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A Novel Framework design for Semantic based Image retrieval as a Cyber Forensic Tool

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Abstract*: Cyber forensics includes the areas of computer forensics, network forensics and internet forensics. Digital images were commonly used in cyber forensics to collect criminal images, fingerprints, images of crime events and so on. Since the current cyber forensic tools are not very much furnished with the course of action of huge image data, it becomes a big issue to obtain image evidence to prosecute the criminal, most of the evidence is available in the form of raw semantics. Cyber forensic investigators often face the challenge of manually examining an enormous quantity of digital image information to identify direct evidence with the assistance of this semantics. Semantic based image retrieval system (SBIR) is therefore the recent and best option to solve this drawback. The main purpose of this research is to design for cyber forensic tools a novel framework of semantic-based image retrieval system. We therefore present a deep learning framework based on the Convolution neural network(GoogLeNet) for recognizing distinct facial expressions from the Yale facial image database for cyber associated forensic tools, the presented framework is very effective for classification and detection based on semantics or verbal descriptions. The network has accomplished a decent accuracy of 86.25 % after training.

***Keywords* : Cyber Forensics, CBIR, CNN, GoogLeNet, SBIR, Image, Semantics, Deep learning and facts.**

I. INTRODUCTION

As the general public has turned out to be increasingly reliant on computers, networks and internet related innovations, which are despite the fact that an aid yet in a few circumstances it has ended up being to be bane. The computerized world is getting to be focuses of crime activities, for example web defacement, vandalism and cyber war. Cyber forensics is another and quickly developing field which is associated with examination of the cyber crimes for gathering potential evidences. Cyber forensics comprises forensics on computer, network and Internet [12].

Cyber forensic investigations are frequently involved in the examination of digital images found on the target media. Any picture in the digital form can be created or copied and stored is called as a digital image or simply image. An image can be illustrated as vector graphic or raster graphic. The images created by mathematical statements (Lines and shapes of 2D or 3D images) are called vector graphics. The images captured or scanned from a sample are called as raster graphics.

Verbal facts about an image, pixel and its characteristics are called an image's semantics. Simply the significance of an image is called semantics of an image. Image retrieval based on semantics of an image is mainly essential in forensic examination [17].

Now some facial image recovery issues are occurring for a few days in forensic examination. The issue of facial retrieval is about retrieving facial images from a set of images that are applicable to user demands. The SBIR is based on verbal facts associated with an image [14]. It is expected that the retrieval system will display the images in the database that match the verbal facts.

The verbal fact or description of people's facial image is almost always semantic in nature, using words like oval face, lips and nose. SBIR deal with the retrieval of images based on the facial features, such as verbal facts of a person's nose, eyes, and lips, not on the raw image data but on the semantics and then the composite image matches with the data set images [15]. In forensic investigation of criminal identity and other apps, facial recognition technologies are in high demand. The smooth bio-metric features of the face have to be combined in many law enforcement apps to obtain the target face from a dataset [14].

We can determine different facial expressions based on its features like happy, sad, surprise, happy face with glasses, sad face with glasses, and sad face with moustache, using computer vision, especially using Convolution neural network (CNN). CNN has potential capability through its pre trained CNN named as GoogLeNet. GoogLeNet has been trained on over 1000 million of images, this network learns rich features representation of different images, and this network takes input and then provide outputs as label for an image. The real face is one of the most essential areas of the body to define low and high features of people. Now we will see short experimental description on CNN with respect to facial features recognition using CNN.

About DWT:

The discrete wavelet transformation (DWT) is a transformation technique that uses a discrete set of image compression scales in accordance with specific guidelines. To put it another way, this technique breaks down the signal into a set of wavelets that are mutually orthogonal, sometimes called discrete-time continuous wavelet transformation that implements it for the discrete time series.

