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FACE RECOGNITION IN VIDEO ANDEMOTION RECOGNITION

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Abstract: Recently face recognition has become an important area of research in computer vision, neuroscience, and psychology. In this process a new colour face recognition (FR) method is introduced. The effectiveness of colour information plays an important role when face images are taken under strong variations in illumination, as well as with low spatial resolutions. The proposed method has 3 steps. In the first step the input colour image is converted into various colour space models. In the second step eigen values and eigen vectors are extracted from each colour space models. In the final step a nearest neighbour classifier is designed for classifying the face images based on the extracted features.

1. **Keywords:** Facial recognition, Video analysis, Emotion detection, Facial expression analysis, Computer vision, Deep learning, Neural networks, Image processing, Human-computer interaction, Affective computing.

I. INTRODUCTION:

Spoofing attack is the action of outwitting a biometric sensor by presenting acounterfeit biometric evidence of a valid user. It is a direct attack to the sensory input of a biometric system and the attacker does notneed previous knowledge about the recognition algorithm. Most of the biometric modalities are not resistant to spoofing attacks: the biometric systems are usually designed to only recognize identities without concern whether the identity is live or not. Despite the existence of very sophisticated biometric authentication and verification systems nowadays, implementing anti-spoofing schemes for them is still in its infancy. Depending on the biometric modality being attacked, fabricating fake biometric data can have different levels of difficulty. While creating an artificial finger to spoof a fingerprint recognition system, or printing contact lens to spoof an iris recognition system may require some expertise, it is very easy to create a copy of someone's face. All that is needed is a photograph of the person, which can be easily found on the Internet or taken directly from the user at distance. The assumptions that the artificial biometric evidence can bypass a biometric recognition system, are not only chimerical: in the authors have shown how to successfully spoof a laptop authentication system usingonly a printed photograph.

Literature Survey:

The role of emotion is evident in our daily lives. Human beings use different kinds of emotions to show compassion and establish relationships with others (Seiter, 2016). These emotions express the emotional conditions in our daily lives. The comprehensive list of emotions ranges from anger to happiness, wondering, suspicion, skepticism, sorrow and grief. However, they are frequently witnessed in our daily lives. Therefore, it is quite easy to understand the inner feelings of a person with the use of the facial expressions that are quite visible. Thus, the facial expressions and emotional recognitions are interrelated with each other (Beswick, 2014). Some of the techniques and the authors for the face recognition in various ways arementioned with their demerits. The details and results of the existing methods are as follows:

I. Chingovska, A. Anjos, and S. Marcel, **"On the effectiveness of local binary patterns in face anti-spoofing,"** in Proc. IEEE Int. Conf. Biometrics Special Interest Group (BioSIG), Darmstadt, Germany, Sep. 2012 Spoofing a face recognition system is one of the simplest biometric modalities to pull off because all that is required is a straightforward photo of the individual. Identifying face spoofing attacksis a challenge that we tackle in this paper. We focus on three main forms of attacks: printed photographs,photos and films shown on various-sized electronic screens, and textural features based on Local BinaryPatterns (LBP). We present REPLAYATTACK, a brand-new face spoofing database that is freely accessible, in this regard.

II. Di Wen, Hu Han, and Anil K. Jain, "Face Spoof Detection with Image Distortion Analysis," Access by IEEE Transactions on Forensics and Security (2015). To our knowledge, this is the first mobile spoofface database. On the contrary, four features are designed specifically for face feature representation in our method, and we demonstrate the effectiveness of these features for spoof face detection. While a number of face spoof detection techniques have been proposed, their generalization ability has not been adequately addressed. The proposed approach is extended to multi-frame face spoof detection in videos using a voting-based scheme. We have also collected a face spoof database, called MSU MFSD, using two mobile devices.

III. J. Yang, Z. Lei, S. Liao, and S. Z. Li, **"Face liveness detection with com-ponent dependent descriptor,"** in Proc. IEEE Int. Conf. Biometrics (ICB) , Jun. 2013.The proposed method is denoted by '5'. In this paper, we propose a component-based face coding approach for liveness detection. We have introduced a component-based coding frame-work for face liveness detection. Moreover, we also conduct the proposed method with holistic coding for a single image to show the efficiency of component de-pendentcoding for each database. As a result, the proposed method achieve better performance for all the databases. We propose a component dependent coding method to better make use of the differences among different regions. VQ algorithm is a simple yet effective coding method.

IV. Saptarshi Chakraborty1 and Dhrubajyoti Das, "**An overview of face liveness detection,**" by International Journal on Information Theory (IJIT), Vol.3, No.2, April (2014). In this work, face liveness detection approaches are categorized based on the various types techniques used for liveness detection. A review of the latest works regarding face liveness detection works is presented. A review of most interesting approaches for liveness detection was presented. It presented a categorization based on the type of techniques used and types of liveness indicator/clue used for face liveness detection which helps understanding different spoof attacks scenarios and their relation to the developed solutions. This work provided an overview of different approaches of face liveness detection.

V. Z. Zhang, J. Yan, S. Liu, Z. Lei, D. Yi, and S. Z. Li, **"A face anti-spoofing database with diverse attacks,"** in Proc. IEEE 5th IAPR Int. Conf. Biometrics (ICB), Mar./Apr. 2012. In this paper we releasea face anti-spoofing database with diverse attacks to serve as an evaluation platform in the literature. Theabove observation motivates us to release a comprehensive database to serve as an evaluation platform for the face anti-spoofing issue. In this paper we release a face anti-spoofing database which covers a diverse range of potential attack variations.

