A

Project Synopsis on

# TOUCHLESS SECURITY

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## Bachelor of Technology

In

Computer Science & Engineering



Department of Computer Science & Engineering

## August, 2022

### CERTIFICATE

This is to certify that **Atefa Rizvi** (1900540130018) and **Simoni Verma** (1900540130046) ha**s** carried out the research work presented in the synopsis titled **“Touchless Security”** submitted for partial fulfillment for the award of the **Bachelor of Technology in Computer Science & Engineering** from **BBDITM, Lucknow** under my supervision.

It is also certified that:

1. This synopsis embodies the original work of the candidate and has not been earlier submitted elsewhere for the award of any degree/diploma/certificate.
2. The candidate has worked under my supervision for the prescribed period.
3. The synopsis fulfills the requirements of the norms and standards prescribed by the AKTU and BBDITM, Lucknow, India.
4. No published work (figure, data, table etc) has been reproduced in the synopsis without express permission of the copyright owner(s).

Therefore, I deem this work fit and recommend for submission for the award of the aforesaid degree.

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Place: Lucknow

### DECLARATION

I hereby declare that the synopsis titled **“Touchless Security”** is an authentic record of the research work carried out by me under the supervision of Mr. Anurag Shukla, Department of Computer Science & Engineering, for the period from August,2022 to Nov, 2022 at BBDITM, Lucknow. No part of this synopsis has been presented elsewhere for any other degree or diploma earlier.

I declare that I have faithfully acknowledged and referred to the works of other researchers wherever their published works have been cited in the synopsis. I further certify that I have not willfully taken other's work, para, text, data, results, tables, figures etc. reported in the journals, books, magazines, reports, synopsis, theses, etc., or available at web-sites without their permission, and have not included those in this B.Tech synopsis citing as my own work.

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**1 Computer vision v/s**

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# ABSTRACT

Face Recognition has become one of the most popular technologies where Deep Learning is used. Face recognition is used for identity authentication, access control, passport verification in airports, law enforcement, forensic investigations, social media platforms, disease diagnosis, police surveillance, casino watchlists and many more.

Modern state of the art Face Recognition solutions leverages graphics processor technologies, GPU, which has dramatically improved over the decades. (In particular, Nvidia released the CUDA framework which allowed C and C++ applications to utilize the GPU for massive parallel computing.) It utilizes Deep Learning (aka Neural Networks) which requires GPU power to perform massive compute operations in parallel. Deep Learning is one approach to Artificial Intelligence that simulates how the brain functions by teaching software through examples, several examples (big data), instead of hardcoding the logic rules and decision trees in the software. (One important contribution in Deep Learning is the creation of ImageNet dataset. It pioneered the creation of millions of images, a big data collection of images that were labelled and classified to teach computer for image classifications.) Neural networks are basically layers of nodes where each node is connected to nodes in the next layer feeding information. Deep nets are very deep neural networks with several layers made possible using GPU compute power. Many neural networks topologies exist such as Convolutional Neural Networks (CNN) architecture which particularly applies to Computer Vision, from image classification to face recognition.

Facial Emotion Recognition is a technology used for analysing sentiments by different sources, such as pictures and videos. It belongs to the family of technologies often referred to as ‘affective computing’, a multidisciplinary field of research on computer’s capabilities to recognise and interpret human emotions and affective states and it often builds on Artificial Intelligence technologies. Facial expressions are forms of non-verbal communication, providing hints for human emotions. For decades, decoding such emotion expressions has been a research interest in the field of psychology (Ekman and Friesen 2003; Lang et al. 1993) but also to the Human Computer Interaction field (Cowie et al. 2001; Abdat et al. 2011). Recently, the high diffusion of cameras and the technological advances in biometrics analysis, machine learning and pattern recognition have played a prominent role in the development of the FER technology.

FER analysis comprises three steps: a) face detection, b) facial expression detection, c) expression classification to an emotional state (Figure 1). Emotion detection is based on the analysis of facial landmark positions (e.g. end of nose, eyebrows). Furthermore, in videos, changes in those positions are also analysed, in order to identify contractions in a group of facial muscles (Ko 2018). Depending on the algorithm, facial expressions can be classified to basic emotions (e.g. anger, disgust, fear, joy, sadness, and surprise) or compound emotions (e.g. happily sad, happily surprised, happily disgusted, sadly fearful, sadly angry, sadly surprised) (Du et al. 2014). In other cases, facial expressions could be linked to physiological or mental state of mind (e.g. tiredness or boredom).

