



Student attendance system with face recognition using deep learning

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Abstract: Managing student attendance is a repetitive and time-consuming task for both teachers and school administrators., we thought of automating this task by deploying the recent advances of deep learning. In this paper, we propose an attendance management system based on facial detection and recognition. The classroom is continuously photographed using a camera. An in-depth analysis is applied to the captured images to detect the facial features of the students. then, a pattern recognition model predicts their identities. We have used deep learning models based on Convolutional Neural Network (CNN). The results of the experiment validate the proposed architecture. The process of marking the students' attendance is maintained without any human intervention.

Keywords: Deep learning, Computer vision, Automatic attendance, Face recognition, Face detection, Convolutional Neural Network, Web development.

1. Introduction

Nowadays, the attendance system is of great significance in enterprises, schools, governments, and other places where personnel management is needed. Attendance through fingerprint recognition requires queuing for identification, which consumes a lot of time. In the case of a finger injury, the accuracy of fingerprint recognition will be greatly reduced. By scanning the ID card for attendance, the identity of the cardholder cannot be verified, which will also produce fraudulent attendance behavior. Checking attendance by mobile phone location is similar to scanning an ID card, which cannot confirm the user's identity, and the location information can also be forged. With the continuous development of machine learning and artificial intelligence technology, the methods of face detection, face recognition, and face landmarks detection have changed greatly. As an important biological feature, the human face has been widely used in the attendance system. The dynamic face recognition technology takes a photo of the current attending students within the classroom building. The user only needs to appear within the scope of video surveillance, and the system can automatically recognize it. Because of its real-time and convenience, this technology has become a hot research direction for the attendance system. An attendance system based on dynamic and multi-face recognition is designed using deep learning approaches. We also designed a user interaction interface for the attendance system[1].

2. Overview

the attendance system depends on face recognition technology which has basic steps as a pipeline to be followed:

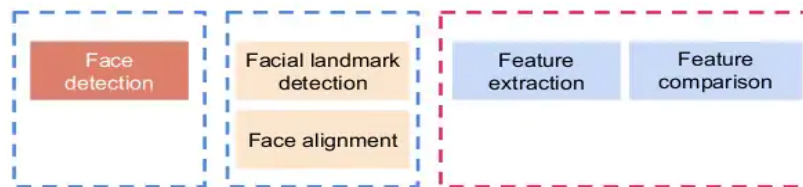


Fig1: face recognition pipeline

2.1 What is Face Detection

The first step in face recognition is the detection of the face. Face detection helps identify which parts of an image or video should be focused on to determine age, gender, and emotions using facial expressions. In a facial recognition system, face detection data is required for algorithms that discern which parts of an image or video are needed to generate a faceprint. Face detection applications use algorithms and ML to find human faces within larger images, which often incorporate other non-face objects such as landscapes and other human body parts like feet or hands. Face detection algorithms typically start by searching for human eyes -- one of the easiest features to detect. The algorithm might then attempt to detect eyebrows, the mouth, nose, nostrils, and the iris. Once the algorithm concludes that it has found a facial region, it applies additional tests to confirm that it has detected a face[2].

2.2 What is landmark detection

Facial landmark detection algorithms aim to automatically identify the locations of the facial key landmark points on facial images or videos. Those key points are either the dominant points describing the unique location of a facial component (e.g., eye corner) or an interpolated point connecting those

dominant points around the facial components and facial contour. Facial landmark detection is challenging for several reasons. First, facial appearance changes significantly across subjects under different facial expressions and head poses. Second, environmental conditions such as illumination would affect the appearance of the faces on the facial images. Third, facial occlusion by other objects or self-occlusion due to extreme head poses would lead to incomplete facial appearance information[3].

2.3 What is face recognition

Face recognition is the science that involves the understanding of how faces are recognized by biological systems and how this can be emulated by computer systems. Biological systems employ different types of visual sensors (i.e., eyes), which have been designed by nature to suit a certain environment where the agent lives. Similarly, computer systems employ different visual devices to capture and process faces as best indicated by each particular application. These sensors can be video cameras (e.g., a camcorder), infrared cameras, or among others, 3D scans. Face recognition systems work by capturing an incoming image from a camera device in a two-dimensional or three-dimensional way depending on the characteristics of the device. These ones compare the relevant information of the incoming image signal in real-time in photo or video in a database, being much more reliable and secure than the information obtained in a static image. In this comparison of faces, it analyses mathematically the incoming image without any margin of error and verifies that the biometric data matches the person [4].

