AN IMPROVED FACIAL EXPRESSION RECOGNITION METHOD USING COMBINED HOG AND GABOR FEATURES

Zewar Fadhlulddin Hasan [a]

[a] Information Technology, Duhok Private Technical Institute, Duhok Kurdistan Region, Iraq (Zhiwar.f.hasan@dhk-pti.com)

ABSTRACT:

Lately, face recognition technology has been a significant study and a topic for generations. It remains a difficult task because of the variability of wide interclass. The subject of facial expression recognition is addressed in this research using a practical method. This method can recognize the human face and it is various features such as the eyes, brows, and lips. The motions or deformations of the face muscles are the cause of facial expressions. In addition, computer vision tasks such as texture recognition and categorization are commonly used. Furthermore, feature extraction basically discovers groups of features that demonstrate an image of visual texture. It is a critical phase to complete the operation. This work extracts features utilizing Histogram of Oriented Gradients (HOG) and Gabor approaches and then combines extracted features to improve the accuracy of facial expression detection. The derived features were particularly sensitive to object deformations. Later on, the classification of facial expression is handled using (Support Vector Machine) SVM. Analyze the proposed approach on FER 2013 data to see how well it performs. The proposal has a categorization rate of 63.82% on average. The proposed technique determines the comparable classification accuracy as shown in experimental findings. To improve this work it is planned to use deep features and combined them with HOG or Gabor, as well as to show the efficiency of the work it can be implemented with more datasets such as the JAFFE database.

KEYWORDS: facial expression recognition, HOG features, GABOR feature, FER2013 dataset, SVM.

1. INTRODUCTION

Fears of identity steal and password hacking have become a reality since society's information foundation and personal identification system have improved interest for security causes. The identification procedure in a computer system is based on the recognition of (username and password). However, this system can be easily failed to achieve the goal in the event of the loss or giving an authentication, as well as forgotten passwords or codes disclosure. Behavioral systems, on the other hand, are systems that are based on user behavior. It is nearly impossible to steal a person's personality. Yet, facial expression recognition acts a significant part in the interaction of social intelligence (Ekman and Friesen, 1971; Chen et al., 2014; Zebari et al., 2021; Majumder et al., 2018; Feng et al., 2004).

In the area of the recognition of patterns, facial expression recognition (FER) plays a significant influence, and researchers work very hard to establish a FER system for applications of the human-computer interaction. Plus, facial expression gives sensitive information signs for building a FER system and is often regarded as the most successful instrument for rapidly identifying the emotions and intentions of humans. Ekman and Friesen (1971) named six fundamental emotions in 1971 (sad, surprise, happy, fear, surprise, disgust, and anger), and each one is linked to a specific facial expression that is easily recognized across cultures. In the realm of computer vision, facial expression recognition has long become a fascinating and demanding problem. The goal of most researchers is to create a system that can recognize distinct expressions in photographs automatically. The challenge of recognizing facial expressions is incredibly difficult. Many aspects, such as lighting, position, deformation, and untamed surroundings, might add to the complication. Furthermore, facial emotions are small changes in facial muscle activity that are difficult to detect and portray (Chen et al., 2014).

Human-computer interface (HCI) systems, multimedia, surveillance, and driving safety are only a few examples of the applications built on FER systems. The FER problem might be resolved in a variety of ways, which can be loosely divided into two groups. The first set of techniques categorizes expressions using Action Unit (AU) which is small but distinct muscular motions that are important to the expression. The FER problem is frequently converted to the challenge of AU identification using AU-based approaches (Zebari et al., 2021). Local changes in faces, on the other hand, are difficult to detect, making precise AU detection difficult for computers. The performance of AU detection can potentially be impacted by external factors such as lighting or posture variations. The second type of technique uses hand-crafted patterns to extract visual information. In order to train a classifier for FER and represent the expressional image, extracted features are employed. Researchers, on the other hand, find it challenging to create a pattern hand-crafted that may be used in a variety of situations. Several machine learning methods have been developed for effective recognition performance, but owing to a lack of the ideal necessary group of features for classification, they have not yet achieved optimal performance (Majumder et al., 2018). Feature extraction is the process of extracting features from data using domain knowledge in order to make machine learning algorithms work. Creating features is tough, time-intensive, and requires specialist expertise. Many machine learning algorithms have been developed for effective recognition performance, but due to a lack of the ideal set of features necessary for classification, they have not yet achieved optimal performance. Feature extraction is the process of extracting features from data using domain knowledge in order to make machine learning algorithms work. It's challenging, time-consuming, and takes specialist expertise to come up with features (Feng et al., 2004).