VI. Nesli Erdogmus and Sebastien Marcel, "**Spoofing in 2D Face Recognition with 3D Masks and Anti-spoofing with Kinect,**" Access by IEEE Transactions on Forensics and Security 9(7):1084-1097 (2013).In this paper, we inspect the spoofing potential of subject-specific 3D facial masks for 2D face recognition. Utilization of 3D masks in spoofing attacks becomes easier / cheaper each day with the advancements in 3D printing technology. For this purpose, the scans of subjects were acquired by a 3D scanner and the masks were manufactured using a 3D printing service. A possible extension to this work is to explore the spoofing performances in 3D face recognition systems and to devise methods to detect attacks using pure 3D data, instead of 2.G. Pan, L. Sun, Z. Wu, and S. Lao**, "Eyeblink-based anti- spoofing in face recognition from a generic web camera,"** in Proc. IEEE 11th Int. Conf. Comput. Vis.(ICCV), Oct. 2007, pp. 1–8, It could be easily integrated into the existing face recognition systems. This paper investigates eyeblinks as liveness detection against photo spoofing in face recognition. The approach requires no extra hardware except for a generic webcamera. From the static view, the essentialdifference between the live face and photograph is that a live face is a fully three-dimensional object while a photograph could be considered as a two-dimensional planar structure.

III. EXISTING SYSTEM:

The LBP based anti-spoofing method guarantees different levels of certainty

for different types of attacks and different databases. The convenience of the proposed opensource framework isdemonstrated for the face mode, by comparing the security guarantee of four baseline face verification systems before and after they are secured with anti-spoofing algorithms. There is no consistency in the results with regards to the types of attacks, nor the attacks from different databases. In case a certain frame in the input video streampresents no detected face, the face detection is borrowed from any previous frame which had one. Its purpose isto serve for an objective comparison of different verification systems with regards to their verification performance and vulnerability to spoofing, taking into account the system's application-dependent susceptibilityto spoofing attacks and cost of the errors. Yet, some disparities between the real face and spoof-attack images may become evident once the images are translated into a proper feature space. The system calculates the LBP histogram in two different ways, and perform all the experiments separately on the both versions of the feature vectors.

PROPOSED SYSTEM AND WORKING METHODOLOGY:

While more accurate and reliable than ever, the trustworthiness of biometric verification systems is compromised by the emergence of spoofing attacks. In other words, the cues that distinguish two different types of face spoofing attacks from real accesses differ in their essence and should be grasped in their own unique way. The various face spoofing attacks differ from the real accesses in their own particular manner: the devices that are used introduce different artifacts and the amount and type of movement they possess is different. Firstly, it introduces REPLAY-ATTACK, a novel spoofing attack database containing three types of possible attacks using three different media and two different recording conditions.

DISADVANTAGES:

- Image quality is very low. ○ Difficult to capture an image.
- It has more complexity in handling the unreadable image.
- It is more expensive to handle.

PROBLEM STATEMENT:

Problem statement for face recognition and emotion recognition in existing projects can be defined as accurately identifying and recognizing individuals based on their facial features and emotions in an automated manner. Although there have been significant advancements in facial recognition and emotion recognition technology, there are still several challenges that need to be addressed in existing projects. Some of these challenges include:

1. Accuracy: The accuracy of face recognition and emotion recognition systems is crucial, as even a small error rate can lead to incorrect identification or interpretation of emotions.
2. Variations in facial expressions: Facial expressions can vary greatly depending on factors such as culture, gender, age, and personal habits. This can lead to difficulties in accurately identifying emotions.
3. Lighting conditions: Face recognition and emotion recognition systems are highly sensitive to lighting conditions, and variations in lighting can affect the accuracy of the system.
4. Real-time processing: Real-time processing of large volumes of data can be a challenge for face recognition and emotion recognition systems. This can result in delays and reduced system performance.
5. Integration with other systems: Integration with other systems, such as security systems or customer service systems, can be complex and require additional development and testing to ensure compatibility and accuracy.

Overall, the challenges of face recognition and emotion recognition systems in existing projects are diverse and require a comprehensive approach to ensure accurate and efficient operation while addressing privacy concerns.

PROPOSED METHOD:

➢ As the necessity for higher levels of security rises, technology is bound to swell to fulfill these needs. Any new creation, enterprise, or development should be uncomplicated and acceptable for end users in order to spread worldwide.

➢ This strong demand for user-friendly systems which can secure our assets and protect our privacy without losing our identity in a sea of numbers, grabbed the attention and studies of scientists toward what's called biometrics.

➢ In this process, face image descriptors are hand-crafted of ***LBP, and Machine Learning,*** representative methods.

LOCAL BINARY PATTERN:

➢ Local Binary Pattern (LBP) is a simple and effective feature extraction technique used in computer vision and image processing. It is mainly used for image classification, object recognition, and face detection. LBP extracts texture information from an image by comparing the intensity of a central pixel with its surrounding pixels.

