Real Time System for Recognition and Detection of Face in Fraudulent Behaviour

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***Abstract*— Using Deep Learning approaches, automated facial recognition (AFR) seeks to recognize individuals in pictures or videos. Automatic face detection is frequently utilized in many different applications, from simple authentication systems to sophisticated ones. Since it entails significant fluctuations in both acquisition conditions as well as in facial emotions and pose changes, automatic face recognition of faces acquired by digital cameras in unrestricted, real-world environments is still a very difficult task. The cascade classifiers are well-known methods for face detection that aid in more precise criminal identification. In light of these major difficulties, as well as the created solutions and applications based on Deep Learning techniques, this paper introduces the topic of computer-automated face recognition utilizing the Cascade classifier.**

***Keywords*— Automated Face Recognition (AFR), Cascade Classifier, Fraud Detection, Deep Learning**

I. INTRODUCTION

Due to ML algorithms' capacity to recognize prior fraud trends in subsequent transactions and learn from them, fraud detection is made possible. In terms of information processing speed, machine learning algorithms seem to be superior to humans. Additionally, ML systems are able to identify complex fraud qualities that a person cannot possibly pick up on. Given the limited resources of time and labor, swift and precise real-time identification of potentially fraudulent transactions offers advantages in terms of cost and time savings. When used to combat fraud, machine learning gives analysts the ability to spot trends and put a stop to illegal activity before it has a negative financial impact on an Financial Services Industries (FSI).

The benefits of applying ML to a fraud solution are detecting fraud in the future and minimizing human error and faster risk evaluation thanks to effective data pattern recognition and it also increased automation, which results in a decrease in the resources needed for manual work. ML improved ability to distinguish between "legitimate" and fraudulent transactions lowering downstream human intervention, bad user experience, and false positives. Many face-detection methods have been proposed over several years. Reliable techniques for recognition during bigger excessive fluctuations have been found, despite significant progress in the ability to recognize faces under minor differences in illumination, facial expression, and stance. Face recognition is necessary for many face applications, including facial expression analysis and face popularity. Yet, in real-world applications, the big visible versions of faces, including occlusions, substantial position variations, and strong lighting, create good demands for those tasks. Modern Deep learning face detectors are almost perfect and outperform humans in this setting.

They would assume human form in situations like security where their accuracy is most useful. Their collection of rules-driven judgments may have significant ramifications, making the issue of reliability and robustness against malicious activities critical. Face detection is one of these initiatives, which is widely utilized as a pre-requisite for Face Id, which facilitates criminal tracking or admissions policy administration. The cascade face detector given by viola and jones provides accurate performance with real-time performance by using haar-like features and AdaBoost to train cascaded classifiers. Yet, while having more sophisticated features and classifiers, investigations show that this detector may suffer severe degradation in practical applications using large-scale visual representations of human faces. Recent advances in the computer vision fields of face popularity and photo categorization have been made possible by convolutional neural networks (CNN). Li et al. employ cascaded CNNs for face recognition, however they ignore the inherent relationship between facial landmark localization and bounding field regression in favor of demanding bounding box calibration at a higher computational cost from face detection. Yang et al. train deep convolutional neural networks to provide excessive response in face areas that further produce candidate windows of faces based on facial attributes. Unfortunately, due to the intricate CNN structure, this method is time-consuming to employ in practice.

Through the use of a more sophisticated face identification algorithm and a faster, higher overall performance method to channel the bayonet face reputation machine with the least amount of computational energy, the research's objective is to increase the operating speed of the face popularity device. While preserving dependable detection and reputation performance, it may be run on low-end devices with limited processing power. In this article, I present a unique methodology for incorporating these tasks into the use of unified cascaded CNNs using multi-assignment learning. There are three parts to the suggested CNNs. In the first stage, it quickly creates candidate windows using a shallow CNN. The window frames are then refined using a more complex CNN to reject a wide range of non-faces residential windows. In order to improve the output of facial landmark positions, it ultimately uses a more effective CNN. This familiarization with the multi-mission framework may greatly improve the set of rules' performance.