In this paper, we present the most effective techniques for dealing with the problem of the FER system. Once given an image of a face, the system immediately spots the face and takes the facial elements. After that, a Histogram Oriented Gradient (HOG) and Gabor features are used to encode and concatenate these facial

elements into a single feature vector. A linear SVM is trained using these feature vectors.

2. LITERATURE REVIEW

The learning techniques of the machines based on Convolutional Neural Networks (CNNs) have had a lot of success in the computer vision field lately. Many factors, such as deformation, pose, the wild environment, and illumination, can be added to the difficulty of facial expression recognition. Furthermore, facial expressions are small changes in facial muscle movement, which can be difficult to detect and represent. Regarding face emotion recognition, (Feng et al., 2004). It is widely used in intelligent security, Natural Language Processing, visual object recognition, and robotic manufacturing, (Kumar et al., 2016). The methods of the traditional facial expressions, on the other hand, were primarily focused on frontal face expressions. There have been numerous attempts to recognize facial expressions. Gabor wavelets and Geometry based features were examined by (Mahmud and Al Mamun, 2017). Proposed a coarse-to-fine categorization framework. Generating vectors of the basic model and calculating the distance between the model vectors and the feature vectors were part of the coarse stage. After that, at the fine step, the classifier of a K-nearest neighbor was used to accomplish the last classification. The face sections of the height and breadth were determined to be exceptional characteristics in the facial emotion identification by (Khandait et al., 2012). Zhang and Tjondronegoro (2011) used characteristics of salient distance to identify a facial expression based on aspects of facial and movements of muscle. They obtained salient distance characteristics by extracting features of 3-D Gabor, selecting "salient" patches, then matching them. Shan et al. (2009) considered The Local Binary Pattern (LBP) as a valuable texture descriptor and might be utilized to describe face emotions. They used a Boosted-LBP method to determine the most notable LBP characteristics. The SVM was trained using the boosted-LBP features, which resulted in a high recognition rate.

To depict a discriminative textural pattern, appearance characteristics are taken from face image intensities. Regarding emotion identification, the author (Tsai and Chang, 2018) merged the Haar-like features approach with the self-quotient image (SQI). The system uses the Gabor filter (GF), the discrete cosine transform (DCT), and angular radial transform (ART) all at the same time. For facial expression identification, Ryu et al., (2017) employed a coarse grid to get stable codes (strongly associated with non-expression) and a finer grid to get active codes (primarily connected to appearance) as features. Liu et al. (2017) extracted HOG features and LBP features from the salient spaces well-defined on the faces then he reduced the features fused dimensions with HOG and LBP by using the Principal Component Analysis (PCA). In the DWT domain, Nigam et al. (2018) utilized Support Vector Machine (SVM) and obtained the feature of Histogram of Oriented Gradients (HOG). Turan and Lam (2018) tested 27 local descriptors, with the best results coming from the Local Phase Quantization (LPQ) and Local Gabor Binary Pattern Histogram Sequence (LGBPHS). To distinguish face emotions from static photos, Bougourzi et al. (2019) used a mixture of characteristics of a binaries statistical image, local phase quantization, and directed gradients histograms. For identifying facial expressions, Meena et al. (2020) employed curve let transform and graph signal processing. Not only has the size of the feature vectors been lowered, but facial expression recognition has also improved significantly. To establish a more robust representation of features for every single class of facial expression, Ashir et al. (2020) used

compressive identifying and sensing with the acquired compressed facial signal statistical analysis