- The LBP operator computes a binary code for each pixel in an image by thresholding the pixel's value with the value of its neighbors. A circular neighborhood of 8 surrounding pixels is typically used, althoughlarger or smaller neighborhoods can also be used.
- Here's an example of how LBP works on a grayscale image:

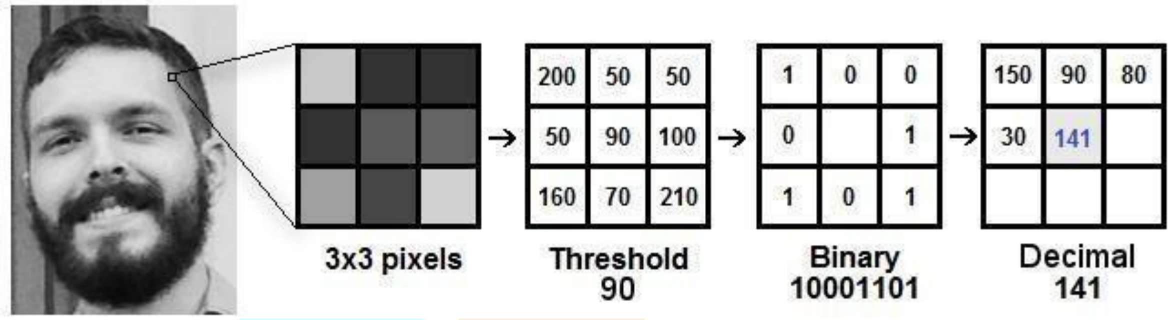


Fig : Working of LBP Algorithm

- In this example, the LBP operator compares the intensity of the central pixel (denoted by the green circle) with its surrounding pixels. If a neighbor's intensity is greater than or equal to the central pixel's intensity,a 1 is assigned to that neighbor's position in the binary code. Otherwise, a 0 is assigned. This process is repeated for each pixel in the image, resulting in a binary code for each pixel.
- The binary codes are then used to generate a histogram of patterns in the image, which can be used as a feature vector for image classification or other tasks. Here's an example of a histogram of LBP patterns for an image:

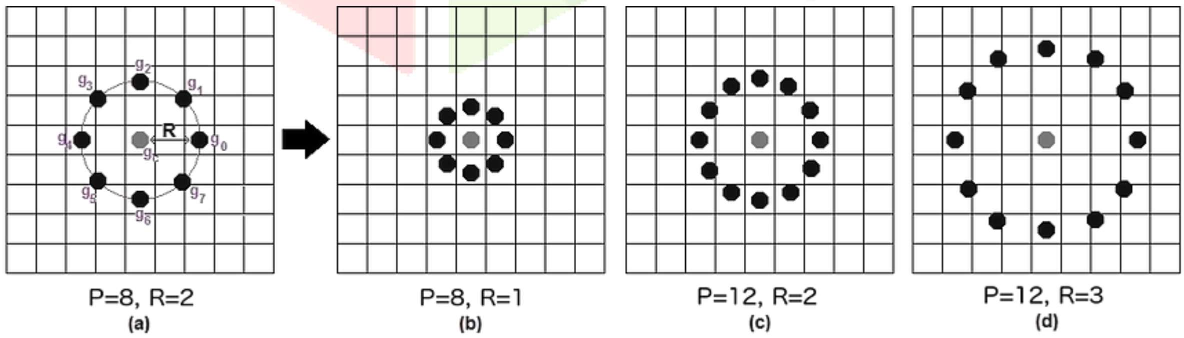


Fig : Circular Neighborhood Points of LBP

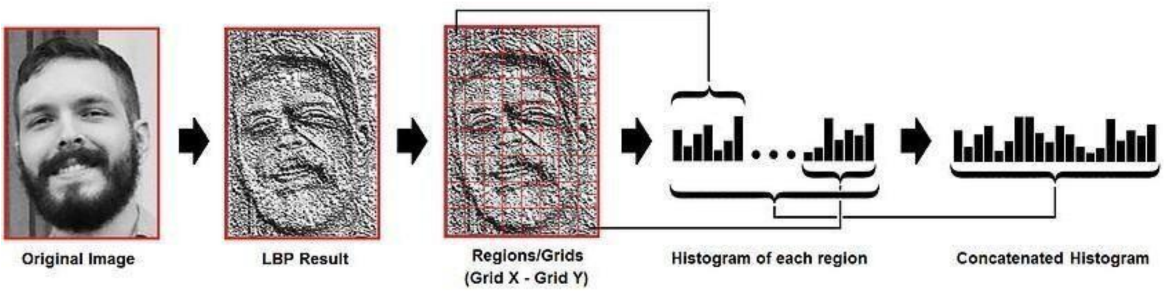


Fig 3.3: LBPH Output Pattern

➢ In this histogram, each bin corresponds to a unique LBP pattern. The height of each bin represents the frequency of that pattern in the image. This histogram can be used as a feature vector for image classification, object recognition, or other tasks.

➢ Overall, LBP is a powerful and computationally efficient technique for extracting texture information from images. Its simplicity and effectiveness make it a popular choice for many computer vision tasks.

CONVOLUTIONAL NEURAL NETWORKS:

❖ CNN stands for Convolutional Neural Network. It is a type of deep learning neural network that is commonly used in image and video recognition and processing tasks.

❖ CNNs are designed to process and classify images and video data by identifying and extracting features, such as edges, corners, and patterns, from the raw pixel data. The network consists of multiple layers, including convolutional, pooling, and fully connected layers, which work together to extract and classifythe features in the input data.

❖ The convolutional layer performs convolutions, which involve sliding a filter or kernel over the input image to detect specific features. The pooling layer reduces the dimensionality of the output by down sampling the input data. The fully connected layer performs the final classification task by connecting every neuron in the previous layer to every neuron in the next layer.