2.4 Problem definition

Building an automated attendance system that is reliable, efficient, and which saves time. In recent times, machine learning is enhancing and making human life smart, and hence following or using the same old traditional approaches in daily chores and tasks is like wasting time, energy, and effort for no reason. attendance system which uses face recognition algorithms to record the attendance of the class and manage the class database. The system seeks its application in every classroom to record the attendance of the students smartly and take over the traditional attendance approaches.

2.5 System objective

We introduce a system that uses facial recognition technology to record attendance automatically by acquiring images through a high-resolution digital camera. The data acquired is fed to the computer for classification. However, for a machine to be able to identify a person based on their characteristics, it needs to be trained by the use of different algorithms suitable for the purpose. The algorithms defined in the paper are therefore able to recognize faces by means of comparing the test images; acquired on runtime, with the face images stored in the training database, and decisions are made using suitable classifiers. Once the test face matches a stored image, attendance is marked.

3. Literature survey

In recent times, different techniques, methods, and algorithms have been used to perform facial recognition and increase the accuracy of facial recognition for taking attendance.

In [6] presents a novel methodology of taking students' attendance through the face recognition technique. The facial features of the students are extracted via Local Binary Pattern (LBP) and

Histogram of Oriented Gradients (HOG). Both LBP and HOG features are combined to create a new feature vector. A classification model is implemented using a Support Vector Machine (SVM) classifier which predicts students based on comparisons made between the features of the query image and the features of the images stored in the student database.

The results of the experiment have shown that the proposed system works efficiently well in almost all lighting conditions. It recognizes the faces of the students accurately and updates the attendance status. It also recognizes the faces even in the presence of spectacles. The combining of LBP and HOG features has increased the accuracy of face recognition way better than other methods. The implemented system also preserves the wastage of time and the proxy data entries that often take place in the case of manual attendance marking.

In [7] presents a methodology for recognizing the human face based on the features derived from the image. The proposed methodology is implemented in two stages. The first stage detects the human face in an image using a viola-Jones algorithm. In the next stage, the detected face in the image is recognized using a fusion of Principal Component Analysis and Feed Forward Neural Network. The performance of the proposed method is compared with existing methods. Better accuracy in recognition is realized with the proposed method. The proposed methodology uses Bio ID-Face-Database as a standard image database. The accuracy of face detection and recognition of the proposed method is compared with the existing methods. With the PCA algorithm, an image identification of 72% is realized and with the ANN algorithm, an image identification of 92% is achieved.

In [8] aspires to present the comparison of two face recognition techniques Haar Cascade and Local Binary Pattern edified for the classification. As a result, the accuracy of Haar Cascade is more than the Local Binary Pattern but the execution time in Haar Cascade is more than Local Binary Pattern. The execution is performed on both Haar cascade and LBP classifier by using a number of images. As a result, the Haar cascade has more accuracy than the LBP classifier but the time taken by the LBP classifier is less than the Haar cascade classifier compared to other researchers. The Haar cascade classifier detects more faces than the LBP classifier in an image.

3.1 Algorithms Comparison

After a long time of experiments to choose the best classification and detection algorithms from the literature survey and based on the following comparisons. We used Multi-task Cascaded Convolutional Networks (MTCNN) which are an effective method to detect faces, identify the position of the face in the picture and mark five landmarks through deep Convolutional Neural Network (CNN) Table 1. FaceNet is a technology of face recognition, which is also based on CNN technology, exhibiting high accuracy Table 2.

