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Advanced Face Recognition based Non-Vaccination Population Finder and Alert System

[1]K. Ashokkumar, [2]P. Sumathi, [3]A. Kaviraj, [4]C. Sindhu, [5]R. VeereshKumar, [6]R. Deepika

[1]*Department of Information Technology, SNS College of Engineering Coimbatore, India*
[2]*Department of Information Technology, SNS College of Engineering Coimbatore, India*
[3]*Department of Information Technology, SNS College of Engineering Coimbatore, India, rajannu2525@gmail.com*
[4]*Department of Information Technology, SNS College of Engineering Coimbatore, India, sindhusindhu7214@gmail.com*
[5]*Department of Information Technology, SNS College of Engineering Coimbatore, India, ra.veereshkumar@gmail.com*
[6]*Department of Information Technology, SNS College of Engineering Coimbatore, India, deepikaselvakumar421@gmail.com*

Abstract

Vaccinations are an important and effective cornerstone of preventive medical care with significant health benefits. Vaccination is crucial to limit the pandemic spread of SARS-CoV-2/COVID-19. The government has started vaccination to prevent the continuous spread of corona infection in India. Therefore, besides the development and supply of vaccines, it is essential that sufficient individuals are willing to get vaccinated, but concerning proportions of populations worldwide show vaccine hesitancy. However, it soon became clear that to end the pandemic, we would have to address another ubiquitous problem: the widespread hesitancy toward or downright rejection of vaccination. To achieve population immunity first we have to find the non-vaccinated population to this end, this project proposed an Aadhaar-based facial recognition system is used to find non-vaccination citizen and alert them using Artificial Intelligence. Deep learningin the form of Convolutional Neural Networks (CNNs) to perform the face recognition and seems to be an adequate method to carry outface recognition due to its high accuracy.A CNN is a type of Deep Neural Network (DNN) that is optimized for complex tasks such as image processing, which is required for facial recognition. CNNs consist of multiple layers of connected neurons: there is an input layer, an output layer, and multiple layers between these two.In the context of the coronavirus disease (COVID-19) pandemic, A face recognition-based person’s current vaccination status to protect against COVID-19 can then be used for continuity of care or as proof of vaccination for purposes other than health care. Facial recognition technology (FRT) along with the Aadhaar to authenticate people before entering into any kinds of service.This project provides COVID-19 vaccination status using their face and attest that an individual has received a vaccine or not and alert them to get vaccinated.

Keywords: Facial recognition technology (FRT), Deep Neural Network (DNN), Convolutional Neural Networks (CNNs).

1. INTRODUCTION

A vaccine can confer active immunity against a specific harmful agent by stimulating the immune system to attack the agent. Once stimulated by a vaccine, the antibody-producing cells, called B cells (or B lymphocytes), remain sensitized and ready to respond to the agent should it ever gain entry to the body. A vaccine may also confer passive immunity by providing antibodies or lymphocytes already made by an animal or human donor. Vaccines are usually administered by injection (parenteral administration), but some are given orally or even nasally (in the case of flu vaccine). Vaccines applied to mucosal surfaces, such as those lining the gut or nasal passages, seem to stimulate a greater antibody response and may be the most effective route of administration. (For further information, see immunization.).

A. Covid 19:

At the end of 2019, a novel coronavirus now known as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was identified as the cause of a cluster of pneumonia cases in Wuhan, a city in the Hubei Province of China. It rapidly spread, resulting in a global pandemic. In February 2020, the World Health Organization named the disease COVID-19, which stands for coronavirus disease 2019.The world is in the midst of a COVID-19 pandemic. As WHO and partners work together on the response -- tracking the pandemic, advising on critical interventions, distributing vital medical supplies to those in need--- they are racing to develop and deploy safe and effective vaccines.

Vaccines save millions of lives each year. Vaccines work by training and preparing the body's natural defenses – the immune system – to recognize and fight off the viruses and bacteria they target. After vaccination, if the body is later exposed to those disease-causing germs, the body is immediately ready to destroy them, preventing illness.

There are several safe and effective vaccines that prevent people from getting seriously ill or dying from COVID-19. This is one part of managing COVID-19, in addition to the main preventive measures of staying at least 1 metre away from others, covering a cough or sneeze in your elbow, frequently cleaning your hands, wearing a mask and avoiding poorly ventilated rooms or opening a window. As of 15 November 2021, WHO has evaluated that the following vaccines against COVID-19 have met the necessary criteria for safety and efficacy:

- AstraZeneca/Oxford vaccine
- Johnson and Johnson
- Moderna
- Pfizer/BionTech
- Sinopharm
- Sinovac
- COVAXIN

B. Covid19 Vaccination in India

COVID-19 vaccines in India and elsewhere are mostly two shot vaccines. High efficiency requires both doses of COVID-19 vaccines to be administered that can provide protection against fatal infection. As the second wave of COVID-19 infection picked up, India saw a high rate of COVID infection and deaths among the elderly people and people with comorbidities. Elderly and the people with comorbidities were the ones who were at high risk of COVID-19 infection, and hence they were prioritized to receive COVID-19 vaccine shots relative to others in the phase wise vaccine rollout. Many among them who were vaccinated with the first dose contracted COVID-19 infection and some of them died as the first dose alone was not meant to build sufficient immunity to fight severe COVID infection. However, the myth developed particularly in the rural areas that covid vaccines were causing deaths and illness. This too likely contributed to vaccine hesitancy during the third and the fourth phase of the vaccination drive.

