An Effective Method for Recognition of Facial Expressions from Occluded Images

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Abstract: The occluded facial expression recognition (FER) technology is challenge in PC vision space. Numerous strategies have been applied to acquire exact and proficient outcomes in facial expressions. In this paper we proposed Local Binary pattern (LBP) method to recognize the occluded facial expressions from the images or faces. And also doing accuracy based comparison with the Wasserstein Generative Adversarial Network (WGAN) method and LBP method. The LBP which is a surface depiction strategy, that portrays the surface component of an image. The WGAN network which is used to measure the real/fake of the generated images. Finally, after the comparison of LBP and WGAN find which one is better method based on the accuracy performance. That is, the proposed method or already existing method. The exploratory outcome shows that the proposed method is superior to the existing method. Therefore, this method proposed in the paper realizes face recognition with occlusion in complex environment and meets the needs of practical applications. The proposed methods are tested using FER dataset.

***Key Words* - Facial Expression Recognition, Local Binary pattern, Occlusion, Wasserstein Generative Adversarial Network.**

I.INTRODUCTION

Most of the facial expression recognition is done in the area of machine learning. The machine learning is an application of artificial intelligence (AI), that provides system the ability to automatically learn and improve from experience without being explicitly programs. Machine learning mainly focuses on the development of computer programs, that can access the data and use it learn for themselves. The other use, it is applicable in many fields. Such as, image and speech recognition, medical diagnosis, prediction, classification etc. Then the artificial intelligence, which have the recognition ability in human expression. Human vision is easily replicated by computer learns human vision and performs necessary action to get accurate output.

The computer interaction also used in the case of facial expression recognition. Facial expression recognition is the errand of characterizing the expression on face images into different classifications. Such as anger, happy, sad, surprise and neutral. Facial expression is used to detect the expressions in human faces. This innovation is a supposition examination device and can consequently distinguish the five essential or universal expressions. Facial expression recognition is a type of non-verbal communication, which is the principle methods for communicating social information between human beings. Partial occlusion introduced in the face is one of the significant obstructions for precise FER in true conditions. FER is a difficult subject since it is an interdisciplinary innovation, and the innovative work of FER can advance both the hypothetical importance and life applications [19], [22]. As of now, the vast majority of the connected works of this innovation is to distinguish un-occluded facial expression images, and the amazing exploration results are unending. In any case, in fact, the facial expression images by the picture getting device consistently have incomplete occlusion, which for the most part fuse occlusions from hands, glasses, covers, and so forth. These occlusions can meddle with the extraction of enunciation features and impact the precision of expression affirmation [6]. When recognizing the facial expression in occlusion cases, a system can see precisely under occluded conditions is for the need vital. With issues, like light and clamor, being addressed in a steady progression, analysts accept that a really good vigorous acknowledgment technique should be cable to solve the problem of expression recognition under occlusion. The computer interaction also used in the case of facial expression recognition. Facial expression recognition is the errand of characterizing the expression on face images into different classifications. Such as anger, happy, sad, surprise and neutral. Facial expression is used to detect the expressions in human faces. This innovation is a supposition examination device and can consequently distinguish the five essential or universal expressions. Facial expression recognition is a type of non-verbal communication, which is the principle methods for communicating social information between human beings. Partial occlusion introduced in the face is one of the significant obstructions for precise FER in true conditions. FER is a difficult subject since it is an interdisciplinary innovation, and the innovative work of FER can advance both the hypothetical importance and life applications [19], [22]. As of now, the vast majority of the connected works of this innovation is to distinguish un-occluded facial expression images, and the amazing exploration results are unending. In any case, in fact, the facial expression images by the picture getting device consistently have incomplete occlusion, which for the most part fuse occlusions from hands, glasses, covers, and so forth. These occlusions can meddle with the extraction of enunciation features and impact the precision of expression affirmation [6]. When recognizing the facial expression in occlusion cases, a system can see precisely under occluded conditions is for the need vital. With issues, like light and clamor, being addressed in a steady progression, analysts accept that a really good vigorous acknowledgment technique should be cable to solve the problem of expression recognition under occlusion.

In real life conditions there is a high probability that a few pieces of the face become impeded by shades, a cap, a scarf, hands moving over the mouth, a mustache or hair, and so on. Occlusion can significantly change the visual appearance of the face and seriously weaken the performance of FER frameworks [2]. The presence of occlusion builds the trouble of extricating discriminate highlights from occluded facial parts because of mistaken component area, defective face arrangement or face enlistment blunder. A FER framework with occlusion taking care of limit means to accomplish precise feeling acknowledgment in any event, when a segment of the face is occluded. The framework can be helpful in different genuine situations, especially those with habitually happening occluded, for example, students wearing glasses in web based coaching, patients wearing clinical masks in clinical finding, and players with present varieties in game amusement [20]. This paper plans to overcome this issue. It is normal that it can fill in as a decent reference for creating methods toward hearty FER within the sight of occlusion. For the above analysis, here we build an occlusion FER methods comparison based on the proposed Local binary pattern (LBP) and the existing method Wasserstein generative adversarial network (WGAN). This paper presents an up to date trend of major methods employed towards achieving the dreamed occluded FER system. In this paper section 1 is the introduction, Section 2 related works. Section 3 proposed method. Section 4 is the experimental results. Section 5 is comparison between LBP and WGAN. Then the section 6 is about the experimental result and discussion and finally the section 7 is the conclusion.