The important contributions of this study are we suggest a fresh cascaded CNN-based face identification system and meticulously build a lightweight CNN structure for real-time functionality. We suggest a strong approach for online complicated pattern mining to boost overall performance. To show the proposed method's huge performance gain over the most recent approaches in each Face Detection job, extensive experiments are carried out on difficult benchmarks.

Cascade Classifiers and Haar Features for Object Detection

The techniques utilized for object detection are Cascade Classifiers and Haar Features. It is a deep learning approach in which a cascade function is trained using a large number of photos. There are two types of these images: positive images that include the target object and negative images that do not. According to different target objects, there are several types of cascade classifiers. In our project, we'll utilize a classifier to identify the target object by taking the human face into account. The goal of the Haar Feature selection method is to extract human facial features. Comparable to convolution kernels are har features. These characteristics are various combinations of rectangles in black and white. We calculate the total number of pixels under each white and black rectangle in each feature computation.

II. Literature Survey

One of the most challenging and painful tasks in the field of computer vision and precognition is improving the accuracy of object detection, particularly the detection of the human face and eyes. International teams of researchers are developing a system that permits the usage of common objects in several applications. According to Kasinski, Haar cascade classifiers are being employed more and more in face-quit eye identification. It describes a three-stage, HCC-based hierarchical face, and eye identification method. To identify faces, the HCC has 2500 usable facial expressions. 2900 pictures could still be waiting for a call. Face detectors include pictures of 2500 left or right eyes, as well as pictures of terrible television sets that strain your eyes. Face recognition detects fraud 13% of the time and is generally helpful 94% of the time. With an accuracy rating of 88 percent and a false-positive rate of 1%, eyes can be detected.

Zhang employed three deep convolutional network ranges, ranging from coarse to exceptional, that is mostly based on deep convolutional network techniques and excel at predicting the location of faces and landmarks. Recent studies have revealed that in this area, Deep Learning Techniques can be learned, and this can be very advantageous. The concept network (p-net), the refinement community (r-net), and the output network are the three steps that the author advises CNNs to have for eye detection (o-net). According to experimental findings, these procedures outperform contemporary approaches while preserving real-time performance in several stressful assessments.

According to Kavi Dilip Pandya's face detection, it is crucial to eliminate background information. Face detection would be easier if irrelevant data, such as noise and non-face parts, were removed. Most detection algorithms use some form of feature-based analysis as one of their primary methods. Thus, careful feature selection is essential.For face identification, at least two features must be chosen. Because relying solely on one attribute could lead to inaccurate detection. Face detection becomes extremely difficult as a result of variable facial expressions and poses. Face detection is highly impacted by lightning conditions. Most applications are real-time in nature, therefore computations must be quick and should use less main memory.

According to another literature review, by M.Tamilselvi1 and Dr. S.Karthikeyan , face recognition is a very difficult task in the field of image analysis and computer vision that has attracted a lot of attention in recent years due to its numerous applications in a variety of various fields. In this study, just a few classical facial recognition methods are mentioned. The approaches of SVM and HMM can yield superior face recognition results in some face databases, but they require more complicated algorithms. Exorbitant amounts of research have been put into this field, and while significant progress has been made, notable outcomes have been attained, and current face recognition systems have progressed to a certain level of maturity when used in limited circumstances, these techniques are still far from being able to perform as intended.

