REAL-TIME COMMUNICATION SYSTEM POWERED BY AI FOR SPECIALLY ABIED

NALAIYA THIRAN PROJECT REPORT

IBM-Project-9389-1658999257

Team ID: PNT2022TMID08443

Submitted by

M. PRADEEP	(814319104037)		
R. RAVI KUMAR	(814319104042)		
S. SUREN	(814319104055)		
K. VIGNESH	(814319104058)		

in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINNERING IN COMPUTER SCIENCE AND ENGINEERING

DHANALAKSHMI SRINIVASAN ENGINEERING COLLEGE (AUTONOMOUS) PERAMBALUR-621212

PROJECT REPORT

1. INTRODUCTION

- 1.1 Project Overview
- 1.2 Purpose

2. LITERATURE SURVEY

- 2.1 Existing problem
- 2.2 References
- 2.3 Problem Statement Definition

3. IDEATION & PROPOSED SOLUTION

- 3.1 Empathy Map Canvas
- 3.2 Ideation & Brainstorming
- 3.3 Proposed Solution
- 3.4 Problem Solution fit

4. REQUIREMENT ANALYSIS

- 4.1 Functional requirement
- 4.2 Non-Functional requirements

5. PROJECT DESIGN

- 5.1 Data Flow Diagrams
- 5.2 Solution & Technical Architecture
- 5.3 User Stories

6. PROJECT PLANNING & SCHEDULING

- 6.1 Sprint Planning & Estimation
- 6.2 Sprint Delivery Schedule
- 6.3 Reports from JIRA

7. CODING & SOLUTIONING

- 7.1 Feature 1
- 7.2 Feature 2

8. TESTING

- 8.1 Test Cases
- 8.2 User Acceptance Testing

9. RESULTS

9.1 Performance Metrics

10. ADVANTAGES & DISADVANTAGES

- 11. CONCLUSION
- 12. FUTURE SCOPE
- 13. APPENDIX

Source Code

GitHub & Project Demo Link

ABSTRACT

People with impaired speech and hearing uses Sign language as a form of communication. Disabled People use this sign language gestures as a tool of non-verbal communication to express their own emotions and thoughts to other common people. Conversing with people having a hearing disability is a major challenge. Deaf and Mute people use hand gesture sign language to communicate, hence normal people face problems in recognizing their language by signs made. Hence there is a need for systems that recognize the different signs and conveys the information to normal people. But these common people find it difficult to understand their expression, thus trained sign language expertise are needed during medical and legal appointment, educational and training session. Over the past few years, there has been an increase in demand for these services. Other form of services such as video remote human interpret using the high-speed Internet connection, has been introduced, thus these services provides an easy to use sign language interpret service, which can be used and benefited, yet have major limitations. To address this problem, we can implement artificial intelligence technology to analyse the user's hand with finger detection. In this proposed system we can design the vision based system in real time environments. And then using deep learning algorithm named as Convolutional neural network algorithm to classify the sign and provide the label about recognized sign.

1. INTRODUCTION

1.1 PROJECT OVERVIEW

Sign language recognition is the process of translating the user's gestures and signs into text. It aids those who are unable to interact with the general population in communication Using image processing methods and neural networks, the motion is mapped to pertinent text in the training data, transforming unprocessed photos and videos into text that can be read and understood. People who are dumb are typically prohibited from having regular conversations with other people in society. They sometimes struggle to communicate with regular people through gestures because the majority of people only recognise a small number of them. People who are deaf or have hearing loss are unable to communicate vocally, so they must frequently use some type of visual communication. The primary form of communication for the deaf and dumb community is sign language. Similar to other languages, it contains grammar and vocabulary, but it communicates primarily through images.

1.2 PURPOSE

The problem occurs when those who are stupid or deaf attempt to use these grammars of sign language to interact with others. This is because the majority of individuals are not familiar with these grammar standards. It has been noted that a foolish person can only communicate with members of his or her family or the deaf community. The popularity of international programmes and the financing they get highlight the value of sign language. In this age of technology, a computer-based solution is highly desired by the dumb community. Teaching a computer to recognise speech, facial expressions of emotion, and human gestures are some steps toward achieving this goal. Gestures are used to convey information nonverbally. Humans are capable of an endless amount of motions at any given moment. Since human motions are seen visually, computer vision researchers are particularly interested in them. The project's objective is to develop an HCI that can recognise human motions. These motions must be translated into machine language using a challenging programming process. In our paper, we concentrate on Image Processing and Template Matching for better output creation.

2. LITERATURE REVIEW

2.1 EXISTING PROBLEM

2.1.1 TITLE: A STUDY ON ARABIC SIGN LANGUAGE RECOGNITION FOR DIFERENTLY ABLED USING ADVANCED MACHINE LEARNING CLASSIFERS

AUTHOR: MOHAMMED MUSTAFA,2021.

Around 70 million people use sign language worldwide, and an automated method for translating it could significantly improve communication between sign language users and those who might not understand it. Nonverbal communication that includes the use of other bodily parts is called sign language. Face expressions, together with movements of the hands, eyes, and lips used in sign language communication to communicate information. People who have trouble hearing or speaking rely heavily on sign language as a form of communication in daily life. The inconsistent shape, size, and posture of the hands or fingers in an image was however shown by computer translation of sign language, which was highly complicated. SLR can be used in two main ways: based on picture or sensor. The main advantage of image-based frameworks is that people do not need to use complicated equipment. In any case, the preprocessing process necessitates large computations. Sensors frameworks use gloves fitted with sensors rather of relying just on cameras. Like spoken language, sign language does not confined to a certain location or region. It is trained differently over the world (Shin et al. 2019). It is sometimes referred to as Chinese Sign Language, American Sign Language, African Sign Language, and Arabic Sign Language (ArSL). India does not have a standardised sign language with important modifications, unlike sign languages in Europe and America. However, a dictionary of ISL was just created by Coimbatore's Vivekananda University for the Ramakrishna Missions. there are nearly there are currently 2037 signs available in Indian Sign Language (ISL). Similar to how SLR models are separated into sensor glove based and visionbased categories. Recent research on SLR can be divided into contact-based and vision-based methods. Physical interaction between sensing devices is a component of the contact-based technique and clients. It often employs an instrumented glove that uses electromyography, inertial estimation, electromagnetic to capture information on the executed sign's position, extension, direction, and angle.

2.1.2 TITLE: SIGN LANGUAGE TRANSFORMERS: JOINT END-TO-END SIGN LANGUAGE RECOGNITION AND TRANSLATION

AUTHOR: NECATI CIHAN CAMG"OZ, 2021.

The translation is improved by having a mid-level sign gloss representation, which efficiently recognises the various signs, according to earlier research on sign language translation. Performance significantly In fact, gloss level tokenization is necessary for the state-of-the-art in translation to function. We present a unique architecture based on transformers that simultaneously learns Continuous Sign Language Recognition and Translation while being end-to-end trainable. This is accomplished by combining the recognition and translation issues into a single, unified architecture employing a Connectionist Temporal Classification (CTC) loss. This collaborative approach achieves significant performance improvements while simultaneously resolving two related sequence-to-sequence learning problems without the need for ground-truth timing information. The primary form of communication for the Deaf community is sign language, which is their native tongue. They use a variety of complementing channels as visual languages to communicate ideas. This comprises both manual and non-manual characteristics, such as head, shoulder, and torso movement as well as manual characteristics like hand shape, movement, and stance. The purpose of sign language translation is to either extract an equivalent spoken language sentence from written text or translate written text into a video of signs. A clip of someone doing the continuous sign. However, a large portion of this latter work is done in the field of computer vision, where linguists refer to these channels as articulators. Word embedding with spatial embedding has concentrated on understanding the order of sign glosses rather than providing a complete translation into a spoken language counterpart (Sign Language Translation, or SLT). This distinction is crucial because spoken and sign languages have significantly different grammatical structures. Word order variations, the use of multiple channels to convey simultaneous information, and the use of direction and space to indicate the relationships between objects are just a few examples of these differences.

2.1.3 TITLE: SIGN LANGUAGE RECOGNITION SYSTEMS: A DECADE SYSTEMATIC LITERATURE REVIEW

AUTHOR: ANKITA WADHAWAN,2020.

As spoken languages are pronounced with the lips and heard with the ear, they utilise the "vocal-auditory" channel. Additionally, all writing systems come from, or are spoken languages' representations. Because they use the "corporalvisual" channel, which is created with the body and perceived with the eyes, sign languages (SLs) are unique. SLs are widely used by the deaf communities but are not internationally recognized. They are considered natural languages because deaf people can spontaneously gather and communicate with one another anywhere. SLs have independent vocabularies and grammatical structures and are not descended from spoken languages. The signs that the deaf use actually have the same internal structure as spoken words. The signs of SLs are produced using a small number of different sounds, just as hundreds of thousands of English words are. A fixed number of gestural characteristics. As a result, signs are not complete gestures but rather can be analysed as a collection of linguistically important characteristics. A gloss, the basic component of an SL and the closest representation of a sign's meaning, is made up of combinations of the aforementioned qualities. SLs, comparable to the spoken ones contain a list of grammatically flexible rules that apply to both manual and non-manual elements. Signers utilise both of them concurrently (and frequently with a flexible temporal structure) to create phrases in an SL. A particular feature may be the most important consideration when interpreting a gloss, depending on the context. It can change a verb's meaning, provide spatial and temporal context, and distinguish between things and people. A signer's glosses can be inferred from video recordings using a process known as sign language recognition (SLR). Despite the fact that there is a lot of labour, There is a severe paucity of comprehensive experimental research in the subject of SLR. Additionally, most articles don't release their code or present findings from all available datasets. As a result, experimental findings in the field of SL are rarely repeatable and interpretable.

2.1.4 TITLE: A COMPREHENSIVE STUDY ON SIGN LANGUAGE RECOGNITION METHODS

AUTHOR: NIKOLAS ADALOGLOU,2020

The sign language is used widely by people who are deaf-dumb these are used as a medium for communication. A sign language is nothing but composed of various gestures formed by different shapes of hand, its movements, orientations as well as the facial expressions. There are around 466 million people worldwide with hearing loss and 34 million of these are children. `Deaf' people have very little or no hearing ability. They use sign language for communication. People use different sign languages in different parts of the world. Compared to spoken languages they are very less in number. In existing system, lack of datasets along with variance in sign language with locality has resulted in restrained efforts in finger gesture detection. Existing project aims at taking the basic step in bridging the communication gap between normal people and deaf and dumb people using Indian sign language. Effective extension of this project to words and common expressions may not only make the deaf and dumb people communicate faster and easier with outer world, but also provide a boost in Developing autonomous systems for understanding and aiding them. The Indian Sign Language lags behind its American Counterpart as the research in this field is hampered by the lack of standard datasets. In addition to the intrinsic challenges of human motion analysis (such as variations in the participants' appearances, the characteristics of the human silhouette, and the execution of the repetition of operations, the presence of obstructions, etc.) A signer's glosses can be inferred from video recordings using a process known as sign language recognition (SLR). Despite the fact that there is a lot of labour, There is a severe paucity of comprehensive experimental research in the subject of SLR. Additionally, most articles don't release their code or present findings from all available datasets.