II. RELATED WORK

In recent years, the major awareness of facial expression recognition is the increasing attention of its applications from some knowledge domains. That is, there are showing problems, e.g. occlusions. To recognize the occluded facial expression image is one of the problem is now. For solving this problem some research and development on FER can promote both the theoretical significance and life applications. Most of the related works are successfully identify the occluded images. But there is lack of accuracy is showing their results and some approaches attempt to minimize occlusion effect by re-covering texture or facial features. The main related approaches are described in this section. Some approaches attempt to minimize occlusion impact by recovering texture and/or geometric facial features. Bourel et al. [25] proposed an approach to facial expression recognition with occlusions of mouth, upper face and left/right half of the face from video frames, based on a localized representation of facial expression features and on data fusion. For tracking and recovering facial fiducial points, an enhanced Kanade-Lucas tracker was used. Then, independent local spatio-temporal vectors are created from geometrical relations between facial fiducial points, demonstrating to be robust to partial facial occlusions.

Towner et al. [25] depicted three methods dependent on PCA to recuperate the places of the upper and lower facial fiducial focuses. The outcomes showed that more facial expression is contained in the lower half of the face, being less precisely the recreation of that piece of the face.

Zhang et al. [26] proposed a technique strong to impediments utilizing a Monte Carlo calculation for extricating a bunch of Gabor based formats from picture datasets. Then, at that point, layout coordinating is applied to track down the most comparable highlights situated inside a space around the separated formats, creating highlights hearty to occlusion, i.e., the occluded parts are covered by a portion of the irregular formats. In the wake of applying arbitrarily occluded patches over faces in both preparing and testing stages (coordinated with procedure), this methodology acquired 75.0% and 48.8% acknowledgment rates for CK and JAFFE datasets, separately.

Approaches that break down the effect and impacts of occlusion types are for the most part dependent on surface appearance highlights. Kotsia et al. [27] introduced an examination of incomplete occlusion impact on facial expression recognition, inferring that occlusions on the left/right half of the face didn't influence acknowledgment rates, i.e., that the two areas contained less discriminant data for facial expression recognition. Besides, mouth impediment caused a higher lessening in facial expression recognition execution than eye occlusion, since mouth occlusion influenced more the feelings of outrage, dread, satisfaction and pity, though eye occlusion influenced disdain and shock. Basically different types of occlusion can have done in face. Such as mouth occlusion, left eye occlusion, right eye occlusion and nose occlusion. But here they try to occlude only mouth occlusion and eye occlusion.

Zhang et al. [26], as referenced beforehand, likewise played out an investigation of the impediment impacts for both coordinated and mis-coordinated with preparing and test procedures. In their technique, the example designs were not very much figured out how to diminish the impact of randomized fix impediment, which followed the mis-coordinated with methodology, i.e., utilizing no blocked pictures for preparing and halfway blocked pictures for testing. Subsequently, acknowledgment rates were more terrible than following the coordinated with methodology. Moreover, it was presumed that occluded facial expression recognition relies upon the occluded area size. It was prescribed to utilize the very sort of occlusions during preparing stage as that normal to be available in tried examples.

2.1 Occluded Images

Facial occlusion, like shades, scarf, cover and so on, is one basic factor that influences the performance of face recognition. Regrettably, faces with occlusion are very basic in reality, particularly in uncooperative situation. At that point the reconstructed images are utilized for face recognition. Hiding any part in our face is called occlusion and that image is called occluded images. Then the several types of occlusions are real occlusions, imperfect faces, synthetic occlusions, occluding square and occluding individual images. In real occlusions, Gallery images are the identification photographs liberated from occlusion while test images are faces occluded by practical images like, sunglasses or a scarf. Sometimes the hands also make occlusions. Next one is imperfect faces. Which is the display images being conspicuous confirmation photographs liberated from occlusion while test face pictures are imperfect faces. consequently, the name imperfect face recognition is given by topic specialists. The imperfect means, which may occur by light effects, false colors etc. Here the face images are may be half face or partially hidden faces of images. The third occlusion type is Synthetic occlusions. Here the Gallery images or display images are captured from in uncontrolled scheme and some probe faces. This type of faces is unclear and here using synthetic occlusions to stimulate the real type of occlusions. Most of the synthetic type of images are blurred or dim. This type of synthetic occluded images is made artificially. Fourth is Occluding square. In occluding square Display images are sans occlusion recognizable photos while test face images are occluded with square shape like white and dim square shapes. And the last occlusion type is occluding individual images. Here the display images are photographs freed from occlusion while test face pictures are occluded with unimportant pictures like a primate, or anon-square picture.