C. Problem Identified:

From the beginning of this COVID-19 pandemic, it has been witnessed that very less attention has been paid on risk communication, leading to social isolation and discrimination of COVID patients, community resistance toward testing, etc., It is of utmost importance to carry out intensive risk communication and advisory activities to make people aware who actually require it and how much protection it can give.

In due course of time, the demand of vaccine might keep on decreasing. Further, acceptability of vaccine for the general population is also questionable. History revealed poor utilization of flu vaccine introduced after H1N1 pandemic. Hence, a pre-introduction acceptability survey among the general population is recommended. Although vaccination against COVID19 is voluntary, generating a certificate after vaccination may point to a purported design to force people to adopt vaccines as it may be mandated for travel and other businesses. Underutilized vaccines may create an economic burden for the society.COVID-19 digital certificate to show proof of only COVID-19 vaccinations in India.

However, in the context of vaccination certificates, it is necessary to examine the risks that have been repeatedly highlighted by the Indian and global communities, namely the growing market for counterfeit certificates of various kinds.Europol, for example, has also warned in its reports of the risks of misuse – in particular of test certificates. False certificates can pose a significant risk to public health. The authorities of one Member State must be sure that the information contained in a certificate issued in another Member State is reliable, that it has not been falsified, that it belongs to the person presenting it and that anyone verifying the information has access to only the minimum amount of information necessary.To achieve population immunity first we have to find the non-vaccinated population to this end, this project proposed an Aadhaar-based facial recognition system is used to find non-vaccination citizen and alert them using Artificial Intelligence.

D. Image and Video Classification, Segmentation:

Convolutional Neural Networks out-perform humans on many vision tasks including object classification. Given millions of labeled pictures, the system of algorithms is able to begin identifying the subject of the image. Many photo-storage services include facial recognition, driven by Deep Learning.

E. Project Scope:

India is looking at adding Aadhaar-based facial recognition in an effort to make its COVID-19 vaccination procedure contactless. To test the efficacy of the facial recognition system, which is based on data obtained from the Aadhaar database.Aadhaar is already the “preferred” mode of identity verification and for vaccination certificates.Using facial recognition at vaccine centers risks further marginalizing vulnerable people who may be misidentified and refused the vaccine, and raises fears the controversial technology could become the norm at all centers.

F. Objective of the project:

The main objective of the project is to develop an “Aadhaar-based facial recognition system could soon replace biometric fingerprint or iris scan machines at COVID-19 vaccination finder across the country in order to avoid non-vaccination,”

II. METHODOLOGY

The aim of this project is to face detection systems for people with dark skin using a hybrid algorithm based on Gaussian and Explicit rule model.

There has been significant development in the facial recognition technology during past few decades. This technology has been widely used by different organizations and governments for defense, security, and surveillance projects. Furthermore, it has now been incorporated into our daily usages, such as consumer applications, personal data protection, or cyber-security, particularly while using smartphones. Most of these systems work very efficient, however, there are some challenges related to the accuracy of results of facial recognition systems when tested on images of people with dark skin. This article highlights the variation in accuracy of existing facial recognition algorithms when applied to dark-skinned people. Furthermore, as a principal contribution it presents a hybrid algorithm based on Gaussian and Explicit rule model that improves the accuracy for face-detection for dark skinned people. The results showed that Gaussian and Explicit Rule hybrid algorithm optimally improved the face detection rate for people with dark skin [1].

Humans express and perceive emotions in a multimodal manner. The multimodal information is intrinsically fused by the human sensory system in a complex manner. The feature descriptors for audio and video representations are extracted using simple Convolutional Neural Networks (CNNs), leading to real-time processing. Undoubtedly, collecting annotated training data remains an important challenge when training emotion recognition systems, both in terms of effort and expertise required. The proposed approach of end-to-end neural network architecture, called TA-AVN solves this problem by providing a natural augmentation technique that allows achieving a high accuracy rate even when the amount of annotated training data is limited. This article proposes a novel audio-visual multimodal fusion framework for emotion recognition based on a random selection of analysis windows collected from individual temporal segments of the input video and the proposed method can be easily adapted to work also when the amount of available annotated data is limited [2].

With the breakthrough of computer vision and deep learning, there has been a surge of realistic looking fake face media manipulated by AI such as Deep Fake or Face2Face that manipulate facial identities or expressions. The fake faces were mostly created for fun, but abuse has caused social unrest. For example, some celebrities have become victims of fake pornography made by Deep Fake. There are also growing concerns about fake political speech videos created by Face2Face. To maintain individual privacy as well as social, political, and international security, it is imperative to develop models that detect fake faces in media. This article proposes a hybrid face forensics framework based on a convolutional neural network combining the two forensics approaches to enhance the manipulation detection performance. To validate the proposed framework is used a public Face2Face dataset and a custom Deep Fake dataset collected on our own. The proposed model is a type of convolutional neural networks containing two types of feature extractors to simultaneously extract content features and trace features from a face image. The former feature extractor is trained by transferring and fine-tuning the feature extractor of a pre-trained object recognition model. Thus, the extracted features are specialized to represent various contents in a face. The latter feature extractor is based on the local relationship between neighboring pixels, by first applying the multi-channel constrained convolution [3].