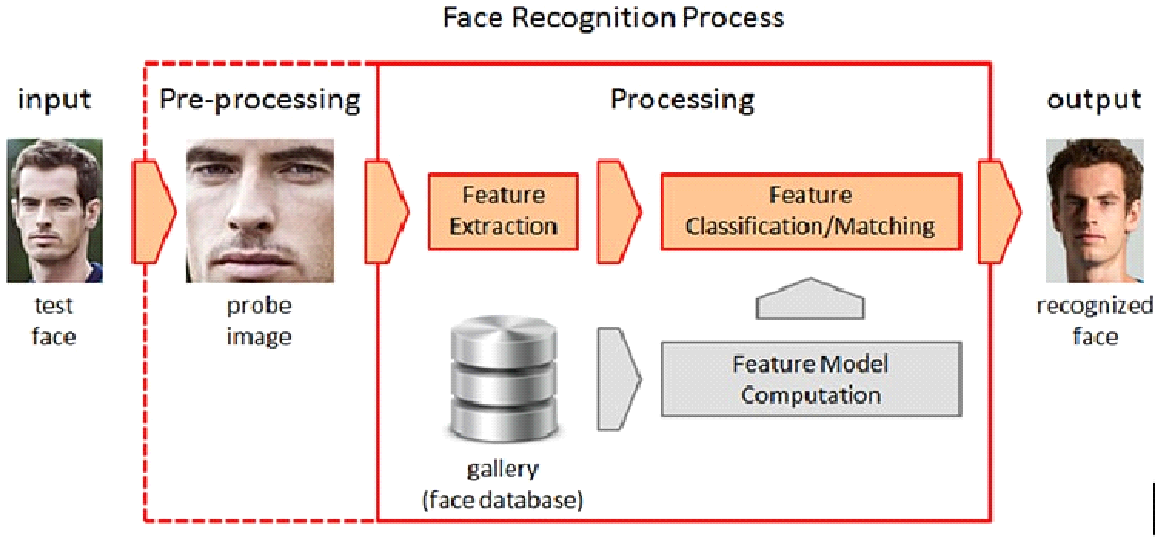
Lang Ye proposed a customized CNN architecture to improve eye detection precision while utilizing the unprocessed color values of picture pixels. The primary sensor locates the roughly defined bounding boxes of strong eye patches. The second step rules out any other bounding boxes and assesses whether the strong bounding boxes are connected to the eyes. 8300 samples of eyeballs from mild environmental conditions have been gathered. Ultimately, based on the size of the validation set, all samples were split into training and validation datasets of 500 samples each. The second layer of CNN performs better than the first tier, with accuracy rates of 73% and recall prices of 76%, respectively.

III. Project Idea

It is a Face Detection deep learning Convolutional Neural Network (CNN) Algorithm that finds faces in still photos or moving videos. For Face Detection Using a Boosted Cascade of Basic Features, the technique uses edge or line detection characteristics. In this research, Cascade Classifiers with the combination of Haar Features are utilized to recognize and detect faces using deep learning techniques.

CASCADE CLASSIFIERS AND HAAR FEATURES:

The techniques used for object detection are Cascade Classifiers and Haar Features. It is a deep learning method in which a cascade function is trained using a large number of images. There are two types of these images: positive images that include the goal object and negative images that do not. According to different target objects, there are various kinds of cascade classifiers. In our project, we'll use a classifier to identify the objective object by taking the human face into account. The goal of the Haar Feature selection method is to extract human facial characteristics. Comparable to convolution kernels are her characteristics. These characteristics are various combinations of rectangles in black and white. We calculate the total number of pixels under each white and black rectangle in each feature computation.