Algorithm	Creator	year	Dataset	Method/ Backbone	Accuracy
LBP	Silva	2015	CMU-PIE	based on a local binary operator Over CNN	94.74%
viola-Jones	Paul Viola and Michael Jones	2001	MIT-CMU	Based on classifiers cascades	93.24%

AdaBoost	Yoav Freund and Robert Schapire	2003	Titanic dataset	Ensemble Method in Machine Learning	88.88%
Haar Cascade	Alfred Haar	1909	ImageNet dataset	ResNet-50 backbone as baseline	96.24%
MTCNN [23]	G. J. Edwards, and C. J. Taylor	2001	WIDER-FACE dataset	FaceNet and pre-trained ImageNet	98.9%
R-CNN [20]	Shaoqing	2007	PASCAL VOC	based on CNN detector	66.0%
Fast R-CNN [20]	Ross Girshick	2007	PASCAL VOC	based on CNN detector	70.0%

Table 1 . face recognition algorithms survey.

Algorithm	Creator	year	Dataset	Method/ Backbone	Accuracy
FaceNet [13]	Google	2015	Labeled Faces in the Wild	Deep convolutional network	99.63%
DeepID3 [13]	The Chinese University of Hong Kong	2015	Labeled Faces in the Wild		99.53%
SphereFace [14]	Georgia Institute of Technology	2017	Labeled Faces in the Wild	PyTorch framework	99.42%
Dlib [15]	Davis E. King	2009	Labeled Faces in the Wild	ResNet-10	99.38%
VGG-Face [16]	The University of Oxford	2015	YouTube Faces DB	ResNet 50	97.40%
DeepFace [17]	Facebook	2014	Labeled Faces in the Wild		97.35%
OpenFace [18]	Carnegie Mellon University	2016	Labeled Faces in the Wild	PyTorch deep learning framework	92.92%
ArcFace [19]	Imperial College London		large-scale image and video database	MobileFaceNet	99.40%

Table 2 . face recognition algorithms survey.

4. Mechanism

In this paper, a real-time attendance taking system is implemented using deep learning approaches to detect the faces of each student from a video stream and then recognize the faces by cross-referencing the detected faces with the ones stored in the system. This system also has the ability to detect and recognize multiple people on the screen automatically in real-time from the video stream.

For both detecting and recognizing faces, Deep convolutional neural network (DCNN) models are used. Multitasking Cascading Convolutional Networks (MTCNN) is used for face detection and alignment, followed by FaceNet and Inception-ResNet-v1 models to extract face features and create embeddings and store them into the database to be compared later by binary classification for face verification and matching.

4.1 Convolutional neural network (CNN)

A convolutional neural network (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data.

Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and output an activation value. When you input an image in a ConvNet, each layer generates several activation functions that are passed onto the next layer[24].

4.2 Residual Network (ResNet)

Deep Residual Network (ResNet) is an Artificial Neural Network that is created with the aim of overcoming the problem of lower accuracy when creating a plain ANN with a deeper layer than a shallower ANN [10]. In other words, the purpose of the Deep Residual Network is to make ANN with deeper layers with high accuracy [9]. The concept of the Deep Residual Network is to make ANN that can update the weight to a shallower layer (reduce degradation gradient). The concept is implemented using a "shortcut connection". The concept of a residual network is shown in Fig. 2

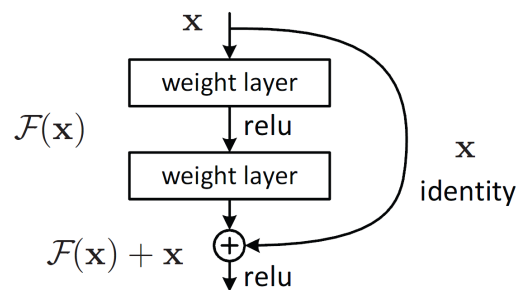


Fig.2 Residual learning: a building block

Inception-ResNet-v1 is one of the ResNet pre-trained models which is a convolutional neural network that is trained on more than a million images from the ImageNet database. The network is 572 layers deep and can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many

animals. As a result, the network has learned rich feature representations for a wide range of images [31].

4.3 Multitasking Cascading Convolutional Networks (MTCNN)

Multitasking Cascading Convolutional Networks (MTCNN) is a framework developed as a face detection and face alignment solution. The process consists of three stages of convolutional networks capable of recognizing faces and prominent locations such as the eyes, nose, and mouth.

In the first stage, a shallow CNN is used to quickly produce filter windows. The second stage optimizes the proposed filter windows through a more complex CNN. Finally, the third stage uses a third CNN, one more complex than the other, to improve the result and output the positions of the facial features[28].

