

# FACIAL IN-PAINTING USING DEEP LEARNING IN MACHINE LEARNING

Madhushree G M<sup>1</sup>, Rakshitha K<sup>2</sup>, Rakshitha M<sup>3</sup>, Tanuja H R<sup>4</sup>, Drakshayini K B<sup>5</sup>

<sup>1,2,3,4</sup>Student, Dept. of Information Science, Vidya Vikas Institute of Engineering and Technology, Mysore, Karnataka, India

<sup>5</sup>Professor, Dept. of Computer Science, Vidya Vikas Institute of Engineering and Technology, Mysore, Karnataka, India

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**Abstract** -Facial in-painting is the task of generating plausible facial structures for missing pixels in a face image. We introduce a Deep Learning approach for face in-painting, which makes use of the observable region of an abstracted face as well as its inferred high-level facial attributes, namely gender, ethnicity, and expression. Based on the intuition that the realism of a face in-painting result depends significantly on its overall consistency with respect to these high-level attributes, our approach selects a guidance face that matches the targeted attributes and utilizes it together with the observable input face regions to in-paint the missing areas. This approach is effective in in-painting facial components such as the mouth or the eyes that could be partially or completely abstracted in the input face. The in-painting is performed on the intrinsic image layers instead of the RGB colour space to handle the illumination differences between the target face and the guidance face to further enhance the resulting visual quality.

**Key Words:** Deep learning, face alignment, face matching.

## 1. INTRODUCTION

Face recognition playing a major role in science and technology, grabbing the attention of researchers due to its benefits, half recorded face or a blurred face sometimes becomes a major evidence in crime detection. Usually in CC camera's due to its fixed direction sometimes the face of the major evidence person was recorded as blur or it may half recorded( like upper half face recorded or lower half of the face is recorded), this type of pictures needs to be reconstructed and this is known as image reconstruction or restoration( constructing the missed portions of the image).There are many image restorations method [1],[2],[3]. Traditional in-painting methods are mainly based on diffusion and texture exemplar based filling[1]. When a key region missing (it is the only information in the image, which cannot be obtained from existing information, such as the nose loss of a single face picture), the target regions cannot be filled from existing information. Therefore, the traditional method does not have a semantic in-painting. The in-painting techniques are used to fill out the missing regions also remove the unwanted object. The above discussed techniques are providing the better result but they are also lacking in certain things. If we consider the size of object to recover, some of the techniques unable to produce the good result, because some of the techniques are designed for small

image gaps only. If we complete the images with large gaps then it will give the result but the result quality will be poor and. Some of the techniques produce single resolution image result as referred in [2]. They use a single forward network pass instead of solving an optimization problem that involves many forward and backward passes.

In-order to overcome this problems and improve the accuracy of the face recognition we are proposing a new technique by using deep learning for the improvement in training stability and also we are using real time dataset for a better efficiency.

## 2. LITERATURE SURVEY

To design an intelligent lighting system which aims to power saving and self-governing operation on fair affordable for the streets. Literature survey is something when we look at a literature in a surface level. It is a phase where one tries to know of what are all the literature related to one area of interest. Here are the few survey papers related to our project facial in-painting,

*"Learning deep facial expression features from image and optical flow sequences using 3D CNN"* by Jianfeng Zhao published on 2018, they used 3D CNN technology to design to learn high level emotional features from the image, optical flow, accumulative optical flow cubes, but it doesn't takes previously trained 2D network to extract features it often use more memory. her they have used one 3D CNN was designed to learn high-level emotional features from the image, optical flow, and accumulative optical flow cubes. The experimental results show that the designed 3D CNN can learn more discriminative features hidden in data cubes to recognize facial expression. The learned features learned from image cubes contain not only static features but also dynamic features, whereas the deep features extracted from optical flow or accumulative optical flow cubes mainly contain motion information of the facial movements. Both of them can model high-level abstractions of the emotional information and be used to recognize facial expression [1].

*"Physiognomy generation system"* by keerthana mouli under VTU in 2018-19, they proposed facial in-painting under GAN technology, currently small signal MMIC and LNA market is dominated by GaA's devices and there is no standard dataset used and also it costs more due to costly technology involved in it [2].