# INTRODUCTION

*“Individual commitment to a group effort—that is what makes a team work, a companywork, a society work, a civilization work.”—Vince Lombardi.*

Science and technology are constantly evolving and it is only fair that we make use of it in the best way possible. What we have visioned with this project is make use of the advanced technology

to improve the lives of all the people around us.

Using artificial intelligence and machine learning we have created a software that can recognize facial features and that individual’s speech. Both working in harmony with each other as we believe recognizing just the face is not enough and a new factor involving speech must also be included.

A facial recognition system is a technology capable of identifying or verifying a person from a digital image or a video frame from a video source. At a minimum, a simple real-time facial recognition system is composed of the following pipeline:

1. **Face Enrolment.** Registering faces to a database which includes pre- computing the face embeddings and training a classifier on top of the face embeddings of registered individuals.
2. **Face Capture.** Reading a frame image from a camera source.
3. **Face Detection.** Detecting faces in a frame image.
4. **Face Encoding/Embedding.** Generating a mathematical representation of each face (coined as embedding) in the frame image.
5. **Face Identification.** Inferring each face embedding in an image with face embeddings of known people in a database.

More complex systems include features such as **Face Liveness Detection** (to counter spoofing attacks via photo, video or 3d mask), face alignment, **face augmentation** (to increase the number of dataset of images) and face verification (to confirm prediction by comparing cosine similarity or Euclidean distance with each database embedding).

We were always fascinated by the idea of a machine that could learn and adapt by itself. AI made that possible, allowing us to create this project and bring light to our vision.

Why face and speech recognition? Well after the pandemic we noticed that many things were needed to be implemented in a touchless manner where proper hygiene could be maintained and this project could make that possible if implemented in a proper way. We could also use this software to strengthen the security of many applications that we use in our daily life.

Why facial emotion recognition is important? Facial expression recognition or computer-based facial expression recognition system is important because of its ability to mimic human coding skills. Facial expressions and other gestures convey nonverbal communication cues that play an important role in interpersonal relations. These cues complement speech by helping the listener to interpret the intended meaning of spoken words. Therefore, facial expression recognition, because it extracts and analyzes information from an image or video feed, it is able to deliver unfiltered, unbiased emotional responses as data.

# 2. LITERATURE REVIEW

This section gives an overview on the major human face recognition techniques that apply mostly to frontal faces, advantages and disadvantages of each method are also given. The methods considered are eigenfaces (eigenfeatures), neural networks, dynamic link architecture, hidden Markov model, geometrical feature matching, and template matching. The approaches are analyzed in terms of the facial representations they used..

* 1. **Eigenfaces :** Eigenface is one of the most thoroughly investigated approaches to face recognition. It is also known as Karhunen- Loève expansion, eigenpicture, eigenvector, and principal component. References [26, 27] used principal component analysis to efficiently represent pictures of faces. They argued that any face images could be approximately reconstructed by a small collection of weights for each face and a standard face picture (eigenpicture). The weights describing each face are obtained by projecting the face image onto the eigenpicture. Reference [28] used eigenfaces, which was motivated by the technique of Kirby and Sirovich, for face detection and identification.
  2. **Neural Networks :** The attractiveness of using neural networks could be due to its non linearity in the network. Hence, the feature extraction step may be more efficient than the linear Karhunen-Loève methods. One of the first artificial neural networks (ANN) techniques used for face recognition is a single layer adaptive network called WISARD which contains a separate network for each stored individual [35]. The way in constructing a neural network structure is crucial for successful recognition. It is very much dependent on the intended application. For face detection, multilayer perceptron [36] and convolutional neural network [37] have been applied. For face verification, [38] is a multi-resolution pyramid structure. Reference [37] proposed a hybrid neural network which combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimension reduction and invariance to minor changes in the image sample. The convolutional network extracts successively larger features in a hierarchical set of layers and provides partial invariance to translation, rotation, scale, and deformation. The authors reported 96.2% correct recognition on ORL database of 400 images of 40 individuals.
  3. **Graph Matching** :Graph matching is another approach to face recognition. Reference [41] presented a dynamic link structure for distortion invariant object recognition which employed elastic graph matching to find the closest stored graph. Dynamic link architecture is an extension to classical artificial neural networks. Memorized objects are represented by sparse graphs, whose vertices are labeled with a multiresolution description in terms of a local power spectrum and whose edges are labeled with geometrical distance vectors. Object recognition can be formulated as elastic graph matching which is performed by stochastic optimization of a matching cost function. They reported good results on a database of 87 people and a small set of office items comprising different expressions with a rotation of 15 degrees. The matching process is computationally expensive, taking about 25 seconds to compare with 87 stored objects on a parallel machine with 23 transputers. Reference [42] extended the technique and matched human faces against a gallery of 112 neutral frontal view faces. Probe images were distorted due to rotation in depth and changing