Niu et al. (2021) proposed a method that combines rotated BRIEF and orientated FAST with the LBP features retrieved from the facial expressions. To start, each image is exposed to a face-detection algorithm in order to extract extra useful properties. Secondly, LBP and LBP features are extracted from the face region to enhance the computation speed; In particular, zoning is used in a new way in classic ORB to prevent the concentration of the feature. Characteristics are not affected by modifications in grayscale, size, or rotation. Lastly, (SVM) is used to classify mixture features. Lekdioui et al. (2017) proposed a technique based on unique facial decomposition for identifying facial expressions. Firstly, using the facial features recognized through the Intra-Face algorithm, seven areas of interest representing the key components of the face (right eye, left eye, right and left eyebrows, between eyebrows, mouth, and nose) are retrieved. The features are then extracted using several local descriptors such as LTP, Dynamic LTP, CLBP, and LBP. Lastly, to complete the recognition job, the feature vector representing the image of the face is fed into a multiclass supporting vector machine. To begin, extract form characteristics from various places on a face. Then, using expression photos, multi-orientation Gabor wavelet coefficient features are retrieved. As a classifier, Support Vector Machines (SVM) were utilized. Linear classifiers function well on facial point data because the face contains certain fixed special points. As a result, SVM performs admirably in our FER system. The results of our experiments suggest that employing face shape data and the Gabor wavelet coefficient based on SVM is more accurate and quicker than most other previously proposed approaches (Bakchy et al., 2017). A three-dimensional face recognition method has been introduced by Zebari et al. (2021), in their study different methods have been exploited namely, Gabor, Local Binary Pattern (LBP), and Local Ternary Pattern (LTP) to extract features from the image then the extracted features fed to Support Vector Machine (SVM). A feature combination concept has been applied in this study LBP with Gabor and LTP with Gabor. Based on the experimental result it is shown that the LTP and Gabor obtained higher accuracy.

A novel method of expression recognition based on cognition and mapped binary patterns are given. To begin, the method relies on the LBP operator in order to extract the facial outlines. Second, a pseudo-3-D model is employed to split the face area into six sub-regions based on facial emotion. The mapped LBP approach is used for feature extraction in the sub-regions and global facial expression pictures. Then two classifications, SoftMax and support vector machine, are used with two types of models of emotion classification, circumflex emotion and the basic emotion model (Qi et al. 2018). The study in (Ibrahim et al., 2021) proposed a method for facial expression using Histogram of Oriented Gradient (HOG), Diagonal-HOG (D-HOG), and Local Binary Pattern (LBP) with Support Vector Machine (SVM). After the pre-processing stage has been done, this study extracts some features based on D-HOG, and all features have been combined to improve the recognition accuracy. The proposed method was evaluated using the JAFFE database.

3. PROPOSED METHOD

Muscle movements are responsible for facial emotions, and these movements might be viewed as a sort of deformity. Lips motions, for example, cause the mouth to close or open, while brow movements cause the brows to rise or fall. These motions resemble deformations in nature. The proposed methodology is explained in detail in this section. Figure 1 shows that the input images are processed (face detection, noise reduction, and histogram equalization) before HOG and Gabor features are extracted. The performance of facial expression recognition was evaluated by computing the classification performance through the use of SVM.

3.1. Pre-processing

For any image recognition field, preprocessing is essential. In order to improve the overall system performance for facial emotion detection, appropriate preprocessing can remove noise from the image and strengthen the needed information. Face detection, noise reduction, and histogram equalization are image-preprocessing approaches used in this study. In order to improve the effectiveness of the algorithm, this study uses all of these methods. An illustration of this is a grayscale image with only one channel as input to the classifier. Reducing the difference among training samples while also reducing computational storage and speeding up the training process are all benefits of using this technique.

It is a difficult computer vision challenge to locate and recognize faces in images using image recognition. FER systems must go through this process as a first phase. OpenCV's Haar cascade classifier is used, or more current deep learning-based algorithms utilizing OpenCV library. Both methods use classical machine learning (feature-based). OpenCV has a cascade classifier for face recognition that is able to utilize. The pre-trained model's XML file could be specified as a parameter to the constructor. An image could be processed with the method to find faces using the detect Multiscale function, which returns boxes for all faces found. The parameters Scale Factor and main Neighbors should be fine-tuned for each dataset since the Scale factor determines how the input image is scaled before detection.
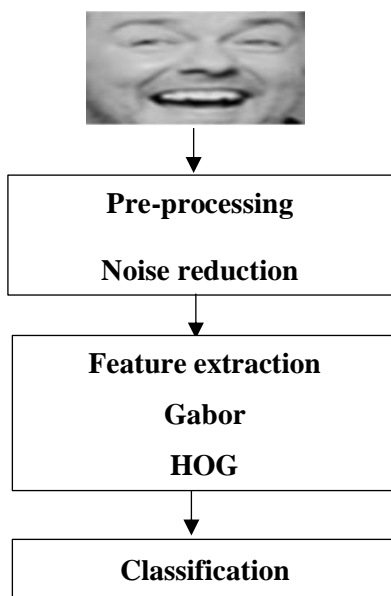

Figure 1. proposed method scheme

A. Histogram equalization

With this method, the intensity range of an image can be extended by stretching the most frequent pixel intensity. Low-contrast areas would have higher contrast and the accumulated histogram could expand linearly as a result of the distribution improvement (Ibrahim et al., 2021). A digital image's contrast can be improved using histogram equalization. Each pixel value undergoes transformation, which results in a new image that is created by performing an independent action on each pixel. The original image's histogram is used to build this transformation. To properly distribute the intensity across the whole range of possible values, the histogram equalization "spreads" the histogram. For low-contrast photos, equilibrating is a useful technique (the set of pixels are of close intensity). The approach is quick, simple, and completely automated. Although this method boosts the overall contrast of photographs, it has a number of drawbacks, including the loss of some features, the brightening of some local areas, and the failure to preserve the brightness of the image.