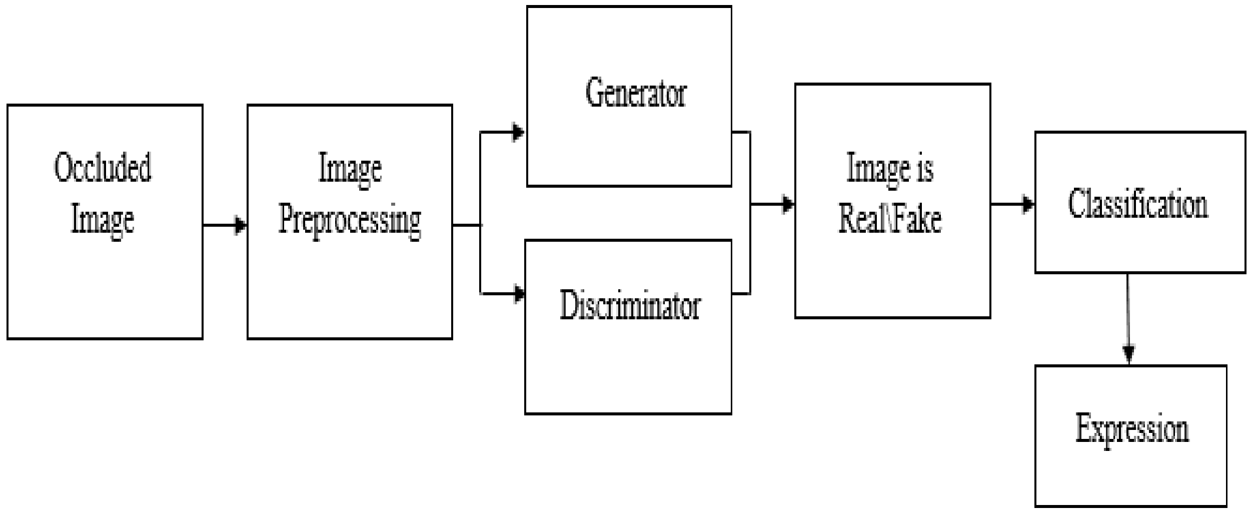

Figure 1. Framework of the occluded facial expression recognition based on the WGAN.

2.2 WGAN Method

The Wasserstein generative adversarial network (WGAN) is an extended method of generative adversarial networks (GAN) [1]. WGAN is a product of a combination of game theory and deep learning. It is unsupervised probability distribution of real data and generative new data sets with high similarity. Mainly it is used to measure the real/fake of the generated images. The WGAN is composed of generator and discriminators learns the distribution of real sample data and to generate the most realistic fake data. Here the discriminator is a double classifier, which needs to identify if the input data is a real sample or a fake data generated by the generator. In WGAN they are proposing three loss function. They are Weighted reconstruction loss, Triplet loss function and adversarial loss function. This three loss functions are mainly generated to remove the error maximum occurring. In weighted reconstruction loss to make the generated de-occluded images more similar to the original un-occluded images. That is, both the complementing of the occluded area and un-occluded are use more similar. The triplet loss is the similarity between images can be represented by the spatial distance between images. Adversarial is to measure the distance between probability distribution.
It is used to constrain the generator together to achieve the purpose of optimizing image quality. The generator network mainly compliments the occluded area of the facial expression image under the double constrain. The weighted reconstruction loss function is to make the generated complemented more similar to original un-occluded image. The image un-occluded image is formed from an occlude and un-occluded images. That is, they look the similar position from the occluded and the un-occluded image. Similar position is identifying by measuring pixel difference. The generated image and the original un-occluded image are measured by square of L2 norm [1]. The triplet loss function is a measure of the difference of the square of L2 norm between the generated image, original un-occluded image and the occluded image. WGAN can be also used for to generating visually realistic images.

2.3 Module Split Up

The WGAN can be used for module split up mainly three steps. They are Image pre-processing, Occluded image complementing and Facial expression recognition. The image preprocessing is mainly using for avoid the interference of illumination, posture and other factors on FER. Then also it ensures that the consistency of face size, position and image quality. The image pre-processing has mainly five steps. Five steps are shown below,

2.3.1 Face Positioning: Face positioning is a computer vision technology for identifying the geometric structure of human faces in digital images. It given the location and size of a face, it automatically determines the shape of the face components such as eyes and nose.

2.3.2 Face Cropping: To automatically detect faces in images and applies a rectangular crop focused on either all faces or on the biggest face.

2.3.3 Pixel Normalization: The objective of the face normalization is to reduce the effect of useless and redundant information such as background, hair, cloth etc. So, it is enhancing to the recognition process. Normalization is performed images with the same size and the same range of gray values. After image preprocessing generate two inputs as original un-occluded image and irreverent area occluded image.

2.4 Occluded Image Complementing

In this stage they are only focusing on occluded image. Before giving the occluded image into the generator. They adding three loss functions. That is, weighted reconstruction loss, triplet loss and adversarial loss. After adding three loss functions, we got generated complementation image. This generate complemented image is the input of D2.

2.5 Facial Expression Recognition

In facial expression recognition, there is two discriminators D1 and D2. D1, it determines real or fake of the generated images and D1 perform based on adversarial loss function. D2, it predicts classification labels (happy, anger, sad, surprise and neutral) of facial expression images [1]. D2 is based on classification loss function. Here we using input of D1 is original image un-occluded image and the input of D2 is generated complementation image. The above traditional facial expression recognition and classification methods are very effective for small datasets. The facial expression recognition also important in emotion detection etc. The facial expression recognition has mainly seven types. They are, happy, sad, anger, disgust, fear, surprise and neutral. Which is also called the universal expressions.