2.1.5 TITLE: TRANSFERRING CROSS-DOMAIN KNOWLEDGE FOR VIDEO SIGN LANGUAGE RECOGNITION

AUTHOR: DONGXU LI,2020

As a fundamental sign language interpretation task, word-level sign language recognition (WSLR) aims to help deaf people communicate. However, WSLR is very difficult because it requires quick body movements, facial expressions, and complex, fine-grained hand gestures. Isolated Sign Words Web News Sign Words Localizer has been demonstrated recently using deep learning approaches. Our model learns domain-invariant characteristics to transfer knowledge from web news signs to WSLR models. Our model recognises the example frames in the figure as the signature that best captures the gesture on the WSLR job, their advantages. Although the largest existing datasets have a limited number of instances, e.g., on average 10 to 50 instances per word, annotating WSLR datasets requires domain-specific knowledge. This is significantly less than typical video datasets on action learning and recognition, for example. The sign recognition task's inadequate training data may cause overfitting or in some other way hinder WSLR's performance. Models under realistic circumstances. On the other hand, there are many readily available news videos with subtitles available online that could be useful for WSLR. Despite the availability of sign news videos, it is quite difficult to translate this knowledge to WSLR. First, there are no annotations of temporal location or categories and just flimsy labels for the presence of signs in subtitles. Furthermore, these labels are loud. In this study, we provide a technique for transferring cross-domain knowledge from news signs to WSLR models to enhance their performance. More specifically, using a base WSLR model in a sliding window fashion, we first create a sign word localizer to extract sign words. Then, we suggest jointly coarse-aligning two domains. Employing isolated and news indicators to train a classifier. We compute and store the centroid of each class of the coarsely-aligned new words in an external memory termed prototype memory after getting the representations of the coarselyaligned news words.

2.2 REFERENCES

- [1] Mohammed Mustafa, "A study on arabic sign language recognition for differently abled using advanced machine learning classifers",2020.
- [2] Necati Cihan Camg"oz, ": Sign language transformers: joint end-to-end sign language recognition and translation",2021.
- [3] Ankita Wadhawan, "Sign language recognition systems: a decade systematic literature review", 2020
- [4] Nikolas Adaloglou " a comprehensive study on sign language recognition methods",2020.
- [5] Dongxu li," transferring cross-domain knowledge for video sign language recognition",2020

2.3 PROBLEM STATEMENT DEFINITION

The sign language is used widely by people who are deaf-dumb these are used as a medium for communication. A sign language is nothing but composed of various gestures formed by different shapes of hand, its movements, orientations as well as the facial expressions. There are around 466 million people worldwide with hearing loss and 34 million of these are children. `Deaf' people have very little or no hearing ability. They use sign language for communication. People use different sign languages in different parts of the world. Compared to spoken languages they are very less in number. In existing system, lack of datasets along with variance in sign language with locality has resulted in restrained efforts in finger gesture detection. Existing project aims at taking the basic step in bridging the communication gap between normal people and deaf and dumb people using Indian sign language. Effective extension of this project to words and common expressions may not only make the deaf and dumb people communicate faster and easier with outer world, but also provide a boost in Developing autonomous systems for understanding and aiding them. The Indian Sign Language lags behind its American Counterpart as the research in this field is hampered by the lack of standard datasets

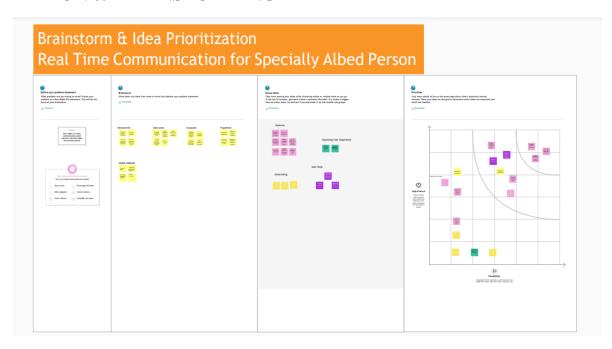
3. IDEATION & PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS

Specially Abled User Empathy Map Canvas



3.2 IDEATION & BRAINSTORMING



3.3 PROPOSED SOLUTION

In computer vision-based gesture recognition, the camera is used as input, and image processing is done before recognition. The techniques utilised to recognise the processed motions after that include Neural Network approaches and the region of interest algorithm. A vision-based sign language identification system has a fundamental drawback in that the process of gathering images is sensitive to a variety of environmental factors, including camera positioning, background circumstances, and lightning sensitivity. However, it is more practical and economical than using a camera and tracker to gather information. However, neural network techniques like the Hidden Markov Model are integrated with camera data for increased accuracy.

3.4 PROBLEM SOLUTION FIT

People who are deaf-dumb frequently employ sign language as a means of communicating. A sign language is nothing more than a collection of varied hand gestures created by varying hand shapes, movements, and orientations, as well as face expressions. 34 million of the 466 million people with hearing loss in the world's population are children. People who identify as "deaf" have very little or no hearing. They communicate using sign language. Around the world, many sign languages are used by people. They are quite few in number when compared to spoken languages. In computer vision-based gesture recognition, the camera is used as input, and image processing is done before recognition. The techniques utilised to recognise the processed motions after that include Neural Network approaches and the region of interest algorithm. A vision-based sign language identification system has a fundamental drawback in that the process of gathering images is sensitive to a variety of environmental factors, including camera positioning, background circumstances, and lightning sensitivity. However, it is more practical and economical than using a camera and tracker to gather information. However, neural network techniques like the Hidden Markov Model are integrated with camera data for increased accept.

4.REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENT

HAND IMAGE ACQUISITION:

The hand gesture, during daily life, is a natural communication method mostly used only among people who have some difficulty in speaking or hearing. However, a human computer interaction system based on gestures has various application scenarios. In this module, we can input the hand images from real time camera. The inbuilt camera can be connected to the system. Gesture recognition has become a hot topic for decades. Nowadays two methods are used primarily to perform gesture recognition. One is based on professional, wearable electromagnetic devices, like special gloves. The other one utilizes computer vision. The former one is mainly used in the film industry. It performs well but is costly and unusable in some environment. The latter one involves image processing. However, the performance of gesture recognition directly based on the features extracted by image processing is relatively limited. Hand image captured from web camera. The purpose of Web camera is to capture the human generated hand gesture and store its image in memory. The package called python framework is used for storing image in memory.

BINARIZATION

Background subtraction is one of the major tasks in the field of computer vision and image processing whose aim is to detect changes in image sequences. Background subtraction is any technique which allows an image's foreground to be extracted for further processing (object recognition etc.). Many applications do not need to know everything about the evolution of movement in a video sequence, but only require the information of changes in the scene, because an image's regions of interest are objects (humans, cars, text etc.) in its foreground. After the stage of image preprocessing (which may include image denoising, post processing like morphology etc.) object localization is required which may make use of this technique. Detecting foreground to separate these changes taking place in the foreground of the background. It is a set of techniques that typically analyze the video sequences in real time and are recorded with a stationary camera. All detection techniques are based on modeling the background of the image i.e. set the background and detect which changes occur. Defining the background can be very difficult when it contains shapes, shadows, and moving objects. In defining the background it is assumed that the stationary objects could vary in color and intensity over time. Scenarios where these techniques apply tend to be very diverse. There can be highly variable sequences, such as images with very different lighting, interiors, exteriors, quality, and noise. In addition to processing in real time, systems need to be able to adapt to these changes. The implement the techniques to extract the foreground from background image. Using Binarization approach to assign the values to background and foreground. Foreground pixels are identified in real time environments.

REGION OF FINGER DETECTION

Segmentation refers to the process of partitioning a digital image into multiple segments. In other words, grouping of pixels into different groups is known as Segmentation. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The division of an image into meaningful structures, image segmentation, is often an essential step in image analysis, object representation, visualization, and many other image processing tasks. But segmentation of a satellite image into differently textured regions (groups) is a difficult problem. One does not know a priori what types of textures exist in a satellite image, how many textures there are, and what regions have certain textures. The monitoring task can be performed by unsupervised segmentation and supervised segmentation techniques. A region of interest (ROI) is a subset of an image or a dataset identified for a particular purpose. In other words, region of interest (ROI) can be defined as a portion of an image which is needed to be filtered or to be performed some other operation on.

CLASSIFICATION OF FINGER GESTURES

Artificial Neural Networks (ANN) can learn and therefore can be trained to recognize patterns, find solutions, forecast future events and classify data. CNN is well documented to be used for traffic related tasks. Neural Networks learning and behavior is dependent on the way its individual computing elements are connected and by the strengths of these connections or weights. These weights can be adjusted automatically by training the network according to a specified learning rule until it performs the desired task correctly. CNN is a supervised learning method i.e. a machine learning algorithm that uses known dataset also known as training dataset. These known parameters help CNN to make predictions. Input data along with their response values are the fundamental components of a training dataset. In order to have higher predictive power and the ability to generalize for several new datasets, the best way is to use larger training datasets. The fingers can be classified by using convolutional neural network algorithm. CNN is a common method of training artificial neural networks so as to minimize the objective function. It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop).

SIGN RECOGNITION

Sign Language is a well-structured code gesture, every gesture has meaning assigned to it. Sign Language is the only means of communication for deaf people. With the advancement of science and technology many techniques have been developed not only to minimize the problem of deaf people but also to implement it in different fields. From the classification of sign features, label the signs with improved accuracy rate.

4.2 NON FUNCTIONAL REQUIREMENTS

Usability

The system shall allow the users to access the system with pc using web application. The system uses a web application as an interface. The system is user friendly which makes the system easy

Availability

The system is available 100% for the user and is used 24 hrs a day and 365 days a year. The system shall be operational 24 hours a day and 7 days a week.

Scalability

Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands.

Security

A security requirement is a statement of needed security functionality that ensures one of many different security properties of software is being satisfied.

Performance

The information is refreshed depending upon whether some updates have occurred or not in the application. The system shall respond to the member in not less than two seconds from the time of the request submittal. The system shall be allowed to take more time when doing large processing jobs. Responses to view information shall take no longer than 5 seconds to appear on the screen.

Reliability

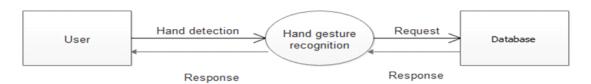
The system has to be 100% reliable due to the importance of data and the damages that can be caused by incorrect or incomplete data. The system will run 7 days a week. 24 hours a day.

5. PROJECT DESIGN

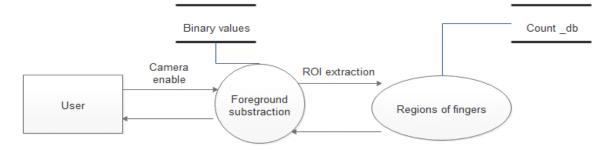
5.1 DATA FLOW DIAGRAMS

A data flow diagram is a two-dimensional diagram that explains how data is processed and transferred in a system. The graphical depiction identifies each source of data and how it interacts with other data sources to reach a common output. Individuals seeking to draft a data flow diagram must identify external inputs and outputs, determine how the inputs and outputs relate to each other, and explain with graphics how these connections relate and what they result in.