Scaling function which defines its scaling characteristics can build the wavelet. The restriction of orthogonal scaling functions to their discrete translations implies such mathematical conditions listed almost anywhere e. g. The formula for dilation

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$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k).$$

Where, S - factor for scaling. In addition, the area between the function has to be standardized and the scaling structure has to be orthogonal to translating its integer e. g.

$$\int_{-\infty}^{\infty} \phi(x)\phi(x+l)dx = \delta_{0,l}$$

We can get outcomes of all these equations after implementing some more circumstances. The wavelet is taken from the scaling function.

$$\psi(x) = \sum_{k=-\infty}^{\infty} (-1)^k a_{N-1-k} \psi(2x - k)$$

Where, N - An even integer.

The collection of wavelets as we use to decay the signal forms an orthonormal baseline.

The discrete wavelet transform (DWT) algorithms have a strong place in signal processing in several research and business fields. As DWT offers octave-scale frequency as well as spatial timing of the analysed signal, it is constantly used to fix and treat more and more sophisticated issues.

Most of the image compression and image analysis uses the DWT for images. JPEG 2000 is one implementation of the 2D DWT. The heart of the algorithm is to break down the image into the DWT elements and then build trees of the DWT extracted coefficients to determine which elements can be omitted before saving the image. We can eliminate extraneous data in this manner, but there is also a huge advantage that the DWT is lossless. Which filter(s) are used in JPEG 2000, we don't understand, but we can understand for sure that the standard is lossless. This implies that without any artefacts or quantization mistakes we will be able to reconstruct the initial information. JPEG 2000 also has a loss option where we can further reduce the file size by eliminating more of the DWT coefficients in a way that is imperceptible to average usage.

About CNN:

CNN could be a gradable neural network that usually extracts features options by convolving input with a gaggle of kernel filters. Then pooling of obtained feature is done and filtered resolute next layer [25]. Within the following, we are going to introduce CNN algorithm.

$X^1 \in R^{M1xM1}$

Above given equation represents the l^{th} layer of i^{th} map, kernel filter of lth layer connected to the i^{th} maps in the $(l-1)^{th}$.

Layer and index map

$M_j = \{ i \mid i^{th}$

Set in the layer $(l\text{-}1)^{th}$

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right)$$

Above represents equation of the convolution operation.

Where, f(.)- ReLU(Rectified Linear Unit) activation function non-linear f (z) = max (0, z).

Pooling equation is:

$$x_j^l = down(x_i^{l-1})$$

Where sum-sampling function is b^i_j

For multiclass classification an effective method is applied known as softmax regression, suppose for a given data you have T categories, the training data for the each category are denoted as where (x_i, y_i) are feature vector and labels apart Cross entropy loss function given as:

$$J(\theta) = -\frac{1}{N}\left[\sum_{i=1}^{N}\sum_{t=1}^{T} 1\{y_i = t\} \log \frac{e^{\theta_t^T x_i}}{\sum_{l=1}^{T} e^{\theta_l^T x_i}}\right]$$

Here θ represents model parameters, Normalization factor is

$$\sum_{l=1}^{T} e^{\theta_l^T x_i}$$

Below diagram shows decomposition of input image. The first level decomposed image encompassed with four rescaled coefficients as furnished below

1. Coefficient of approximation
2. Coefficient of Horizontal
3. Coefficient of Vertical
4. Coefficient of Diagonal

About GoogleNet:

The ImageNet Large-Scale Visual Recognition Challenge (ILSVRC 2014) competition launched GoogLeNet in 2014. GoogleNet is designed by a researcher from Google. GoogLeNet accomplished a 6.67 false positive rate that is quite near to the performance model at the human level. The best example for the convolution neural network (CNN) is GoogLeNet. It is also called as pre-trained ImageNet. It was proved very powerful model. It contains 22 layers initially and further it has enhanced. Using GoogleLeNet learning is typically much quicker and easier than training a scratch-based network. GoogLeNet generally handles classification, extraction and learning activities. GoogleNet contains a novel approach known as inception model.