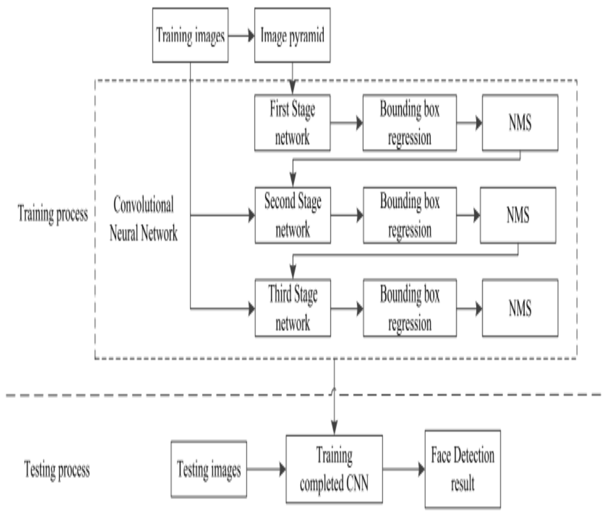
College attendance management for students has become one of the hot issues in the society, so the management of college students should be strengthened. However, most college students still use traditional manual attendance for daily attendance, using paper signatures or teacher orders, but now with the gradual rise of technology, some new methods point out that gradually, a few colleges and universities will use punch card fingerprints and smart attendance methods. Although there are some ways to stimulate attendance, the effect is not so effective. This article proposes a linear discriminant analysis (LDA) algorithm to overcome the above issues. This algorithm is to find a set of linear transformations that minimize the intra-class dispersion between each category and maximize the inter-class dispersion [4].

Heterogeneous face recognition (HFR), referring to matching face images across different domains, is a challenging problem due to the vast cross-domain discrepancy and insufficient pairwise cross-domain training data. This article proposes a quadruplet framework for learning domain-invariant discriminative features (DIDF) for HFR, which integrates domain-level and class-level alignment in one unified network. The domain-level alignment reduces the cross-domain distribution discrepancy. The class-level alignment based on a special quadruplet loss is developed to further diminish the intra-class variations and enlarge the inter-class separability among instances, thus handling the misalignment and adversarial equilibrium problems confronted by the domain-level alignment. Extensive experiments are conducted on four challenging benchmarks, quantitative comparisons against some state-of-the-art HFR methods demonstrate the effectiveness and superiority of the proposed DIDF method in heterogeneous face recognition [5].

With the continuous development of deep learning, face detection methods have made the greatest progress. For real-time detection, cascade CNN based on the lightweight model is still the dominant structure that predicts face in a coarse-to-fine manner with strong generalization ability. Compared to other methods, it is not required for a fixed size of the input. However, MTCNN still has poor performance in detecting tiny targets. This article proposes a new face detection model RFEMTCNN which takes advantage of the Inception-V2 block and receptive field block to enhance the feature discriminability and robustness for small targets. This author uses the Global Average Pooling (GAP) to replace the second to last fully connected layers in order to enforce correspondences between feature maps and categories, avoid overfitting, and reduce the network parameters. The AM-Soft max loss function is introduced to enhance the discriminability of the R-Net [6].

Face detection is generally a key component of the humancentered ‘‘smart city’’, relating to facial expression analysis, identification, individual service, etc. Despite being widely researched, it remains a difficult problem to build real-time face detectors with high accuracy under natural conditions. This article proposes a real-time face detector named You Only Move Once(YOMO), which consists of depthwise separable convolutions and contains multiple feature fusion structures in the form of top-bottom. Each detection module is only responsible for detecting faces within the corresponding scale.A random cropping strategy that is more consistent with multi-scale detection structures allows each detection module to be trained by a sufficient number of samples. The proposed ellipse regressor can greatly improve the detection recall rate under the continuous measures of FDDB. YOMO has only 21 million parameters and achieves superior performance with 51 FPS for a 544 × 544 input image on a GPU [7].

Deep learning achieves substantial improvements in face detection. However, the existing methods need to input fixed-size images for image processing and most methods use a single network for feature extraction, which makes the model generalization ability weak. In response to the above problems, our framework leverages a cascaded architecture with three stages of deep convolutional networks to improve detection performance. This article proposed the convolutional neural network is a face detection network based on regression theory. The network replaces the standard convolution in MTCNN with the separable residual module and deletes the task of facial landmarks position. Therefore, only two tasks of face classification and bounding box regression are carried out in the detection stage. The detection accuracy of the network is improved by using the cascading convolutional neural network and the method of expanding the channel in the separable residual module. The depth wise separable convolution is used to reduce the amount of network computation to maintain a fast detection speed [8].



Although face recognition algorithms have been greatly successful recently, in real applications of very low-resolution (VLR) images, both super-resolution (SR) and recognition tasks are more challenging than those in high-resolution (HR) images. Given the rare discriminative information in VLR images, the one-to-many mapping relationship between HR and VLR images degrades the SR and recognition performances. This article proposed a semi-coupled dictionary learning method for VLR face image feature representation and mapping. The learned LR features are transformed into HR space for simultaneously recognition and hallucination and comprehensively analyzed the role of locality constrained representation in recognition and SR tasks including selection of parameters and optimization of its semi-coupled version.