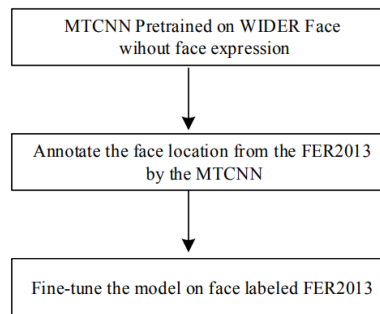


Fig.3 MTCNN training procedure

MTCNN is mainly based on 3 separate CNN models: P-Net, R-Net, and O-Net.

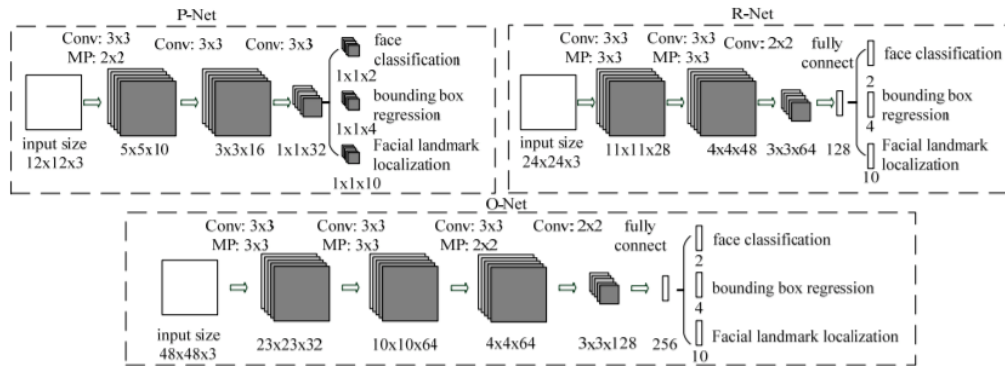


Fig.4 MTCNN Architecture

- **The Proposal Network (P-Net):** This first stage is a fully convolutional network (FCN). The difference between a CNN and an FCN is that a fully convolutional network does not use a dense layer as part of the architecture. This Proposal Network is used to obtain candidate windows and their bounding box regression vectors [31].
- **The Refine Network (R-Net):** All candidates from the P-Net are fed into the Refine Network. Notice that this network is a CNN, not an FCN like the one before since there is a dense layer at the last stage of the network architecture. The R-Net further reduces the number of candidates, performs calibration with bounding box regression, and employs non-maximum suppression (NMS) to merge overlapping candidates [31].

The R-Net outputs whether the input is a face or not, a 4 element vector which is the bounding box for the face, and a 10 element vector for facial landmark localization.

- **The Output Network (O-Net):** This stage is similar to the R-Net, but this Output Network aims to describe the face in more detail and output the five facial landmarks' positions for eyes, nose, and mouth [31].

4.4 Binary classification

It is a process or task of classification, in which a given data is being classified into two classes. It's basically a kind of prediction about which of two groups the thing belongs to.

suppose, two emails are sent to you, one is sent by an insurance company that keeps sending their ads, and the other is from your bank regarding your credit card bill. The email service provider will classify the two emails, the first one will be sent to the spam folder and the second one will be kept in the primary one[28].

5. System implementation

The proposed system is generated using a web application. We have used the flask framework and SQLite database. Different stages of the application are presented next.