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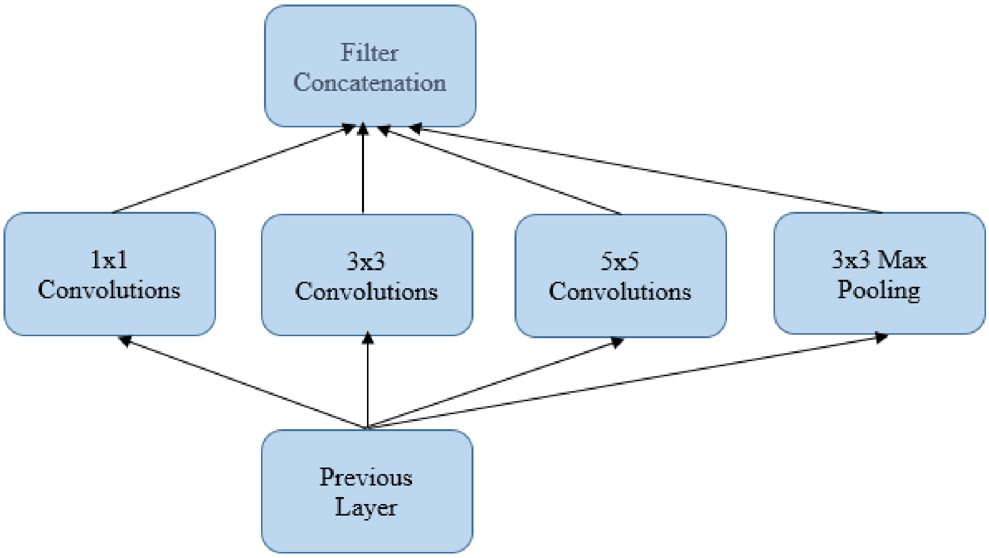

Fig 2: Inception Module

In a single layer it represents multiple kinds of "feature extractors". These extractors indirectly help to improve performance of network because the network at training itself have many choices to achieve the task. It has two options to turn the input, or to pool it directly. The final architecture contains multiple stacked model, even training process is different in google net as most layers which are at the top has its own output layer. This helps model in parallel training as well as joint training. This network actually works with machine potency and so that it can run on individual users with low computer resources especially with low memory.

The whole article is summarized as follows, the introduction of cyber forensics is described in Section one, image retrieval system and about conventional neural networks (CNN). Section two contains the recent related researches on semantic based image retrieval systems. Section three describes the problem definition. Section four describes about the anticipated methodology of this research paper and contains information on DWT and GoogLeNet also. In this section we also described about considered Yale dataset. The methodology clearly described using various flow diagrams including network layer graph for better understanding. Section five describes about the results. Section six concludes this research article.

II. RECENT RELATED RESEARCHES

Tanya Piplani [1] proposed two approaches known as Caption based retrieval and Embedding space retrieval. In Caption based retrieval a special CNN (Convolutional Neural Network) design is used to extract image based features and converting the input into a vector of embedding that is semantically rich. In Embedding space retrieval, a pre-trained CNN (Convolutional Neural Network) called ResNet-101 is used to obtain semantic data from images to generate content characteristics.

Max H. Quinn et al. [2] described a novel architecture called Situate to recover the visual condition of a reference in an image collection. It combines visual-based object location models with probabilistic models portraying learned multi-object interactions and also learns these models from labelled training images. Through an active search process, it applies these models to a current image that tries to ground components of the query scenario in the picture that is, generate bounding boxes that locate appropriate items and interactions, and eventually provide a situation matching score for the image case.

Umar Manzoor et al. [4] proposed an ontology-based approach that utilizes domain-specific ontology for user-related image retrieval. A person can either offer the keyword as text input or the picture itself can be entered. Semantic based Image Retrieval is based on a hybrid strategy and utilizes classification methods based on form, color and texture. On a big amount of test instances, the suggested scheme has been tested; experimental findings demonstrate the efficiency and effectiveness of the suggested method.

M. Kalimuthu et al. [5] Recommended APSO and Squared Euclidian Distance (SED) facial retrieval system. The method suggested consists of three phases: extraction of features, optimization and retrieval of images. The features are at first obtained from either the image set. Throughout the second phase, a well-known adaptive particle swarm optimization (APSO) method, a semantic distance between all these features is shortened. A square Euclidian distance (SED) measure will be used in the last third stage to obtain facial images that are less distant from the input query image.