The performance of most face recognition systems (FRSs) in unconstrained environments is widely noted to be sub-optimal. One reason for this poor performance may be the lack of highly effective image pre-processing approaches, which are typically required before the feature extraction and classification stages. Furthermore, it is noted that only minimal face recognition issues are typically considered in most FRSs, thus limiting the wide applicability of most FRSs in real-life scenarios. Therefore, it is envisaged that installing more effective pre-processing techniques, in addition to selecting the right features for classification, will significantly improve the performance of FRSs. This article proposes a new enhancement method has been applied to improve the performance of face recognition systems in unconstrained environments by using state-of-the-art convolutional neural networks. A set of effective hybrid features that can be extracted from the enhanced images has been presented to improve the recognition performance. Detailed performance analysis has been provided to confirm the effectiveness of the face image enhancement approach to increase recognition performance considering all constraints in the face database.

III. SYSTEM ANALYSIS

This project provides COVID-19 vaccination status using their face and attest that an individual has received a vaccine or not and alert them to get vaccinated.Proposed an Aadhaar-based facial recognition system is used to find non-vaccination citizen and alert them using Artificial Intelligence. Deep learning in the form of Convolutional Neural Networks (CNNs) to perform the face recognition. Face Recognition - DCNN

CNNs are a category of Neural Networks that have provenvery effective in areas such as image recognition and classification. CNNs are a type of feed-forward neural networks made up of many layers. CNNs consist of filters or kernels or neurons that have learnable weights or parameters and biases. Each filter takes some inputs, performs convolution and optionally follows it with a non-linearity. A typical CNN architecture can be seen as shown in Fig.3.3.The structure of CNN contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers.

A. Convolutional Layer:

Convolutional layer performs the core building block of a Convolutional Network that does most of the computational heavy lifting. The primary purpose of Convolution layer is to extract features from the input data which is an image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input image. The input image is convoluted by employing a set of learnable neurons. This produces a feature map or activation map in the output image and after that the feature maps are fed as input data to the next convolutional layer.

B. Pooling Layer:

Pooling layer reduces the dimensionality of each activation map but continues to have the most important information. The input images are divided into a set of non-overlapping rectangles. Each region is down-sampled by a non-linear operation such as average or maximum. This layer achieves better generalization, faster convergence, robust to translation and distortion and is usually placed between convolutional layers.

C. ReLU Layer:

ReLU is a non-linear operation and includes units employing the rectifier. It is an element wise operation that means it is applied per pixel and reconstitutes all negative values in the feature map by zero. In order to understand how the ReLU operates, we assume that there is a neuron input given as x and from that the rectifier is defined as f(x)= max (0, x) in the literature for neural networks.

D. Fully Connected Layer:

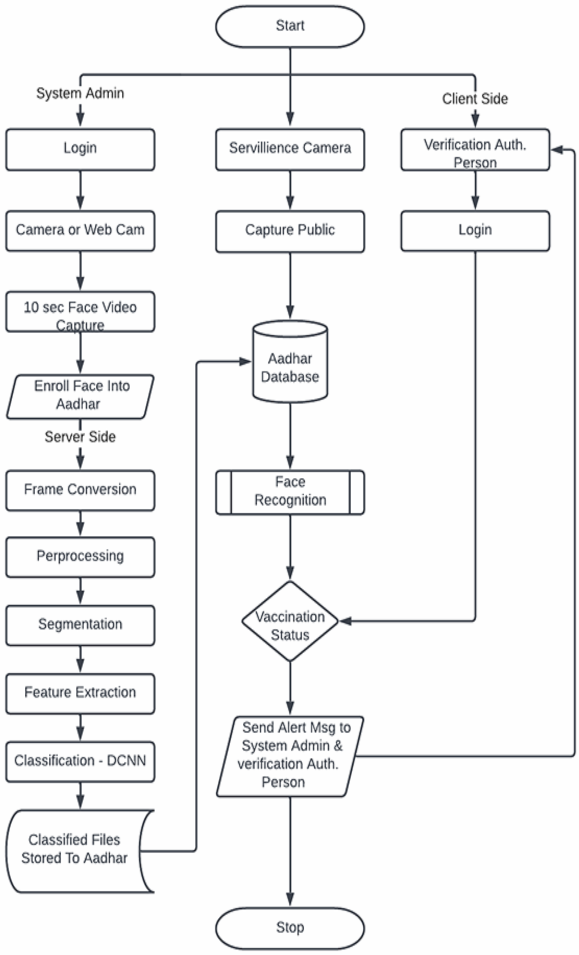
Fully Connected Layer (FCL) term refers to that every filter in the previous layer is connected to every filter in the next layer. The output from the convolutional, pooling, and ReLU layers are embodiments of high-level features of the inputimage. The goal of employing the FCL is to employ thesefeatures for classifying the input image into various classesbased on the training dataset. FCL is regarded as final poolinglayer feeding the features to a classifier that uses Softmax activation function. The sum of output probabilities from theFully Connected Layer is 1. This is ensured by using the Softmax as the activation function. The Softmax function takes a vector of arbitrary real-valued scores andsquashes it to a vector of values between zero and one that sumto one.

E. Advantages:

The system stores the faces that are detected and automatically marks vaccinated or not or Dose 1.