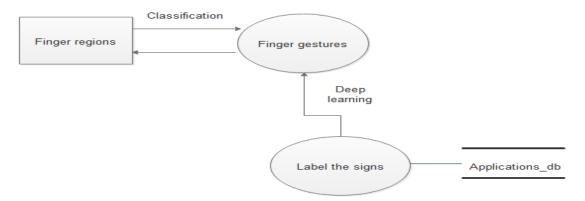
LEVEL 0:



Level 1:

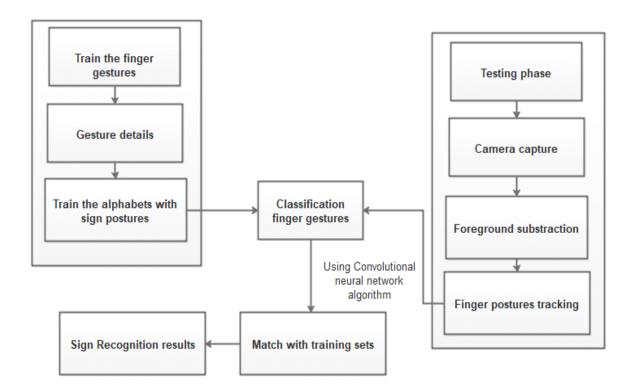


Level 2:



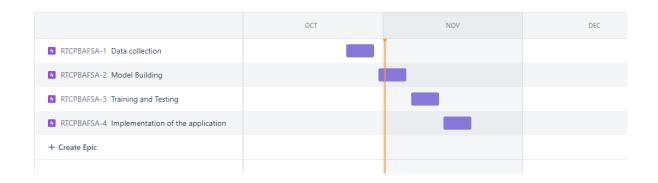
5.2 SOLUTION & TECHNICAL ARCHITECTURE

Software architecture involves the high level structure of software system abstraction, by using decomposition and composition, with architectural style and quality attributes. A software architecture design must conform to the major functionality and performance requirements of the system, as well as satisfy the non-functional requirements such as reliability, scalability, portability, and availability. Software architecture must describe its group of components, their connections, interactions among them and deployment configuration of all components.



6. PROJECT PLANNING & SCHEDULING

6.1SPRINT PLANNING & ESTIMATION



6.2 SPRINT DELIVERY SCHEDULE

Project Tracker, Velocity & Burndown Chart: (4 Marks)

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	10	6 Days	24 Oct 2022	29 Oct 2022	8	29 Oct 2022
Sprint-2	10	6 Days	31 Oct 2022	04 Nov 2022	5	04 Nov 2022
Sprint-3	10	6 Days	07 Nov 2022	11 Nov 2022	7	11 Nov 2022
Sprint-4	10	6 Days	14 Nov 2022	18 Nov 2022	5	18 Nov 2022

6.3 REPORTS FROM JIRA

JIRA has categorized reports in four levels, which are

- Agile
- Issue Analysis
- Forecast & Management
- Others

Velocity:

$$AV = \frac{sprint\ duration}{velocity}$$

$$AV = 6/10 = 0.6$$

Burndown chart:



SPRINT BURNDOWN



7. CODING & SOLUTION

7.1 FEATURE 1

```
import csv
import numpy as np
import tensorflow as tf
from sklearn.model selection import train test split
RANDOM SEED = 42
dataset = 'model/keypoint_classifier/keypoint.csv'
model_save_path = 'keypoint_classifier_new.h5'
NUM CLASSES = 26
X_dataset = np.loadtxt(dataset, delimiter=',', dtype='float32',
usecols=list(range(1, (21 * 2) + 1)))
y_dataset = np.loadtxt(dataset, delimiter=',', dtype='int32', usecols=(0))
print(len(X_dataset))
print(len(y_dataset))
print(y dataset)
print(X_dataset.shape)
train_ratio = 0.80
test_ratio = 0.20
X_train, X_test, y_train, y_test = train_test_split(X_dataset, y_dataset,
test_size=1-train_ratio, random_state=RANDOM_SEED)
model = tf.keras.models.Sequential([
    tf.keras.layers.Input((21 * 2, )),
    tf.keras.layers.Dropout(0.2),
tf.keras.layers.Dense(20, activation='relu'),
    tf.keras.layers.Dropout(0.4),
    tf.keras.layers.Dense(10, activation='relu'),
    tf.keras.layers.Dense(NUM_CLASSES, activation='softmax')
1)
model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['ac
curacy'])
cp callback = tf.keras.callbacks.ModelCheckpoint(model save path, verbose=1,
 save weights only=False)
es callback = tf.keras.callbacks.EarlyStopping(patience=20, verbose=1)
model.summary()
hist=model.fit(X_train,y_train,epochs=500,batch_size=128,validation_data=(X_test,
y_test),callbacks=[cp_callback, es_callback])
```

```
import matplotlib.pyplot as plt
scores = model.evaluate(X_test,y_test, verbose=0)
#print("CNN Error: %.2f%%" % (100 - scores[1] * 100))
model.save(model_save_path,include_optimizer=False)
plt.plot(hist.history['accuracy'])
plt.plot(hist.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
from keras.models import load model
from sklearn.metrics import classification report, confusion matrix
import numpy as np
import time
import matplotlib.pyplot as plt
def plot confusion matrix(cm,
                           target_names,
                           title='Confusion matrix',
                           cmap=None,
                           normalize=True):
    import itertools
    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy
    if cmap is None:
        cmap = plt.get_cmap('Blues')
    plt.figure(figsize=(20, 20))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.4f}".format(cm[i, j]),
```

```
color="white" if cm[i, j] > thresh else "black")
            plt.text(j, i, "{:,}".format(cm[i, j]),
                      color="white" if cm[i, j] > thresh else "black")
    plt.tight layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label\naccuracy={:0.4f};
misclass={:0.4f}'.format(accuracy, misclass))
    plt.savefig('model/keypoint_classifier/confusion_matrix.png')
model = load_model('model/keypoint_classifier/keypoint_classifier_new.h5')
pred_labels=[]
start_time = time.time()
pred_probabs = model.predict(X_test)
end time = time.time()
pred_time = end_time - start_time
avg_pred_time = pred_time / X_test.shape[0]
print('Average prediction time: %fs' % (avg_pred_time))
for pred probabs in pred probabs:
    pred labels.append(list(pred probab).index(max(pred probab)))
cm = confusion_matrix(y_test, np.array(pred_labels))
classification_report = classification_report(y_test, np.array(pred_labels))
print('\n\nClassification Report')
print('----
print(classification_report)
plot_confusion_matrix(cm, range(26), normalize=False)
```

7.2 FEATURE 2

```
from flask import Flask, render_template, flash, request, session
from flask import render_template, redirect, url_for, request
import smtplib
app = Flask(__name__)
app.config.from_object(__name__)
app.config['SECRET_KEY'] = '7d441f27d441f27567d441f2b6176a'
app.config['DEBUG']
@app.route("/")
def homepage():
    return render template('index.html')
@app.route("/UserLogin")
def UserLogin():
    return render template('UserLogin.html')
@app.route("/start", methods=['GET', 'POST'])
def start():
    if request.method == 'POST':
        import csv
        import copy
        import mediapipe as mp
        from model import KeyPointClassifier
        from app files import calc landmark list, draw info text, draw landmarks,
get_args, pre_process_landmark
        from PIL import Image, ImageDraw, ImageFont
        import numpy as np
        args = get_args()
        cap_device = args.device
        cap_width = args.width
        cap_height = args.height
        use_static_image_mode = args.use_static_image_mode
        min_detection_confidence = args.min_detection_confidence
        min_tracking_confidence = args.min_tracking_confidence
        cap = cv.VideoCapture(cap device)
        cap.set(cv.CAP_PROP_FRAME_WIDTH, cap_width)
        cap.set(cv.CAP PROP FRAME HEIGHT, cap height)
        mp_hands = mp.solutions.hands
        hands = mp_hands.Hands(
                    image_mode=use_static_image_mode,
```

```
min_detection_confidence=min_detection_confidence,
            min_tracking_confidence=min_tracking_confidence,
        keypoint_classifier = KeyPointClassifier()
encoding='utf-8-sig') as f:
            keypoint_classifier_labels = csv.reader(f)
            keypoint classifier labels = [
                row[0] for row in keypoint_classifier_labels
        flag = 0
        import win32com.client as wincl
        speak = wincl.Dispatch("SAPI.SpVoice")
        while True:
            key = cv.waitKey(10)
            if key == 27: # ESC
                break
            ret, image = cap.read()
            if not ret:
                break
            image = cv.flip(image, 1)
            debug_image = copy.deepcopy(image)
            # print(debug image.shape)
            # cv.imshow("debug_image",debug_image)
            image = cv.cvtColor(image, cv.COLOR_BGR2RGB)
            image.flags.writeable = False
            results = hands.process(image)
            image.flags.writeable = True
            if results.multi_hand_landmarks is not None:
                for hand_landmarks, handedness in
zip(results.multi_hand_landmarks, results.multi_handedness):
                    landmark_list = calc_landmark_list(debug_image,
hand_landmarks)
                    pre_processed_landmark_list =
pre_process_landmark(landmark_list)
                    hand_sign_id =
keypoint_classifier(pre_processed_landmark_list)
                    debug_image = draw_landmarks(debug_image, landmark_list)
                    flag += 1
                    print(flag)
                    if (flag == 100):
                        flag = 0
                        speak.Speak(keypoint_classifier_labels[hand_sign_id])
                    debug image = draw info text(
```

8. TESTING

8.1 TEST CASES

A test case has components that describe input, action and an expected response, in order to determine if a feature of an application is working correctly. A test case is a set of instructions on "HOW" to validate a particular test objective/target, which when followed will tell us if the expected behavior of the system is satisfied or not.

Characteristics of a good test case:

• Accurate: Exacts the purpose.

• Economical: No unnecessary steps or words.

• Traceable: Capable of being traced to requirements.

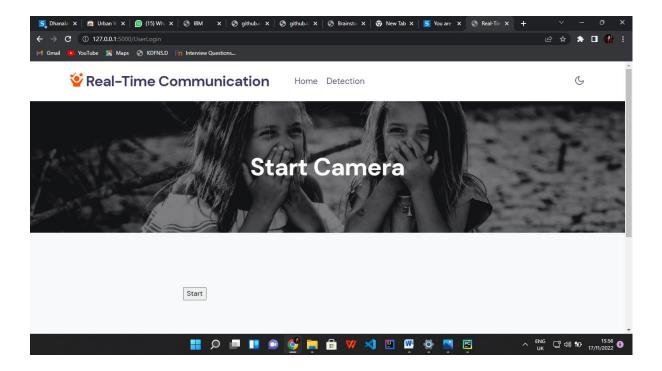
• Repeatable: Can be used to perform the test over and over.

• Reusable: Can be reused if necessary

S.N	FUNCTION	DESCRIPTIO	EXPECTE	ACTUA	STATU
\mathbf{O}		N	D OUTPUT	L	S
				OUTPU	
				T	
1	Framework	Generate the	Individual	Individual	Success
	construction	GUI for admin	page for	page for	
		and user	admin and	admin	
			user	and user	
2	Read the	Comments	Comments	Comment	Success
	comments	Analysis	in text	s in text	
			format	format	
3	Classification	Classify the	Finger	Finger	Success
		Datasets	Gestures	Gestures	
4	Rules	Block the	Block the	Block the	Success
	implementatio	comments and	users	users	
	n	friends			

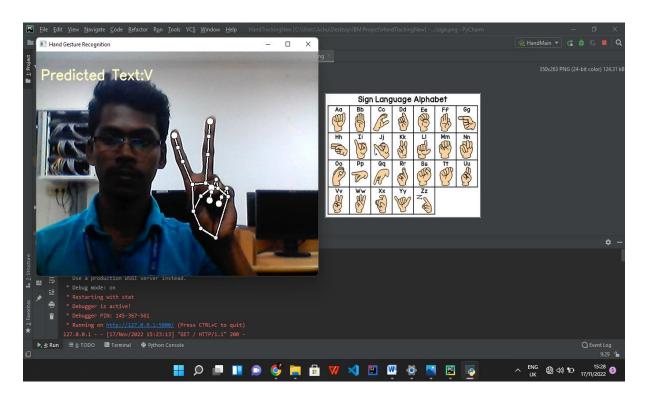
8.2 USER ACCEPTANCE TESTING

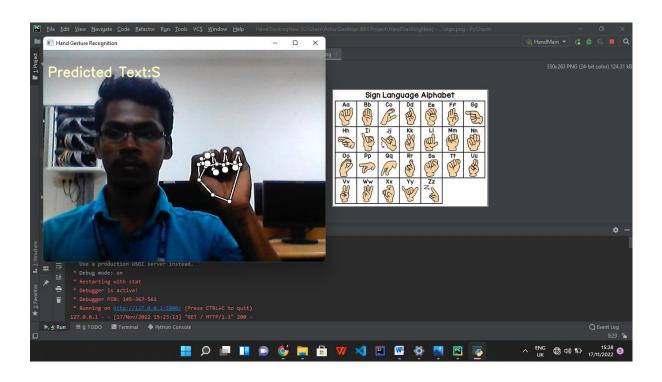
Acceptance testing can be defined in many ways, but a simple definition is the succeeds when the software functions in a manner that can be reasonable expected by the customer. After the acceptance test has been conducted, one of the two possible conditions exists. This is to fine whether the inputs are accepted by the database or other validations. For example accept only numbers in the numeric field, date format data in the date field. Also the null check for the not null fields. If any error occurs then show the error messages. The function of performance characteristics to specification and is accepted. A deviation from specification is uncovered and a deficiency list is created. User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.



