第 49 卷第 04 期
2022 年 4 月
湖南大学学报（自然科学版）
Journal of Hunan University（Natural Sciences）
Vol. 49. No. 04.
April 2022

Open Access Article

# MULTI-FEATURE AWARE POSE AND GEOMETRY BASED FACIAL EXPRESSION RECOGNITION USING DEEP LEARNING

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## 1. Abstract

Facial expressions are the primary way to express intentions and emotions. In real life, computers can understand the emotions of humans by analysing their facial expressions. Facial Expression Recognition (FER) plays an important role in human-computer interaction necessity and medical field [1]. In the past, the facial features are extracted manually for recognizing the expressions. In the present, it is an important hotspot in computer vision, Internet of Things, and artificial intelligence fields. Certain processes are involved to recognize the facial expression in an efficient manner such as,

- Preprocessing
- Segmentation
- Feature Extraction
- Classification

Various algorithms are designed manually for feature extraction and other feature extraction algorithms such as Local Binary Pattern (LBP), Gabor wavelet, Histogram of Oriented Gradient (HOG) [2],[3]. Various challenges are involved in the FER to recognize accurate expressions of facial images. For robust classification of facial expression, consideration of illumination and pose of the facial image is important. The poses and facial identity learning are essential to get accurate results. Several existing works faced challenges regarding identity, pose variation, and inter-subject variation. For estimating the pose of the facial images existing methods used hand-crafted features. For detecting the pose of the facial images, pose normalization is performed by considering the angle in the existing works [3]. Previous works also considering pixel-based normalization to increase the accuracy for recognizing the facial expression [2]. On the other hand, general illumination effect of the images also affects the accuracy, by contrast, occlusion, etc. Segmentation is one of the major processes to partition the facial images to extract the features. Various existing methods used different techniques to segment the facial images such as bounding box-based segmentation, region-based segmentation, cluster-based segmentation, etc., by using various algorithms such as Discrete Cosine Transform (DCT), K-means Clustering algorithm, etc. For extracting the features after segmenting the facial images various

Received: January 24, 2022 / Revised: February 22, 2022 / Accepted: March 27, 2022 / Published: April 30, 2022
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Machine learning (ML) algorithms such as Support Vector Machines (SVM), Naive Bayes, K-Nearest Neighbours (KNN), and Deep Learning (DL) algorithms such as Convolutional Neural network (CNN), Generative Adversarial Network (GAN), Long-Short Term Memory Networks (LSTM) [2], [3], [4]. After extracting the features from the facial images, classification is performed to identify the facial expressions (happy, sad, anger etc.). Various classifiers are used in the previous works for classification processes such as VGG-16, VGG-19, ResNet, etc [2], [4]. These classifiers get the extracted feature as input and classify the expressions. For training and testing purposes various datasets are used but, mostly FER-2013, CK+, and JAFFE datasets are used [1], [2], [3].

***Keywords:*** *Facial Expression Recognition, Deep Learning, Capsule Neural Network, Fuzzy C-means Clustering, Segmentation, Facial Landmark Detection*

1. 摘要

面部表情是表达意图和情绪的主要方式。在现实生活中，计算机可以通过分析人类的面部表情来理解人类的情绪。面部表情识别（FER）在人机交互的必要性和医学领域发挥着重要作用[1]。过去，面部特征是人工提取的，用于识别表情。目前，它是计算机视觉、物联网、人工智能领域的重要热点。涉及以有效方式识别面部表情的某些过程，例如，

- 预处理
- 细分
- 特征提取
- 分类

为特征提取和其他特征提取算法手动设计了各种算法，例如局部二值模式 (LBP)、Gabor 小波、定向梯度直方图 (HOG) [2]、[3]。 FER 涉及各种挑战，以识别面部图像的准确表达。对于面部表情的鲁棒分类，考虑面部图像的照明和姿势很重要。姿势和面部识别学习对于获得准确的结果至关重要。一些现有的作品在身份、姿势变化和主体间变化方面面临挑战。为了估计面部图像的姿势，现有方法使用了手工制作的特征。为了检测面部图像的姿势，姿势归一化是通过考虑现有作品中的角度来执行的[3]。以前的工作还考虑了基于像素的归一化以提高识别面部表情的准确性 [2]。另一方面，图像的一般光照效果也会影响精度，如对比度、遮挡等。分割是对人脸图像进行分割以提取特征的主要过程之一。现有的各种方法使用不同的技术对人脸图像进行分割，如基于边界框的分割、基于区域的分割、基于聚类的分割等，通过使用各种算法，如离散余弦变换（DCT）、K-means 聚类算法等用于在分割面部图像后提取特征的各种机器学习 (ML) 算法，如支持向量机 (SVM)、朴素贝叶斯、K-最近邻 (KNN) 和深度学习 (DL) 算法，如卷积神经网络 (CNN)、生成对抗网络 (GAN)、长短期记忆网络 (LSTM) [2]、[3]、[4]。从面部图像中提取特征后，进行分类以识别面部表情（快乐、悲伤、愤怒等）。以前的工作中使用了各种分类器来进行分类过程，例如 VGG-16、VGG-19、ResNet 等 [2]、[4]。这些分类器将提取的特征作为输入并对表达式进行分类。出于训练和测试目的，使用了各种数据集，但主要使用 FER-2013、CK+ 和 JAFFE 数据集 [1]、[2]、[3]。

关键词：面部表情识别、深度学习、胶囊神经网络、模糊 C 均值聚类、分割、面部标志检测

## 2. Research Aim and Objective

The aim of this research is to identify the facial expression from the facial images by using Deep learning technique. In addition, this research identifies the problems of considering adequate features, high false-positive rate, less accuracy, and so on.