- Provide authorized access.
- Multiple face detection.
- Provide methods to maximize the number of extracted faces from an image.
- Ease of use.
- Manipulate and recognize the faces in real time using live video data.
- Multipurpose software.
- Can be used in different places.
- Vaccination Alert
- Vaccination Certificate with Face and QR

IV. SYSTEM IMPLEMENTATION



The COVID-19 vaccines are essential, lifesaving commodities in the current pandemic and ensuring equitable & indiscriminate access to the vaccines for all is of paramount importance.Millions of vulnerable people are at risk of missing out on COVID-19 vaccines as India uses its national digital identity for registration. However, deploying Aadhaar-based FRT for the verification process, deprives the citizens who do not possess or have not linked their Aadhaar cards to the Co-Win portal or the on-site register, of the vital vaccines," it said.

A. Covid 19 Vaccination Finder Web App:

Covid Vaccine Intelligence Network (Co-WIN), a portal set up to aid India's Covid immunisation drive.In this portal an Aadhaar-based facial recognition system is developed to find Covid-19 vaccination finder across the country in order find to Non-Vaccinated Population."Facial recognition authentication is used as one of the methods for Aadhaar Authentication for online verification of beneficiary prior to COVID-19 vaccination wherein facial template is captured and send to UIDAI for verification of image of beneficiary,"

B. Face Recognition Module:

Face Enrollment-This module begins by registering a few frontal face of Bank Beneficiary templates. These templates then become the reference for evaluating and registering the templates for the other poses: tilting up/down, moving closer/further, and turning left/right.

Face Image Acquisition-Cameras should be deployed in ATM to capture relevant video. Computer and camera are interfaced and here webcam is used.

Frame Extraction-Frames are extracted from video input. The video must be divided into sequence of images which are further processed. The speed at which a video must be divided into images depends on the implementation of individuals. From we can say that, mostly 20-30 frames are taken per second which are sent to the next phases.

Pre-processing-Face Image pre-processing are the steps taken to format images before they are used by model training and inference. The steps to be taken are:

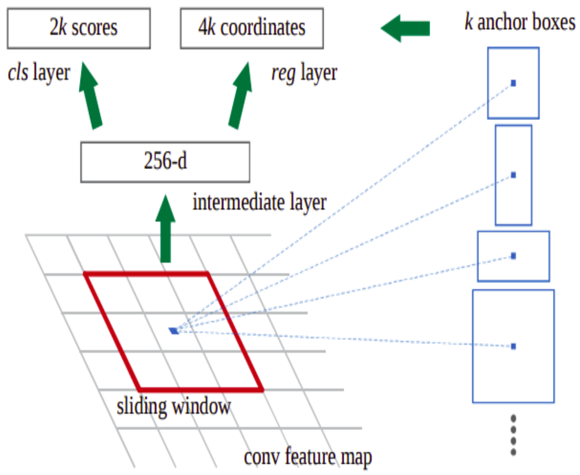
- Read image
- RGB to Grey Scale conversion
- Resize image
- Original size (360, 480, 3) — (width, height, no. RGB channels)
- Resized (220, 220, 3)
- Remove noise (Denoise)
- smooth our image to remove unwanted noise. We do this using gaussian blur.

Binarization-Image binarization is the process of taking a grayscale image and converting it to black-and-white, essentially reducing the information contained within the image from 256 shades of grey to 2: black and white, a binary image.

Face Detection-Therefore, in this module, Region Proposal Network (RPN) generates RoIs by sliding windows on the feature map through anchors with different scales and different aspect ratios. Face detection and segmentation method based on improved RPN. RPN is used to generate RoIs, and RoI Align faithfully preserves the exact spatial locations. These are responsible for providing a predefined set of bounding boxes of different sizes and ratios that are going to be used for reference when first predicting object locations for the RPN.

Face Image segmentation using region growing (RG) method The region growing methodology and recent related work of region growing are described here. RG is a simple image segmentation method based on the seeds of region. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points. This approach to segmentation examines the neighbouring pixels of initial "seed points" and determines whether the pixel neighbours should be added to the region or not based on certain conditions. In a normal region growing technique, the neighbour pixels are examined by using only the "intensity" constraint. A threshold level for intensity value is set and those neighbour pixels that satisfy this threshold is selected for the region growing.

RPN-A Region Proposal Network, or RPN, is a fully convolutional network that simultaneously predicts object bounds and objectless scores at each position. The RPN is trained end-to-end to generate high-quality region proposals. It works on the feature map (output of CNN), and each feature (point) of this map is called Anchor Point. For each anchor point, we place 9 anchor boxes (the combinations of different sizes and ratios) over the image. These anchor boxes are cantered at the point in the image which is corresponding to the anchor point of the feature map.



Ficture.3. *Training of RPN.*

To know that for each location of the feature map we have 9 anchor boxes, so the total number is very big, but not all of them are relevant. If an anchor box having an object or part of the object within it then can refer it as a foreground, and if the anchor box doesn't have an object within it then we can refer it as background.

So, for training, assign a label to each anchor box, based on its Intersection over Union (IoU) with given ground truth. We basically assign either of the three (1, -1, 0) labels to each anchor box. Label = 1 (Foreground): An anchor can have label 1 in following conditions,

If the anchor has the highest IoU with ground truth.

If the IoU with ground truth is greater than 0.7.

(IoU>0.7).

Label = -1 (Background): An anchor is assigned with -1 if IoU< 0.3.