facial expression. Encouraging results on faces with large rotation angles were obtained. They reported recognition rates of 86.5% and 66.4% for the matching tests of 111 faces of 15 degree rotation and 110 faces of 30 degree rotation to a gallery of 112 neutral frontal views. In general, dynamic link architecture is superior to other face recognition techniques in terms of rotation invariance; however, the matching process is computationally expensive.

* 1. **Hidden Markov Models (HMMs)** : Stochastic modeling of nonstationary vector time series based on (HMM) has been very successful for speech applications. Reference [43] applied this method to human face recognition. Faces were intuitively divided into regions such as the eyes, nose, mouth, etc., which can be associated with the states of a hidden Markov model. Since HMMs require a one-dimensional observation sequence and images are two-dimensional, the images should be converted into either 1D temporal sequences or 1D spatial sequences.

Facial expression recognition is composed of three major steps: (1) Face detection and preprocessing of image, (2) Feature extraction and (3) Expression classification. The objective of this paper is to understand the basic difference between the face recognition and facial expression recognition and to investigate the effective facial expression recognition rates by acknowledging the existing proposed models.

### BASIC TERMINOLOGIES

1. Face Detection: Face detection is to determine that a certain picture contains a face we need to be able to define the general structure of face. Luckily human faces do not greatly differ from each other; we all have noses, eyes, foreheads, chins and mouths; and all of these compose the general structure of a face. It is a concept of two-class classification: face versus nonface. Face detection can be regarded as a specific case of objectclass detection. In object-class detection, the task is to find the locations and sizes of all objects in an image that belong to a given class.
2. Face Identification: In this the system compares the given individual to all the other individuals in the database and gives a ranked list of matches.
3. Face Verification: In this the system compares the given individual with who that individual says they are and gives a yes or no decision.
4. Facial Expressions: Facial expression is one or more motions or positions of the muscles beneath the skin of the face. These movements express the emotional state of the person to observers. It is a form of non-verbal communication. It plays a communicative role in interpersonal relations. The common ones are: happy, sad, surprise, anger, fear, disgusting.
   1. **Comparative study( Of Different Papers by using Table)**

Table 1

|  |  |  |
| --- | --- | --- |
| Methodology | Computer Vision | Convolutional Neural Network |
| Approach | When a computer looks at an image with a specific goal, the irrelevant information is not taken into account. This helps reduce the | Accuracy in image recognition problems. This helps us to get the results accurate and differentiate between mask and no mask. |

|  |  |  |
| --- | --- | --- |
|  | types of bias that humans might introduce to a process, whether intentionally or unintentionally. |  |
| When the device fails because of a virus or other software issues, it is highly probable that Computer Vision and image processing will fail. | CNN automatically detects the important features without any human supervision. |
| If there is no good GPU they are quite slow to train (for complex tasks). They use to need a lot of training data. |
| Time and error rate are reduced in the process of Computer Imagining. It reduces the cost of hire and train special staff (human force) to do the activities that computers does. | It is computationally very expensive and time consuming to train with traditional CPUs. |
| Once we train the system, the predictions are pretty fast. |