The main objective of this research is to recognize the facial expressions from the facial images with low false positive rate and high accuracy. The remaining research objectives are described as follows,

- To increase the facial image quality preprocessing is initialized by performing normalization to estimate the pose and angle of the facial image and also reduce the illumination effects to increase the accuracy of the facial expression.
- To extract the features efficiently, cluster-based segmentation is performed to estimate the facial objects such as eyebrows, eyes, nose, and mouth which reduces the loss of small expressions.
- Multi-feature is extracted in the feature extraction process by considering both low-level and high-level features of the facial images to increase the accuracy of facial expression recognition.
- For increasing the quality of images and identify the pose of the facial images we perform bi-level preprocessing by normalizing the images considering illumination and pose of the facial image. For illumination normalization grayscale algorithm is used to reduce the occlusion, contrast etc. For pose normalization geometry-based polar transformation algorithm is used to estimate the pose for obtaining accurate results.
- To reduce the false positive rate, cluster-based segmentation is performed by using Improved Fuzzy C-means clustering algorithm and detects the facial landmarks precisely.

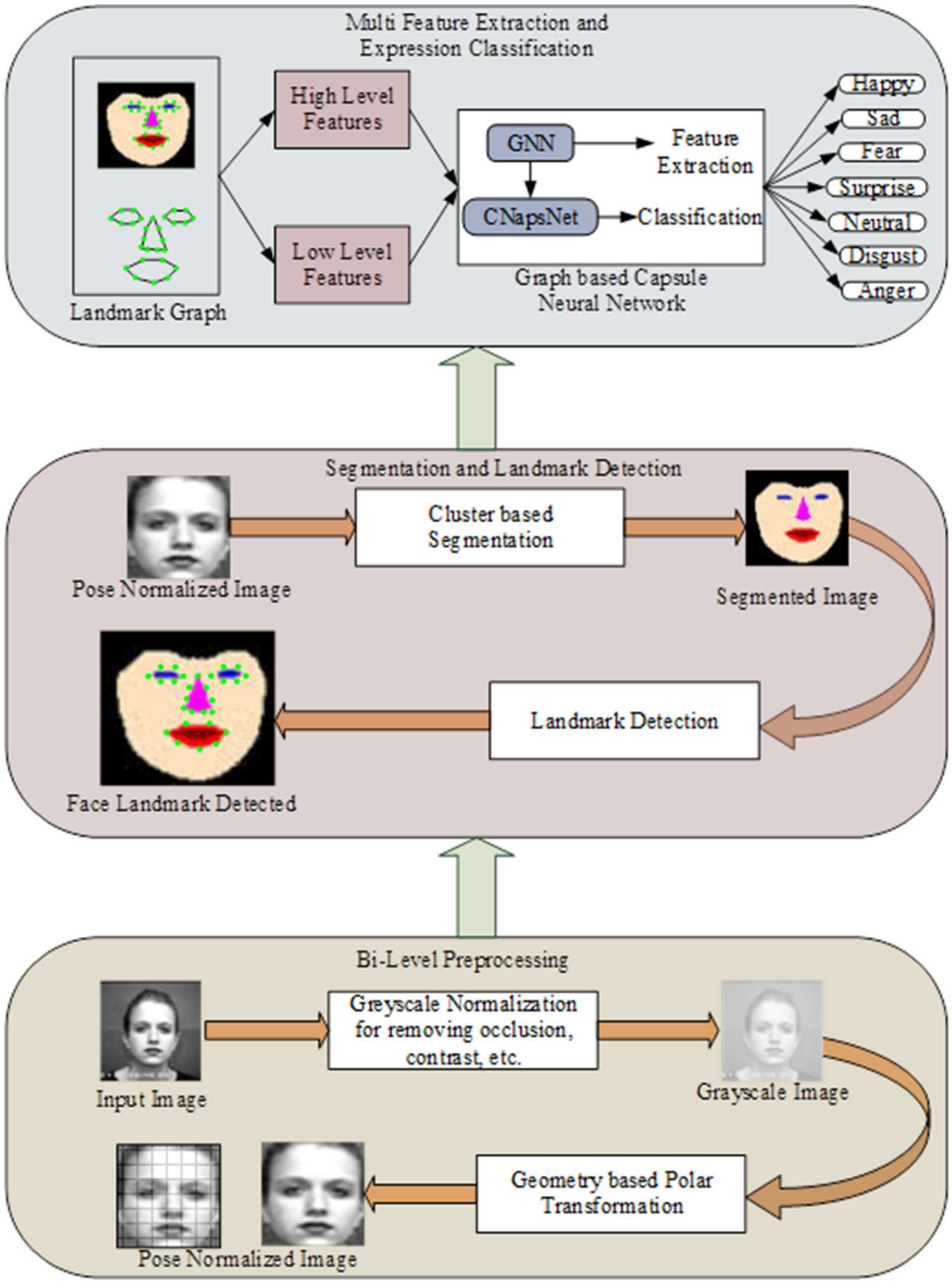
## 3. Introduction

In this research, we have given importance to recognize facial expressions by using hybrid deep learning method. The accuracy of the facial expression is improved by performing preprocessing, segmentation, landmark detection, and feature extraction from the facial images. The important aim of this research is to develop expression recognition with high accuracy based on effective segmentation and classification. For facial expression recognition, we have taken CK+ (Cohn Kanade) and Japanese Female Facial Expressions (JAFFE) datasets. It has three sequential phases such as,

- Bi-level preprocessing
- Clustering-based Segmentation and Facial Landmark Detection
- Multi-Feature Extraction and Facial Expression Classification

### 3.1 Bi-level Preprocessing

We have taken the facial image as input from the given dataset i.e. CK+ dataset. Initially, bi-level preprocessing is performed for the facial images such as illumination normalization and pose normalization. In the illumination normalization occlusion, blurring effect; contrast, and shadowing effect are reduced by using **Grayscale algorithm** to convert the normal facial image to grayscale image to eliminate these respective effects. After performing illumination normalization, facial angle and geometry are normalized by performing pose normalization by using **Geometry-based Polar transformation** to remove the background from the facial image and obtain frontal facial view for better facial expression recognition. The angle of the face is rotated within the image to get the frontal face pose by using polar transformation. At the same time, the position of the face is also important to recognize accurate facial expressions by using geometry transformation.