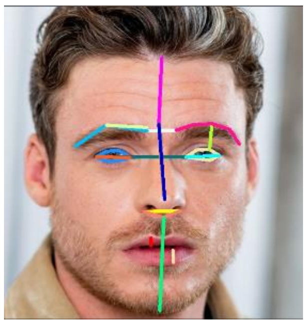
Label = 0: If it doesn't fall under either of the above conditions, these types of anchors don't contribute to the training, they are ignored.

After assigning the labels, it creates the mini-batch of 256 randomly picked anchor boxes, all of these anchor boxes are picked from the same image. The ratio of the number of positive and negative anchor boxes should be 1:1 in the mini-batch, but if there are less than 128 positive anchor boxes then we pad the mini-batch with negative anchor boxes. Now the RPN can be trained end-to-end by backpropagation and stochastic gradient descent (SGD). The processing steps are

- Select the initial seed point
- Append the Neighbouring pixels intensity threshold
- Check threshold of the neighbouring pixel
- Thresholds satisfy-selected for growing the region.
- Process is iterated to end of all regions.

C. Feature Extraction:

After the face detection, face image is given as input to the feature extraction module to find the key features that will be used for classification.With each pose, the facial information including eyes, nose and mouth is automatically extracted and is then used to calculate the effects of the variation using its relation to the frontal face templates.



Ficture.4. *Face Features*

Forehead Height: distance between the top edge of eyebrows and the top edge of forehead.

Middle Face Height: distance between the top edge of eyebrows and nose tip.

Lower Face Height: distance between nose tip and the baseline of chin.

Jaw Shape: A number to differentiate between jaw shapes. this number can be replaced if you use Face Shape Recognition, see (this) notebook.

Left Eye Area

Right Eye Area

Eye to Eye Distance: distance between eyes (closest edges)

Eye to Eyebrow Distance: distance between eye and eyebrow (left or right is determined by whice side of the face is more directed to the -screen-)

Eyebrows Distance: horizontal distance between eyebrows

Eyebrow Shape Detector 1: The angle between 3 points (eyebrow left edge, eyebrow center, eyebrow right edge), to differentiate between (Straight | non-straight) eyebrow shapes

Eyebrow Shape Detector 2: A number to differentiate between (Curved | Angled) eyebrow shapes.

Eyebrow Slope

Eye Slope Detector 1: A method to calculate the slope of the eye. it's the slope of the line between eye's center point and eye's edge point. this detector is used to represent 3 types of eye slope (Upward, Downward, Straight).

Eye Slope Detector 2: Another method to calculate the slope of the eye. it's the difference on Y-axis between eye's center point and eye's edge point. this detector isn't a 'mathematical' slope, but a number that can be clustered into 3 types of eye slope (Upward, Downward, Straight).

Nose Length

Nose Width: width of the lower part of the nose

Nose Arch: Angle of the curve of the lower edge of the nose (longer nose = larger curve = smaller angle)

Upper Lip Height

Lower Lip Height

The features we extracted can be grouped into three categories. The first category is the first order statistics, which includes maximum intensity, minimum intensity, mean, median, 10th percentile, 90th percentile, standard deviation, variance of intensity value, energy, entropy, and others. These features characterize the Gray level intensity of the tumour region.

The second category is shape features, which include volume, surface area, surface area to volume ratio, maximum 3D diameter, maximum 2D diameter for axial, coronal and sagittal plane respectively, major axis length, minor axis length and least axis length, sphericity, elongation, and other features. These features characterize the shape of the tumour region.

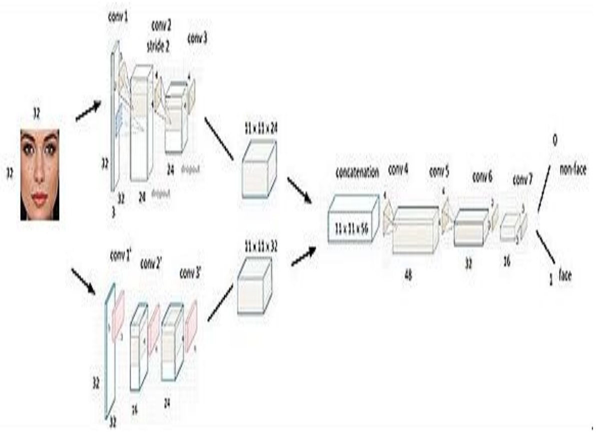
The third category is texture features, which include 22 Gray level co-occurrence matrix (GLCM) features, 16 Gray level run length matrix (GLRLM) features, 16 Gray level size zone matrix (GLSZM) features, five neighbouring gray tone difference matrix (NGTDM) features and 14 Gray level dependence matrix (GLDM) Features. These features characterize the texture of the tumour region.

	image_id	lefteye_x	lefteye_y	righteye_x	righteye_y	nose_x	nose_y	leftmouth_x	leftmouth_y	rightmouth_x	rightmouth_y
0	000001.jpg	69	109	106	113	77	142	73	152	108	154
1	000002.jpg	69	110	107	112	81	135	70	151	108	153
2	000003.jpg	76	112	104	106	108	128	74	156	98	158
3	000004.jpg	72	113	108	108	101	138	71	155	101	151
4	000005.jpg	66	114	112	112	86	119	71	147	104	150

Ficture.4. *Facial Attribute*

D. Face Classification:

DCNN algorithms were created to automatically detect and reject improper face images during the enrolment process. This will ensure proper enrolment and therefore the best possible performance



The CNN creates feature maps by summing up the convolved grid of a vector-valued input to the kernel with a bank of filters to a given layer. Then a non-linear rectified linear unit (ReLU) is used for computing the activations of the convolved feature maps. The new feature map obtained from the ReLU is normalized using local response normalization (LRN). The output from the normalization is further computed with the use of a spatial pooling strategy (maximum or average pooling). Then, the use of dropout regularization scheme is used to initialize some unused weights to zero and this activity most often takes place within the fully connected layers before the classification layer. Finally, the use of softmax activation function is used for classifying image labels within the fully connected layer.