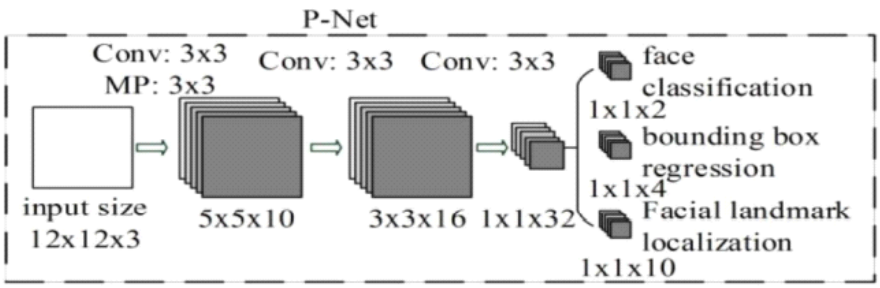


IV. THEORETICAL ANALYSIS

FACE DETECTION

A system called a multi-task cascaded convolutional network (MTCNN) was created as a solution for both face alignment and face identification. The method uses three degrees of convolutional networks, which can recognize faces and facial landmarks like the eyes, nose, and mouth. Finally, in the third stage, it employs a third CNN that is more complicated than the others to further improve the output of facial landmark locations. To complete the task of face identification and alignment simultaneously, MTCNN is a method of face detection and alignment that is largely based on deep convolutional neural networks. In comparison to the conventional method, MTCNN performs better overall, can accurately locate the face, and is speedier in addition to being able to hit upon in real-time. Before using these networks, the original image must be scaled to a unique size to create a photo pyramid to achieve a face reputation on a uniform scale.

The first step is to resize the image to unique scales and build an image pyramid, which serves as the input for the next three-stage cascaded community. The R-Net plays calibration with bounding field regression and employs NMS to integrate overlapping candidates. The P-Net produces two outputs, a 10-element vector for facial landmark localization and a 4-detail vector for boundary field. The Integral Image calculates each pixel from the original image to equal the total of all the pixels in the Original Image.



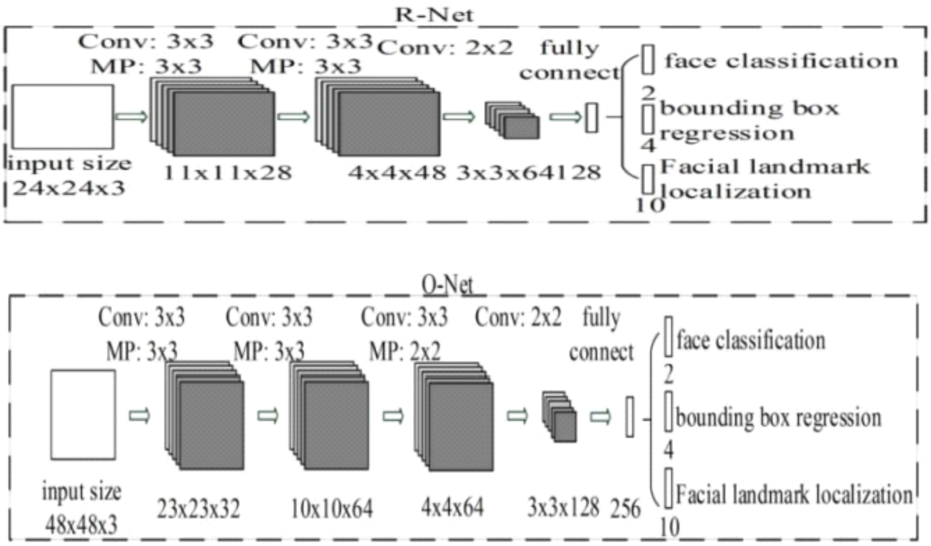
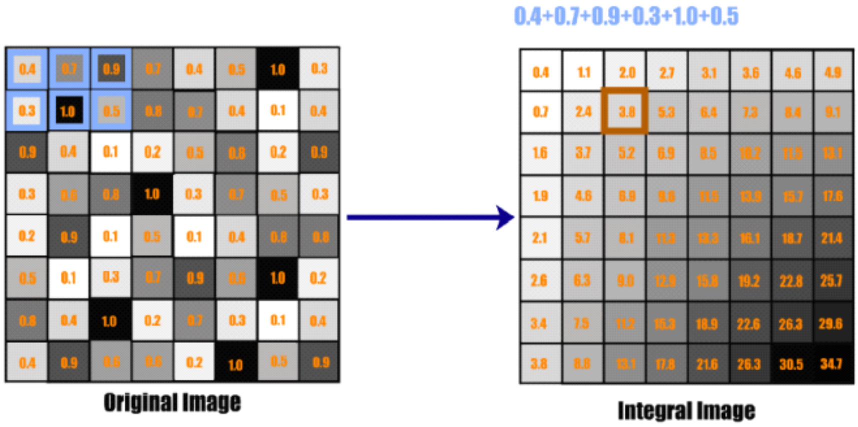