9. RESULTS

9.1 PERFORMANCE METRICS





10. ADVANTAGES & DISADVANTAGES

DISADVANTAGES

- Need hardware control to detect the hands
- Hand segmentation become complex of various backgrounds
- Segmentation accuracy is less in hand tracking

ADVANTAGES

- Segmentation accuracy is high
- Easy to detect the finger postures
- Track fingers and sign recognition with less computational steps
- No need for additional hardware system

11. CONCLUSION

The ability to look, listen, talk, and respond appropriately to events is one of the most valuable gifts a human being can have. However, some unfortunate people are denied this opportunity. People get to know one another through sharing their ideas, thoughts, and experiences with others around them. There are several ways to accomplish this, the best of which is the gift of "Speech." Everyone can very persuasively transfer their thoughts and comprehend each other through speech. Our initiative intends to close the gap by including a low-cost computer into the communication chain, allowing sign language to be captured, recognised, and translated into speech for the benefit of blind individuals. An image processing technique is employed in this paper to recognise the handmade movements. This application is used to present a modern integrated planned system for hear impaired people. The camera-based zone of interest can aid in the user's data collection. Each action will be significant in its own right.

12. FUTURE SCOPE

Despite it having average accuracy, our system is still well-matched with the existing systems, given that it can perform recognition at the given accuracy with larger vocabularies and without an aid such as gloves or hand markings. In future, we can extend the framework to implement various deep learning algorithms to recognize the signs and implement in real time applications.

13. APPENDIX

SOURCE CODE

from flask import Flask, render_template, flash, request, session from flask import render template, redirect, url for, request

```
import smtplib
      app = Flask(__name__)
     app.config.from_object(__name__)
     app.config['SECRET_KEY'] = '7d441f27d441f27567d441f2b6176a'
    app.config['DEBUG']
     @app.route("/")
     def homepage():
       return render_template('index.html')
     @app.route("/UserLogin")
     def UserLogin():
       return render_template('UserLogin.html')
@app.route("/start", methods=['GET', 'POST'])
     def start():
       error = None
       if request.method == 'POST':
         import csv
         import copy
         import cv2 as cv
         import mediapipe as mp
```

```
from model import KeyPointClassifier
    from app files import calc landmark list, draw info text,
draw_landmarks, get_args, pre_process_landmark
    from PIL import Image, ImageDraw, ImageFont
    import numpy as np
   args = get_args()
    cap_device = args.device
    cap_width = args.width
    cap_height = args.height
    use_static_image_mode = args.use_static_image_mode
    min_detection_confidence = args.min_detection_confidence
    min tracking confidence = args.min tracking confidence
    cap = cv.VideoCapture(cap_device)
    cap.set(cv.CAP_PROP_FRAME_WIDTH, cap_width)
    cap.set(cv.CAP_PROP_FRAME_HEIGHT, cap_height)
    mp_hands = mp.solutions.hands
    hands = mp_hands.Hands(
      static image mode-use static image mode,
      max_num_hands=1,
      min_detection_confidence=min_detection_confidence,
      min tracking confidence=min tracking confidence,
```

)

```
keypoint_classifier = KeyPointClassifier()
```

```
with
open('model/keypoint_classifier_label.csv',
encoding='utf-8-sig') as f:
      keypoint_classifier_labels = csv.reader(f)
      keypoint_classifier_labels = [
        row[0] for row in keypoint_classifier_labels
      1
    flag = 0
    import win32com.client as wincl
    speak = wincl.Dispatch("SAPI.SpVoice")
    while True:
      key = cv.waitKey(10)
      if key == 27: # ESC
        break
      ret, image = cap.read()
      if not ret:
         break
      image = cv.flip(image, 1)
      debug_image = copy.deepcopy(image)
      # print(debug_image.shape)
      # cv.imshow("debug_image",debug_image)
```

```
image.flags.writeable = False
      results = hands.process(image)
      image.flags.writeable = True
      if results.multi hand landmarks is not None:
         for hand_landmarks, handedness in
zip(results.multi_hand_landmarks, results.multi_handedness):
           landmark list = calc landmark list(debug image,
hand landmarks)
           # print(hand_landmarks)
           pre_processed_landmark_list =
pre_process_landmark(landmark_list)
           hand_sign_id =
keypoint_classifier(pre_processed_landmark_list)
           debug_image = draw_landmarks(debug_image,
landmark list)
           flag += 1
           print(flag)
           if (flag == 100):
             flag = 0
             speak.Speak(keypoint_classifier_labels[hand_sign_id])
           debug_image = draw_info_text(
```

image = cv.cvtColor(image, cv.COLOR_BGR2RGB)

```
debug_image,
                handedness,
                keypoint_classifier_labels[hand_sign_id])
         cv.imshow('Hand Gesture Recognition', debug_image)
       cap.release()
       cv.destroyAllWindows
        return render_template('UserLogin.html')
   if __name__ == '__main__':
app.run(debug=True, use_reloader=True)
   import mediapipe as mp
   import cv2
   import numpy as np
   import uuid
   import os
   "import subprocess as sp
   programName = "notepad.exe"
   #fileName = "sms.txt"
   #sp.Popen([programName, fileName])
   sp.Popen([programName])'''
   mp_drawing = mp.solutions.drawing_utils
   mp_hands = mp.solutions.hands
   cap = cv2.VideoCapture(0)
```

```
with mp_hands.Hands(min_detection_confidence=0.8,
min tracking confidence=0.5) as hands:
  while cap.isOpened():
    ret, frame = cap.read()
    #BGR 2 RGB
    image = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
    # Flip on horizontal
    image = cv2.flip(image, 1)
    # Set flag
    image.flags.writeable = False
    # Detections
    results = hands.process(image)
    # Set flag to true
    image.flags.writeable = True
    #RGB 2BGR
    image = cv2.cvtColor(image, cv2.COLOR_RGB2BGR)
   # print(results)
    # Rendering results
    if results.multi_hand_landmarks:
      for num, hand in enumerate(results.multi_hand_landmarks):
```

$mp_drawing.draw_landmarks (image, hand, \\ mp_hands.HAND_CONNECTIONS,$

 $mp_drawing. DrawingSpec(color=(14,\ 22,\ 76),\ thickness=2,\ circle_radius=4),$

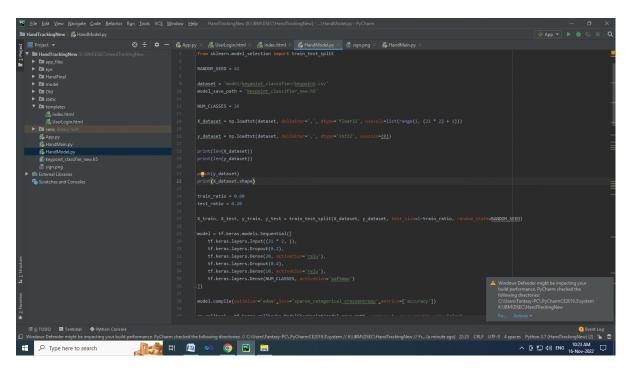
mp_drawing.DrawingSpec(color=(24, 44, 250), thickness=2, circle_radius=2),

cv2.imshow('Hand Tracking', image)

if cv2.waitKey(10) & 0xFF == ord('q'): break

cap.release()

cv2.destroyAllWindows()



2022-11-16 10:23:27.058620: W

tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_110.dll'; dlerror: cudart64_110.dll not found

2022-11-16 10:23:27.059995: I

tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.

18256

18256

[0 0 0 ... 25 25 25]

(18256, 42)

2022-11-16 10:23:45.396541: W

tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'nvcuda.dll'; dlerror: nvcuda.dll not found

2022-11-16 10:23:45.405263: W

tensorflow/stream_executor/cuda/cuda_driver.cc:269] failed call to cuInit: UNKNOWN ERROR (303)

2022-11-16 10:23:45.425596: I

tensorflow/stream_executor/cuda/cuda_diagnostics.cc:169] retrieving CUDA diagnostic information for host: DESKTOP-9BF8NUN

2022-11-16 10:23:45.426393: I

tensorflow/stream_executor/cuda/cuda_diagnostics.cc:176] hostname: DESKTOP-9BF8NUN

2022-11-16 10:23:45.472047: I

tensorflow/core/platform/cpu_feature_guard.cc:151] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations: AVX AVX2

To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.

Model: "sequential"