Ben Bradshaw [11] defined an image retrieval model based on image semantics. A monolithic, deterministic method is suggested in order to obtain these semantics. In this situation the labels obtained are person-made, normal, indoors & outdoors. The monolithic structure joins analyses of class probability along a lot of levels to create a later assessment of class affiliation quantity. The suggested algorithm can dictate outcomes at any point in the incident, with the exception of earlier work in this field, and only a small number of images are needed to train the model.

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III. PROBLEM DEFINITION

As when the amount of digital images accessible increases significantly, the capacity to search across digital images is becoming relatively important. Moreover, defining any image that is available and influencing which digital images are comparable to many other digital images that become inconvenient for individuals. The current CBIR technique uses visual content images to find and retrieve images from the necessary databases. Face images usually vary from many other CBIR images because in their general setup facial images are difficult, nonlinear and preferable. In current techniques, image retrieval techniques mainly use low-level features such as color, texture, and shape. Pictorial features are acquired inevitably which use image processing methods to represent the raw material of an image. CBIR method generally produces comparable color, images, and shape-based image retrieval produces images that obviously have the same shape [18]. Consequently, the present CBIR systems that are used with low-level features for the general purpose of image retrieval facial images are not efficient, particularly if the user's query is a verbal fact. These facts are not locating the semantic elements of a face. By fact, people also tend to use all the verbal facts of semantic characteristics to specify what they have been looking for and find it difficult to use low-level features. A past few years developed biometric safety CBIR system [15] is applied to low-level facial images. This technique has obtained a precise face image recovery of approximately 95 percent accuracy, however, this method does not apply to real-time information.

In addition, low-level feature-based CBIR does not generate precise outcomes in face images with the same individuals at various features such as Glasses, No Glasses, Moustache and No Moustache, etc. The current technologies therefore present some disadvantages in the retrieval of facial images using semantic queries or verbal descriptions; that is, during retrieval they are not regarded in the semantic features.

IV. PROPOSED METHODOLOGY

We described an accurate model for the image retrieval system based on semantics as a cyber-forensic tool using CNN based pre-trained deep learning network (GoogLeNet) and Discrete Wavelet Transform (DWT) domain. This proposed method investigates its chance and potential benefits of studying the filters in the DWT domain of convolutional neural network (CNN) to image recognition. We initiated the discrete transformation of the wavelet on face images to extract features. Finally, the classification process will be done by deep learning through GoogLeNet. It is a type of pre-trained neural network that has been used in several areas such as classification, decision-making, and so on.

This proposed method retrieves more related features from the given input image. The overall process diagram of the architecture is presented in below figure.