## Conclusion

Different methods and approaches of face mask detection and recognition have been reviewed in this paper. In comparison, Haar-like features are digital image features used in object recognition. They owe their name to their intuitive similarity with Haar wavelets and were used in the first real- time face detector. The key advantage of a Haar-like feature over most other features is its calculation speed. Adaboost can be less susceptible to the over fitting problem than most learning algorithms. Bad feature of adaptive boosting is its sensitivity to noisy data and outliers. In real-world scenarios human faces might be occluded by other objects such as facial mask. This makes the face recognition process a very challenging task. Deep learning-based method and quantization-based technique achieves a high recognition performance. MobileNetV2 is a very effective feature extractor for object detection and segmentation. MobileNetV2 provides a very efficient mobile-oriented model that can be used as a base for many visual recognition tasks. For the best of our knowledge, this work addresses the problem of masked face recognition and different approaches during COVID19 pandemic.

The facial expression recognition can be tested using physiological signals, as the physiological signals are strongly co-related to human emotions. These signals are not controllable by humans. The main signals on which facial expressions are responsible are temperature, respiration, skin conductance, and cardiac function. The efficient output can be produced using physiological signals.

# 3. Proposed Work

Pre-processing and cropping filter: The images of the dataset are already cropped around the face, so there is no need of a face detection stage to localize the face from each image. To do so, we detect 68 facial landmarks using Dlib-ml open- source library. According to the eyes location, we apply a 2D rotation to make them horizontal. The next step is to apply a cropping filter in order to extract only the non- masked region. To do so, we firstly normalize all face images into 240 x 240 pixels. Next, we use the partition into blocks. The principle of this technique is to divide the image into 100 fixed-size square blocks (24 x 24 pixels in our case). Then we extract only the blocks including the non-masked region (blocks from number 1 to 50). Finally, we eliminate the rest of the numbers of the blocks.Feature extraction layer: They extract deep features using VGG16 face CNN descriptor [20] from the 2D images. It is trained on ImageNet dataset which has over 14 million images and 1000 classes. Its name VGG16 comes from the fact that it has 16 layers. Its layers consist of convolutional layers, Max Pooling layers, Activation layers, Fully connected layers. There are 13 convolutional layers, 5 Max Pooling layers and 3 Dense layers which sums up to 21 layers but only 16 weight layers. In this work, we only consider the feature maps (FMs) at the last convolutional layer, also called channels. These features will be used in the following in the quantization stage.

Deep bag of features layer: From the ith image, we extract feature maps using the feature extraction layer described above. In order to measure the similarity between the extracted feature vectors and the codewords also called term vectors, we applied the RBF kernel as a similarity metric as proposed in. Thus, the first sub layer will be composed of RBF neurons, each neuron is referred to as a codeword. The size of the extracted feature map denes the number of the feature vectors that will be used in the BoF layer. Here we refer by Vi to the number of feature vectors extracted from the ith image.

The most used automatic algorithm is of course k-means. Let F the set of all the feature vectors, defined by F = {Vij, i = 1

… V, j = 1 … Vi} and Vk is the number of the RBF neurons centers referred by ck. Note that these RBF centers are learned afterward to get the final codewords. The quantization is then applied to extract the histogram with a pre-defined number of bins, each bin is referred to as a codeword. RBF layer is then used as a similarity measure, it contains 2 sub layers:

RBF layer: Measures the similarity of the input features of the probe faces to the RBF centers. Formally: the jth RBF neuron (Xj) is defined by: (Xj) = exp (l/x cj l/2 /j) , (1) Where x is a feature vector and cj is the center of the jth RBF neuron.

Quantization layer: The output of all the RBF neurons is collected in this layer that contains the histogram of the

global quantized feature vector that will be used for the classification process. The final histogram is defined by:

Where (V) is the output vector of the RBF layer over the ck bins.

Once the global histogram is computed, pass the classification stage to assign each test image to its identity. To do so, a Multilayer perceptron classier (MLP) is applied where each face is represented by a term vector. Deep BoF network can be trained using back- propagation and gradient descent. Note that the 10 cross-validation strategy is applied in our experiments on the RMFRD dataset. V = [v1,., vk] the term vector of each face is noted, where each vi refers to the occurrence of the term i in the given face. t is the number of attributes, and m is the number of classes (face identities). Test faces are defined by their codeword V MLP uses a set of term occurrences as input values (vi) and associated weights (wi) and a sigmoid function (g) that sums the weights and maps the results to an output (y).