### 3.2 Clustering-based Segmentation and Facial Landmark Detection

After performing successful bi-level preprocessing, segmentation and facial landmark detection are performed. Segmentation of facial images is mainly performed to recognize the facial objects such as eyebrows, eyes, nose, mouth, and lips by using **Improved Fuzzy C-means clustering algorithm.** Traditional fuzzy c-means clustering algorithm is used for partitioning the images into segments but, it can't determine the center of the cluster. To overcome such drawbacks improved fuzzy c-means clustering algorithm is used to initialize the cluster's center by using **Firefly algorithm** along with fuzzy c-means clustering algorithm. After fulfilling the segmentation process, detection of facial landmarks is also performed effectively. 44 Feature points are used in the facial landmark for better facial expression recognition. 10 feature points are used for eyebrows (5 feature points for each eyebrow), 12 feature points for eyes (6 feature points for each eye), 9 feature points for nose, and 13 feature points for mouth (7 feature points for lips).

### 3.3 Multi-Feature Extraction and Facial Expression Classification

Various features are extracted from the landmark detected image and it is classified into two levels such as high-level features and low-level features. The high-level features are extracted based on the facial objects such as eyebrows, eyes, nose, lips, and mouth and the corresponding features such as *eyebrow slant, eye size, eye spacing, pupil size, nose length, nose width, nose wrinkle, mouth openness, mouth width, mouth curvature, tight lips, and lips droop*. The low-level features are *shape, texture, and color*. These features are extracted and classified by using deep learning algorithms such as **Graph-based Capsule Neural Network (GCapsNet).** The traditional capsule neural network has high complexity for large number of data sets. To overcome this drawback we integrate the capsule neural network with Graph neural network. Large number of datasets is managed by using Graph neural network and the classification is performed by capsule neural network to select the optimal features to reduce the overfitting and increase the accuracy. Seven important facial expressions are classified depend upon the extracted features; they are *neutral, happy, sad, fear, disgust, surprise, and anger.* Evaluation of the proposed work is performed by considering the following performance metrics,

- Accuracy
- Precision
- Recall
- Confusion matrix
- Facial landmark detection error

## 4. Literature Survey

[1] The author proposed an approach to recognize the facial expression from the static facial image by using hybrid deep learning networks. Initially, the expressional features were extracted from the facial image by using spatial attention convolutional neural network (SACNN). In this neural network, VGG-19 is used as a spatial attention module which is used to extract the pixel-based features from the facial images. After extracting the features, landmark detection is performed based on geometry of the facial

image by using attention mechanism based on long short-term memory networks (ALSTM), and this mechanism was also used to estimate different landmark regions' importance. Here FER-2013, CK+, and JAFFE datasets are used for experiment. The author used SACNN for extracting the pixel-based expressional features from the facial images. However, SACNN needs huge trained images to extract features effectively that increase the complexity for classification of facial expressions. Here, Batch normalization layer is included in the SACNN to reduce the internal covariance shift but, it needs huge batch size to normalize the outputs of the convolution layer to produce better results and Lack of considering the size of batch leads to high false-positive rate. To discover the facial landmarks from the extracted facial features ALSTM was used and it is also used to evaluate the landmark region's importance adaptively. However, lack of considering the overfitting problem when exploring the facial landmarks that decrease the accuracy of the facial expression classification.