B. Adaptive Median Filter

Pre-processing can be divided into two categories: noise reduction as well as contrast enhancement. Many people utilize the median filter. A filter is applied in a non-linear fashion. The kernel's size could be (N x N), and it can be set to slide or convolution over a malformed (M x M) picture. An image's median kernel value was calculated, and after that, the pixel's frequency in the image is changed with that kernel's median value (Zebari et al., 2019; Mandal and Mukhopadhyay, 2013).
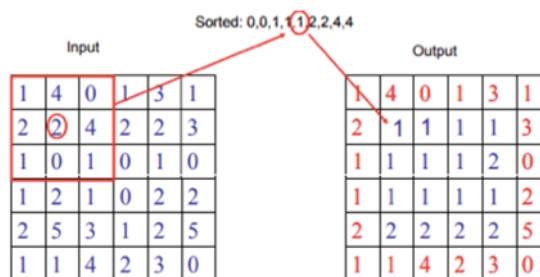

Figure 2. Sorting in Median Filter

The adaptive median filter is intended to remove the problems that are associated with the traditional median. Adaptive median filters provide the primary benefit of allowing the size of the kernel around the distorted image to be varied, resulting in a more accurate final output. The adaptive filter has an additional key advantage over the median filter because it does not change all the adjacent pixels of median value, unlike the median filter. When an adaptive filter is in operation, it performs a two-step procedure: firstly, it determines the median value for the kernel, and then it determines if the present pixel value is an impulsive (salt and pepper noise) or not. If a pixel's value is damaged, the algorithm either replaces it with the median value or keeps the value of the grayscale pixel in question. By doing so, it is possible to assure that only the pixels containing impulse noise are modified and that all other pixel values remain unchanged.

3.2. Feature extraction

FER in the later stage is feature extraction after face detection. When using facial feature extraction, the primary goal is to obtain a reliable and accurate representation of the various facial features without altering the original face data. Features are extracted from images to obtain information or user data, such as values, vectors, and symbols (Taher et al., 2021). Image characteristics include the "non-image" interpretations and descriptions that were extracted from the image. Characteristics extracted from facial motion and deformation are referred to as appearance-based features since they are based on how a person looks. It is possible that the output image will be a static image. To extract local or global or hybrid face features, an appropriate facial feature extraction algorithm is used on the input image. These features are decreased in size before being fed to the classifier, which makes it easier for the classifier to make decisions on face.

Expression identification and recognition. The performance of the algorithms, which are typically the FER system's bottleneck, can be affected directly via feature extraction. In conventional FER techniques, it is critical to consider applicability as well as practicality when selecting an acceptable feature extraction method. Gabor feature extraction and Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM) classifier were used in this study to extract features from FER systems.

A. HOG Feature

HOG features are extremely sensitive to object permanent deformation. HOG constructs spatial and direction cells utilizing gradients but then assembles histograms of these gradients from overlapped spatial blocks utilizing the gradients. For the aim of object recognition in computer vision and image processing systems, the HOG is a feature extraction technique that is commonly utilized. When applied to a specified portion of an image or region of interest, this approach counts the occurrences of events with a gradient orientation. (Zebari et al., 2020).

The following are the most significant aspects of HOG:

- The object's structure is the primary concentration of HOG. By using this method, both the direction and magnitude of the edges are extracted from the edges.
- It makes utilize of an identification window of 64x128 pixels, which means that the image is first translated into the shape (64, 128).
- The image is then subsequently broken into small sections, and the gradient and direction of every part are computed separately for each of the smaller parts. As a result, it is subdivided into 8x16 cells that are then separated into blocks with 50% overlap, yielding a total of 7x15 = 105 blocks, with each block consisting of 2x2 cells that contain eight pixels apiece.
- A histogram of a 9-bin is generated by taking 64 gradient vectors from each block (8 x 8 pixel cell) and grouping them together.

