes to the model have significantly improved its accuracy. The model's accuracy has gone from 0.6192 to 0.9141, and the validation accuracy has improved from 0.6062 to 0.7854. This is a significant improvement and shows the effectiveness of the changes we made to the model.

In comparison to the previous model, we switched from ResNet50 to InceptionV3. The main difference between these two models is the size of the images they take as input. InceptionV3 takes images with a size of 299x299, while ResNet50 takes images with a size of 228x228. Additionally, we also changed the pooling from average to max, as our dataset consisted of hand poses and taking parts of the image was not necessary. The improvements made to the model show that these changes were necessary and effective in increasing the accuracy of the model.

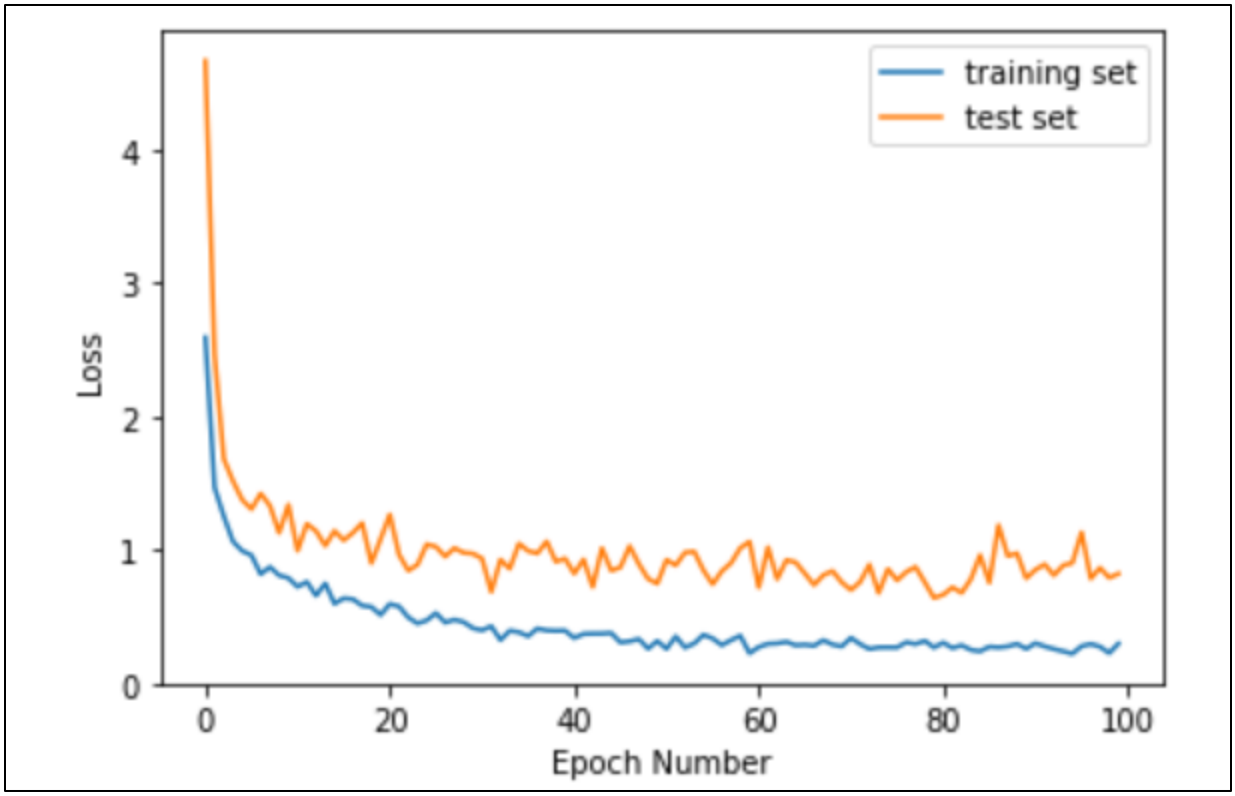


*Figure 25 Loss to epoch diagram after improvements*

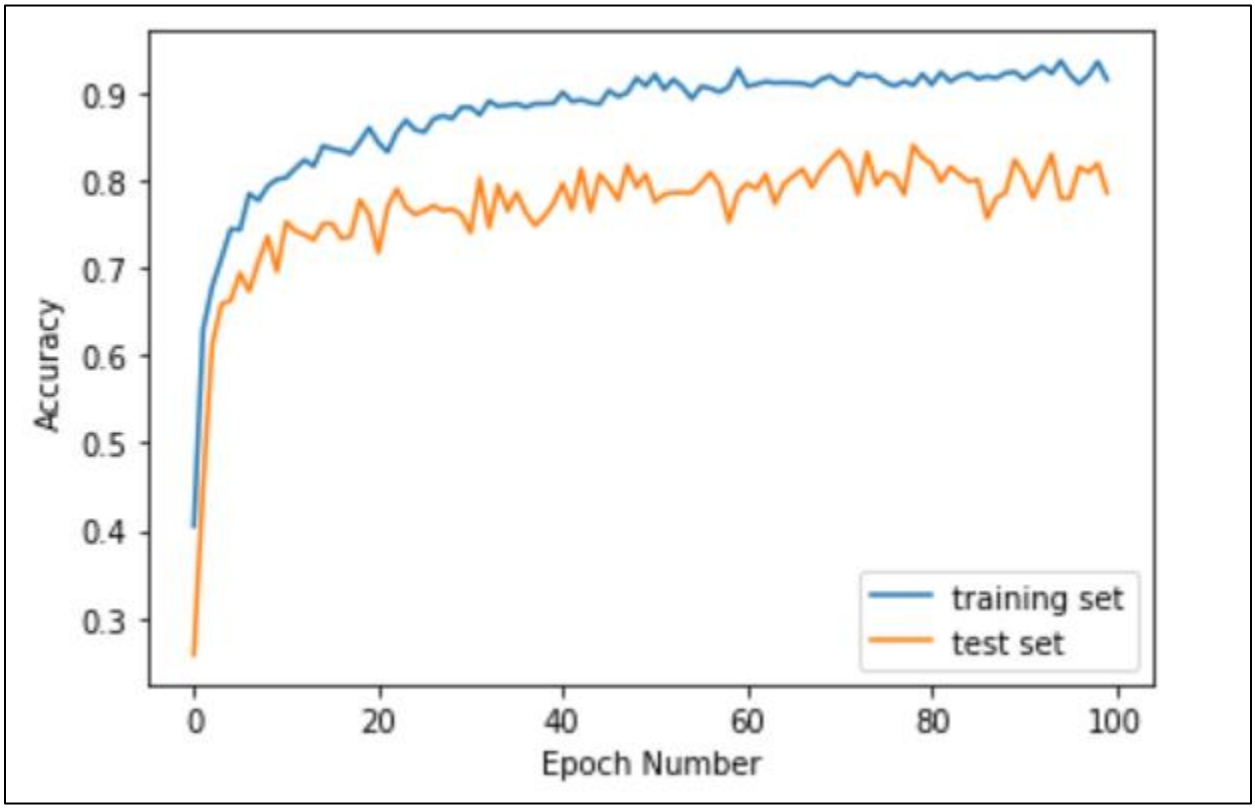


*Figure 26, Accuracy to epoch diagram after improvements*

# CHAPTER 5
# EXPERIMENTS AND RESULTS

## 5.1 Experiments

In building our machine learning model, we employed a variety of software and tools to create an effective solution. As the main platform, we chose to use Kaggle Notebook, a powerful and interactive environment for data science and machine learning. Kaggle Notebook provides a seamless user experience with a cloud-based platform, enabling us to develop, test and implement our model with ease.