❖ CNNs have shown remarkable performance in many computer vision tasks, including image recognition, object detection, and segmentation, and are widely used in a variety of applications, including self-drivingcars, medical image analysis, and facial recognition systems.

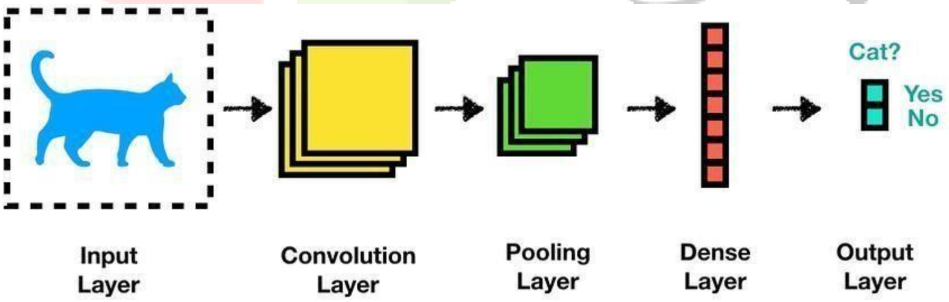


Fig: Basic Blocks Of CNN

I. Convolutional Neural Network (CNN) Works in Steps:

a) Input data: The input data for a CNN is typically an image or a series of images. The image is represented as a matrix of pixel values.

b) Convolutional layers: The first layer in a CNN is usually a convolutional layer. This layer applies a set offilters to the input image to extract features. Each filter is a small matrix that slides over the input image and performs a dot product between the filter values and the pixel values in the image.

c) Activation function: After each convolutional layer, an activation function such as ReLU (Rectified Linear Unit) is applied to introduce non-linearity and allow the network to learn more complex features.

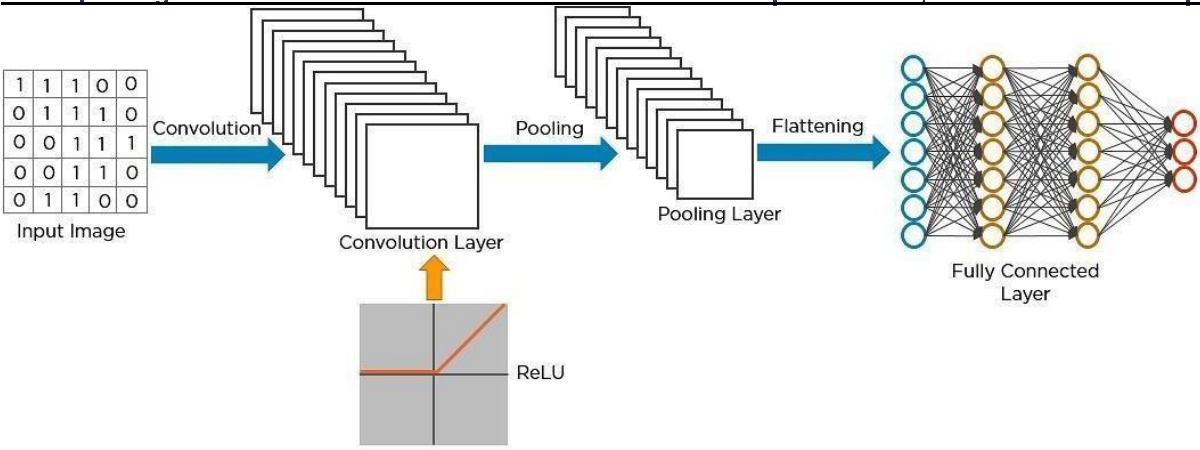


Fig Pooling layers of image

d) Pooling layers: A pooling layer reduces the dimensionality of the feature maps generated by the convolutional layer. Common types of pooling include max pooling and average pooling, which reduce the size of the feature maps by taking the maximum or average value of a local neighborhood.

e) Fully connected layers: The final layers of a CNN are typically fully connected layers that take the flattened output from the previous layers and classify the input image into a specific category.

f) Output layer: The output layer of the CNN provides the final classification of the input image. The number of neurons in the output layer corresponds to the number of classes that the CNN is trained to recognize.

g) Training: During training, the CNN adjusts the weights of the filters and the fully connected layers to minimize the error between the predicted output and the true label. This process involves backpropagationand gradient descent algorithms.

h) Inference: After training, the CNN can be used to classify new images by feeding the image through the network and obtaining the output classification from the final layer.

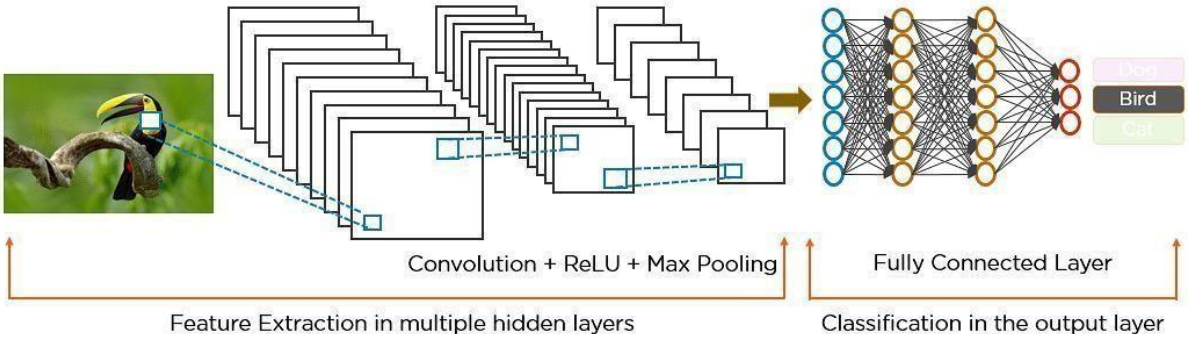


Fig Output Pattern Of CNN I. **Advantages:**

✓ It is easy to implement and can readily be combined with any existing feature descriptor, thus leading toa more compact and expressive feature descriptor.