Layer (type) Output Shape Param #

=======

dropout (Dropout)	(None, 42)	0	
dense (Dense)	(None, 20)	860	
dropout_1 (Dropout)	(None, 20)	0	
dense_1 (Dense)	(None, 10)	210	
dense_2 (Dense)	(None, 26)	286	
	========	========	=======================================
Total params: 1,356 Trainable params: 1,356			
Non-trainable params: 0			
_			
Epoch 1/500			
110/115 [===================================			
Epoch 00001: saving model to keypoint_classifier_new.h5			
115/115 [===================================			
Epoch 2/500			
92/115 [===================================			
Epoch 00002: saving model to keypoint_classifier_new.h5			
115/115 [=======] - 0s 2ms/step - loss: 2.8336 - accuracy: 0.1576 - val_loss: 2.5658 - val_accuracy: 0.2393			

```
Epoch 3/500
accuracy: 0.1987
Epoch 00003: saving model to keypoint_classifier_new.h5
2.5600 - accuracy: 0.2045 - val_loss: 2.1658 - val_accuracy: 0.4291
Epoch 4/500
accuracy: 0.2660
Epoch 00004: saving model to keypoint_classifier_new.h5
2.2942 - accuracy: 0.2716 - val_loss: 1.8626 - val_accuracy: 0.5112
Epoch 5/500
accuracy: 0.3141
Epoch 00005: saving model to keypoint_classifier_new.h5
2.1152 - accuracy: 0.3181 - val_loss: 1.6628 - val_accuracy: 0.5271
Epoch 6/500
accuracy: 0.3447
Epoch 00006: saving model to keypoint_classifier_new.h5
1.9914 - accuracy: 0.3452 - val_loss: 1.5173 - val_accuracy: 0.5999
Epoch 7/500
accuracy: 0.3737
Epoch 00007: saving model to keypoint_classifier_new.h5
1.9015 - accuracy: 0.3768 - val_loss: 1.3988 - val_accuracy: 0.6465
```

```
Epoch 8/500
accuracy: 0.3854
Epoch 00008: saving model to keypoint_classifier_new.h5
1.8250 - accuracy: 0.3900 - val_loss: 1.3196 - val_accuracy: 0.6525
Epoch 9/500
accuracy: 0.4152
Epoch 00009: saving model to keypoint_classifier_new.h5
1.7564 - accuracy: 0.4185 - val_loss: 1.2383 - val_accuracy: 0.6585
Epoch 10/500
accuracy: 0.4237
Epoch 00010: saving model to keypoint_classifier_new.h5
1.7084 - accuracy: 0.4285 - val_loss: 1.1719 - val_accuracy: 0.7065
Epoch 11/500
accuracy: 0.4456
Epoch 00011: saving model to keypoint_classifier_new.h5
1.6624 - accuracy: 0.4440 - val_loss: 1.1348 - val_accuracy: 0.7347
Epoch 12/500
accuracy: 0.4604
Epoch 00012: saving model to keypoint_classifier_new.h5
1.6145 - accuracy: 0.4614 - val_loss: 1.0654 - val_accuracy: 0.7226
```

```
Epoch 13/500
accuracy: 0.4662
Epoch 00013: saving model to keypoint_classifier_new.h5
1.5992 - accuracy: 0.4672 - val_loss: 1.0411 - val_accuracy: 0.7511
Epoch 14/500
accuracy: 0.4733
Epoch 00014: saving model to keypoint_classifier_new.h5
1.5833 - accuracy: 0.4755 - val_loss: 1.0114 - val_accuracy: 0.7757
Epoch 15/500
accuracy: 0.4846
Epoch 00015: saving model to keypoint_classifier_new.h5
1.5573 - accuracy: 0.4850 - val_loss: 0.9931 - val_accuracy: 0.7933
Epoch 16/500
accuracy: 0.4942
Epoch 00016: saving model to keypoint_classifier_new.h5
1.5181 - accuracy: 0.4914 - val_loss: 0.9478 - val_accuracy: 0.8108
Epoch 17/500
accuracy: 0.5118
Epoch 00017: saving model to keypoint_classifier_new.h5
1.4872 - accuracy: 0.5097 - val_loss: 0.9215 - val_accuracy: 0.8379
```

```
Epoch 18/500
accuracy: 0.5140
Epoch 00018: saving model to keypoint_classifier_new.h5
1.4802 - accuracy: 0.5134 - val_loss: 0.8900 - val_accuracy: 0.8401
Epoch 19/500
accuracy: 0.5140
Epoch 00019: saving model to keypoint_classifier_new.h5
1.4632 - accuracy: 0.5136 - val_loss: 0.8831 - val_accuracy: 0.8442
Epoch 20/500
accuracy: 0.5307
Epoch 00020: saving model to keypoint_classifier_new.h5
1.4315 - accuracy: 0.5293 - val_loss: 0.8566 - val_accuracy: 0.8488
Epoch 21/500
accuracy: 0.5280
Epoch 00021: saving model to keypoint_classifier_new.h5
1.4121 - accuracy: 0.5301 - val_loss: 0.8331 - val_accuracy: 0.8535
Epoch 22/500
accuracy: 0.5400
Epoch 00022: saving model to keypoint_classifier_new.h5
1.3945 - accuracy: 0.5430 - val_loss: 0.8175 - val_accuracy: 0.8442
```

```
Epoch 23/500
accuracy: 0.5458
Epoch 00023: saving model to keypoint_classifier_new.h5
1.3813 - accuracy: 0.5473 - val_loss: 0.8004 - val_accuracy: 0.8502
Epoch 24/500
accuracy: 0.5403
Epoch 00024: saving model to keypoint_classifier_new.h5
1.3866 - accuracy: 0.5383 - val_loss: 0.8011 - val_accuracy: 0.8590
Epoch 25/500
accuracy: 0.5489
Epoch 00025: saving model to keypoint_classifier_new.h5
1.3556 - accuracy: 0.5495 - val_loss: 0.7652 - val_accuracy: 0.8647
Epoch 26/500
accuracy: 0.5460
Epoch 00026: saving model to keypoint_classifier_new.h5
1.3578 - accuracy: 0.5529 - val_loss: 0.7676 - val_accuracy: 0.8656
Epoch 27/500
accuracy: 0.5498
Epoch 00027: saving model to keypoint_classifier_new.h5
1.3498 - accuracy: 0.5503 - val_loss: 0.7649 - val_accuracy: 0.8683
```

```
Epoch 28/500
accuracy: 0.5545
Epoch 00028: saving model to keypoint_classifier_new.h5
1.3368 - accuracy: 0.5542 - val_loss: 0.7624 - val_accuracy: 0.8598
Epoch 29/500
accuracy: 0.5687
Epoch 00029: saving model to keypoint_classifier_new.h5
1.3222 - accuracy: 0.5650 - val_loss: 0.7400 - val_accuracy: 0.8850
Epoch 30/500
accuracy: 0.5628
Epoch 00030: saving model to keypoint_classifier_new.h5
1.3157 - accuracy: 0.5653 - val_loss: 0.7223 - val_accuracy: 0.8798
Epoch 31/500
accuracy: 0.5714
Epoch 00031: saving model to keypoint_classifier_new.h5
1.2907 - accuracy: 0.5679 - val_loss: 0.7276 - val_accuracy: 0.8639
Epoch 32/500
accuracy: 0.5664
Epoch 00032: saving model to keypoint_classifier_new.h5
1.3095 - accuracy: 0.5679 - val_loss: 0.7148 - val_accuracy: 0.8727
```

```
Epoch 33/500
accuracy: 0.5738
Epoch 00033: saving model to keypoint_classifier_new.h5
1.2880 - accuracy: 0.5731 - val_loss: 0.7160 - val_accuracy: 0.8946
Epoch 34/500
accuracy: 0.5785
Epoch 00034: saving model to keypoint_classifier_new.h5
1.2772 - accuracy: 0.5768 - val_loss: 0.7071 - val_accuracy: 0.8864
Epoch 35/500
accuracy: 0.5804
Epoch 00035: saving model to keypoint_classifier_new.h5
1.2640 - accuracy: 0.5800 - val_loss: 0.6843 - val_accuracy: 0.8951
Epoch 36/500
accuracy: 0.5781
Epoch 00036: saving model to keypoint_classifier_new.h5
1.2605 - accuracy: 0.5782 - val_loss: 0.6959 - val_accuracy: 0.8866
Epoch 37/500
accuracy: 0.5791
Epoch 00037: saving model to keypoint_classifier_new.h5
1.2700 - accuracy: 0.5788 - val_loss: 0.6757 - val_accuracy: 0.8836
```

```
Epoch 38/500
accuracy: 0.5785
Epoch 00038: saving model to keypoint_classifier_new.h5
1.2661 - accuracy: 0.5798 - val_loss: 0.6870 - val_accuracy: 0.8861
Epoch 39/500
accuracy: 0.5865
Epoch 00039: saving model to keypoint_classifier_new.h5
1.2666 - accuracy: 0.5863 - val_loss: 0.6776 - val_accuracy: 0.8886
Epoch 40/500
accuracy: 0.5819
Epoch 00040: saving model to keypoint_classifier_new.h5
1.2475 - accuracy: 0.5865 - val_loss: 0.6579 - val_accuracy: 0.8877
Epoch 41/500
accuracy: 0.5890
Epoch 00041: saving model to keypoint_classifier_new.h5
1.2407 - accuracy: 0.5900 - val_loss: 0.6638 - val_accuracy: 0.8907
Epoch 42/500
accuracy: 0.5897
Epoch 00042: saving model to keypoint_classifier_new.h5
1.2345 - accuracy: 0.5923 - val_loss: 0.6583 - val_accuracy: 0.8976
```

```
Epoch 43/500
accuracy: 0.5898
Epoch 00043: saving model to keypoint_classifier_new.h5
1.2389 - accuracy: 0.5894 - val_loss: 0.6443 - val_accuracy: 0.9017
Epoch 44/500
accuracy: 0.5895
Epoch 00044: saving model to keypoint_classifier_new.h5
1.2284 - accuracy: 0.5957 - val_loss: 0.6446 - val_accuracy: 0.8814
Epoch 45/500
accuracy: 0.5898
Epoch 00045: saving model to keypoint_classifier_new.h5
1.2342 - accuracy: 0.5920 - val_loss: 0.6420 - val_accuracy: 0.8894
Epoch 46/500
accuracy: 0.6007
Epoch 00046: saving model to keypoint_classifier_new.h5
1.2136 - accuracy: 0.5967 - val_loss: 0.6500 - val_accuracy: 0.8916
Epoch 47/500
accuracy: 0.5977
Epoch 00047: saving model to keypoint_classifier_new.h5
1.2161 - accuracy: 0.5987 - val_loss: 0.6331 - val_accuracy: 0.8990
```

```
Epoch 48/500
accuracy: 0.5997
Epoch 00048: saving model to keypoint_classifier_new.h5
1.2125 - accuracy: 0.5965 - val_loss: 0.6354 - val_accuracy: 0.8913
Epoch 49/500
accuracy: 0.5950
Epoch 00049: saving model to keypoint_classifier_new.h5
1.2094 - accuracy: 0.5958 - val_loss: 0.6305 - val_accuracy: 0.8896
Epoch 50/500
accuracy: 0.6036
Epoch 00050: saving model to keypoint_classifier_new.h5
1.2069 - accuracy: 0.6020 - val_loss: 0.6356 - val_accuracy: 0.8781
Epoch 51/500
accuracy: 0.6006
Epoch 00051: saving model to keypoint_classifier_new.h5
1.1921 - accuracy: 0.6004 - val_loss: 0.6250 - val_accuracy: 0.8905
Epoch 52/500
0.6040
Epoch 00052: saving model to keypoint_classifier_new.h5
1.1970 - accuracy: 0.6018 - val_loss: 0.6193 - val_accuracy: 0.8973
```

```
Epoch 53/500
accuracy: 0.6006
Epoch 00053: saving model to keypoint_classifier_new.h5
1.1867 - accuracy: 0.6040 - val_loss: 0.6195 - val_accuracy: 0.8905
Epoch 54/500
accuracy: 0.5999
Epoch 00054: saving model to keypoint_classifier_new.h5
1.1982 - accuracy: 0.6034 - val_loss: 0.6126 - val_accuracy: 0.9022
Epoch 55/500
accuracy: 0.6052
Epoch 00055: saving model to keypoint_classifier_new.h5
1.1891 - accuracy: 0.6052 - val_loss: 0.6119 - val_accuracy: 0.9025
Epoch 56/500
accuracy: 0.6090
Epoch 00056: saving model to keypoint_classifier_new.h5
1.1923 - accuracy: 0.6111 - val_loss: 0.6000 - val_accuracy: 0.8932
Epoch 57/500
accuracy: 0.6075
Epoch 00057: saving model to keypoint_classifier_new.h5
1.1847 - accuracy: 0.6083 - val_loss: 0.6094 - val_accuracy: 0.8847
```

```
Epoch 58/500
accuracy: 0.6047
Epoch 00058: saving model to keypoint_classifier_new.h5
1.1793 - accuracy: 0.6088 - val_loss: 0.5927 - val_accuracy: 0.9055
Epoch 59/500
accuracy: 0.6108
Epoch 00059: saving model to keypoint_classifier_new.h5
1.1726 - accuracy: 0.6128 - val_loss: 0.5974 - val_accuracy: 0.8883
Epoch 60/500
accuracy: 0.6074
Epoch 00060: saving model to keypoint_classifier_new.h5
1.1812 - accuracy: 0.6064 - val_loss: 0.5945 - val_accuracy: 0.8959
Epoch 61/500
accuracy: 0.6187
Epoch 00061: saving model to keypoint_classifier_new.h5
1.1763 - accuracy: 0.6180 - val_loss: 0.5959 - val_accuracy: 0.8954
Epoch 62/500
accuracy: 0.6126
Epoch 00062: saving model to keypoint_classifier_new.h5
1.1689 - accuracy: 0.6122 - val_loss: 0.6045 - val_accuracy: 0.8886
```

```
Epoch 63/500
accuracy: 0.6137
Epoch 00063: saving model to keypoint_classifier_new.h5
1.1605 - accuracy: 0.6163 - val_loss: 0.5836 - val_accuracy: 0.8938
Epoch 64/500
accuracy: 0.6141
Epoch 00064: saving model to keypoint_classifier_new.h5
1.1614 - accuracy: 0.6173 - val_loss: 0.5813 - val_accuracy: 0.8872
Epoch 65/500
accuracy: 0.6175
Epoch 00065: saving model to keypoint_classifier_new.h5
1.1624 - accuracy: 0.6152 - val_loss: 0.5924 - val_accuracy: 0.8927
Epoch 66/500
accuracy: 0.6192
Epoch 00066: saving model to keypoint_classifier_new.h5
1.1645 - accuracy: 0.6194 - val_loss: 0.5849 - val_accuracy: 0.8844
Epoch 67/500
accuracy: 0.6226
Epoch 00067: saving model to keypoint_classifier_new.h5
1.1431 - accuracy: 0.6238 - val_loss: 0.5791 - val_accuracy: 0.8823
```

```
Epoch 68/500
accuracy: 0.6123
Epoch 00068: saving model to keypoint_classifier_new.h5
1.1443 - accuracy: 0.6172 - val_loss: 0.5880 - val_accuracy: 0.8875
Epoch 69/500
accuracy: 0.6295
Epoch 00069: saving model to keypoint_classifier_new.h5
1.1328 - accuracy: 0.6270 - val_loss: 0.5684 - val_accuracy: 0.8951
Epoch 70/500
accuracy: 0.6196
Epoch 00070: saving model to keypoint_classifier_new.h5
1.1536 - accuracy: 0.6200 - val_loss: 0.5748 - val_accuracy: 0.8823
Epoch 71/500
accuracy: 0.6275
Epoch 00071: saving model to keypoint_classifier_new.h5
1.1411 - accuracy: 0.6290 - val_loss: 0.5631 - val_accuracy: 0.8916
Epoch 72/500
accuracy: 0.6242
Epoch 00072: saving model to keypoint_classifier_new.h5
1.1378 - accuracy: 0.6267 - val_loss: 0.5608 - val_accuracy: 0.8957
```

```
Epoch 73/500
accuracy: 0.6301
Epoch 00073: saving model to keypoint_classifier_new.h5
1.1246 - accuracy: 0.6284 - val_loss: 0.5640 - val_accuracy: 0.8861
Epoch 74/500
accuracy: 0.6317
Epoch 00074: saving model to keypoint_classifier_new.h5
1.1265 - accuracy: 0.6310 - val_loss: 0.5636 - val_accuracy: 0.8847
Epoch 75/500
accuracy: 0.6295
Epoch 00075: saving model to keypoint_classifier_new.h5
1.1357 - accuracy: 0.6277 - val_loss: 0.5488 - val_accuracy: 0.8992
Epoch 76/500
accuracy: 0.6338
Epoch 00076: saving model to keypoint_classifier_new.h5
1.1209 - accuracy: 0.6354 - val_loss: 0.5549 - val_accuracy: 0.8984
Epoch 77/500
accuracy: 0.6261
Epoch 00077: saving model to keypoint_classifier_new.h5
1.1364 - accuracy: 0.6211 - val_loss: 0.5514 - val_accuracy: 0.8968
```

```
Epoch 78/500
accuracy: 0.6229
Epoch 00078: saving model to keypoint_classifier_new.h5
1.1218 - accuracy: 0.6243 - val_loss: 0.5397 - val_accuracy: 0.8872
Epoch 79/500
accuracy: 0.6320
Epoch 00079: saving model to keypoint_classifier_new.h5
1.1108 - accuracy: 0.6339 - val_loss: 0.5436 - val_accuracy: 0.8938
Epoch 80/500
accuracy: 0.6325
Epoch 00080: saving model to keypoint_classifier_new.h5
1.1056 - accuracy: 0.6310 - val_loss: 0.5308 - val_accuracy: 0.8995
Epoch 81/500
accuracy: 0.6307
Epoch 00081: saving model to keypoint_classifier_new.h5
1.1193 - accuracy: 0.6317 - val_loss: 0.5384 - val_accuracy: 0.8861
Epoch 82/500
accuracy: 0.6309
Epoch 00082: saving model to keypoint_classifier_new.h5
1.1157 - accuracy: 0.6311 - val_loss: 0.5318 - val_accuracy: 0.9014
```

```
Epoch 83/500
accuracy: 0.6326
Epoch 00083: saving model to keypoint_classifier_new.h5
1.1131 - accuracy: 0.6312 - val_loss: 0.5483 - val_accuracy: 0.8883
Epoch 84/500
accuracy: 0.6311
Epoch 00084: saving model to keypoint_classifier_new.h5
1.1039 - accuracy: 0.6326 - val_loss: 0.5479 - val_accuracy: 0.8921
Epoch 85/500
0.6359
Epoch 00085: saving model to keypoint_classifier_new.h5
1.1086 - accuracy: 0.6360 - val_loss: 0.5398 - val_accuracy: 0.8962
Epoch 86/500
accuracy: 0.6366
Epoch 00086: saving model to keypoint_classifier_new.h5
1.1118 - accuracy: 0.6356 - val_loss: 0.5381 - val_accuracy: 0.9001
Epoch 87/500
accuracy: 0.6316
Epoch 00087: saving model to keypoint_classifier_new.h5
1.1143 - accuracy: 0.6326 - val_loss: 0.5444 - val_accuracy: 0.8855
```

```
Epoch 88/500
accuracy: 0.6334
Epoch 00088: saving model to keypoint_classifier_new.h5
1.0979 - accuracy: 0.6354 - val_loss: 0.5263 - val_accuracy: 0.8886
Epoch 89/500
accuracy: 0.6365
Epoch 00089: saving model to keypoint_classifier_new.h5
1.1047 - accuracy: 0.6340 - val_loss: 0.5320 - val_accuracy: 0.9033
Epoch 90/500
accuracy: 0.6390
Epoch 00090: saving model to keypoint_classifier_new.h5
1.1010 - accuracy: 0.6378 - val_loss: 0.5295 - val_accuracy: 0.9003