[2] In this paper, authors proposed an approach for recognizing the facial expression by using deep convolution neural network (DCNN) with local gravitational force descriptor. Initially, the local features are extracted from the facial image by using the local gravitational force descriptor. After extracting the local features, DCNN is used to classify the facial expressions by dividing it into two major branches. The first branch of DCNN is used to extract the geometric features such as curves, edges, and lines present in the facial images. The second branch of DCNN is used to extract holistic features and classification. The classification score of facial expressions is computed by using a technique named score level fusion. Here FER-2013, CK+, and JAFFE datasets are used for experiment. Geometric features such as curves, lines, and edges of the facial images are considered by using DCNN. However, these geometric features of the facial images are not enough to classify the facial expressions accurately that leads to high false-positive rate. Here, DCNN is used for both feature extraction and classification of facial expressions from the corresponding features but, DCNN felt difficult to classify the facial expression when the facial image contains rotation or some angle of tilt that leads to less accuracy and more layers were used for the three types of layers present in the DCNN. Especially the number of max-pooling layers present is 5. However, more max-pooling layers present in the DCNN increase the probability of losing the efficient features that leads to high false positive rate. Preprocessing process is performed to align the angle and pose of the facial image. However, lack of considering the illumination parameters leads to face occlusion, contrast, etc., which decreases the classification of facial expressions accuracy.

[3] The author proposed an approach for facial expression recognition (FER) by using hybrid deep learning algorithms with pose considering face alignment. Initially, the pose-guided face alignment method is used to decrease the intra-class difference present in the facial images by considering three basic steps such as target pose discovery, template generation, and target matching. Angular symmetry is used for redundant features elimination and selects the efficient template by performing clustering with K-means clustering algorithm. Hybrid deep learning algorithms such as CNN and RNN are used for extracting the facial features and VGG-16 and ResNet are used for classification of facial expressions. Here Oulu-CASIA, CK+, AR, and JAFFE datasets are used for experiment. The results from the pose-guided face alignment method were clustered by using K-means clustering algorithm. However, this clustering algorithm cluster the dataset in k number, and the entire k number of clusters

has a single cluster that leads to high complexity to retrieve the extracted features for classification which decreases the performance. In the hybrid deep learning algorithms, RNN also plays an important role in feature extraction. However, the process involved in RNN is difficult which increases the training complexity in classification of facial expression. ResNet is used for classify the facial expression from the extracted features but, the time duration of this network is high that affects the classification with high time complexity. Here, the features are extracted from the clustering output to classify the facial expressions but the clustering of facial images is not enough to extract the features accurately that leads to high false-positive rate.

[4] The authors proposed an approach to discover the facial expressions by using ensemble rule with deep learning algorithm. The face expression recognition algorithms are classified into two types such as feature-based algorithm and convolutional neural network-based algorithm. Initially, the facial landmark is extracted from the input image. Perform frontalization by using frontalization algorithm to manage the pose by rotating and manage the brightness of the image. Shortcut CNN is used to extract the features from the facial image and for FER classification adaptive exponentially weighted average ensemble rule was used. FER-2013, JAFFE, and CK+ datasets were used for experiment. In this paper, the landmarks are detected with 68 feature points to perform facial frontalization but, FER needs few landmarks, for instance, the landmarks of jaw are not important to classify accurate facial expression. Considering all facial landmarks for frontalization increases the classification complexity and decreases the accuracy. Here, frontalization algorithm is used to consider the brightness rotation and pose of the facial images but, lack of considering the geometry features increases the false positive rate. CNN is used to extract the features from the frontalized facial image. However, CNN doesn't consider the coordinate frames of the facial images that lead to less accuracy in recognizing the facial expression.

[5] The author proposed an approach to detect the facial landmark by performing semantic segmentation. Initially, the architecture of semantic segmentation was designed to segment the facial images by encoding them and feature maps of the facial images were extracted from the encoder and the feature maps are decoded by corresponding feature maps. Secondly, VGG-16 is used to extract facial landmarks from the feature maps and extract the features of the facial image. For classification of images, the feature maps are given to the softmax layer and classify the feature maps based on their weights. For experiment analysis authors created the dataset by own and used VGG-16 for training the facial images for classification of feature maps based on weights to create facial landmarks. However, VGG-16 takes more time to train the images and needs more bandwidth that affects the performance.

[6] Authors proposed an approach to identify the facial expression from the facial images by using deep convolutional neural networks. Initially, edge computing is involved to ensure the privacy of the facial images from the cloud. The generative adversarial network (GAN) is modified by including circular consensus to create CycleGAN to train the facial images effectively. Information of class constraints is also included in the CycleGAN to improve style conversion process. The normal

classifier of GAN i.e. discriminator is also modified by including an auxiliary expression classifier to classify the facial expressions efficiently. For experiment analysis authors used JAFFE, CK+, and FER-2013 datasets to identify the recognition rate and GAN is modified by adding circular consensus and an auxiliary expression classifier to create CycleGAN for better classification. However, GAN can't have the ability to predict the state of the facial image that leads to less accuracy.