E. Face Identification:

After capturing the face image from the Camera, the image is given to face detection module. This module detects the image regions which are likely to be human. After the face detection using Region Proposal Network (RPN), face image is given as input to the feature extraction module to find the key features that will be used for classification. The module composes a very short feature vector that is well enough to represent the face image. Here, it is done with DCNN with the help of a pattern classifier, the extracted features of face image are compared with the ones stored in the face database. The face image is then classified as either known or unknown. If the image face is known, then the covid vaccination details of the particular person is displayed.

F. Prediction:

In this module the matching process is done with trained classified result and test Live Camera Captured Classified file. Hamming Distance is used to calculate the difference according to the result the prediction accuracy will be displayed.

G. Non-Vaccination Finder:

This module is capable of identifying or verifying a non-Vaccination person by comparing and analysing patterns, shapes and proportions of their facial features and contours from the trained classified file.When a facial image (probe image) is entered into the system it is automatically encoded by an algorithm and compared to the profiles already stored in the Aadhar database system.

H. Notification:

This information is then passed on to the countries that provided the images, and to those that would be concerned by the profile or a match. The results are returned quickly to enable immediate follow-up action.

I. Performance Analysis:

The important points involved with the performance metrics are discussed based on the context of this project:

- True Positive (TP): There is a Face, and the algorithms detect Card Holder.
- False Positive (FP): There is no Face, but the algorithms detect as Card Holder and display Card Holder name.
- False Negative (FN): There is a Face, but the algorithms do not detect Card Holder and name.

- True Negative (TN): There is no Face, and nothing is being detected.

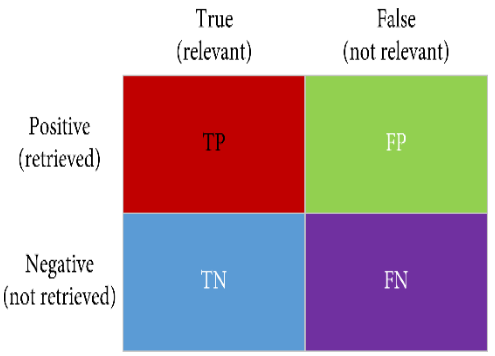


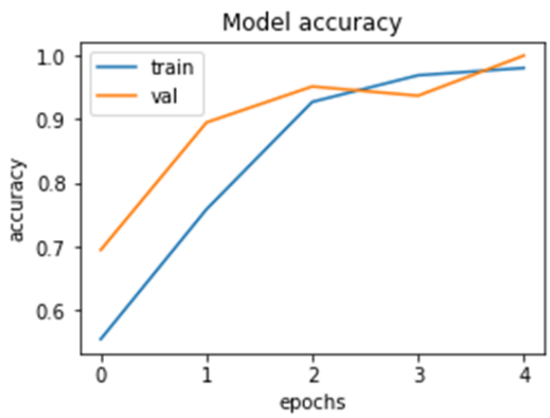
Fig. 8.1. *Parameter Definition*

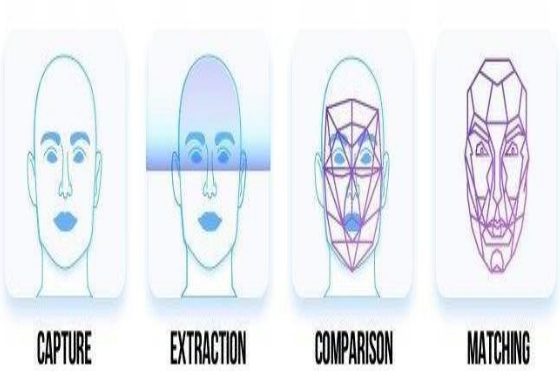
J. Accuracy:

Accuracy is a measure that tells whether a model/algorithm is being trained correctly and how it performs. In the context of this thesis, accuracy tells how well it is performing in detecting Face in ATM Machine. Accuracy is calculated using the following formula.

Accuracy = (T P + T N)/ (T P + T N + F P + F N)

Accuracy: 0.9984025559105432



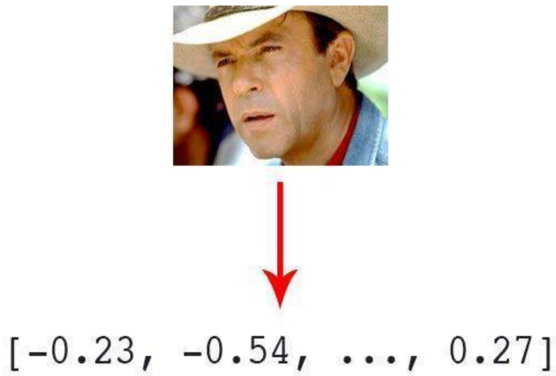


Working of Facial Recognition

Height/width of parts of face like nose & lips (cm) We can consider the ratios as feature vector after rescaling A feature vector can be created by organising these attributes to into a table, say, for a certain set of values of attributes your table may look like this:

Height of face (cm)	Width of face (cm)	Average color of face (R, G, B)	Width of lips (cm)	Height of nose(cm)
23.1	15.8	(255, 224, 189)	5.2	4.4

image now becomes a vector that could be represented as [23.1, 15.8, 255, 224, 189, 5.2, 4.4]. Now can add a number of other features like hair color& spectacles. Keep in mind that a simple model gives the best result. Adding a greater number of features may not give accurate results (See overfitting and underfitting).