Epoch 91/500
accuracy: 0.6404
Epoch 00091: saving model to keypoint_classifier_new.h5
1.1099 - accuracy: 0.6424 - val_loss: 0.5207 - val_accuracy: 0.8976
Epoch 92/500
accuracy: 0.6378
Epoch 00092: saving model to keypoint_classifier_new.h5
1.0881 - accuracy: 0.6413 - val_loss: 0.5105 - val_accuracy: 0.9066
```

```
Epoch 93/500
accuracy: 0.6424
Epoch 00093: saving model to keypoint_classifier_new.h5
1.1004 - accuracy: 0.6419 - val_loss: 0.5191 - val_accuracy: 0.9014
Epoch 94/500
accuracy: 0.6330
Epoch 00094: saving model to keypoint_classifier_new.h5
1.1051 - accuracy: 0.6359 - val_loss: 0.5264 - val_accuracy: 0.8957
Epoch 95/500
accuracy: 0.6401
Epoch 00095: saving model to keypoint_classifier_new.h5
1.0942 - accuracy: 0.6407 - val_loss: 0.5197 - val_accuracy: 0.9020
Epoch 96/500
accuracy: 0.6367
Epoch 00096: saving model to keypoint_classifier_new.h5
1.0891 - accuracy: 0.6346 - val_loss: 0.5178 - val_accuracy: 0.8853
Epoch 97/500
accuracy: 0.6326
Epoch 00097: saving model to keypoint_classifier_new.h5
1.1017 - accuracy: 0.6326 - val_loss: 0.5128 - val_accuracy: 0.8940
```

```
Epoch 98/500
accuracy: 0.6401
Epoch 00098: saving model to keypoint_classifier_new.h5
1.0983 - accuracy: 0.6396 - val_loss: 0.5221 - val_accuracy: 0.8970
Epoch 99/500
accuracy: 0.6468
Epoch 00099: saving model to keypoint_classifier_new.h5
1.0821 - accuracy: 0.6443 - val_loss: 0.5118 - val_accuracy: 0.8976
Epoch 100/500
accuracy: 0.6351
Epoch 00100: saving model to keypoint_classifier_new.h5
1.0998 - accuracy: 0.6352 - val_loss: 0.5243 - val_accuracy: 0.8847
Epoch 101/500
accuracy: 0.6377
Epoch 00101: saving model to keypoint_classifier_new.h5
1.1043 - accuracy: 0.6361 - val_loss: 0.5123 - val_accuracy: 0.9020
Epoch 102/500
accuracy: 0.6439
Epoch 00102: saving model to keypoint_classifier_new.h5
1.0914 - accuracy: 0.6441 - val_loss: 0.5127 - val_accuracy: 0.9055
```

```
Epoch 103/500
accuracy: 0.6405
Epoch 00103: saving model to keypoint_classifier_new.h5
1.0884 - accuracy: 0.6426 - val_loss: 0.5163 - val_accuracy: 0.8820
Epoch 104/500
accuracy: 0.6377
Epoch 00104: saving model to keypoint_classifier_new.h5
1.0768 - accuracy: 0.6417 - val_loss: 0.5036 - val_accuracy: 0.8981
Epoch 105/500
accuracy: 0.6427
Epoch 00105: saving model to keypoint_classifier_new.h5
1.0856 - accuracy: 0.6439 - val_loss: 0.5156 - val_accuracy: 0.9001
Epoch 106/500
accuracy: 0.6441
Epoch 00106: saving model to keypoint_classifier_new.h5
1.0818 - accuracy: 0.6446 - val_loss: 0.4993 - val_accuracy: 0.9064
Epoch 107/500
accuracy: 0.6333
Epoch 00107: saving model to keypoint_classifier_new.h5
1.0891 - accuracy: 0.6350 - val_loss: 0.5161 - val_accuracy: 0.8913
```

```
Epoch 108/500
accuracy: 0.6409
Epoch 00108: saving model to keypoint_classifier_new.h5
1.0764 - accuracy: 0.6437 - val_loss: 0.5144 - val_accuracy: 0.8932
Epoch 109/500
accuracy: 0.6473
Epoch 00109: saving model to keypoint_classifier_new.h5
1.0833 - accuracy: 0.6443 - val_loss: 0.5123 - val_accuracy: 0.8954
Epoch 110/500
accuracy: 0.6399
Epoch 00110: saving model to keypoint_classifier_new.h5
1.0875 - accuracy: 0.6399 - val_loss: 0.5085 - val_accuracy: 0.9058
Epoch 111/500
accuracy: 0.6391
Epoch 00111: saving model to keypoint_classifier_new.h5
1.0625 - accuracy: 0.6419 - val_loss: 0.4986 - val_accuracy: 0.9055
Epoch 112/500
accuracy: 0.6395
Epoch 00112: saving model to keypoint_classifier_new.h5
1.0797 - accuracy: 0.6414 - val_loss: 0.5085 - val_accuracy: 0.9091
```

```
Epoch 113/500
accuracy: 0.6373
Epoch 00113: saving model to keypoint_classifier_new.h5
1.0815 - accuracy: 0.6354 - val_loss: 0.5082 - val_accuracy: 0.9033
Epoch 114/500
accuracy: 0.6493
Epoch 00114: saving model to keypoint_classifier_new.h5
1.0693 - accuracy: 0.6491 - val_loss: 0.4973 - val_accuracy: 0.9151
Epoch 115/500
accuracy: 0.6427
Epoch 00115: saving model to keypoint_classifier_new.h5
1.0646 - accuracy: 0.6456 - val_loss: 0.4903 - val_accuracy: 0.8932
Epoch 116/500
accuracy: 0.6464
Epoch 00116: saving model to keypoint_classifier_new.h5
1.0680 - accuracy: 0.6446 - val_loss: 0.5056 - val_accuracy: 0.9014
Epoch 117/500
accuracy: 0.6539
Epoch 00117: saving model to keypoint_classifier_new.h5
1.0569 - accuracy: 0.6522 - val_loss: 0.5016 - val_accuracy: 0.9099
```

```
Epoch 118/500
accuracy: 0.6482
Epoch 00118: saving model to keypoint_classifier_new.h5
1.0767 - accuracy: 0.6469 - val_loss: 0.4993 - val_accuracy: 0.9091
Epoch 119/500
accuracy: 0.6488
Epoch 00119: saving model to keypoint_classifier_new.h5
1.0682 - accuracy: 0.6461 - val_loss: 0.4982 - val_accuracy: 0.9072
Epoch 120/500
accuracy: 0.6453
Epoch 00120: saving model to keypoint_classifier_new.h5
1.0727 - accuracy: 0.6435 - val_loss: 0.4987 - val_accuracy: 0.8842
Epoch 121/500
accuracy: 0.6524
Epoch 00121: saving model to keypoint_classifier_new.h5
1.0491 - accuracy: 0.6521 - val_loss: 0.5007 - val_accuracy: 0.9042
Epoch 122/500
accuracy: 0.6478
Epoch 00122: saving model to keypoint_classifier_new.h5
1.0773 - accuracy: 0.6452 - val_loss: 0.4941 - val_accuracy: 0.8987
```

```
Epoch 123/500
accuracy: 0.6472
Epoch 00123: saving model to keypoint_classifier_new.h5
1.0651 - accuracy: 0.6478 - val_loss: 0.4970 - val_accuracy: 0.9025
Epoch 124/500
accuracy: 0.6430
Epoch 00124: saving model to keypoint_classifier_new.h5
1.0640 - accuracy: 0.6463 - val_loss: 0.4948 - val_accuracy: 0.9022
Epoch 125/500
accuracy: 0.6445
Epoch 00125: saving model to keypoint_classifier_new.h5
1.0659 - accuracy: 0.6461 - val_loss: 0.4795 - val_accuracy: 0.9058
Epoch 126/500
accuracy: 0.6547
Epoch 00126: saving model to keypoint_classifier_new.h5
1.0561 - accuracy: 0.6575 - val_loss: 0.4909 - val_accuracy: 0.8984
Epoch 127/500
accuracy: 0.6482
Epoch 00127: saving model to keypoint_classifier_new.h5
1.0621 - accuracy: 0.6483 - val_loss: 0.5136 - val_accuracy: 0.9061
```

```
Epoch 128/500
accuracy: 0.6426
Epoch 00128: saving model to keypoint_classifier_new.h5
1.0534 - accuracy: 0.6477 - val_loss: 0.4854 - val_accuracy: 0.8902
Epoch 129/500
accuracy: 0.6465
Epoch 00129: saving model to keypoint_classifier_new.h5
1.0596 - accuracy: 0.6482 - val_loss: 0.4965 - val_accuracy: 0.9022
Epoch 130/500
accuracy: 0.6499
Epoch 00130: saving model to keypoint_classifier_new.h5
1.0591 - accuracy: 0.6501 - val_loss: 0.4972 - val_accuracy: 0.8929
Epoch 131/500
accuracy: 0.6499
Epoch 00131: saving model to keypoint_classifier_new.h5
1.0499 - accuracy: 0.6515 - val_loss: 0.4995 - val_accuracy: 0.9077
Epoch 132/500
accuracy: 0.6483
Epoch 00132: saving model to keypoint_classifier_new.h5
1.0664 - accuracy: 0.6498 - val_loss: 0.4786 - val_accuracy: 0.9129
```

```
Epoch 133/500
accuracy: 0.6463
Epoch 00133: saving model to keypoint_classifier_new.h5
1.0595 - accuracy: 0.6478 - val_loss: 0.4903 - val_accuracy: 0.9132
Epoch 134/500
accuracy: 0.6480
Epoch 00134: saving model to keypoint_classifier_new.h5
1.0671 - accuracy: 0.6480 - val_loss: 0.4963 - val_accuracy: 0.9047
Epoch 135/500
accuracy: 0.6545
Epoch 00135: saving model to keypoint_classifier_new.h5
1.0588 - accuracy: 0.6540 - val_loss: 0.4954 - val_accuracy: 0.9031
Epoch 136/500
accuracy: 0.6581
Epoch 00136: saving model to keypoint_classifier_new.h5
1.0425 - accuracy: 0.6549 - val_loss: 0.4899 - val_accuracy: 0.9099
Epoch 137/500
accuracy: 0.6483
Epoch 00137: saving model to keypoint_classifier_new.h5
1.0497 - accuracy: 0.6502 - val_loss: 0.4888 - val_accuracy: 0.9110
```

```
Epoch 138/500
accuracy: 0.6473
Epoch 00138: saving model to keypoint_classifier_new.h5
1.0603 - accuracy: 0.6498 - val_loss: 0.4996 - val_accuracy: 0.9096
Epoch 139/500
accuracy: 0.6501
Epoch 00139: saving model to keypoint_classifier_new.h5
1.0613 - accuracy: 0.6491 - val_loss: 0.4880 - val_accuracy: 0.9083
Epoch 140/500
accuracy: 0.6466
Epoch 00140: saving model to keypoint_classifier_new.h5
1.0643 - accuracy: 0.6441 - val_loss: 0.4880 - val_accuracy: 0.8918
Epoch 141/500
accuracy: 0.6488
Epoch 00141: saving model to keypoint_classifier_new.h5
1.0591 - accuracy: 0.6493 - val_loss: 0.4965 - val_accuracy: 0.9080
Epoch 142/500
0.6532
Epoch 00142: saving model to keypoint_classifier_new.h5
1.0529 - accuracy: 0.6540 - val_loss: 0.4757 - val_accuracy: 0.9118
```

```
Epoch 143/500
accuracy: 0.6540
Epoch 00143: saving model to keypoint_classifier_new.h5
1.0619 - accuracy: 0.6506 - val_loss: 0.4675 - val_accuracy: 0.9124
Epoch 144/500
accuracy: 0.6514
Epoch 00144: saving model to keypoint_classifier_new.h5
1.0549 - accuracy: 0.6535 - val_loss: 0.4843 - val_accuracy: 0.9025
Epoch 145/500
accuracy: 0.6511
Epoch 00145: saving model to keypoint_classifier_new.h5
1.0568 - accuracy: 0.6527 - val_loss: 0.5036 - val_accuracy: 0.9140
Epoch 146/500
accuracy: 0.6510
Epoch 00146: saving model to keypoint_classifier_new.h5
1.0570 - accuracy: 0.6515 - val_loss: 0.4790 - val_accuracy: 0.9066
Epoch 147/500
accuracy: 0.6524
Epoch 00147: saving model to keypoint_classifier_new.h5
1.0411 - accuracy: 0.6535 - val_loss: 0.4871 - val_accuracy: 0.8954
```

```
Epoch 148/500
accuracy: 0.6551
Epoch 00148: saving model to keypoint_classifier_new.h5
1.0494 - accuracy: 0.6520 - val_loss: 0.4791 - val_accuracy: 0.9102
Epoch 149/500
accuracy: 0.6530
Epoch 00149: saving model to keypoint_classifier_new.h5
1.0344 - accuracy: 0.6558 - val_loss: 0.4750 - val_accuracy: 0.9127
Epoch 150/500
accuracy: 0.6497
Epoch 00150: saving model to keypoint_classifier_new.h5
1.0462 - accuracy: 0.6551 - val_loss: 0.4725 - val_accuracy: 0.9009
Epoch 151/500
accuracy: 0.6511
Epoch 00151: saving model to keypoint_classifier_new.h5
1.0560 - accuracy: 0.6501 - val_loss: 0.4833 - val_accuracy: 0.9105
Epoch 152/500
accuracy: 0.6551
Epoch 00152: saving model to keypoint_classifier_new.h5
1.0294 - accuracy: 0.6577 - val_loss: 0.4714 - val_accuracy: 0.9157
```

```
Epoch 153/500
accuracy: 0.6573
Epoch 00153: saving model to keypoint_classifier_new.h5
1.0395 - accuracy: 0.6603 - val_loss: 0.4699 - val_accuracy: 0.9072
Epoch 154/500
accuracy: 0.6615
Epoch 00154: saving model to keypoint_classifier_new.h5
1.0294 - accuracy: 0.6613 - val_loss: 0.4755 - val_accuracy: 0.9110
Epoch 155/500
accuracy: 0.6520
Epoch 00155: saving model to keypoint_classifier_new.h5
1.0510 - accuracy: 0.6510 - val_loss: 0.4895 - val_accuracy: 0.9096
Epoch 156/500
accuracy: 0.6575
Epoch 00156: saving model to keypoint_classifier_new.h5
1.0415 - accuracy: 0.6571 - val_loss: 0.4716 - val_accuracy: 0.9091
Epoch 157/500
accuracy: 0.6542
Epoch 00157: saving model to keypoint_classifier_new.h5
1.0504 - accuracy: 0.6519 - val_loss: 0.4848 - val_accuracy: 0.9127
```

```
Epoch 158/500
accuracy: 0.6559
Epoch 00158: saving model to keypoint_classifier_new.h5
1.0343 - accuracy: 0.6558 - val_loss: 0.4737 - val_accuracy: 0.9127
Epoch 159/500
accuracy: 0.6553
Epoch 00159: saving model to keypoint_classifier_new.h5
1.0430 - accuracy: 0.6558 - val_loss: 0.4780 - val_accuracy: 0.9170
Epoch 160/500
accuracy: 0.6573
Epoch 00160: saving model to keypoint_classifier_new.h5
1.0398 - accuracy: 0.6558 - val_loss: 0.4715 - val_accuracy: 0.9077
Epoch 161/500
accuracy: 0.6572
Epoch 00161: saving model to keypoint_classifier_new.h5
1.0361 - accuracy: 0.6570 - val_loss: 0.4758 - val_accuracy: 0.9162
Epoch 162/500
accuracy: 0.6579
Epoch 00162: saving model to keypoint_classifier_new.h5
1.0412 - accuracy: 0.6564 - val_loss: 0.4887 - val_accuracy: 0.9170
```

```
Epoch 163/500
accuracy: 0.6536
Epoch 00163: saving model to keypoint_classifier_new.h5
1.0410 - accuracy: 0.6552 - val_loss: 0.4637 - val_accuracy: 0.9179
Epoch 164/500
accuracy: 0.6561
Epoch 00164: saving model to keypoint_classifier_new.h5
1.0386 - accuracy: 0.6572 - val_loss: 0.4703 - val_accuracy: 0.9143
Epoch 165/500
accuracy: 0.6632
Epoch 00165: saving model to keypoint_classifier_new.h5
1.0406 - accuracy: 0.6606 - val_loss: 0.4772 - val_accuracy: 0.9107
Epoch 166/500
accuracy: 0.6583
Epoch 00166: saving model to keypoint_classifier_new.h5
1.0406 - accuracy: 0.6556 - val_loss: 0.4666 - val_accuracy: 0.9168
Epoch 167/500
accuracy: 0.6574
Epoch 00167: saving model to keypoint_classifier_new.h5
1.0302 - accuracy: 0.6598 - val_loss: 0.4742 - val_accuracy: 0.9116
```

```
Epoch 168/500
accuracy: 0.6601
Epoch 00168: saving model to keypoint_classifier_new.h5
1.0291 - accuracy: 0.6590 - val_loss: 0.4696 - val_accuracy: 0.9148
Epoch 169/500
accuracy: 0.6549
Epoch 00169: saving model to keypoint_classifier_new.h5
1.0288 - accuracy: 0.6591 - val_loss: 0.4856 - val_accuracy: 0.8929
Epoch 170/500
accuracy: 0.6526
Epoch 00170: saving model to keypoint_classifier_new.h5
1.0504 - accuracy: 0.6526 - val_loss: 0.4796 - val_accuracy: 0.9135
Epoch 171/500
accuracy: 0.6580
Epoch 00171: saving model to keypoint_classifier_new.h5
1.0274 - accuracy: 0.6587 - val_loss: 0.4709 - val_accuracy: 0.9157
Epoch 172/500
accuracy: 0.6589
Epoch 00172: saving model to keypoint_classifier_new.h5
1.0379 - accuracy: 0.6595 - val_loss: 0.4662 - val_accuracy: 0.9165
```

```
Epoch 173/500
accuracy: 0.6523
Epoch 00173: saving model to keypoint_classifier_new.h5
1.0256 - accuracy: 0.6550 - val_loss: 0.4654 - val_accuracy: 0.9127
Epoch 174/500
accuracy: 0.6613
Epoch 00174: saving model to keypoint_classifier_new.h5
1.0211 - accuracy: 0.6611 - val_loss: 0.4793 - val_accuracy: 0.9181
Epoch 175/500
accuracy: 0.6518
Epoch 00175: saving model to keypoint_classifier_new.h5
1.0399 - accuracy: 0.6542 - val_loss: 0.4721 - val_accuracy: 0.9066
Epoch 176/500
accuracy: 0.6624
Epoch 00176: saving model to keypoint_classifier_new.h5
1.0354 - accuracy: 0.6571 - val_loss: 0.4941 - val_accuracy: 0.9083
Epoch 177/500
accuracy: 0.6611
Epoch 00177: saving model to keypoint_classifier_new.h5
1.0370 - accuracy: 0.6586 - val_loss: 0.4794 - val_accuracy: 0.9094
```

```
Epoch 178/500
accuracy: 0.6624
Epoch 00178: saving model to keypoint_classifier_new.h5
1.0192 - accuracy: 0.6632 - val_loss: 0.4660 - val_accuracy: 0.9140
Epoch 179/500
accuracy: 0.6667
Epoch 00179: saving model to keypoint_classifier_new.h5
1.0111 - accuracy: 0.6673 - val_loss: 0.4686 - val_accuracy: 0.9083
Epoch 180/500
accuracy: 0.6616
Epoch 00180: saving model to keypoint_classifier_new.h5
1.0189 - accuracy: 0.6592 - val_loss: 0.4619 - val_accuracy: 0.9165
Epoch 181/500
accuracy: 0.6607
Epoch 00181: saving model to keypoint_classifier_new.h5
1.0323 - accuracy: 0.6587 - val_loss: 0.4828 - val_accuracy: 0.9135
Epoch 182/500
accuracy: 0.6528
Epoch 00182: saving model to keypoint_classifier_new.h5
1.0396 - accuracy: 0.6548 - val_loss: 0.4881 - val_accuracy: 0.9001
```