[7] Authors proposed an approach to recognize the facial expression by considering the pose and identity invariant of the facial image using dynamic multi-channel metric network (DML-Net). Initially, the DML-Net is used to learn the local and global features from various facial regions by using parallel convolutional networks. To discover the pose and identity-invariant of the facial expressions joint embedded feature learning is used. End-to-End training is performed for the facial images to recognize the facial expressions with low FER loss and overfitting. Here BU-3DFE, Multi-PIE, SFEW 2.0., and KDEF datasets are used to evaluate the facial expressions. DML-Net is used to extracting the features and classification of facial expressions from facial images. However, it is not suitable to classify the facial expressions in unconstrained environments i.e. various datasets.

[8] Authors proposed an approach to identify the facial expression by using CapsField technique. It is a technique with the combination of convolutional neural network (CNN) and capsule neural network. Initially, CNN is used to extract the features from the pre-processed array of facial images. Capsule network is used to route the facial features to select the features hierarchically. These methods reduce the redundancy of the features and make the classification process easier with effective classification of facial expressions. Here authors proposed the dataset named light field faces in the wild (LFFW) for experimental analysis. CNN was used with capsule network to extract the features and classify the facial expressions. However, CNN does not consider the alignment and position of the facial images that leads to less accuracy.

[9] Authors proposed an approach to recognize facial expression by using frequency neural network (FreNet). Initially, the facial images are pre-processed by considering rotation correction; ensuring the eyes are on horizontal line, and resizing using discrete Fourier transform (DCT). Block-FreNet is introduced to reduce the dimension and effective feature learning. The low-level features are extracted by using learnable multiplication kernel. After extracting the low-level features, high-level features are extracted by using a summarization layer. To classify the facial expressions from the extracted features ANN-based classification layer was used. FER-2013 dataset was used for experimental analysis. DCT is used to perform preprocessing for the facial images considering resizing, rotation correction, etc., but lack of considering the geometrical features leads to high false-positive rate.

[10] Authors proposed an approach to identify the facial expression by considering the geometry aware pose invariant using deep learning mechanisms such as generative adversarial network (GAN). Initially, the poses from the facial images were based on angles, and according to facial expressions, the facial landmarks were generated facial landmarks. The identity representation is detached by using

the facial shape geometry which was provided by the facial landmarks. GAN is used to extract the features and perform classification for detecting the facial expressions from the extracted features. Here BU-3DFE, SFEW, and Multi-PIE datasets were used for performing experimental analysis. GAN is used to extract the features from the facial images and perform classification for detecting the facial expressions. However, at the same time, GAN trains the generator and discriminator model that increases the training complexity.

[11] Authors proposed an approach to recognize the facial expression by considering the alignment and synthesis of facial images by using joint deep learning model. Initially, facial alignment is learned to generate the geometry code to perform facial synthesis. In the facial synthesis, three types of losses are considered such as discriminator loss, content similarity loss, and perceptual loss. Facial features are extracted i.e the expression and geometry code are extracted by considering the pose invariant and corresponding facial landmarks. After extracting the codes the facial expression is classified by using the softmax layer. The datasets used are BU-3DFE, SFEW, and Multi-PIE. Here, normalization is performed for the facial landmarks by considering the inter-ocular distance. However, lack of several illumination parameters such as shadowing effect, contrast, etc., leads to less accuracy.

[12] Authors proposed an approach to detect the racial landmarks by using heatmap offset regression technique. Initially, the regression network is divided into two stages such as structural hourglass network (SHN) and global constraint network (GCN). Preprocessing is performed to extract the features accurately. SHN is used to discover the facial landmarks at initial condition by using the heatmap. Improved inception ResNet is used in SHN for contextual feature representation learning. GCN is used to perform offset estimation for efficient landmark location. Loss function is proposed to improve the facial landmarks in a precise manner. Finally, the outputs from SHN and GCN are combined for accurate prediction of facial landmarks. The datasets used are 300W, AFLW, 300-VW, and COFW and heatmap offset regression is used to predict the facial landmarks in a precise manner. However, heatmap doesn’t adapt to the color of the images that leads to less accuracy.

## 5. Experiment and Discussion

### 5.1 Dataset

**CK+** Dataset is used for facial expression recognition using deep learning. Cohn-Kanade (**CK+**) dataset having 593 images ranging from 18 to 50 years of age with both the genders and these images are divided into seven expression classes: anger, contempt, disgust, fear, happiness, sadness, and surprise. The facial image is taken as input from the CK+ dataset and the selected image loaded successfully as shown in Figure 1.