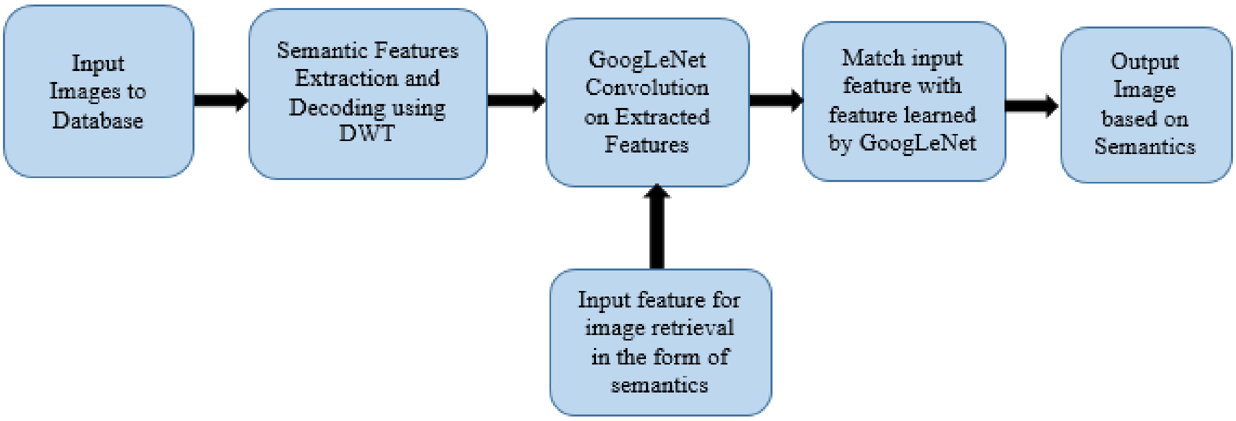

Fig 1: Overall process diagram of the proposed framework

Now we will go through the basic information on important concepts of DWT and GoogLeNet, which are playing the vital role in the proposed methodology of an efficient framework for semantic based facial image retrieval system as a cyber-forensic tool.

Algorithm of deep CNN for Proposed Framework:

Step 1: Input image layer which has input image dimension as 224*224*3, with normalization as zero centre.

Step 2: Second layer Convolution 2-D layer with filter size [7, 7].

Step 3: 3rd layer is a layer of ReLu which conducts a threshold function for each i/p component in which any variable just under zero is assigned to zero.

Step 4: 4th layer by splitting the input into rectangular pooling areas and calculating the maximum of each region, a max pooling layer conducts down-sampling.

Step 5: Cross channel normalisation layer - A local reaction channel-wise layer of normalization performs channel-wise normalization.

Step 6: After that convolution 2-d layer with filter size [1, 1].

Step 7: ReLu layer, convolution layer repeats till 9th layer.

Step 8: Convolution layer as inception module is stacked linearly to get better performance.

Step 9: Last 4 layer of 144 layer are

- Average pooling 2D layer.
- Dropout layer.
- Fully connected layer.

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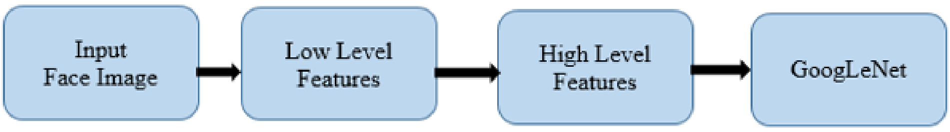
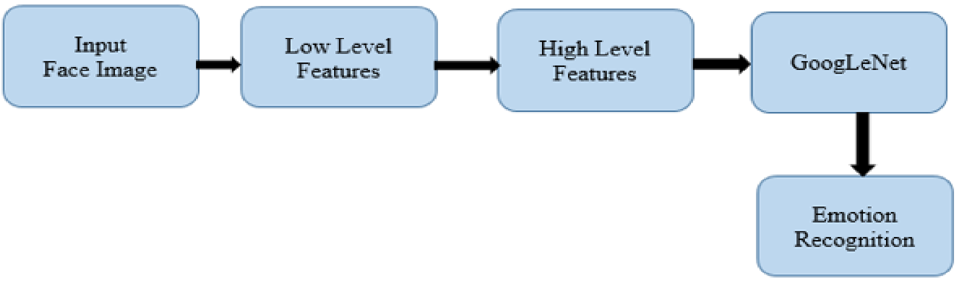
Softmax layer (Softmax function to the input and classification output layer.

Phase wise Methodology Process:

Training Phase (for each emotion of face):



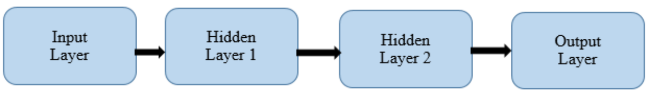
Testing Phase (for each emotion of face):



In training phase, neural network is trained using features which are extracted from discrete wavelet transform. Discrete wavelet transform technique is used to calculate wavelet decomposition. In testing phase, to test unknown image and classify, first wavelet transform of an unknown image is calculated and all features will be extracted. Low-level features are minor details of the image, like lines or dots, that can be picked up by, say, a convolutional filter (for really low-level things) or SIFT or HOG (for more abstract things like edges). High-level features are designed to detect entities and larger shapes in the image on top of low-level features. Convolutional neural networks use both types of features: the first couple convolutional layers will learn filters for finding lines, dots, curves etc. while the later layers will learn to recognize common objects and shapes.
The second step is to use GoogLeNet for extracted features with the desired values and test it to determine the object class of a given unknown image.
Algorithm:
Step 1: Read the input image and resize it. (If not 224*224 size)
Step 2: Image pre-processing is applied.
Step 3: Calculate Wavelet Transform of a given input image.
Step 4: Extract Low Level and High Level features from Discrete Wavelet Transform.
Step 5: For classification, use the pre-trained conventional neural network (GoogLeNet)