The language that we used to build the model was Python, which has gained immense popularity in the field of data science and machine learning due to its simplicity and readability. Additionally, we leveraged HTML, JavaScript, and Flask to create a user-friendly interface for our model. HTML was used to create the basic structure and layout of the web page, while JavaScript was utilized to provide dynamic and interactive features. Flask, on the other hand, was used to create the backend server and handle data processing and communication between the frontend and backend.

In terms of libraries and tools, we utilized several libraries such as Tensorflow, Numpy, Pandas, and Matplotlib. Tensorflow is an open-source software library for machine learning and deep learning, which provides a comprehensive set of tools for building and training machine learning models. Numpy is a library for the Python programming language, used for mathematical and scientific computing, while Pandas is a library used for data manipulation and analysis. Matplotlib, on the other hand, is a plotting library for the Python programming language, used for creating visualizations of data.

Furthermore, we utilized other tools such as OpenCV, a library of programming functions mainly used for real-time computer vision, and Sklearn, a machine learning library for the Python programming language. These tools helped us to improve the performance and accuracy of our model and provided a comprehensive solution for our problem.

Finally, the dataset we used for our model was obtained from the Kaggle website. Kaggle is a well-known platform for data science and machine learning, providing a vast collection of datasets from various sources. Our dataset consisted of images of hand poses, which we used to train and test our model. With the combination of the aforementioned software and tools, and the use of the Kaggle dataset, we were able to build an effective and accurate machine learning model for our problem.

# 5.1 Final Improvements on the model

In order to further improve the model's performance, various modifications were made to the original architecture and data augmentation techniques were employed. The results of these modifications showed a significant increase in accuracy, with a final training accuracy of 95% and a validation accuracy of 87%. Despite not adding any additional layers to the model, the changes made to the data augmentation and model architecture were able to effectively improve its performance. These modifications serve as a testament to the importance of considering various techniques in improving the accuracy of a machine learning model.

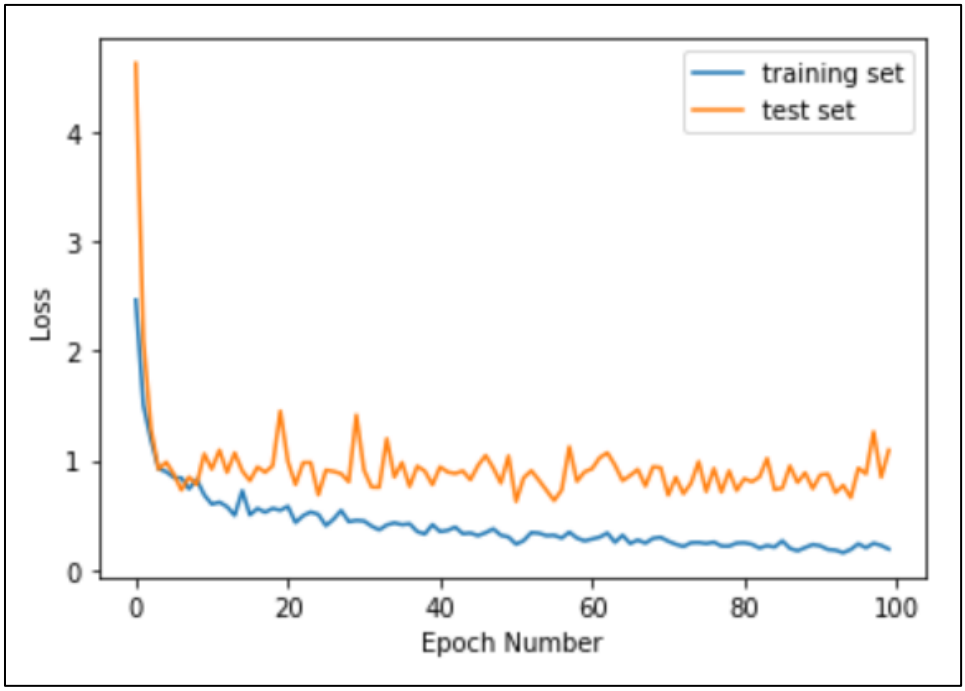


*Figure 27, Last improvements results epoch vs loss*

The loss decreased over the number of epochs, indicating improvement in the model's training process.