✓ Image quality is high.

✓ It can handle unreadable image like finger print, etc.

✓ It is cheaper than existing technologies.

✓ It achieves superior performance to current state-of-the-art methods across different face recognitionscenarios.

✓ It achieves superior performance.

SYSTEM ARCHITECTURE

The following diagram represents the architecture model for face recognition in video and emotion recognition system. It will mainly divide into five major parts in order to illustrate the system briefly.

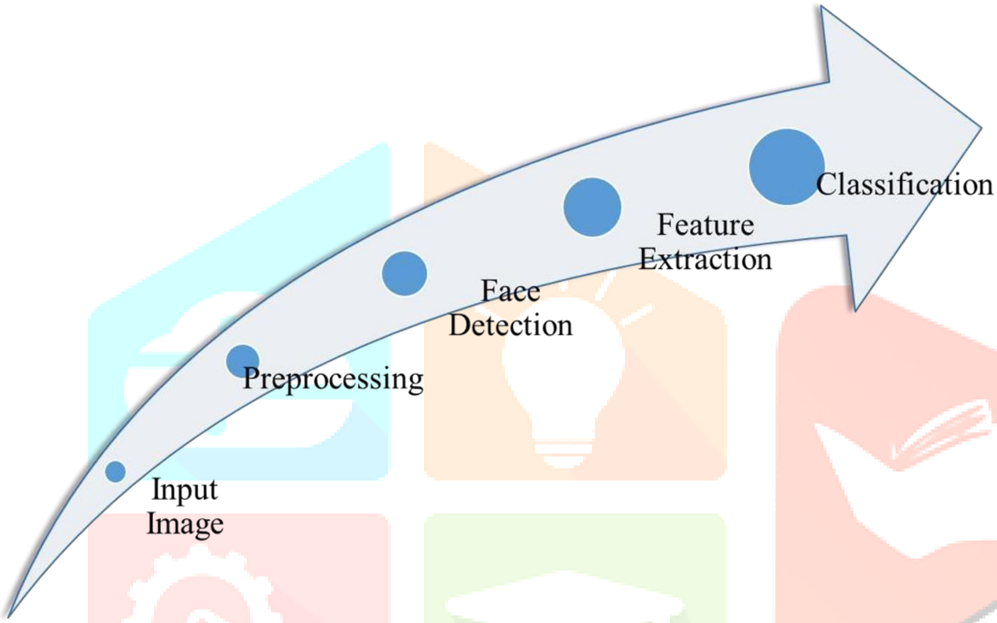


Fig System Architecture

FLOW CHART:

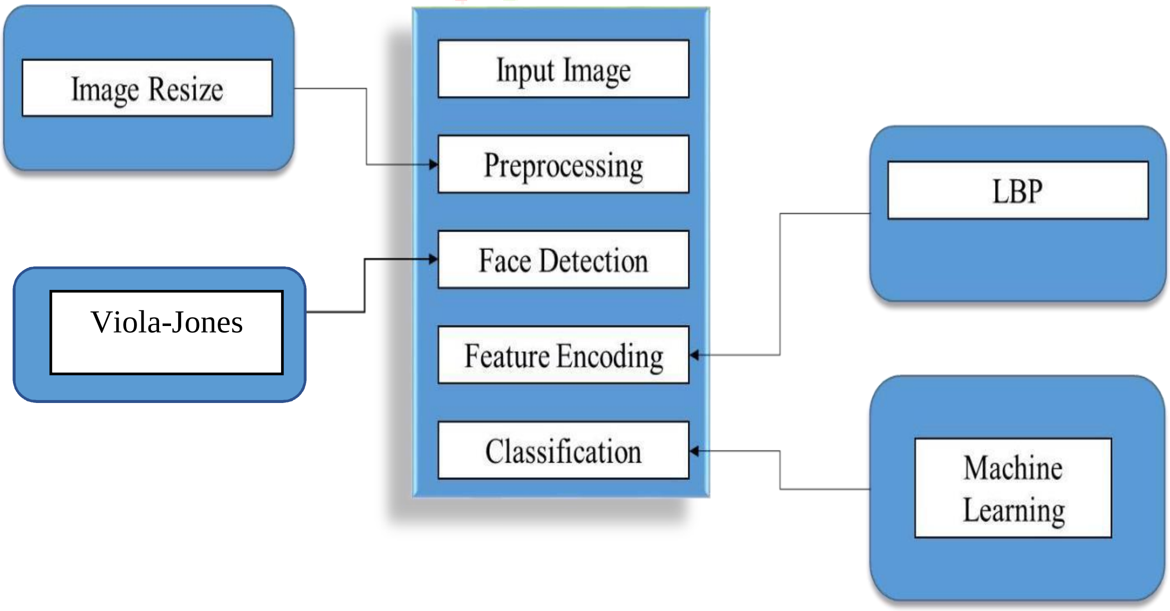


Fig: Flowchart of Face Recognition in Video and Emotion Recognition

MODULES:

- Input Image
- Preprocessing
- Face Detection
- Feature Extraction
- Classification

INPUT IMAGE:

a) Preprocessing: (Image Resize)

- In computer graphics and digital imaging, image scaling refers to the resizing of a digital image. In video technology, the magnification of digital material is known as upscaling or resolution enhancement.
- When scaling a vector graphic image, the graphic primitives that make up the image can be scaled using geometric transformations, with no loss of image quality. When scaling a raster graphics image, a newimage with a higher or lower number of pixels must be generated.
- In the case of decreasing the pixel number (scaling down) this usually results in a visible quality loss.
- From the standpoint of digital signal processing, the scaling of raster graphics is a twodimensional example of sample-rate conversion, the conversion of a discrete signal from a sampling rate (in this case the local sampling rate) to another.

Feature Extraction:

- The Viola–Jones object detection framework is the first object detection framework to provide competitive object detection rates in real-time proposed. Although it can be trained to detect a variety of object classes, it was motivated primarily by the problem of face detection.

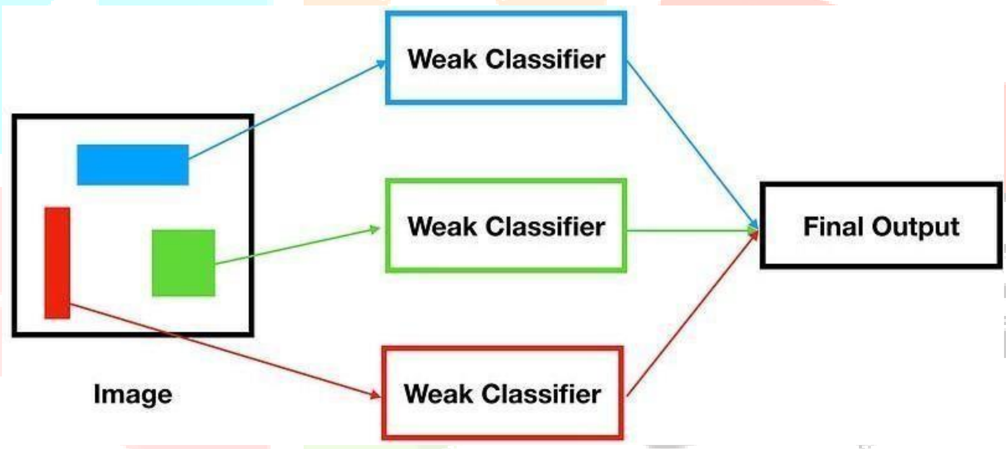


Fig Building Blocks of Viola-Jones Algorithm

- On the basis of the above analysis, we can utilize the ability of the diffusion speed model to efficiently extract anti-spoofing features. More specifically, we straight forwardly employ the value of the diffusion speed itself at each pixel position as our baseline features, given as

$$\mathbf{F}_{\text{base}} = \{s(x, y) | 0 < x \leq W, 0 < y \leq H\},$$

RESULT:

These are the outcomes that we have obtained from this "**FACE RECOGNITION IN VIDEO AND EMOTIONRECOGNITION**".