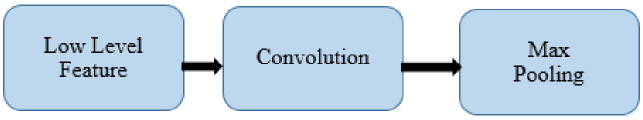
Step 6: Test the given image.
Stop.

CNN Model Phase:

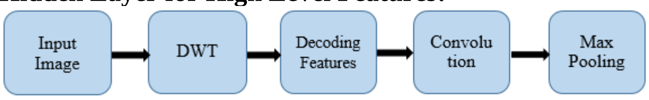


Input Layer: The Input Layer provides an entry point for incoming data. As such it needs to match the format or "shape" of the expected input. For example, an RGB image 224 pixels high and 224 pixels wide might require an Input Layer of 150528 nodes organised into a 3D structure (224* 224 *3). In such a structure each node would represent the Red, Green or Blue value for a given pixel.
Hidden Layer: Hidden layers are so called because they sit between the Input and Output Layers and have no contact with the "outside world". The function is to define input information features and use them to correlate a specified input with the right output. A CNN can have multiple hidden Layers. In the above figure hidden layer 1 describes about low level features (edges, circles) and hidden layer 2 describes about high level features (nose, lips and mouth).
A drawback of deep learning is that the feature representations in hidden layers are not always human readable like the above example. This means that it can be extremely difficult to get insight into what a Deep Learning ANN delivers a specific result, especially if CNN is working in more than 3 dimensions.
Output Layer: The Output Layer provides the CNN's end outcome and is organized by the use case you are working on. For example, if you wanted a CNN to recognise 10 different objects in images you might want 10 output nodes, each representing one of the objects you are trying to find. The final score from each output node would then indicate whether or not the associated object had been found by the CNN.

Hidden Layer for Low Level Features:



Hidden Layer for High Level Features:



Datasets Considered:

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This paper has trained and tested the Yale dataset, Dataset have 16 categorized folder named as big eyes, small eyes, glasses, happy, sad, wink, long nose, moustache, no moustache, no glasses, sleepy, surprise, short nose, long nose, big eyes, small eyes, square face, round face, oval face. All images are resized to 224*224 in pre-processing. There are total 167 images in the dataset out of which 70% is used as training data and 30 % as validation data. Yale Facial Database is approximate 6.4MB in size.

Fig 4: Sample images of Yale dataset

Network Layer Graph (GoogLeNet):

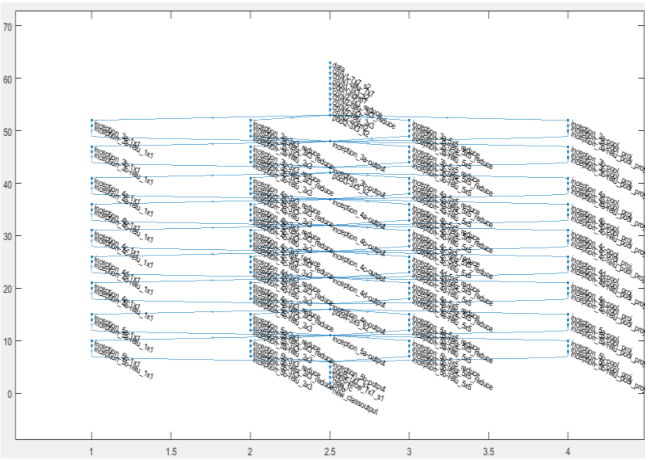

Fig 5: Layer Graph

Network contains 144 layers with 170 connections, we can visualize the layer graph by plotting networghh file of the network. The component of the layer graph is input, Input are the images of dimension 224-by-224-by-3, where 3 indicates the color channel. This dimension of the images is required by the first layer. The image input layer is the first component of the network's Layers property.