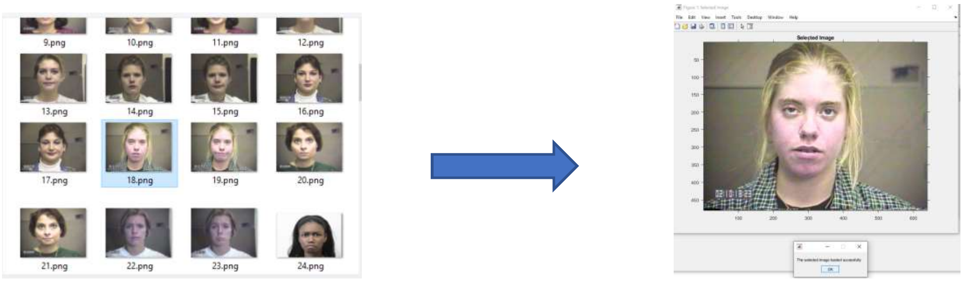



FIGURE 1. Loading of input facial image from dataset

**5.2 Bi-level Preprocessing**

In the bi-level preprocessing, we used the Grayscale algorithm for illumination normalization to convert the normal facial image to a grayscale image. After performing illumination normalization, facial angle and geometry are normalized by performing pose normalization by using geometry-based Polar transformation to remove the background from the facial image.

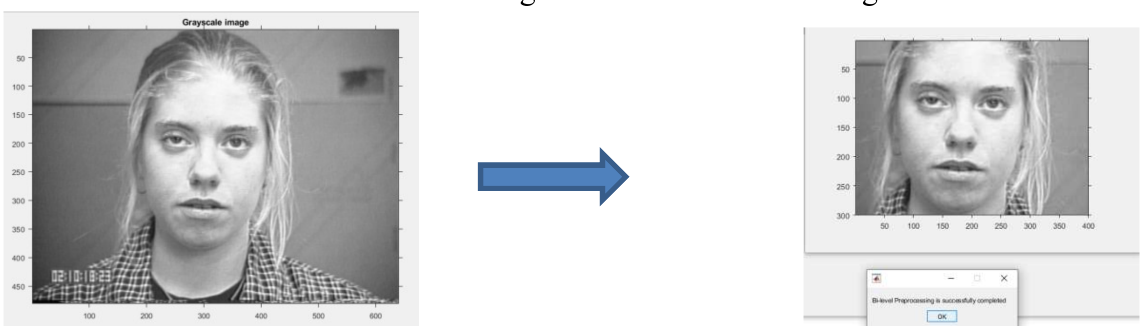



FIGURE 2. Bi-level Preprocessing

**5.3 Segmentation**

After performing Bi-level Preprocessing, the Clustering-based Segmentation and Facial Landmark Detection is performed. In this step, Segmentation of facial images is mainly performed to recognize facial objects such as eyebrows, eyes, nose, mouth, and lips. In this step we used Improved Fuzzy C-means clustering algorithm. Next, initialize the cluster’s center by using the Firefly algorithm.

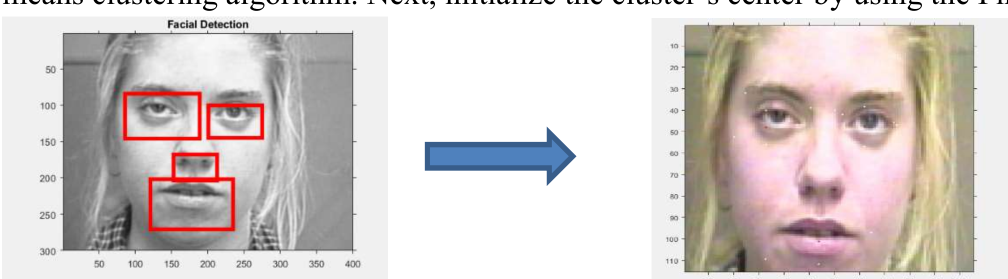



FIGURE 3. Facial Landmark Result

**5.4 Feature Extraction**

Multi-Feature Extraction and Facial Expression Classification: Various features are extracted from the landmark detected image and it is classified into two levels such as high-level features and low-level features. The high-level features are extracted based on the facial objects such as eyebrows, eyes, nose, lips, and mouth and the corresponding features such as eyebrow slant, eye size, eye spacing, pupil size, nose length, nose width, nose wrinkle, mouth openness, mouth width, mouth curvature, tight lips, and lips droop. The low-level features are shape, texture, and color.