III. PROPOSED METHOD

Considering the LBP benefit and qualities, this paper dependent on it to perceive the occluded facial expression pictures. Local Binary Pattern (LBP) is a straightforward yet extremely effective surface administrator which names the pixels of a picture by thresholding the neighborhood of every pixel and thinks about the outcome as a twofold number. Because of this discriminative force and computational straightforwardness [29]. LBP (Local Binary Pattern) depicts nearby surface highlights of pictures. Revolution in-variance and dark in-variance is the fundamental benefit of Local twofold example. [30]. Neighborhood Binary example is a straightforward instrument for the identification of the highlights and is strong to the enlightenment varieties in a picture. Due to its straightforwardness and heartiness, LBP is broadly utilized strategy for the component extraction in a large number of the article acknowledgment strategies just as the facial expression detection. Local Binary Pattern was first presented in 1996 by Ojala et al as an essential double administrator. Local Binary Pattern fills in as an amazing surface classifier. The pixels of the picture are named by the paired administrator by contrasting the middle pixel esteem and the 3x3 neighborhood of every pixel esteems to frame a parallel number (8 cycle) which is then changed over to the decimal worth. The vertical and flat projection is gotten which is a one dimensional component vector for the 2D face picture. For a given pixel at (Xc,Yc), LBP code is acquired utilizing the accompanying condition.

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{7} S(g_p - g_c)2^p,\ S(x) = \begin{Bmatrix} 1 & x \geq 0 \\ 0 & x < 0 \end{Bmatrix}$$

where:

g_c = gray value of center pixel

g_p = gray value of neighbouring pixel of g_c

P = 8 maximum of 8 neighbours of center pixel

R = 1 for selected box of 3*3

Hence, there can be complete $2^8 = 256$ unique qualities that can be relegated to a pixel.

In Fig. 2, of 3x3 size picture block is thought of. Focal pixel esteem is 7 and focus pixel is encircled by the 8 pixels in each of the eight bearings [29]. The LBP changes over each of the 9 pixel esteems in to a solitary worth. This will be finished by contrasting the pixel worth of each adjoining pixel with the focal pixel esteem (that is the power esteem by then). The pixel esteems are normally thought to be in the grayscale. The pixel esteem more noteworthy than or equivalent to the focal pixel is relegated 1 and lower esteem is appointed a 0 since just paired upsides of 0 and 1 can be allotted to the pixels. Presently byte is framed by these 8 pixels encompassing focus one.

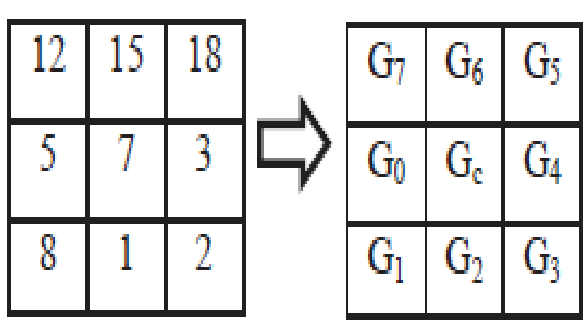

Fig. 2. input block of size 3*3.

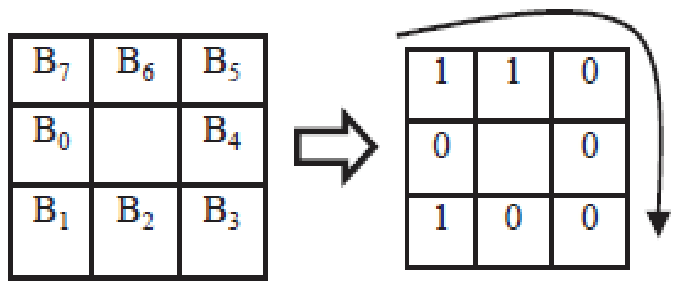

Fig. 3. input block coded in LBP

LBP code is gotten by circularly following the bins in clockwise,
Twofold LBP code = 1 0 1 0
Decimal code = 194

This resultant byte then, at that point is transformed into a decimal number. However long we are reliable with the double qualities, any pixel square can be encoded into a byte as seen previously. Changing over this byte into a decimal worth yields a solitary decimal incentive for the square. Subsequently utilizing the qualities got for every one of the square in the total picture include vectors acquired. These element vectors go about as the contribution for the characterization cycle. Regardless of whether there are changes in easing up conditions, the relative pixel distinction between the focal pixel and the adjoining ones remain stays as before in LBP and it is primary benefit of effective LBP. The paired example stays as before independent of the brightening and turn conditions. By and large upsides of the pixel's increment or reduction if the brilliance of a picture changes which has relative effect same. This property of the LBP makes it truly reasonable for the continuous applications. There are different variations of the LBP that can be joined for better outcomes as: Transition Local Binary Pattern, Direction Coded Local Binary Pattern, Modified Local Binary Pattern, Multi-block LBP, Volume LBP and RGBLBP. Our investigation proposes productive LBP as the component extraction procedure which yields exact and proficient order results. On the off chance that a LBP administrator contains all things considered one 0-1 and one 1-0 change in a parallel code, then, at that point a uniform example exists. The uniform example contains crude underlying data for edges and corners. This data can be utilized to decrease the length of the component vector and carry out a basic pivot invariant descriptor. In our exploration, a uniform-design LBP descriptor is applied to acquire highlights from faces, and the length of the element vector for a solitary cell can be diminished from 256 in the conventional technique to 59. The size of the face area is 130×130, and the LBP face is 128×128, which is isolated into little 16×16 patches with a goal of 8×8. The uniform LBP highlights are separated from every little fix and planned to a 59-dimensional histogram.