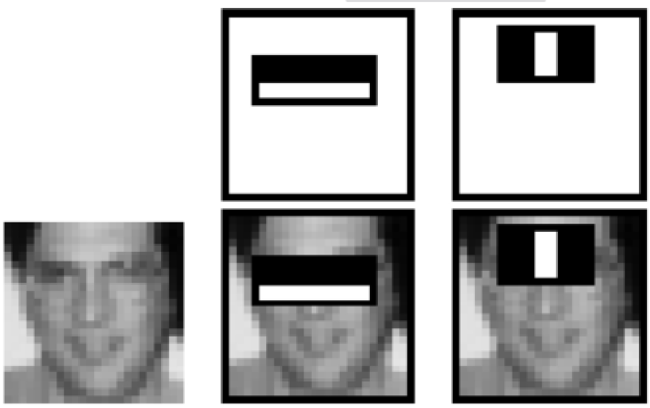
Fig: P-Net, R-Net, O-Net

CONVOLUTION NEURAL NETWORKS

Convolutional neural networks are a subclass of deep feedforward neural networks with convolutional processing. They can extract high-stage semantic data from raw statistics by stacking several processes. To compress information, speed up network training, and utilize less computing input, they employ a pooling layer beneath the convolutional layer. Cascade classifiers and Haar features are used for object detection, and extraction of human face traits is the aim of the Haar Feature selection technique.

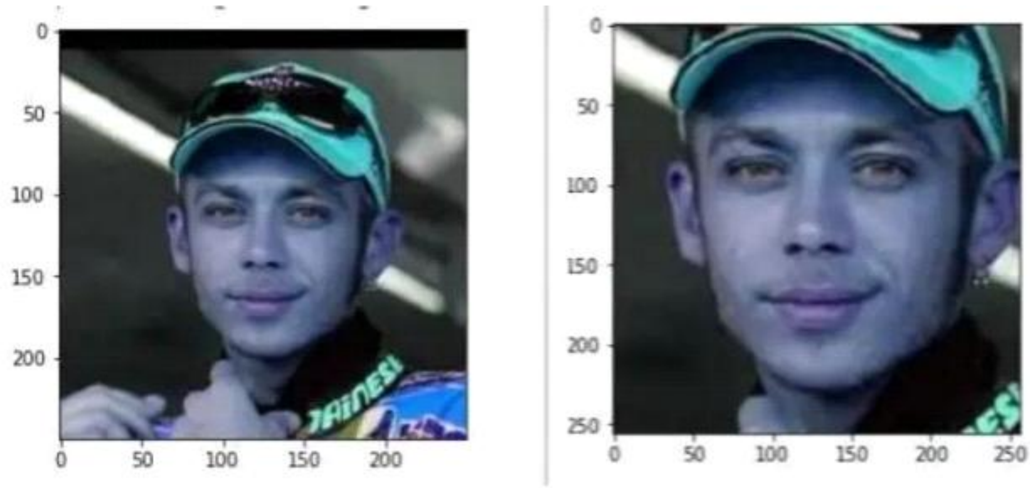


The haar value is closer to 1 if there is an edge in the image separating light pixels on the left from dark pixels on the right, indicating an edge has been detected.



Face Detection With Haar Cascade

On the left, in the rectangle, is an illustration of a picture with pixel values varying from 0.0 to 1.0. The rectangle in the center represents a haar kernel, which consists of all the bright pixels on the left and all the dark pixels on the right. The average pixel values at the brighter and darker regions are compared, and the difference is computed to conduct the haar computation. When the disparity is close to 1, the haar feature will detect an edge.