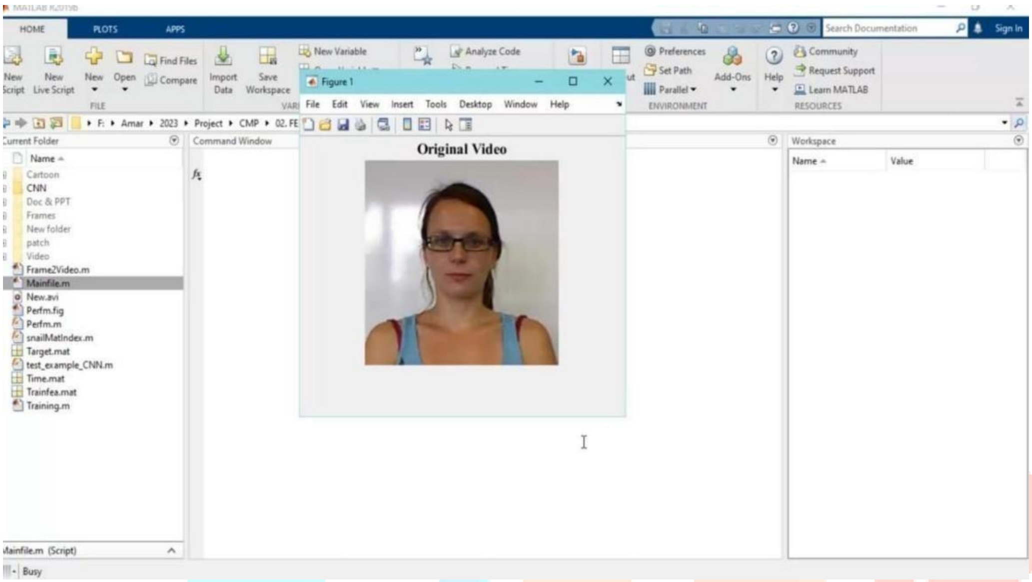


Fig: Input Video

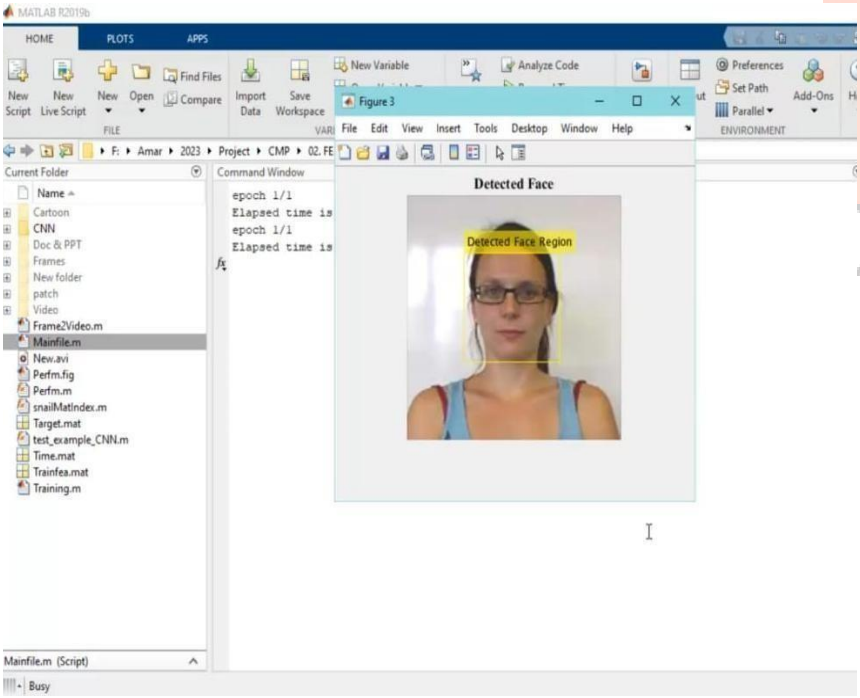
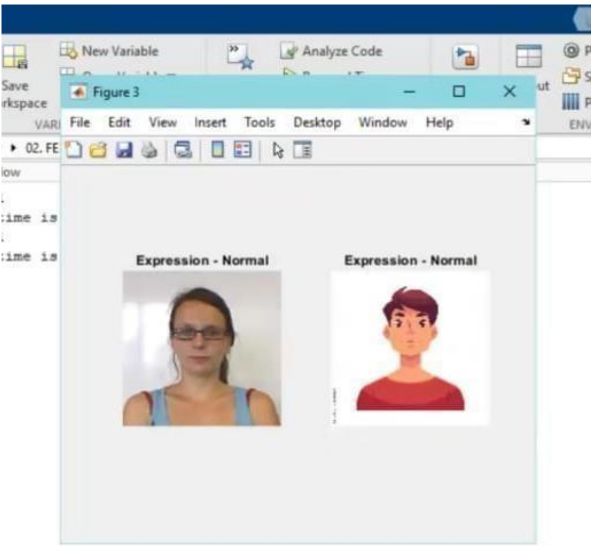


Fig:8.2 Detecting face region



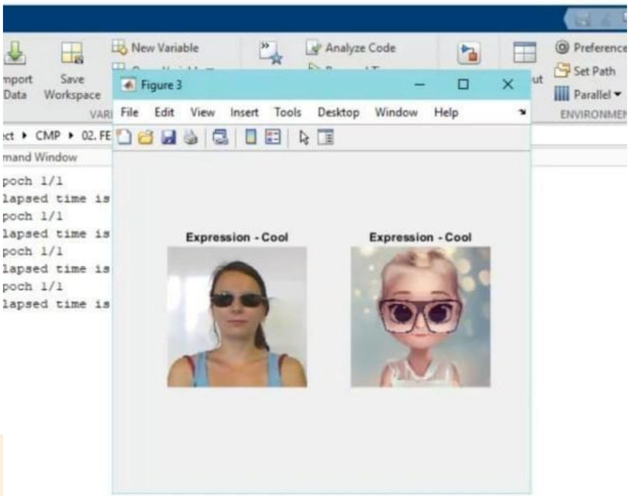
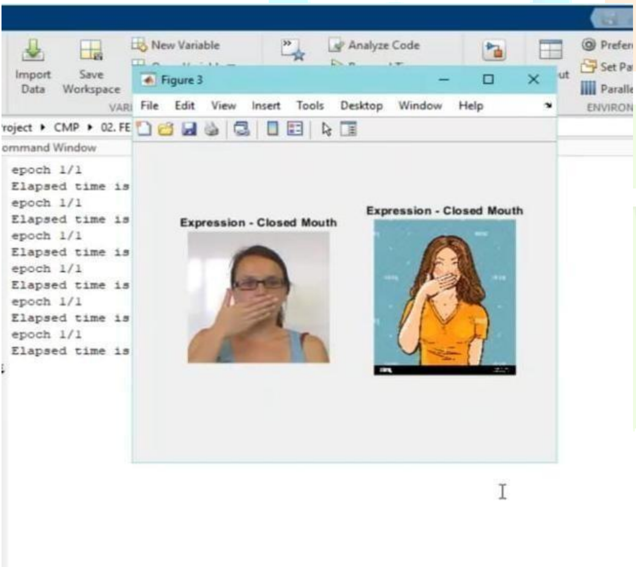