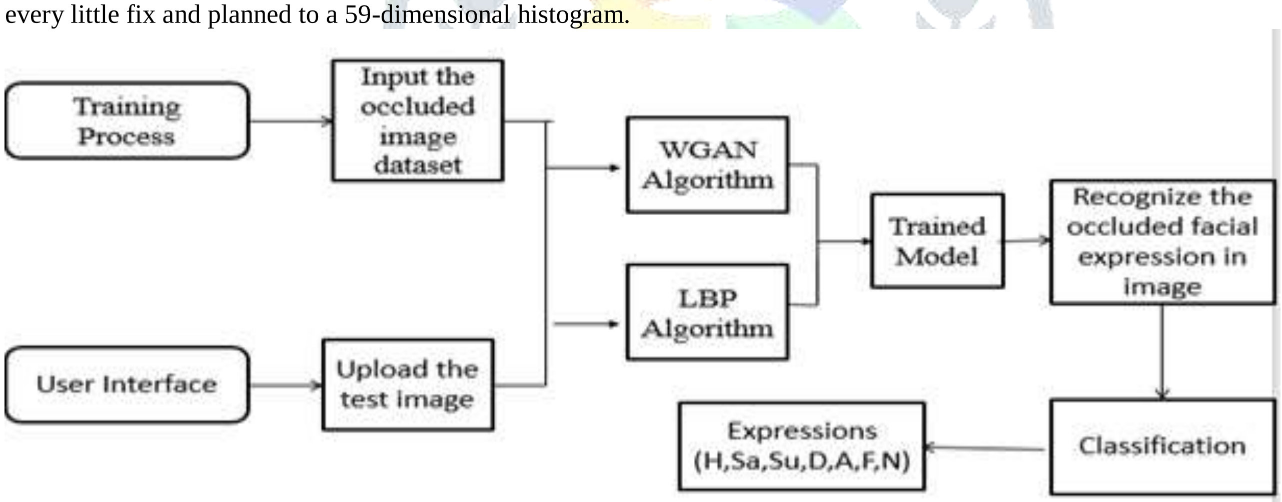

Figure 4. Proposed System Architecture

The proposed method architecture is showed figure 4. Firstly, input the occluded image from the modified FER 2013 dataset. Then it goes to the LBP algorithm, which train the model using LBP algorithm. After that it recognize the occluded facial expression image by using the classification mechanism. Finally, it predicts the output image facial expression from the occluded input image. Here also we predict the output of WGAN for comparing with proposed LBP method. This for show which method is give good accuracy performance. Next figure which is proposed system workflow of LBP. Firstly, input the occluded image which undergoes image preprocessing. The image preprocessing is mainly using for avoid the interference of illumination, posture and other factors on FER. Then also it ensures that the consistency of face size, position and image quality. The image preprocessing ha e five steps. They are face detection, face alignment, face cropping, size normalization and pixel normalization. Also here gives the workflow of our system. Which is firstly we input the occluded image from the desired dataset. Then it undergoes the image preprocessing and detect the face from the input image. After that it goes the algorithm. Here we done this is using two methods. One is proposed method and second one is existing method. Next step is classification based facial expression recognition. Finally, it finds which facial expression have the input the occluded image. That is, happy, sad, surprise, anger and neutral.