*“Facial expression synthesis using manifold learning and belief propagation”* by Li Huang Congyong Su published in 2016, they have used 30 standard datasets and the manifold algorithm is difficult construct but here we found high error suspectability and this algorithm requires more time to learn the training examples and belief propagation running time is exponential in the time of the largest graph clique [3].

*“Image completion using structure and texture GAN network”* by Jingtao Guo, Yi Liu published in 2019, Here structure and texture are the two indispensable parts of image, by using the end-to-end framework to repair an image it will not give special attention to texture and structure hence here they generate distorted structure and inconsistent texture and two algorithms are used that is s GAN that focuses on repairing the sketch structure in the missing region of an image and t GAN that generates consistent texture information in the missing region based on the sketch output by s GAN and the surrounding incomplete image. Later they have used deep convolutional neural networks(CNN) and it is proposed of image completion. Finally they have proposed a new method for image completion by decomposing image completion into sub-tasks and this method also allows a user to manipulate output [4].

*“The visual human face super-resolution reconstruction algorithm based on improved deep residual network”* by Di Fan, Shuai Fang, Guangcai Wang, Shang Gao and Xiaoxin Liu published on July 2019, here they improves the deep residual network from two aspects of residual unit and network structure and proposes a face super resolution reconstruction algorithm, it deals with the problems of insufficient detail recovery and slow network optimization existing in face super resolution reconstruction, this paper discusses the influence of network depth and width on the reconstruction effect, as to determine the network parameters considering both the quality and the time-consuming, and also compares the reconstruction indexes and reconstructed images to similar methods [5].

*“Face completion with Hybrid Dilated Convolution”* by Yuchun Fang, Yifan Li, Xiaokang Tu, Taifeng Tan, Xin Wang published by Elsevier B.V. on 2019, in this paper they aiming at the reconstruction of missing or damaged regions of an incomplete face image by proposing U-net based method combines Hybrid dilated convolution(HDC) and spectral normalization to fill the missing regions in the image, the main idea this method is using HDC to deal with the gridding problem, they validate this method on face sets CelebA and Multi-PIE [6].

*“Low resolution face recognition using a two-branch deep convolutional neural network architecture”* by Erfan Zangeneh , Mohammad Rasmati , Yalda Mohsenzadeh published in 20 July 2019, in this project, they used coupled mappings method for low resolution and high resolution face recognition using deep convolutional neural network. Basically this DCNN proposes two resolutions low and high

into a common space with nonlinear transformation. The high resolution consists of 14 layers and low resolution consists of 5 layers super resolution network which connected to a 14 layer network. Here it can reconstruct a high resolution image from its corresponding [7].

*“Image inpainting based on geometric similarity”* by Kuo-Ming Hung, Yen-Liang chen, and Ching-Tang Hsieh published in 2012, here they used “geometric image inpainting method” for Restoring a large damaged area in the images. And here they proposed a new imaged inpainting algorithm called GII. The most important feature of this image in-painting method is the use of facial self-affinity to carry out progressive image in-painting. In image repairing process there are two modes one is onion peel mode and other is desiderate mode. And image inpainting techniques centered around three major issues that is the image domain analysis, image repairing order and image pixel restoration algorithm [8].

*“New In-painting Algorithm Based on Simplified Context Encoders and Multi-Scale Adversarial Network”* by Haodi Wang .based on Context Encoders, this study modifies the network structure, fine-tunes the convolution kernel and strides in the reconstruct network, and introduces a multi-scale adversarial network which is consist with global discriminator and a local discriminator. The addition of the global discriminator enables the network to ensure global consistency and context continuity of the entire picture while guaranteeing local detail. On this basis, the loss function is modified accordingly. The loss function consists of two parts: reconstruction loss and multi-scale versus learning loss. The network architecture is applied to the Paris dataset, which shows reasonable repair performance. It appears to improve the Context Encoders’ patching and blurring problems, and obtains better in-painting results. Comparing with the in-painting of existing face images, the experiment enhances the generalization ability of the network. Comparing with Context Encoders and GAN-based face image restoration projects, the network structure of this paper is more concise and faster [9].