Machine learning helps you with two main things:

Deriving the feature vector: As it is a difficult process to involve all features by name, we convert it to feature vector. This is then used by the algorithm. A Machine Learning algorithm can intelligently label out many of such features.

Matching algorithms: Once the feature vectors have been obtained, a Machine Learning algorithm needs to match a new image with the set of feature vectors present in the corpus.

There are two main parts to a CNN architecture A convolution tool that separates and identifies the various features of the image for analysis in a process called as Feature Extraction A fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages.

Face Landmark Points

There are mostly two steps to detect face landmarks in an image which are given below:

- Face detection: Face detection is the first methods which locate a human face and return a value in x,y,w,h which is a rectangle.
- Face landmark: After getting the location of a face in an image, then we have to through points inside of that rectangle.

Convolution Layers

There are three types of layers that make up the CNN which are the convolutional layers, pooling layers, and fully-connected (FC) layers. When these layers are stacked, a CNN architecture will be formed. In addition to

these three layers, there are two more important parameters which are the dropout layer and the activation function which are defined below.

1. Convolutional Layer:

This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM). The output is termed as the Feature map which gives us information about the image such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

2. Pooling Layer:

In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations. In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer.

3. Fully Connected Layer:

The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture. In this, the input image from the previous layers is flattened and fed to the FC layer. The flattened vector then undergoes few more FC layers where the mathematical functions operations usually take place. In this stage, the classification process begins to take place.

4. Dropout:

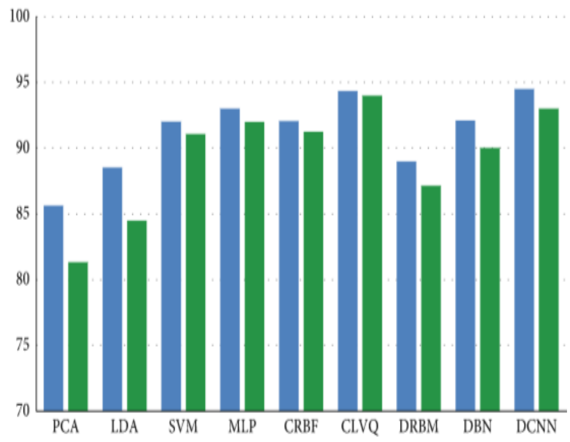
Usually, when all the features are connected to the FC layer, it can cause overfitting in the training dataset. Overfitting occurs when a particular model works so well on the training data causing a negative impact in the model’s performance when used on a new data. To overcome this problem, a dropout layer is utilized wherein a few neurons are dropped from the neural network during training process resulting in reduced size of the model. On passing a dropout of 0.3, 30% of the nodes are dropped out randomly from the neural network.

5. Activation Functions:

Finally, one of the most important parameters of the CNN model is the activation function. They are used to learn and approximate any kind of continuous and complex relationship between variables of the network. In simple words, it decides which information of the model should fire in the forward direction and which ones should not at the end of the network. It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, SoftMax, tanH and the Sigmoid functions. Each of these functions have a specific usage. For a binary classification DCNN model, sigmoid and SoftMax functions are preferred a for a multi-class classification, generally SoftMax us used.

V. RESULT AND DISCUSSION

A comparative evaluation based on the accuracy of the proposed face recognition Deep Convolutional Neural Network (DCNN) system, compared to Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), as statistical approach, Multi-Layer Perceptron (MLP), Combined Radial Basis Function (CRBF), as neural network approach, Deep Restricted Boltzmann Machine (DRBM), Deep Belief Neural Nets (DBNN).The results show that the proposed DCNN achieves higher accuracy compared to other approaches.



Face Recognition Accuracy

VI. CONCLUSION

A facial recognition system is a technology capable of matching a human face from a digital image or a video frame against a database of faces, typically employed to authenticate users through ID verification services, works by pinpointing and measuring facial features from a given image. In the context of the coronavirus disease (COVID-19) pandemic, A face recognition-based person's current vaccination status to protect against COVID-19 can then be used for continuity of care or as proof of vaccination for purposes other than health care. Facial recognition technology (FRT) along with the Aadhaar to authenticate people before entering into any kinds of service. This project provides COVID-19 vaccination status using their face and attest that an individual has received a vaccine or not and alert them to get vaccinated.The proposed classifier performance evaluation was presented as a confusion matrix, in terms of sensitivity, specificity, precision, accuracy, and F1score. Results indicated that the proposed classifier has achieved higher recognition accuracy than ten other classifiers of the state of art.

VII. FUTURE ENHANCEMENT

For the future, we will proceed to enhance the proposed classifier performance to be able to handle the spoof attacks problem that may be occurred by fake subjects. Also, we can apply this technique to vote anywhere in India.

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