5.1 System architecture

The proposed system's architecture based on flexibility is shown in Fig.5 below

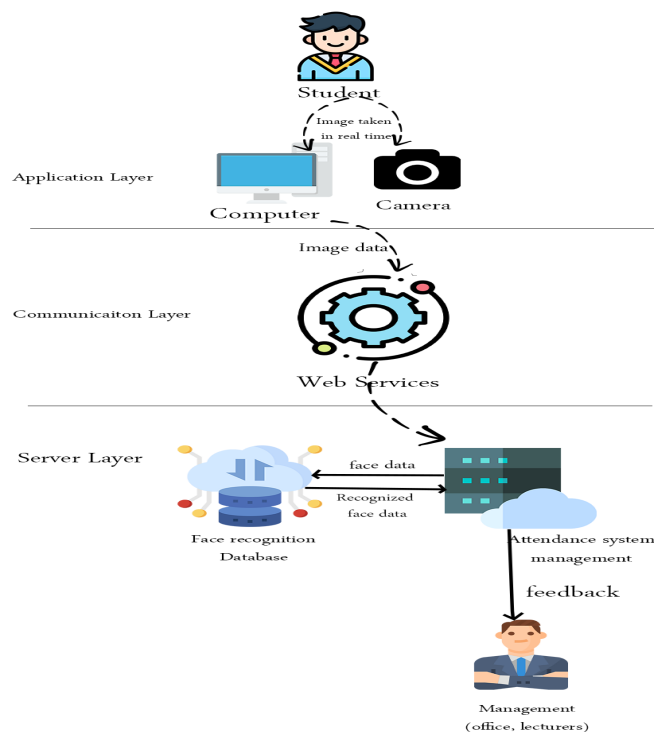


Fig.5 System pipeline

5.2 System pipeline

The proposed methodology for face recognition is based on deep learning algorithms. Fig.6 describes the proposed system block diagram.

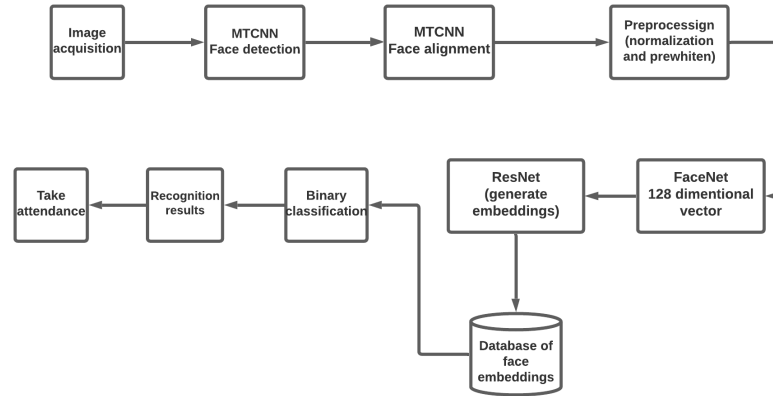


Fig.6 System pipeline

5.2.1 Image acquisition

The data for Deep Learning is a key input to models that comprehend from such data and learn the features for future prediction. Although, various aspects come during the deep learning model development, without which various crucial tasks cannot be accomplished. In other words, data is the backbone of entire model development without that it is not possible to train a machine that learns from humans and predicts for humans.

So, the biggest challenge that faces this project is to apply attendance functionalities with just one image for the unique person and recognize him in many cases or conditions. The images acquired from the data/images folder that you can put a student image and attached with his code into this folder, and the system will apply training techniques for it and save it into the database [28].

5.2.2 Face detection

MTCNN uses three convolutional networks (RNet, ONet, PNet) to detect faces on both live camera and image. It outputs the bounding boxes to mark the face and generates facial landmarks to be used as input to do face alignment. The MTCNN feature descriptor mainly includes three parts: face/non-face classifier, bounding box regression, and landmark location. There are three stages to be done in face detection with MTCNN. In stage one, images/live camera inputs are passed into the program which automatically creates multiple scaled copies of the image. The copies are then fed into P-Net which is the first convolutional network in MTCNN. At the end of stage one, P-Net outputs bounding boxes with high confidence after removing highly overlapped boxes by using Non-Maximum Suppression (NMS). In stage two, out-of-bound bounding boxes are padded and all the bounding boxes resulting from P-Net are passed to the second convolutional network (R-Net). Again, bounding boxes with low confidence are deleted and NMS is employed to remove highly overlapped bounding boxes. Stage three is similar to stage two, except that stage three has a more complicated convolutional network (O-Net) whose output is more precise. We will talk about them in more detail in the following words [28].