Input Image (Left), Aligned Image (Right)

V. Implementation

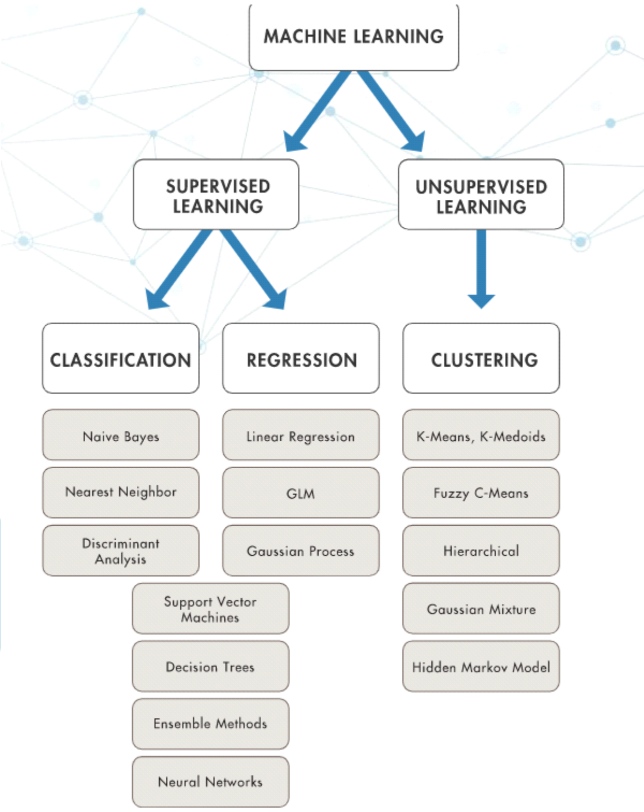
An application for the camera must be installed on any compatible device connected to the camera in order for the facial recognition process to start. The application needs to be configured using a config file with Local Camera ID and Camera Reader type when it is first run. Afterwards, this application can search through its stream of faces using computer vision and a deep neural network. The TensorFlow object detection model and face tracking are the two most useful techniques for doing this. Both of these techniques have worked well and are included in the OpenCV package. When a face is detected, the cropped image is sent to the back end along with an HTTP form data request.

The API then saves this facial image, together with a personID, on the local file system and in the detection log. The dimension vector that describes this face's features is generated at the back end by an algorithm called deep learning Convolutional Neural Network that looks for records where “classified=false" is present. In order to determine whether this new face matches any previously recorded faces, the algorithm then uses to cross-reference this vector with all of the facial entries in the database. This algorithm will either create a new individual ID for a person of an unknown type or will classify the face and match the person ID and facial detection enhanced as a result of deploying in this manner to obtain better accuracy.

MTCNN with Haar Cascade Algorithm results I was able to accurately identify the faces in the pictures using my dataset and the MTCNN approach at a rate of 99%–100%. The application of multiple cascaded convolutional networks in this case seems to have produced good results.

Libraries Used

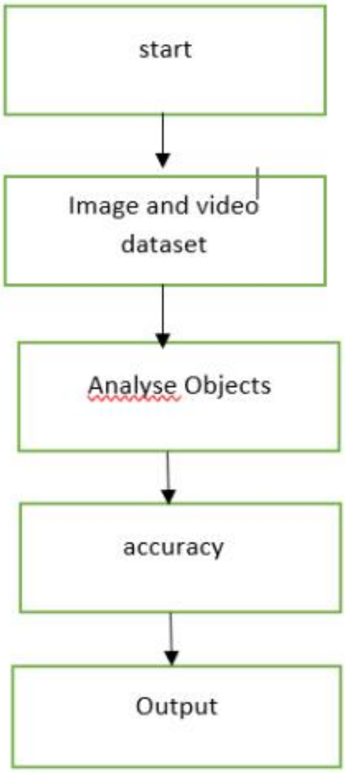
- ***Matplotlib:*** The MATLAB plot gallery provides examples of many ways to display data graphically in MATLAB. Learning through experience is something that humans do naturally, and machine learning helps robots to do the same. To create features from your data and fit machine learning models, use MATLAB®.