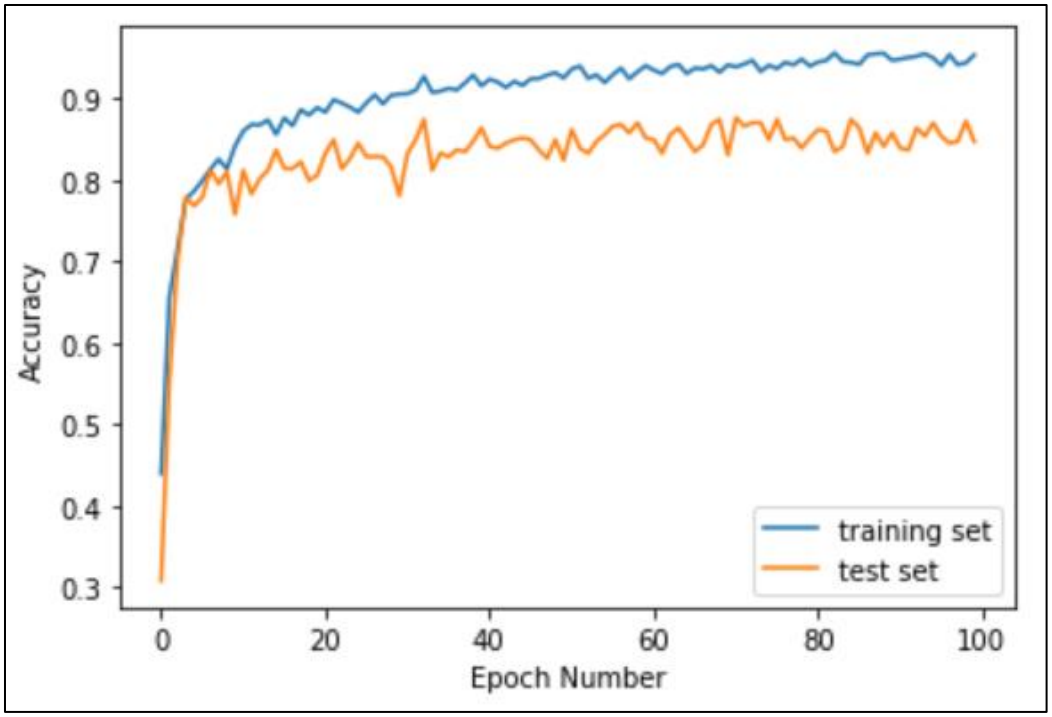


*Figure 28, Last improvements results Accuracy vs epoch*

A graph was created to display the change in accuracy as the number of epochs increased. The graph shows the trend of accuracy improvement as the model was trained for more epochs, indicating that the model was learning from the data and improving its prediction accuracy over time.

## 5.2 Results

The project was designed with a focus on creating an accessible and user-friendly interface for the deaf and mute community. The html page of the project is well organized, with a clear and concise layout that makes it easy to navigate. The page is comprised of several key components, including the project name, the King Abdulaziz University logo, a frame for the camera, and two buttons, "Start Camera" and "Take Photo".

The project name is prominently displayed at the top of the page, showcasing its significance and importance. The King Abdulaziz University logo is placed next to the project name, establishing its affiliation with the esteemed institution.

The camera frame is located in the middle of the page, and is the central component of the project. It is designed to open and display the camera feed when the "Start Camera" button is clicked,

allowing the user to easily capture an image. The "Take Photo" button is then used to capture the current camera frame and send it to the model for prediction.