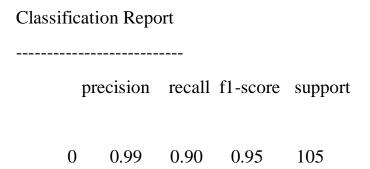
```
Epoch 183/500
accuracy: 0.6603
Epoch 00183: saving model to keypoint_classifier_new.h5
1.0259 - accuracy: 0.6636 - val_loss: 0.4754 - val_accuracy: 0.9137
Epoch 184/500
accuracy: 0.6548
Epoch 00184: saving model to keypoint_classifier_new.h5
1.0320 - accuracy: 0.6572 - val_loss: 0.4697 - val_accuracy: 0.9184
Epoch 185/500
accuracy: 0.6618
Epoch 00185: saving model to keypoint_classifier_new.h5
1.0203 - accuracy: 0.6611 - val_loss: 0.4683 - val_accuracy: 0.9148
Epoch 186/500
accuracy: 0.6627
Epoch 00186: saving model to keypoint_classifier_new.h5
1.0230 - accuracy: 0.6600 - val_loss: 0.4802 - val_accuracy: 0.9143
Epoch 187/500
accuracy: 0.6615
Epoch 00187: saving model to keypoint_classifier_new.h5
1.0256 - accuracy: 0.6608 - val_loss: 0.4767 - val_accuracy: 0.9170
```

```
Epoch 188/500
accuracy: 0.6580
Epoch 00188: saving model to keypoint_classifier_new.h5
1.0294 - accuracy: 0.6603 - val_loss: 0.4765 - val_accuracy: 0.9102
Epoch 189/500
accuracy: 0.6547
Epoch 00189: saving model to keypoint_classifier_new.h5
1.0342 - accuracy: 0.6567 - val_loss: 0.4770 - val_accuracy: 0.9094
Epoch 190/500
accuracy: 0.6656
Epoch 00190: saving model to keypoint_classifier_new.h5
1.0239 - accuracy: 0.6625 - val_loss: 0.4886 - val_accuracy: 0.9066
Epoch 191/500
accuracy: 0.6581
Epoch 00191: saving model to keypoint_classifier_new.h5
1.0256 - accuracy: 0.6584 - val_loss: 0.4849 - val_accuracy: 0.8938
Epoch 192/500
accuracy: 0.6642
Epoch 00192: saving model to keypoint_classifier_new.h5
1.0147 - accuracy: 0.6635 - val_loss: 0.4825 - val_accuracy: 0.9162
```

```
Epoch 193/500
accuracy: 0.6644
Epoch 00193: saving model to keypoint_classifier_new.h5
1.0154 - accuracy: 0.6660 - val_loss: 0.4630 - val_accuracy: 0.9154
Epoch 194/500
accuracy: 0.6586
Epoch 00194: saving model to keypoint_classifier_new.h5
1.0320 - accuracy: 0.6581 - val_loss: 0.4751 - val_accuracy: 0.9113
Epoch 195/500
accuracy: 0.6584
Epoch 00195: saving model to keypoint_classifier_new.h5
1.0252 - accuracy: 0.6580 - val_loss: 0.4821 - val_accuracy: 0.9083
Epoch 196/500
accuracy: 0.6574
Epoch 00196: saving model to keypoint_classifier_new.h5
1.0279 - accuracy: 0.6602 - val_loss: 0.4754 - val_accuracy: 0.9159
Epoch 197/500
accuracy: 0.6580
Epoch 00197: saving model to keypoint_classifier_new.h5
1.0190 - accuracy: 0.6582 - val_loss: 0.4712 - val_accuracy: 0.9083
```

```
Epoch 198/500
accuracy: 0.6662
Epoch 00198: saving model to keypoint_classifier_new.h5
1.0147 - accuracy: 0.6632 - val_loss: 0.4684 - val_accuracy: 0.9124
Epoch 199/500
accuracy: 0.6606
Epoch 00199: saving model to keypoint_classifier_new.h5
1.0172 - accuracy: 0.6600 - val_loss: 0.4815 - val_accuracy: 0.8981
Epoch 200/500
accuracy: 0.6589
Epoch 00200: saving model to keypoint_classifier_new.h5
1.0281 - accuracy: 0.6602 - val_loss: 0.4783 - val_accuracy: 0.9107
Epoch 00200: early stopping
WARNING:tensorflow:No training configuration found in the save file, so the
model was *not* compiled. Compile it manually.
```