This study proposes a method to encode facial components using HOG features. Dalal and Triggs (2005) introduced HOG for the first time. Individuals in the field of computer vision are utilized widely, notably for pedestrian safety. In a patch of an image, HOG identifies the presence of gradient orientation. Object structure and shape might be described by how the local gradient intensity and direction are distributed. FER can be made easier with HOG. When it comes to facial expressions, HOG could distinguish between the various parts that go into making a certain expression. As a result, this work utilizes the HOG to accurately encode the facial features. The size of the cell was set to 8×8, the number of bin sizes is set to 9, and the orientation range was 0 to 180 in our experiments.

B. Gabor Feature

Due to their frequency and direction representations, Gabor's characteristics are comparable to the human vision in terms of performance. In the spatial domain, the feature of 2D is a function of Gaussian kernel modulated by a sine plane wave, which is represented by the symbol. A single main wavelet could be used to produce these filters, which can then be rotated and filtered further. These are the most effective among the various relevant picture features that are currently available, such as edge direction histograms and box filters (Zebari et al., 2020). Gabor filters with varying directions and scales could be used to create a Gabor filter bank by combining them together. The Gabor filter bank, which has eight directions and five scales, has been the most frequently utilized. These filters are being utilized to features extracted from grayscale images, which are then displayed in color. The following is the procedure for obtaining Gabor-based feature extraction: firstly, every filter in the Gabor filter bank is combined with the image in order to obtain Gabor-based feature extraction. Next, to limit the amount of duplicated information in the filtered images, the images are down-sampled. After that, each down-sampled image is turned into a feature vector using a feature vector generator. Following that, each feature vector is normalized to have a mean of zero and a variance of one. When all of these feature vectors are integrated, the resulting feature vector of the image is known as the final feature vector (Shah and Khanna, 2015).

Gabor features were generated, in this study, by using Gabor filters for identification and compositional analysis by exploiting analysis patterns in regions. An oscillator's frequency and stage, as well as the filter size, are all linked together using the Gabor filter. According to findings, the Gabor wavelengths range from 2 to 32 pixels in half-octave intervals utilizing orientations from eight wavelets and scaling of nine. While there are 663,552 components in the final feature vector, not all of them are relevant. In reality, only a tiny number of useful elements are included in this study. First, the eye centers must be found, and then the images must be properly aligned to perform Gabor analysis. Alignment is accomplished by scaling, rotating, and transforming the scene to the desired position. This is how 2D images are registered in most cases. Manual landmark identification is used for normalization. This is done to prevent registration method's misaligned consequences.

3.3. Classification

Classification is a supervised model of learning. It predicts the output depending on beliefs that have previously been seen. Pattern recognition relies on the classifier, which can be used to make conclusions about unseen data or predicts the labels of a class of unseen data based on previously learned images. A large number of categorization algorithms have been created in order to attain the maximum recognition rate possible. In fact, none of the methodologies are appropriate for analyzing diverse facial feature extraction procedures. In order to construct an efficient real-time FER system, a dataset containing a variety of spontaneous expressions is required. Many types of expressions taken into consideration are labeled as follows: fear, sad, happy, disgust, anger, and surprise. The photos of LaBelle dare used to train the classifier and are then provided to it. When it comes to classification, the images of trained and tested are compared in order to predict the anticipated output (Abrahim et al., 2019; Xiang and Zhu, 2017).

After the extracted features were extracted, classification was carried out with an SVM classifier in this study. Being able to discriminate data for training using the hyperplane, SVM is known to have the ability to generalize by mapping nonlinear inputs to high-dimensional feature spaces. SVMs examine the data and look for patterns, which is what they're utilized. When solving classification and regression problems, they build a hyperplane or a set of hyperplanes. When using SVM classifiers to find exclusionary hyperplanes, the classifiers look for the hyperplanes with the largest margin of separation between them. Moreover, a particular classification method extracted the features, where the study investigates whether combining texture descriptors improves performance accuracy by combining and examining them. A feature integration is defined as the concatenation of the feature vectors obtained from two or more distinct image feature extraction methods that are used in conjunction with one another. This study discovered that increasing the variety of features in the combinations would generally result in a significant slowdown in the machine learning phase. Weka is used to accomplish an intermediate step of principal component analysis the new feature vectors preparing to run the machine learning classification algorithm, which is done for performance reasons. As a consequence of combining these methods will be able to specify whether more data provided by some other learning algorithm might enhance the performance of the classifier, whether outcomes from the two-method utilized separately can be averaged, or whether the additional data generally degrades performance.