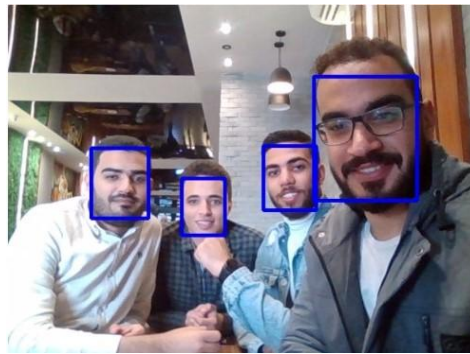


Fig.7 Detecting faces

5.2.3 Face Alignment

Align the face in a way that is as closely centered as possible using landmarks from MTCNN in step 2. In this step, we create a class to do face alignment after getting landmarks from MTCNN. The average positions of face points are extracted from Dlib open source code which is a commonly used aspect ratio for 5 landmarks. This class is called when doing face recognition and inputting face features into the database for both camera mode and picture mode.

5.2.4 Image preprocessing

The processing steps have been done into two techniques: Image normalization, and image prewhitening.

The purpose is to do image normalization with the L2 normalization technique to normalize the input and also overcome the problem of vanishing gradient and exploding gradient. The max-pooling layer is used to reduce the dimensionality of the input and the dropout layer is used to avoid the overfitting problem. Using image prewhitening to subtracts the average and normalizes the range of the pixel values of input images. It makes training a lot easier [28].

5.2.5 Face feature generation

Pre-trained models of FaceNet are used to generate Embedding in 128-Dimensional/512-Dimensional vectors for each transformed image as the face feature. We tried three different model weights including one 128D and two 512D pre-trained weights. The two 512D weights are generated using FaceNet Inception Resnet V1 architecture on CASIA-WebFace and VGGFace2 training dataset. Details for the Face detection and alignment by MTCNN Calculate distance from the existing user and report the closest user or unknown if the distance is higher than threshold Face features by FaceNet in 128 / 512-Dimensional vector 128D model weights are missing, we only know it is trained on the FaceNet Inception Resnet V1 architecture. The CASIA-WebFace dataset consists of 453 453 images over 10 575 identities after face detection. According to the author of the models, the best performing model has been trained on the VGGFace2 dataset consisting of ~3.3M faces and ~9000 classes. Therefore, we implement all three pre-trained weights for camera mode, but only implement weights trained on VGGFace2 for image mode.

Finally, the generated embeddings for each face will be stored in the students' database to be compared with the incoming real-time camera [28].

5.2.6 Binary classification

We used a binary classification technique for a facial recognition network to allow access to one person and to determine whether it matched or not.

Internally compare() function is used to compute the Euclidean distance between the face in the image and all faces in the dataset. If the current image is matched with the 60% threshold with the existing dataset, it will move to attendance marking. Internally compare() function is used to compute the Euclidean distance between the face in the image and all faces in the dataset [28].

5.2.7 Attendance marking

Once the faces are identified with the image stored in the database, python generates roll numbers of present students and returns that, when data is returned, the system generates an attendance table which includes the name, roll number, date, day, and time. You can access the attendances for each student on the attendance page [28].

6. GUI Development

The application graphical user interface (GUI) was developed into two pages, one for real-time camera observation for taking student attendances, and the other for attendance records.