Image feature is acquired from the network's convolution layers. This is the last layer and use the final layer of categorization to categorize the image of the input. Google Net's two layers called loss3-classifying layer and output layer have data about how to merge the features the network extracts into class outcomes, a projected labels, and a drop rate. We need to substitute these two layers with new layers that are tailored to the current information set to retrain a pre-trained network to classify raw images.

Find the names to substitute the two layers. We used to discover Layers to replace the supporting feature. Afterwards, replace by a new fully linked layer with the amount of inputs equal to the amount of categories within the new data set.

V. EXPERIMENTAL RESULTS

Using the Yale facial dataset, the suggested facial image-retrieval framework is analysed. This Yale facial dataset is made up of 167 images in total, which includes the face features of happy, sad, wink, surprise, oval face, round face, moustache face with glasses, sad face with glasses and sad face with No glasses and so on.

Network Training:

224*224*3 type of images are needed by the network for training process, it indicates extra increment activities to be performed on the training images: flip the training images evenly across the vertical axis and evenly convert them up to 30 pixels and scale them up to 10 percent vertical and horizontal. Data enhancement helps avoid overfitting and memorizing the precise information of the training images by the network.

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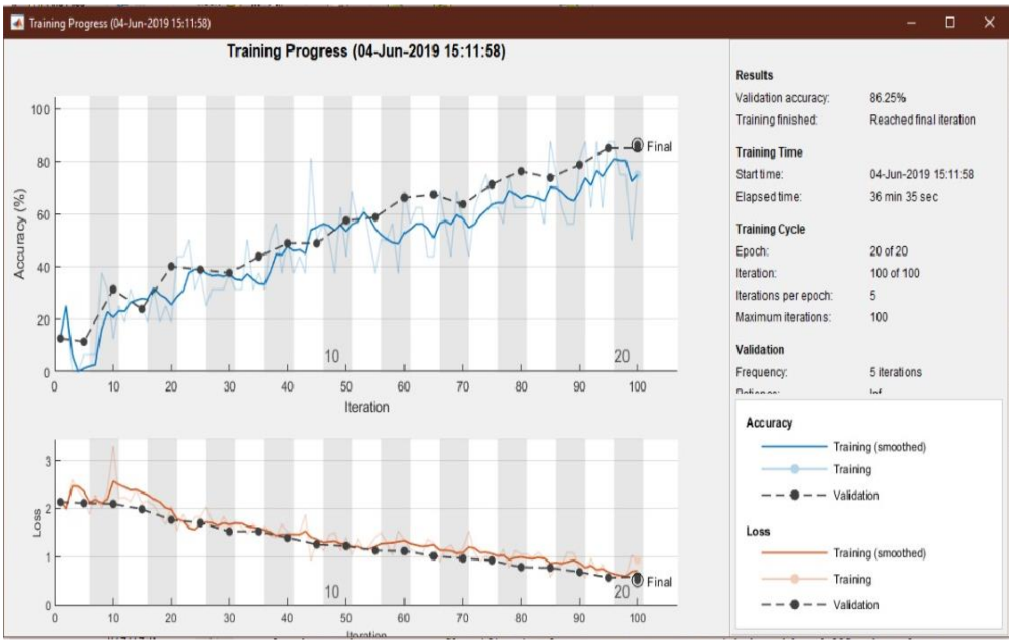

Fig 6: Training Process

Results:

It takes 35 min to complete the training process with accuracy 86.25 %,Total iteration, Training cycle parameter as iteration per epoch are 5, Maximum iterations are 100. We have tested single feature as well as multiple features, we have tested for single feature as image retrieval for happy expression.