### 3. PROPOSED METHOD

Facial in-painting has a good application value in face reconstruction. Deep learning neural network have powerful learning capabilities and can extract high-level semantic features. These features can be used to semantically fill missing regions. Ideal image restoration needs to maintain structural consistency and texture clarity. We introduce a new architecture based on following technologies,

1. **Face detection:** A face detector finds the position of the faces in an image and returns the coordinates of a bounding box for each one of them.
2. **Face alignment:** The goal of face alignment is to scale and crop face images in the same way using a

set of reference points located at fixed locations in the image. This process typically requires finding a set of facial landmarks using a landmark detector and, in the case of a simple 2D alignment, finding the best affine transformation that fits the reference points. More complex 3D alignment algorithms (example: can also achieve face frontalisation, i.e. changing the pose of a face to frontal.

3. **Face representation:** At the face representation stage, the pixel values of a face image are transformed into a compact and discriminative feature vector, also known as a template. Ideally, all the faces of a same subject should map to similar feature vectors.
4. **Face matching:** In the face matching building block, two templates are compared to produce a similarity score that indicates the likelihood that they belong to the same subject.

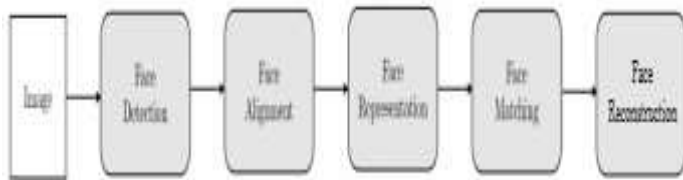


Fig 1. Architecture of proposed system

Feature-based methods refer to methods that leverage local features extracted at different locations in a face image. Unlike geometry-based methods, feature-based methods focus on extracting discriminative features rather than computing their geometry. Feature-based methods tend to be more robust

Technically, geometry-based methods can be seen as a special case of feature-based methods, since many feature-based methods also leverage the geometry of the extracted features. Unlike holistic methods when dealing with faces presenting local variations (e.g. facial expression or illumination). For example, consider two face images of the same subject in which the only difference between them is that the person's eyes are closed in one of them. In a feature-based method, only the coefficients of the feature vectors that correspond to features extracted around the eyes will differ between the two images. On the other hand, in a holistic method, all the coefficients of the feature vectors might differ. Moreover, many of the descriptors used in feature-based methods are designed to be invariant to different variations (e.g. scaling, rotation or translation). One of the first feature-based methods was the modular eigenfaces method proposed in, an extension of the original eigenfaces technique. In this method, PCA was independently applied to different local regions in the face image to produce sets of eigenfeatures. Although showed that both eigenfeatures and eigenfaces can achieve the same accuracy, the eigenfeatures approach provided better accuracy when only a few eigenvectors were used.

A feature-based method that uses binary edge features was proposed. Their main contribution was to improve the Hausdorff distance that was used in to compare binary images. The Hausdorff distance measures proximity between two set of points by looking at the greatest distance from a point in one set to the closest point in the other set. In the modified Hausdorff distance proposed in, each point in one set has to be near some point in the other set. It was argued that this property makes the method more robust to small, non-rigid local distortions. A variation of this method proposed line edge maps (LEMs) for face representation. LEMs provide a compact face representation since edges are encoded as line segments, i.e. only the coordinates of the end points are used. A line segment Hausdorff distance was also proposed in this work to match LEMs. The proposed distance is discouraged to match lines with different orientations, is robust to line displacements, and incorporates a measure of the difference between the number of lines found in two LEMs. A very popular feature-based method was the elastic bunch graph matching (EBGM) method, an extension of the dynamic link architecture proposed. In this method, a face is represented using a graph of nodes. The nodes contain Gabor wavelet coefficients extracted around a set of predefined facial landmarks. During training, a face bunch graph (FBG) model is created by stacking the manually located nodes of each training image. When a test face image is presented, a new graph is created and fitted to the facial landmarks by searching for the most similar nodes in the FBG model. We use HOG feature to classify the face segmentation

#### 4. CONCLUSION

In view of problem of low accuracy of different in painting methods by using different algorithms and technologies we have introduced a technique based on deep learning using techniques like face detection, face alignment, face representation, face matching and validating our technique with real time dataset such as Tufts and Olevit dataset to fill the missing or masked regions in images with plausibly synthesized content. And it can able to generate realistic and semantically plausible images.

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