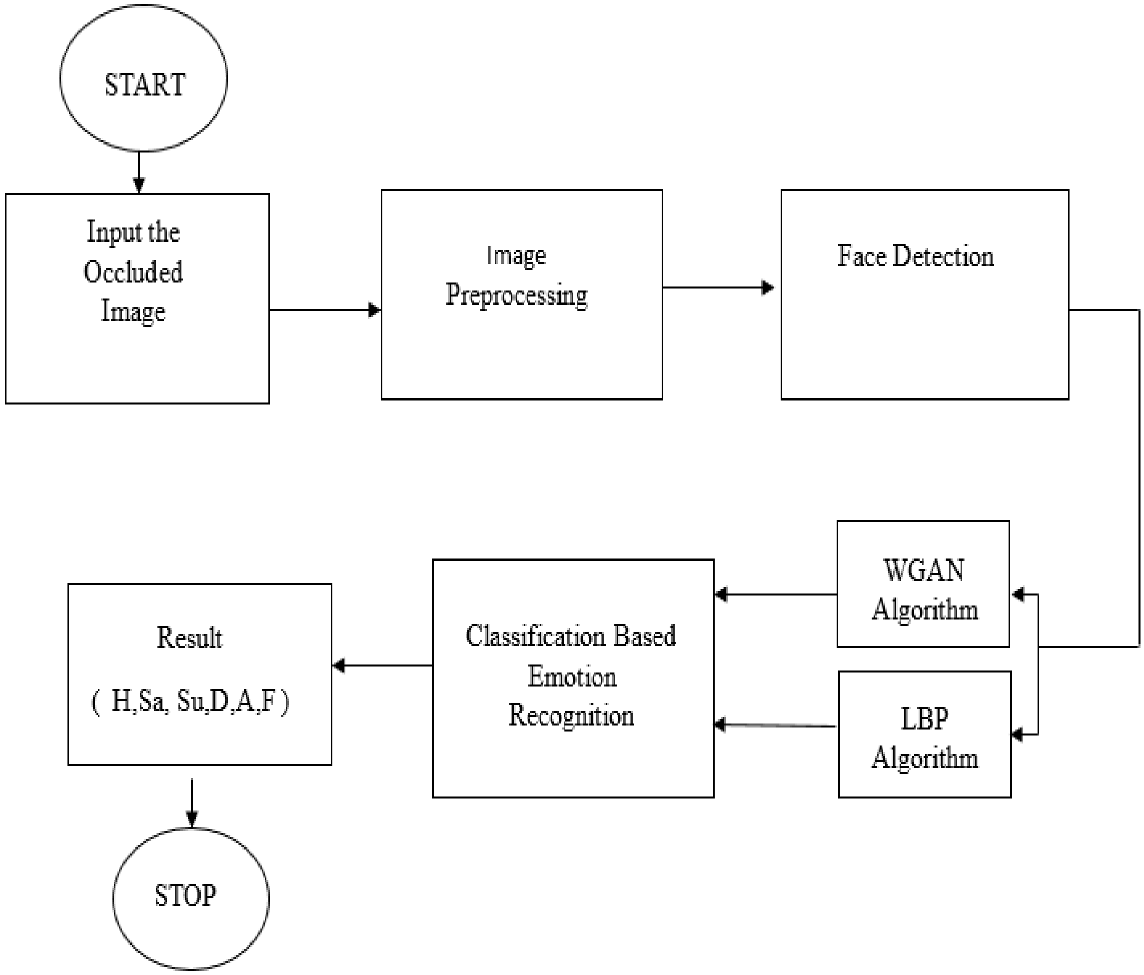

Figure 5. Proposed System Workflow

IV. EXPERIMENTAL RESULTS

4.1 Datasets

An exceptional facial expression datasets datasets are hard to the FER framework. A facial expression dataset is an assortment of pictures or video cuts with looks of a scope of feelings. The greater part of the data sets is normally founded on the essential feelings hypothesis (by Paul Ekman) which expects the presence of six discrete fundamental feelings (outrage, dread, disdain, shock, happiness, bitterness). By and by, more datasets are generally utilized. A portion of the datasets are Japanese Female Facial Expression (JAFFE), Cohn-Kanade, AffectNet and Real World emotional faces information base (RAF-DB). The above datasets contain numerous look pictures. Like front facing faces, side appearances, obscured faces and so on.

In any case, the above examined datasets including just the non-occluded facial expression pictures. Here we need occluded pictures containing datasets. For that the occluded facial expression acknowledgment we utilizing the FER dataset, Facial_image.npz and Facial_Keypoints. These two datasets are taken from the kaggle. The FER are datasets containing furious, disdain, dread, satisfaction, impartial, tragic, shock and the quantity of pictures is 39574. The FER-2013 dataset was made by get-together the consequences of a Google picture search of every feeling and equivalents of the feelings. The CK+ dataset has an aggregate of 5,876 marked pictures of 123 people. Each picture is marked with one of seven feelings: cheerful, tragic, furious, apprehensive, shock, loathing, and disdain. The FER+ dataset is an augmentation of the first FER dataset, where the pictures have been re-named into one of 8 feeling types: nonpartisan, satisfaction, shock, misery, outrage, disdain, dread, and hatred. The information comprises of 48x48 pixel grayscale pictures of countenances. The countenances have been consequently enlisted so the face is pretty much focused and possesses about a similar measure of room in each picture. The assignment is to arrange each face dependent on the feeling displayed in the look into one of seven classifications (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral). The preparation set comprises of 28,709 models and the public test set comprises of 3,589 models. However, one of the downside is it containing non-blocked pictures. So in this paper we occlude all the picture on the FER dataset. Here the FER dataset is essentially utilized for recognizing the face. Figure 6 is the FER dataset. It contains just non-occluded pictures. In any case, in our task we need to blocked datasets. So we occluded the pictures containing in this dataset.

Figure 6. Dataset of FER 2013.

4.2 Face Recognition

Local Binary Patterns or LBP is initially proposed as a surface portrayal strategy, what partitioned picture into local regions. For every locale, each pixel was named with decimal worth. These qualities are gathered into histogram (or call Local Binary Pattern Histogram: LBPH) and registered a histogram similitude for a grouping interaction [11]. The essential strategy for LBP based face portrayal presented by Ahonen [12]. This strategy, facial picture is isolated into nearby areas and concentrates the LBP depiction autonomously. LBP administrator allocate every area into the size of 3*3 areas. The worth of focus pixel is considered as an edge, and the outcome is considered as a double number. On the off chance that the outcome is positive (esteem ≥ edge) the double worth is "1", in any case is "0". After eight-digit paired is delivered, this worth changed over into decimal number again and address as LBP code of the locale [10].