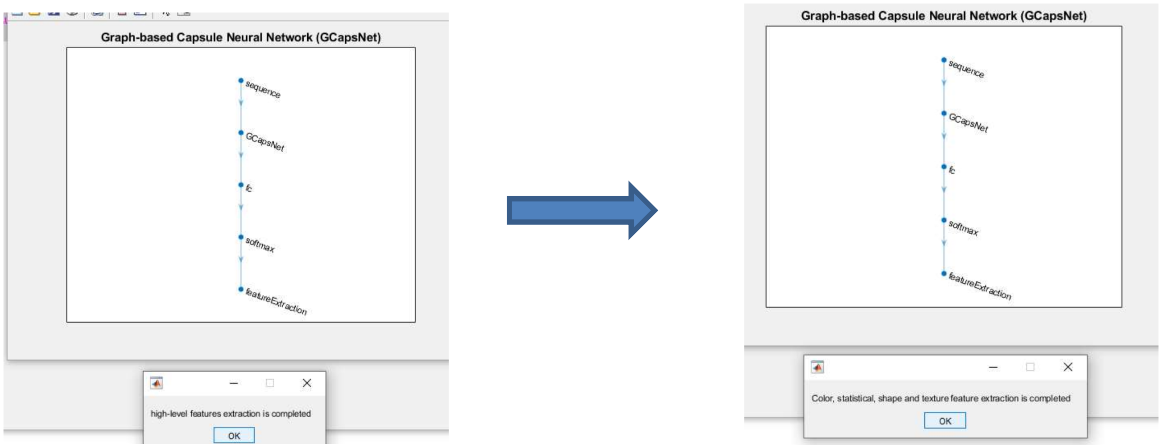
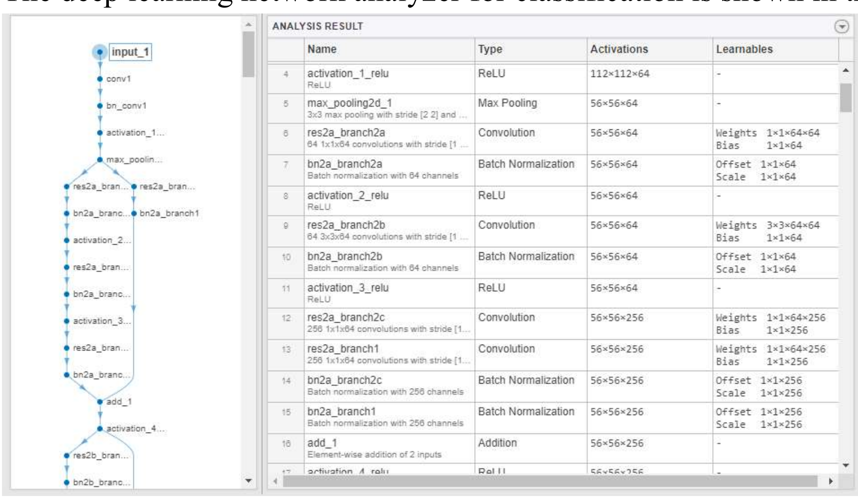



Figure 4. High level and Low level Feature Extraction

## 5.5 Classification

The deep learning network analyzer for classification is shown in the Figure 5 as follows:




| | Name | Type | Activations | Learnables |
|---|---|---|---|---|
| 4 | activation_1_relu<br>ReLU | ReLU | 112×112×64 | - |
| 5 | max_pooling2d_1<br>3x3 max pooling with stride [2 2] and ... | Max Pooling | 56×56×64 | - |
| 6 | res2a_branch2a<br>64 1x1x64 convolutions with stride [1 ... | Convolution | 56×56×64 | Weights 1×1×64×64<br>Bias 1×1×64 |
| 7 | bn2a_branch2a<br>Batch normalization with 64 channels | Batch Normalization | 56×56×64 | Offset 1×1×64<br>Scale 1×1×64 |
| 8 | activation_2_relu<br>ReLU | ReLU | 56×56×64 | - |
| 9 | res2a_branch2b<br>64 3x3x64 convolutions with stride [1 ... | Convolution | 56×56×64 | Weights 3×3×64×64<br>Bias 1×1×64 |
| 10 | bn2a_branch2b<br>Batch normalization with 64 channels | Batch Normalization | 56×56×64 | Offset 1×1×64<br>Scale 1×1×64 |
| 11 | activation_3_relu<br>ReLU | ReLU | 56×56×64 | - |
| 12 | res2a_branch2c<br>256 1x1x64 convolutions with stride [1... | Convolution | 56×56×256 | Weights 1×1×64×256<br>Bias 1×1×256 |
| 13 | res2a_branch1<br>256 1x1x64 convolutions with stride [1... | Convolution | 56×56×256 | Weights 1×1×64×256<br>Bias 1×1×256 |
| 14 | bn2a_branch2c<br>Batch normalization with 256 channels | Batch Normalization | 56×56×256 | Offset 1×1×256<br>Scale 1×1×256 |
| 15 | bn2a_branch1<br>Batch normalization with 256 channels | Batch Normalization | 56×56×256 | Offset 1×1×256<br>Scale 1×1×256 |
| 16 | add_1<br>Element-wise addition of 2 inputs | Addition | 56×56×256 | - |
| 17 | activation_4_relu | ReLU | 56×56×256 | - |