To build the html page, we utilized several technologies, including HTML, CSS, and JavaScript. These technologies were chosen for their flexibility and ease of use, and were carefully combined to create a page that is both visually appealing and functional. The page is optimized for a smooth userexperience, with clear instructions and intuitive navigation, making it accessible for users of all skill levels.

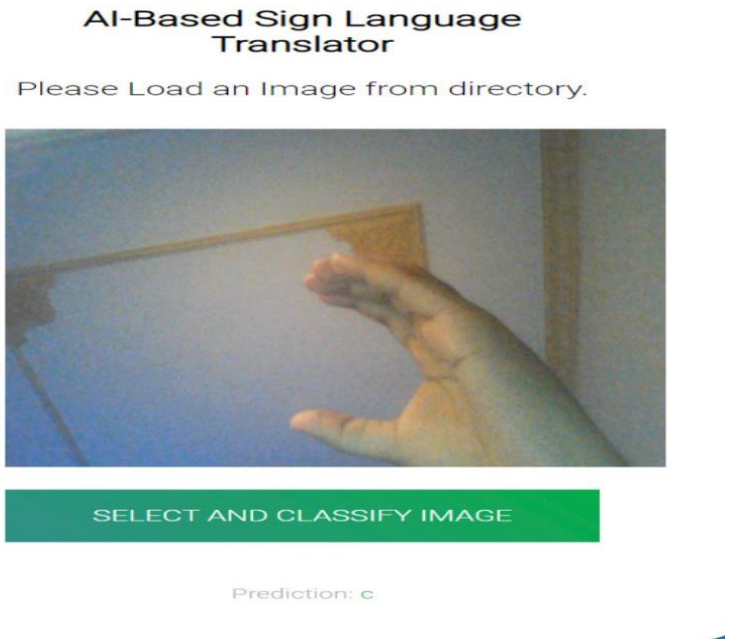


*Figure 29, HTML Page*

## 5.3 Testing the model

In this project, we tested the object detection model by providing it with real hand signs and observing its predictions. The results showed that the model was able to accurately detect and classify hand signs.

# CHAPTER 6
# CONCLUSION

## 6.1 Conclusion

In conclusion, this report has provided a comprehensive overview of the project aimed at addressing the barriers to communication faced by the deaf and mute community. The project utilized technology and programming languages to develop a solution that improved the quality of life for the deaf and mute community by providing equal opportunities for engagement and communication with the world around them. The results showed that the model was able to achieve a high level of accuracy, with an accuracy of 95% and a validation accuracy of 87%. The improvements made to the model through changes in data augmentation and modifications to the model structure contributed significantly to the improvement in accuracy. The results demonstrate the potential for using technology to bridge the communication gap for the deaf and mute community and to provide them with greater opportunities for engagement and communication. It is expected that further research and development in this area will lead to even more innovative solutions that will continue to improve the quality of life for the deaf and mute community.

## 6.2 Future Work

There are several possible future work that can be done to improve The project:

**Fine-tuning a pre-trained model** - Pre-trained models are a great starting point for many projects, but they may not perform optimally on a specific dataset. Fine-tuning a pre-trained model involves updating its weights to better fit the target data.

**Ensemble methods** - Ensemble methods are techniques that combine the predictions of multiple models to produce a better overall prediction. This can improve the performance of the model, especially in cases where the individual models make different errors.

**Hyperparameter tuning** - Hyperparameters are parameters that are not learned from the data, but instead are set by the user. It is important to tune these hyperparameters to get the best performance from a model. Grid search and random search are common methods for hyperparameter tuning.

**Exploring different models** - There are many different types of machine learning models, each with their own strengths and weaknesses. Exploring different models and comparing their performance on the target data can help identify the best model for a specific project.

**Data augmentation** - Data augmentation is a technique that artificially increases the size of the training data by creating new samples from the existing data. This can help to reduce overfitting and improve the generalization of the model.

## 6.3 References


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