Average prediction time: 0.000052s

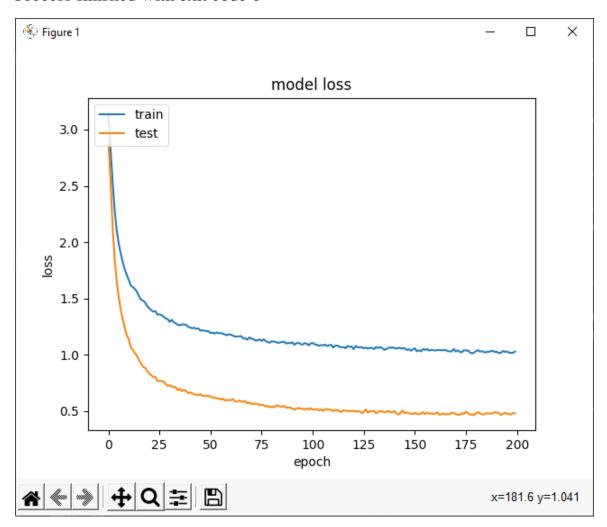


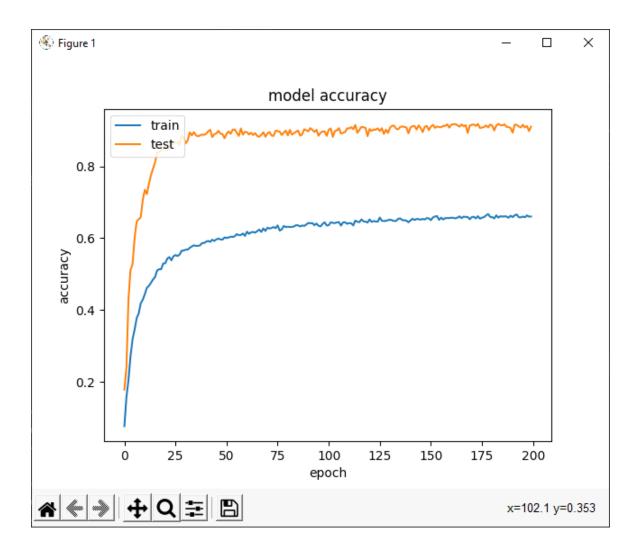
1	0.91	1.00	0.95	99
2	0.92	0.66	0.77	146
3	0.73	0.58	0.65	185
4	0.63	0.95	0.76	168
5	1.00	0.85	0.92	88
6	1.00	0.92	0.96	39
7	0.98	0.75	0.85	73
8	0.91	1.00	0.95	86
9	0.96	1.00	0.98	54
10	0.93	0.93	0.93	123
11	0.95	0.83	0.89	196
12	1.00	0.97	0.98	230
13	0.97	1.00	0.98	143
14	0.95	0.97	0.96	125
15	0.99	1.00	0.99	228
16	0.99	0.96	0.97	193
17	0.87	1.00	0.93	256
18	0.95	0.99	0.97	117
19	0.64	1.00	0.78	140
20	0.92	0.87	0.89	165
21	1.00	0.98	0.99	134
22	0.99	1.00	1.00	139
23	0.99	0.54	0.70	156
24	0.99	1.00	0.99	96
25	0.94	0.95	0.95	168

accuracy 0.90 3652

macro avg 0.93 0.91 0.91 3652 weighted avg 0.92 0.90 0.90 3652

Process finished with exit code 0





GITHUB ACCOUNT LINK:

https://github.com/IBM-EPBL/IBM-Project-9389-1658999257

PROJECT DEMO LINK:

https://drive.google.com/file/d/1H57cyENYduuslVfAioLJ2Ki0m6mN6eo1/view?usp=share_link