- ***Pandas:*** Working with "relational" or "labelled" data can be simple and intuitive thanks to the Python module pandas, which offers quick, adaptable, and expressive data structures. It seeks to serve as the essential, high-level building block for using Python for actual, useful data analysis. Data analysis and manipulation done quickly and effectively. Tools for importing data into in-memory data objects from various file types. On huge datasets, label-based Slicing, Indexing, and Sub setting are possible. Easily joins and merges two datasets. reshaping and pivoting data sets. Using pandas Data Frames, you may store and manage tabular data in rows of observations and columns of variables, as well as uncover important information from the given data set, in a manner akin to that of Excel.

- ***NumPy:*** The Python package NumPy is used to manipulate arrays. Moreover, it has matrices, Fourier transform, and functions for working in the area of linear algebra. You can use it for free because it is an open-source project. Multidimensional array objects and a collection of functions are its main components. Due to its ability to conduct logical and mathematical operations on arrays, it is one of the most popular Python tools for scientific computing. Many mathematical operations can be carried out on arrays with NumPy. It provides a vast library of high-level mathematical functions that work on these arrays and matrices, as well as strong data structures that ensure efficient calculations with arrays and matrices.

FLOWCHART



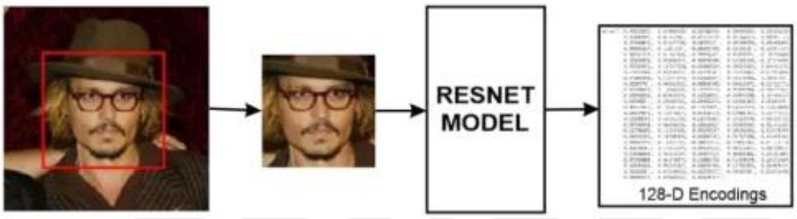


Fig: Flowchart

VI. Experimental Results

The Haar cascade approach was successfully used to identify faces in images. MTCNN with Haar Cascade Algorithm results I was able to identify the faces in the photos for approximately 100 films using my dataset and the MTCNN approach at a rate of 99%-100%. Multigeniture cascaded convolutional networks appear to have produced an excellent outcome in this case. To demonstrate how to use the MTCNN version, the main experiment used my dataset. The second experiment makes use of both the principles from the Haar cascade and my dataset. After using my dataset as a test set of data and producing accuracy rates of 99 percent, whilst Haar cascade produced accuracy rates of 68 percent, a comparison of my recommended face reputation models using MTCNN and Haar cascade is then displayed to showcase my suggested model. I then compared the results of each of my attempts for precision, accuracy, and memory.

Fig: Face Detection using Haar Cascade

COMPARISON OF FACIAL POINT DETECTION RATE USING DIFFERENT METHODS FOR DIFFERENT DATASETS.

Algorithm	Accuracy
Viola-Jones	74.38%
Haar Cascade	94%
MTCNN	99.95%

Fig: Comparison of Facial Point Detection Rate Using Different Methods for Different Datasets.

