IMAGE BASED ATTENDANCE SYSTEM

Problem Statement

Most of the educational institutions are taking attendance as traditional roll call or fingerprint.





Previous Solution

Face attendance system wherein webcam captured frames will be matched against the existing trained images and stored their names in csv file along with date and time.

In our previous solution we used Haarcascade classifiers for face detection. But it

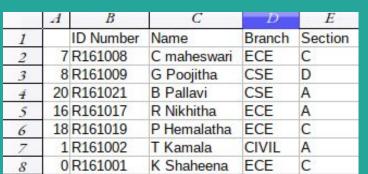




Solution

The faculty would simply take a photograph of the class and uploads it to the cloud system, attendance of the students will be marked, where it contains all students database for verification like images, name of the student.







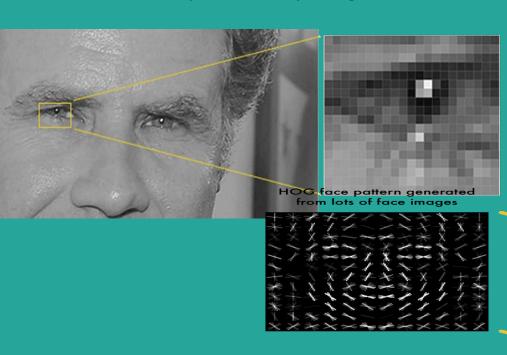


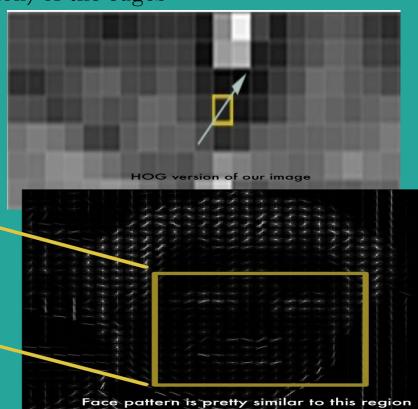
Steps required

- Face Detection
- Feature extraction
- Face recognition
- Write Attendance to csv file

Face Detection

For face detection we used HOG features. This is done by extracting the gradient and orientation (or you can say magnitude and direction) of the edges



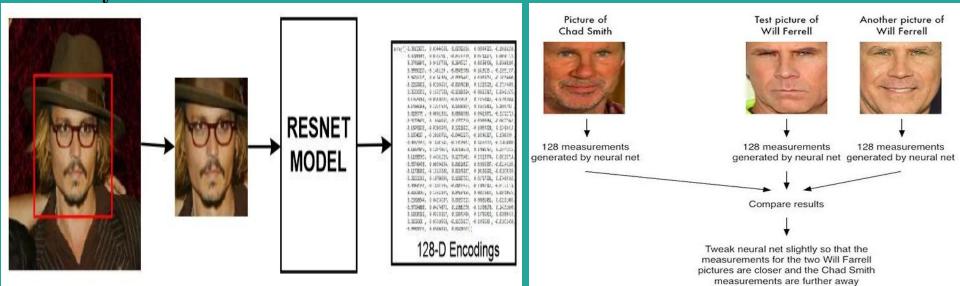


Feature Extraction

Dlib facial recognition network, the output feature vector is 128-d (i.e., a list of 128 real-valued numbers) that is used to quantify the face. Training the network is done using triplets:

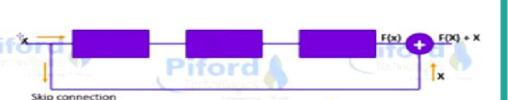
Our network architecture for face recognition is based on ResNet-34.

The network itself was trained on a dataset of ≈ 3 million images, reaching 99.38% accuracy.



Resnet architecture

Residual Block:



Y = F(X) + XLogic behind Residual Networks is make (Y = X)



X is input, Y is output, Y=F(x)

If we make F(x) = 0 then it is easy for us to make input equal to output

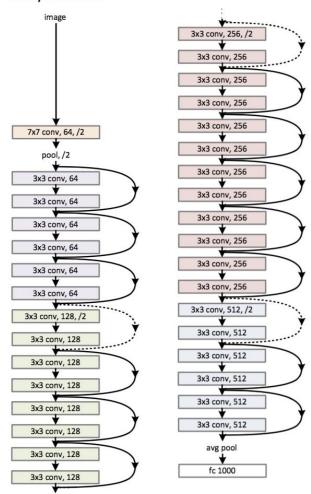
Y=X+F(X)

Y=X+0

∘Y=X

#In Normal networks we learn from Y but in Residual Networks we learn from F(X) and our target is to make F(X) =0 then only we can make input =output.

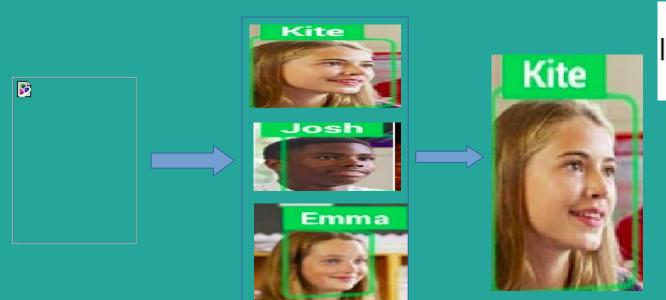
34-layer residual



Face recognition

We have face embeddings for each face in Image. Whenever we pass new face to the system, it calculates its face embeddings and compare it with the ones we already have.

Comparison based on subtraction of known encodings with unknown image encodings. It uses 12 norm.



$$\mathbf{x}| = \sqrt{\sum_{k=1}^{n} |x_k|^2}$$

Results



data collection



	SL NO : ID Number	Name		TING: Email Address
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	5 6 R161022	MULLA SEHARABANU	8465803524 A5	r161022@rouktrky ac in