RMFRD faces were firstly pre-processed as described. Using the normalized 2D faces of sizes 240 x 240 pixels, VGG16 pretrained model is applied to extract the best features from the last convolutional layer as presented. The quantization is then applied to extract the histogram of 70 bins as presented. Finally, MLP is applied to classify faces. In this experiment, the 10 cross-validation strategy is used to evaluate the recognition performance. The experiments are repeated ten times in the RMFRD dataset, where 9 samples are used as the training set and the remaining sample as the testing set, and the average results are calculated.

Vinitha.V1, Velantina.V2, COVID-19 FACEMASK DETECTION WITH DEEP LEARNING AND

COMPUTER VISION, International Research Journal of Engineering and Technology (IRJET), Volume: 07, pp.1-6, Aug 2020.

The mask face detection model that is based on computer vision and deep learning. The model is integration between deep learning and classical machine learning techniques with OpenCV, tensor flow and Keras. We have used deep transfer leering for feature extractions and combined it with three classical machine learning algorithms. We introduced a comparison between them to find the most suitable algorithm that achieved the highest accuracy and consumed the least time in the process of training and detection.

## 3.1 Proposed Approach

1. Train Deep learning model (MobileNetV2) 2.Apply mask detector over images / live video stream

The majority of the images were augmented by OpenCV. The set of images were already labeled mask and no mask.

The images that were present were of different sizes and resolutions, probably extracted from different sources or from machines (cameras) of different resolutions.

Face Mask Detection in webcam stream.

* The flow to identify the person in the webcam wearing the face mask or not. The process is two-fold.
  1. To identify the faces in the webcam. 2.Classify the faces based on the mask.

Identify the Face in the Webcam: To identify the faces a pre- trained model provided by the OpenCV framework was used. The model was trained using web images.

OpenCV provides 2 models for this face detector.

1.Floating-point 16 version of the original Caffe implementation.

2.8 bit quantized version using Tensor flow.

* 1. **Conclusion**

# 4. Conclusion & Future Work

Using artificial intelligence and machine learning we have created a software that can recognize facial features and that individual’s speech.Having several datasets of images per person is not possible for some use cases of Face Recognition. So, finding the appropriate model for that balances accuracy and speed on target hardware platform (CPU, GPU, embedded system) is necessary. The trinity of AI is Data, Algorithms and Compute. This allows selecting each model/algorithm in the pipeline.This supports several models for each step of the Face Recognition pipeline. Somemodels are faster while some models are more accurate. You can mix and match the models for your specific use-case, hardware platform and system requirements.

The accuracy of face detection varies on the trained model. If the model has been trained properly then we see good results however if the model is trained poorly then the results are not satisfactory.Speech detection system provides satisfactory results however in environments with lots of noise the result may vary. We can implement advance measures in the future to prevent this from happening. For Voice recognition, GMM (Gaussian Mixture Model) is used to train on extracted MFCC features from audio wav file.

After investigating various face detection, feature extraction and expression classification methods and techniques we conclude that the effective facial expression recognition can be achieved by ANFIS tool, which is close to 100%

## Future Work

Human recognition with face mask has various applications in different domains. The various methodologies discussed in this paper can be based on the particular demands of the application. As every approach has its very own pros and cons we need to determine the best approach according to the necessity. Face detection is gaining the interest of marketers. It can be used at various domains like airports where this system can be of great importance at airports to detect travellers whether they are wearing mask or not. Travellers data can be captured as videos in the system at the entrance. Hospitals – This system can be integrated with CCTV cameras and that data may be administered to see if their staff is wearing mask or not. Offices – This system can help in maintaining safety standards to prevent the spread of Covid- 19, to detect whether the person is wearing mask or not. The scope of this system extends to security systems of wide range right from Malls, hospitals, IT companies and in many such public areas.

The facial expression recognition can be tested using physiological signals, as the physiological signals are strongly co-related to human emotions. These signals are not controllable by humans. The main signals on which facial expressions are responsible are temperature, respiration, skin conductance, and cardiac function. The efficient output can be produced using physiological signals.

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