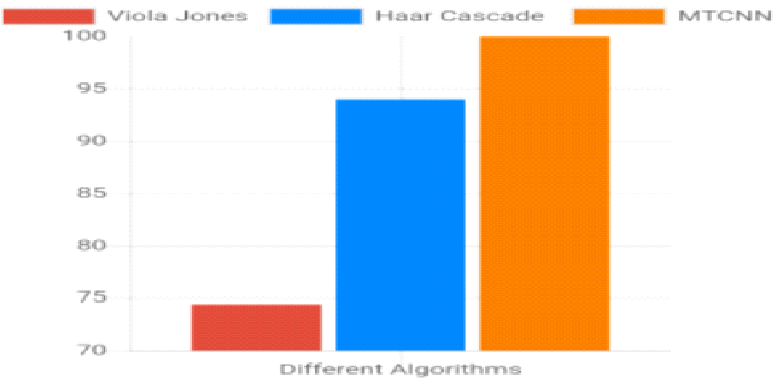


Fig. 6. Comparison Among Different Algorithms for Different Datasets

Fig: Comparison Among Different Algorithms For Different Data Sets

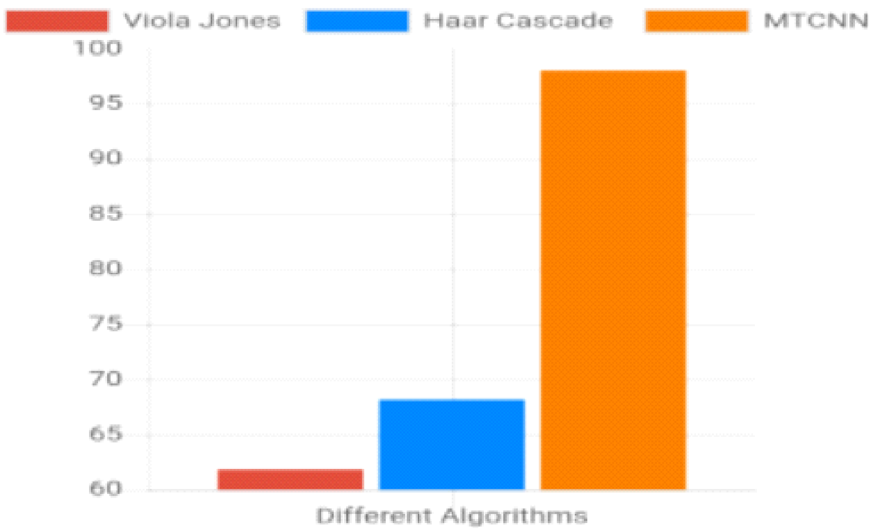


Fig: Comparison Among Different Algorithms For Our Data Sets

CONFUSION MATRIX OF FACIAl POINTS DETECTION(MTCNN)

	Positive	**Negative**
Predicted Positive	17620	335
Predicted Negative	30	280

Below Table, where the accuracy is 98.13 percent and the recall rate is 99.83%, the accuracy charge is 98%. The overall F-1 score is 98.97% at the end. Analyzing all of the comparisons makes it clear that my records are superior for face detection using deep learning techniques (MTCNN). As a result, the overall performance of the deep learning method was pleasing given all of the novel approaches for both my own dataset and other datasets.

CALCULATION OF CONFUSION MATRIX FOR FACIAL POINTS DETECTION

Measure	Value(%)	Derivation
Precision	98.13	PPV=TP/(TP+FP)
Recall	99.83	TPR=TP/(TP +FN)
Specificity	45.53	FPR=FP/(FP+TN)
F-Measure	98.97	F1 = 2TP / (2TP + FP + FN)
Accuracy	98.00	TP+TN / TP+TN+FP+FN

VII. Conclusion

In this study, I offered a multi-task cascaded Convolution neural design for facial recognition as a solution. When implementing my dataset as a test dataset, experimental findings and my other proposed framework demonstrate that my MTCNN approaches regularly beat most of the primary methodologies. My suggested strategy and dataset might be used by many algorithms, especially when you consider that I can increase the accuracy of face detection in a situation by using the popularity of the face in images. In this study, face detection is improved along with the precision of identifying people by their faces.

FUTURE WORK

Face detection is a very popular topic. There are many use cases for biometric protection in the industry. Face recognition has become a very useful tool for people thanks to deep learning. Because deep learning needs a significant amount of data, and we may not always have that much data available, face recognition has become more practical and feasible as a result of the development of One-Shot Learning.

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