Fig: Normal Expression

Fig: Cool Expression



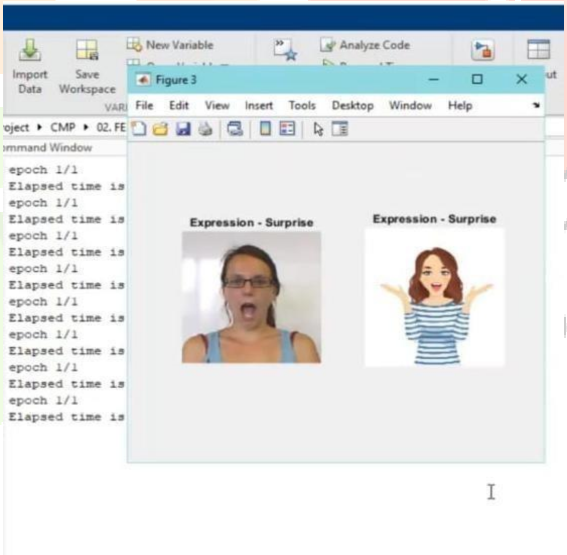


Fig:Shocking Expression

Fig: Surprise Expression

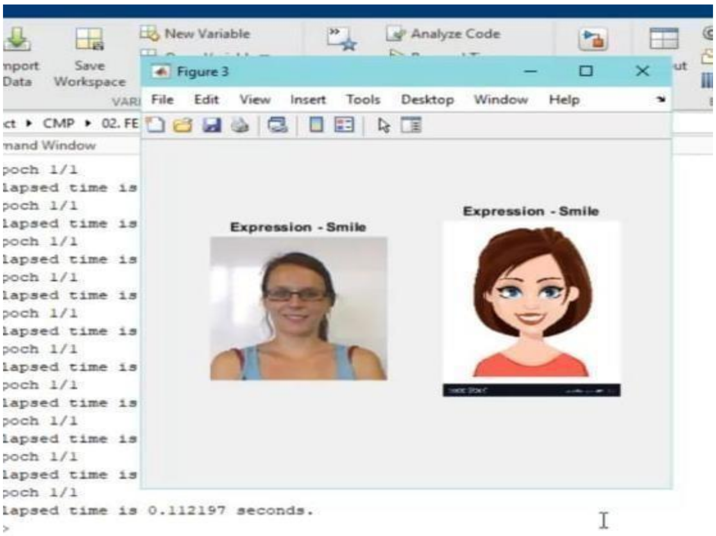


Fig: Smile Expression

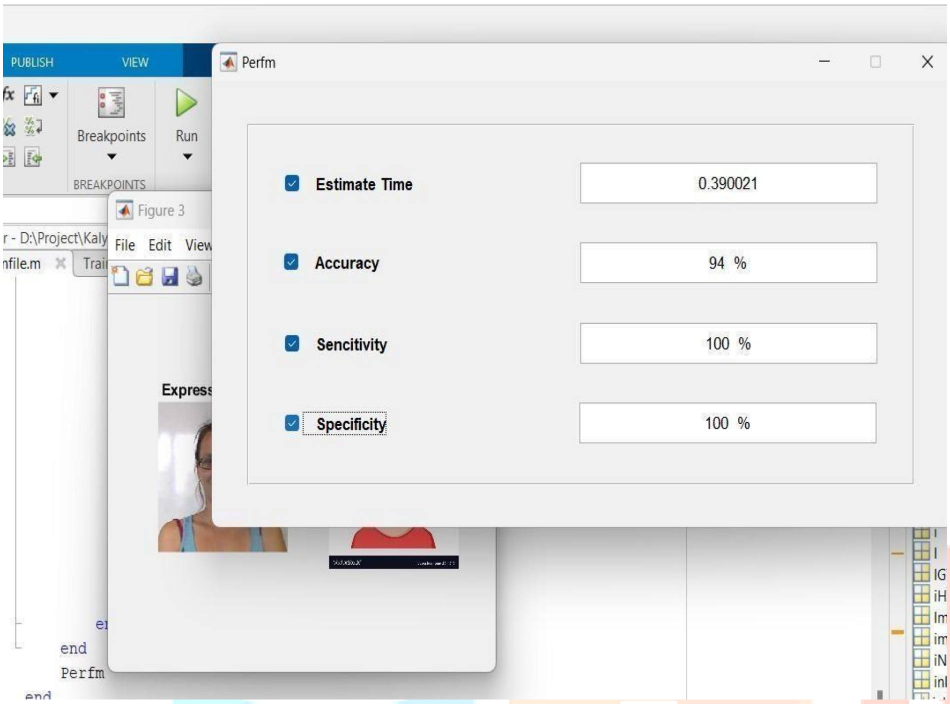


Fig:Performance Analysis

CONCLUSION:

- Due to the degradation of face image quality and large variations of illumination, pose, and expression, therecognition of unconstrained face images is a challenging task.
- Solving this problem demands work in at least two areas: development of an effective face image descriptorand a comprehensive face representation scheme.

APPLICATIONS:

Here are some applications of Integration of face recognition with emotion recognition:

a) **Advertising:** Combining face recognition with emotion recognition can help companies analyze how individuals respond to their advertisements, which can help them create more effective marketing strategies.

b) **Mental Health:** Combining face recognition with emotion recognition can help diagnose and monitor mental health conditions more accurately.

c) **Entertainment:** Combining face recognition with emotion recognition can create more personalized and interactive entertainment experiences for users.

d) **Human-Computer Interaction:** Combining face recognition with emotion recognition can improve theinteraction between humans and computers, making it more natural and intuitive.

It is important to note that the use of these technologies must be done responsibly,taking into account ethical and privacy concerns.

FUTURE SCOPE:

Face recognition in video and emotion recognition have immense potential for the future, and are likelyto have a significant impact in various fields. Some possible future developments in these areas include:

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