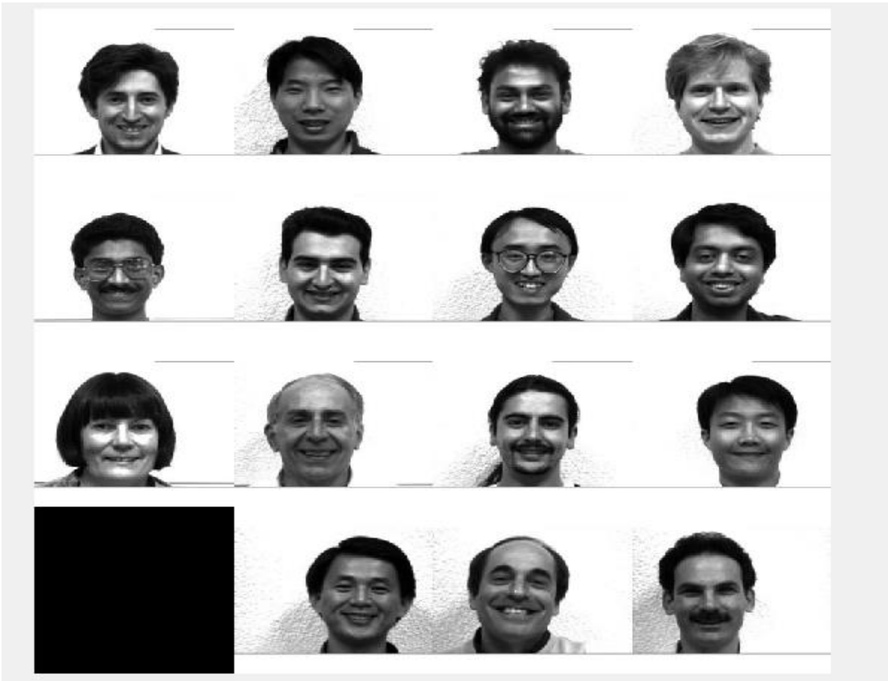

Fig 7: Output of various retrieved face images with single happy feature

Testing result of Single feature & multiple feature images:

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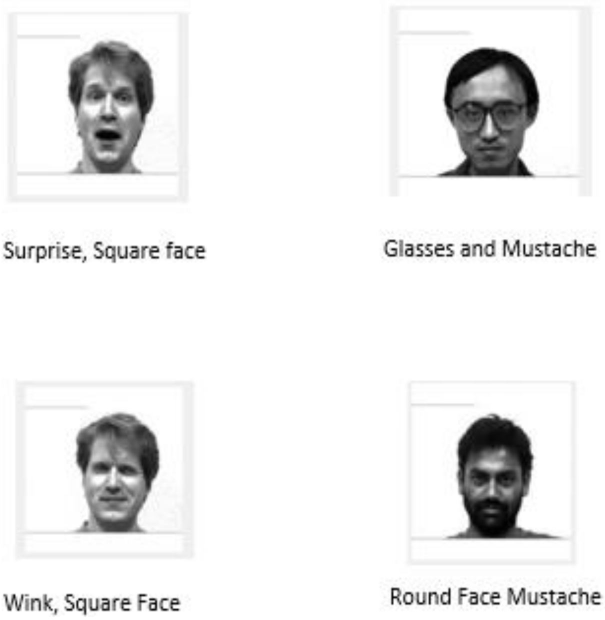

Fig 8: Output of various retrieved face images with multiple features

VI. CONCLUSION

This paper represents about the design of an efficient framework for semantic based facial image retrieval system as a cyber-forensic tool using CNN based deep learning. Since current cyber forensic tools are not set up with beneficial semantic based image retrieval methods, there is a strong need of advancement of novel methods and frameworks in cyber forensics tool development in perspective of image retrieval methods. Our proposed CNN deep learning based semantic based facial expression image retrieval system can also help in solving many real time problems using sentimental analysis, such as it can help in automatic driving, we can monitor from mood of the driver so accidents can be avoided. Finally after 144 layers of deep training we got the best result with 86.25 % accuracy.

We certainly hope that this research article will address the requirements of novice scientists and learners who are actively engaged in the CNN based deep learning, cyber forensics and semantic based image retrieval systems.

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