6.1 Home page screen

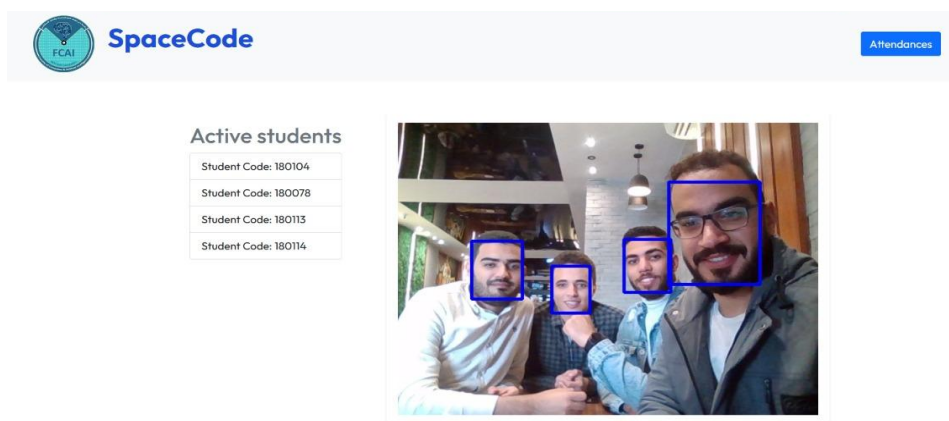



Fig.8 Real time camera processing into home screen

6.2 Attendance records screen



SpaceCode

Attendances

Student attendances

Student Code	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
180113		<ul style="list-style-type: none">Presented at: 11/30/2021, 18:05:58Presented at: 11/30/2021, 21:37:25	<ul style="list-style-type: none">Presented at: 12/01/2021, 08:54:06				<ul style="list-style-type: none">Presented at: 12/05/2021, 13:29:45
180078							<ul style="list-style-type: none">Presented at: 12/05/2021, 14:17:42
180104							<ul style="list-style-type: none">Presented at: 12/05/2021, 14:17:40
180114							<ul style="list-style-type: none">Presented at: 12/05/2021, 14:17:51

Fig.9 Attendance screen

7. Advantages and Disadvantages

The advantages and disadvantages of the proposed system:

Advantages	Disadvantages
High recognizing accuracy from one image.	Need a lot of computation resources
Management system build based on web application	

Table 3: advantages and disadvantages of attendance system

8. Experimental results

In order to demonstrate the efficiency of our modal, we have carried out a test on the Labeled Faces in the Wild (lfw) dataset which contains 13,000 images for 1680 unique people. To have a meaningful representation of the anchor positive distances of faces, it needs to be ensured that a minimal number of examples of anyone identity is present in each mini-batch.

The system achieved an accuracy of 97.5% and 0.0545% loss for 20 epochs as shown in the following figures.

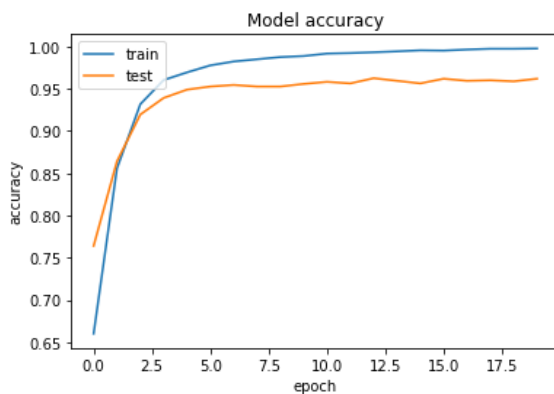


Fig.10 Model accuracy on flw dataset

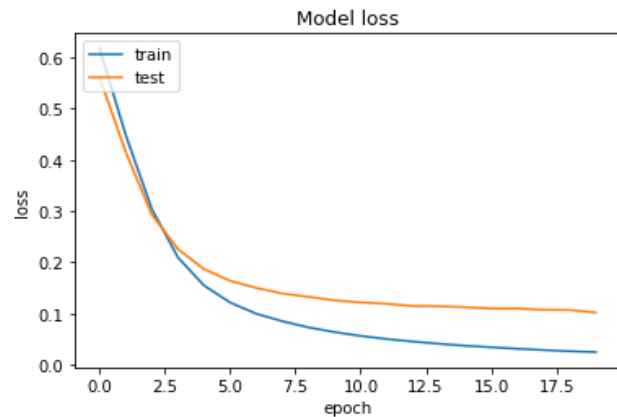


Fig.11 Model learning rate

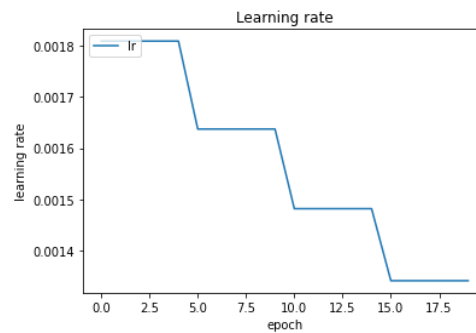


Fig.12 Model learning rate

9. Conclusion

In this paper, We proposed a student attendance system using deep facial recognition. Face detection and recognition are performed by convolutional neural network models MTCNN and FaceNet, also we will make use of the Inception ResNetV1 pre-trained model in our project to extract faces features before classifying these features using CNN. The main feature of face recognition, regardless of the high accuracy in recognizing faces, is that we need only one picture for every student to enable our model from recognizing the student. Based on the results, it can be concluded that the proposed architecture presents a good solution for managing the attendance of students in classrooms.

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