Here initial step of our work is to composing the all pictures into a folder. Then, at that point make datasets for that composing pictures. In make datasets we sort every one of the pictures into indicated organizers. That is here we take primarily five facial expression. Like anger, happy, sad, surprise and neutral. Every one of the five facial expressions have them on folders. Then, at that point the third step is to prepare the each of the five classified facial expressions. At long last, we make a site page for this program. After that we go to the website page and pick needed picture as info. Which shows the figure 7. The information picture is occluded picture and afterward perceive which facial expression lastly we get the yield of that info picture. The facial expression anticipated yield is showed the figure 8.

Figure 7. Input of occluded facial image using by LBP.

Figure 8. Output of occluded facial image using by LBP

V. COMPARISON OF LBP AND WGAN METHOD

LBP image shows local texture feature of an image. WGAN depicts to measure the real/fake of the generated image. Here LBP is the proposed method the robust occluded facial expression recognition. And the WGAN is the existing method. Our main aim is to compare these two methods and prove LBP is better than the already existing WGAN method. Here the comparison between LBP and WGAN is based on the accuracy of each occluded facial expression images.

This paper presents a method of occluded facial expression recognition based on the LBP. The LBP is trained by using three steps. They are writing, create dataset and training. We also trained the dataset using the existing method, WGAN. The figure 9 shows the input of the occluded facial expression recognition of images and figure 10 shows the output of the occluded facial recognition of images by using WGAN method.

Figure 9. Input of occluded facial image using by WGAN

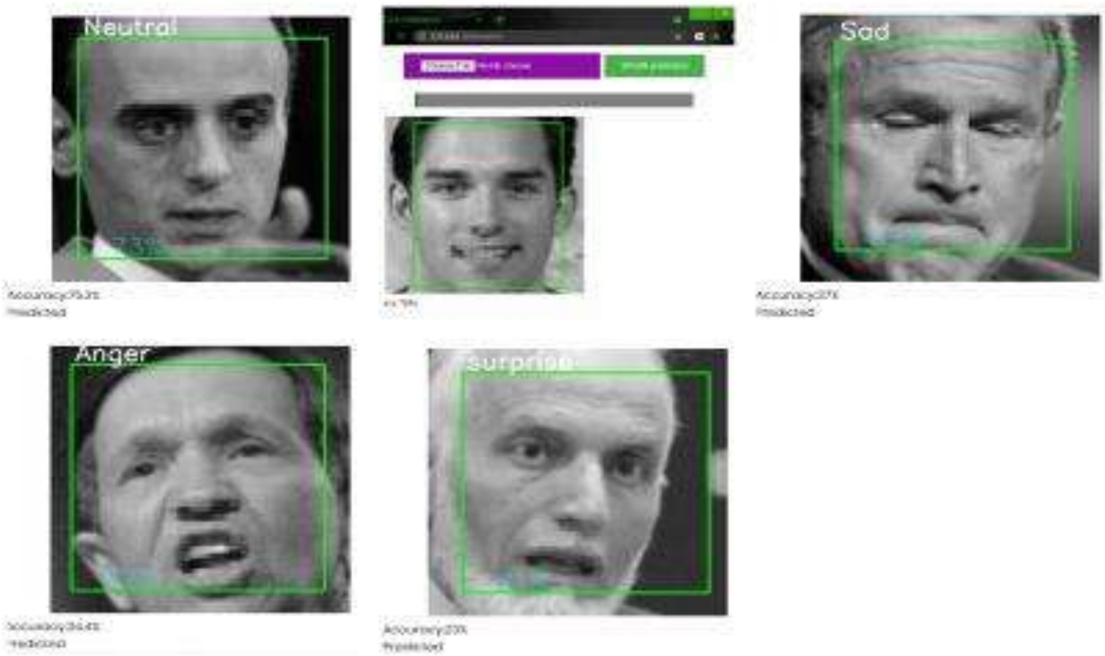

Figure 10. Output of occluded facial image using by WGAN

Here the input of the WGAN model is an occluded image. This images are taken from the dataset of FER 2013. In the datasets all the images are un-occluded images. But in our work we want occluded images. So we occlude the whole dataset containing images. Finally getting output is a blurred image. Which is showing the figure 10. That means the result of output occluded area and the existing method can fill the occluded area naturally. The output images cannot be completely same with the original images. However, the slight difference does not change the resulted output. In early using this method it can only occlude less than 40% occlusion area. But here we can occlude more than 40% occlusion area. That is, using this method we can increase the occlusion area in the case of occluded facial expression recognition. The output of WGAN image is blurred image. Because they recreate the occluded area. And then give the output as blurred image.