Figure 5. Deep Learning Network Analyzer

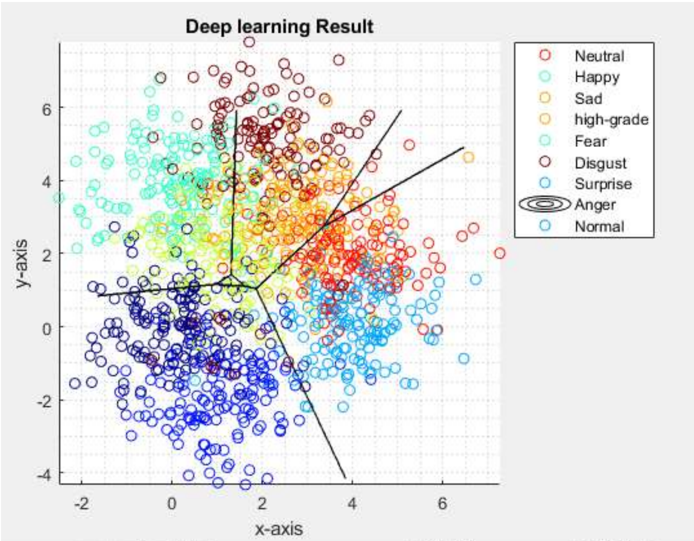



Figure 6. Deep Learning Result

The classification result, " Sad" is shown in the Figure 7 as follows:

```
Multi Class SVM Model for Class Instance 7 --->
  ClassificationSVM
             ResponseName: 'Y'
    CategoricalPredictors: []
               ClassNames: [0 1]
           ScoreTransform: 'none'
          NumObservations: 200
                    Alpha: [43×1 double]
                     Bias: 1.50265762608039
         KernelParameters: [1×1 struct]
           BoxConstraints: [200×1 double]
          ConvergenceInfo: [1×1 struct]
          IsSupportVector: [200×1 logical]
                   Solver: 'SMO'

  Properties, Methods

Classification Result: Sad
fx >>
```

Figure 7. Classification Result

## 5.6 Performance Metrics

Finally, we evaluate the following performance metrics: Accuracy, Precision, Recall, Facial landmark detection error, Confusion matrix.

Figure 8. shows the Accuracy, Recall metrics while Figure 9. shows the Precision and Facial landmark detection error.

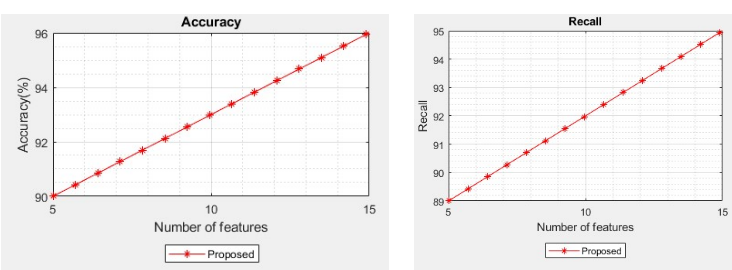



Figure 8. Accuracy, Recall

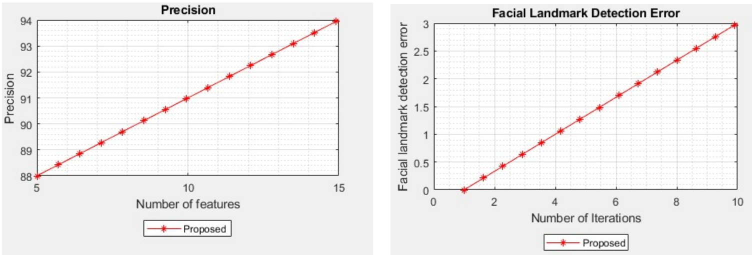


Figure 9. Precision, Facial Landmark Detection Error

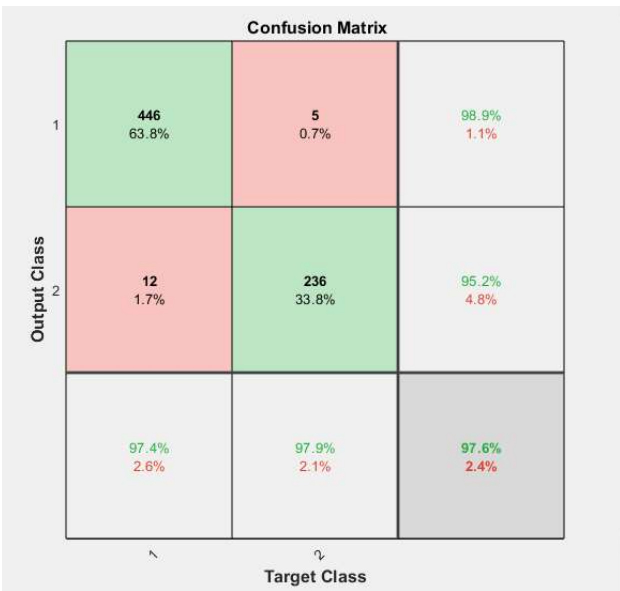


Figure 10. Confusion matrix

**Conclusion**

Facial Expression Recognition is used for classification of facial images into seven different expressions such as Sad, Fear, Anger, Happy etc. In this research, we evaluate the performance by using the following Performance Metrics such as Accuracy, Recall, Precision, Facial Landmark Detection Error, Confusion Matrix.

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