VI. THE EXPERIMENTAL RESULT AND DISCUSSION

To analyze the accuracy of both methods such as LBP and WGAN on occluded facial expression recognition, this study conducts a comparison on the recognition accuracy of occluded facial expression images LBP and WGAN. The experimental results are shown in figure 11. A shown in figure 11, the green regions represents the accuracy performance of WGAN method and the blue region represents the accuracy performance of the LBP method. In this graph we can understand the high accuracy performance is scored as the method LBP. The accuracy is important. Because, the accurate measurements are required for precise amounts, choosing better methods, graph plotting and also it provides correct data. Therefore, we can lead the accurate results. The main important fact of accuracy is, which represents how close the measurement value to its true or actual value.

Using WGAN method the happy accuracy performance is 43%. Then the sad have sad 39%, surprise total accuracy is 42%, anger 39% and finally neutral have 40%. In the case of LBP, the happy got 60%, sad accuracy is 43%, surprise 76% and neutral 64%. For this comparison we can conclude that the proposed system has high accuracy performance compared with WGAN method in occluded facial expression recognition. The accuracy between LBP and WGAN is shown in the table 1. This table is mainly shown for drawing the graph of occluded facial expression recognition accuracy between local binary pattern (LBP) and wasserstein generative adversarial network (WGAN). The accuracy between LBP and WGAN which shows the measurements how close the true value of this two methods and also which helps to bad equipment, processing the poor data or human error can lead to inaccurate results.

Table 1. Accuracy between LBP and WGAN method

	Happy	Anger	Sad	Surprise	Neutral
LBP	60%	61%	43%	76%	64%
WGAN	43%	39%	36%	42%	40%

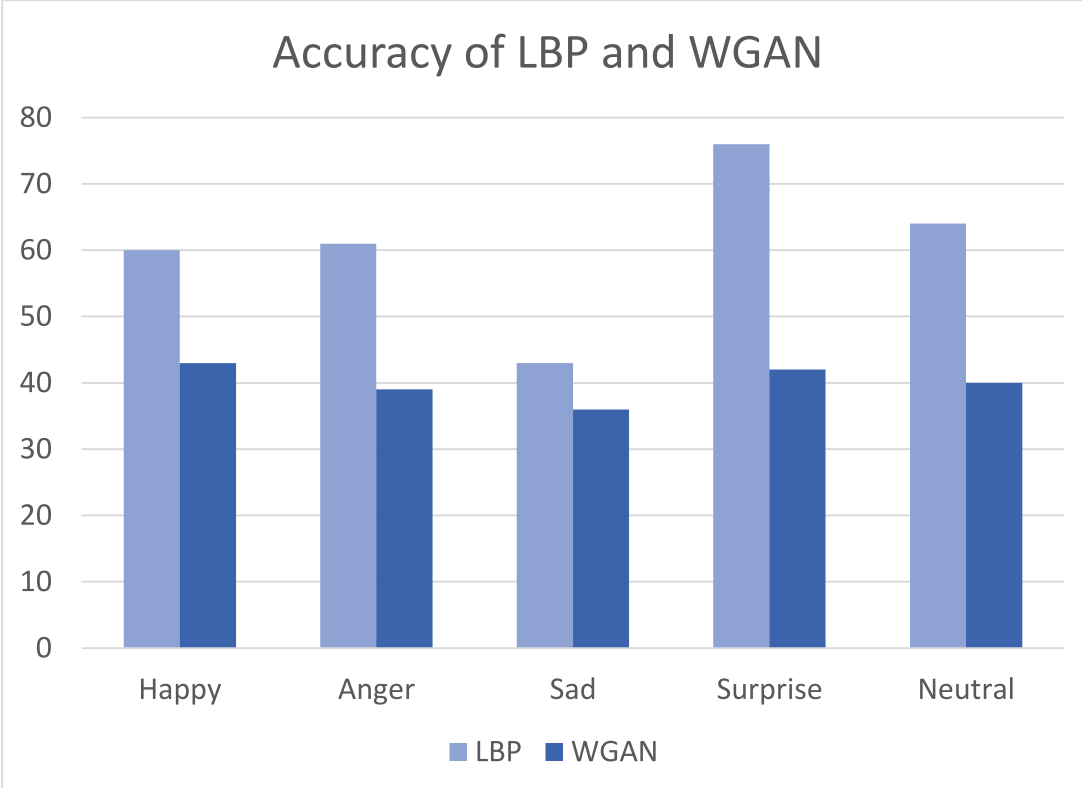

Figure 11. Accuracy between LBP and WGAN method

VII. CONCLUSION

Nowadays, occluded facial expression recognition is the innovation which has a great deal of consideration from specialists. There are many occluded facial expression recognition calculations, which have various attributes. Facial expression recognition has attracted growing thought of late. The earlier decade has seen the headway of various Facial expression recognition (FER) algorithms. This paper proposes an occluded facial expression recognition model based on the local binary pattern (LBP). Then also proposes a comparison between local binary pattern (LBP) and Wasserstein generative adversarial network (WGAN). The local binary pattern (LBP) is the proposed method and the Wasserstein generative adversarial network (WGAN) is the existing method. Here we also train the existing model WGAN and done the comparison with the performance accuracy of each facial expression of occluded images. Finally, we prove that local binary pattern (LBP) have more accuracy than Wasserstein generative adversarial network (WGAN) method.

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