4. EXPERIMENTAL RESULTS

This section contains the specifics of the experimentations that were carried out. An experiment involving the FER 2013 databases was carried out to determine the performance of the proposed FER method. Samples of the FER 2013 dataset that had been trained in the experiment were also included in the testing sample sets. To evaluate the performance of the proposed method this study used MATLAB (2020b) on an operating system with Windows 10 with the processor of Core-i7 and 8 GB of RAM. The most fundamental classifier utilized in the experiments was the SVM, and it was also utilized in this study.

Measurement methods are critical during the training phase, and their choosing is critical for distinguishing between and attaining the best possible classifier for the task at hand. The FER is inherently a classification of multi-class issues, with accuracy (Acc), i.e., properly classified datasets proportion, serving as a primary measuring performance parameter for the system. In order to take into account, the recognition effect for each category of expression in a comprehensive manner, the final accuracy could alternatively be calculated by taking the recognition rate average for each expression class within every class of expression (Liu et al., 2017). The terms "overall accuracy" and "average accuracy" refer to the two techniques of calculating accuracy that is described above. Generally, a higher accuracy equates to enhanced performance in classification. Accuracy is considered and calculated based on the below equation.

$$Acc = (TN+TP)/(TN+TP+FP+FN)$$

Where *FP*, *TN*, and *TP* indicate false positive, true negative, true positive respectively.

4.1. Dataset

It was initially presented in the ICML 2013 Challenges in Representation Learning that the Facial Expression Recognition 2013 (FER2013) database was created. This collection includes 35,887 photos with a resolution of 48 by 48, the majority of which were captured in the wild. 28,709 photos were used in the training process, while a total of 3589 images were used in the validation and testing phases. This database was built by using Google's picture search API and faces were automatically added when they appeared. In addition to six cardinal expressions, there is also a neutral face. FER has a greater diversity in photographs compared to the other datasets, such as facial occlusion (usually with a hand), low contrast images, partial faces, and spectacles. Figure 3 displays four pictures taken from the database of FER (Xiang and Zhu, 2017; Liu et al., 2016; Mollahosseini et al., 2016).

Figure 3. Images from the database of FER.

For some misclassifications, including the terror image previously stated, error analysis was particularly difficult because our algorithms were more accurate than humans could be. In addition, because emotions are so subjective, Bayes error is significant and images frequently have many interpretations.

4.2. Classification result

Depending on the results of this study, the proposed method is capable of dealing with the recognition of facial expressions in a timely manner. The feature extraction strategies that have been used are discussed in detail in the previous section. The HOG and Gabor features are two of the approaches that have been implemented. Following that, a classification technique known as SVM classifiers is used to classify the FER2013 into different classes. This work implements the network for testing the accuracy performance of the introduced method for FER based on all of the image observations collected so far. The FER-2013 dataset is more difficult to train on than the other facial expression recognition datasets since it contains more facial expressions. The uneven nature of distinct emotional classes is another major problem in this dataset, which is in addition to the intra-class fluctuation of the FER. Happiness and neutrality are two classes with a disproportionately large number of cases compared to the others. Table 1 shows the results of the experiment.

Table 1. Obtained Performance Accuracy for FER 2013 based on Different Features

Feature	Accuracy
HOG	57.17%
Gabor	60.02%
Combined Features	63.82%

Table 2 compares the proposed algorithm accuracy with the state-of-the-art algorithm accuracy on the FER 2013 to allow us to compare the performance of our proposed algorithm with the performance of other methods. Gabor and HOG filters are feature descriptors in FER and they are employed in various applications. Table 2 depicts the findings obtained by competing approaches on FER 2013, which was considered the most difficult database in the experiment and thus the most difficult to analyze. On the FER2013 dataset, a scoreboard for the facial expression recognition task was available. The proposed model attained an accuracy of 63.82%; the pre-trained model was ranked second among all the participating teams in terms of accuracy.

Table 2. Comparison Between Some of the Recent Previous Studies and Proposed Study

Algorithm	Accuracy
[34]	65.03%
[35]	61.1%
[36]	61.86%
[37]	57.1%
Proposed Method	**63.82%**

In real-world applications, accuracy is also dependent on a variety of other variables, including the quality images, the surroundings in which the image was managed to capture (controlled or uncontrolled), the individual's age (fine lines on the face can make a massive variation in accuracy), the perspective of face, and light levels, among others. Additionally, accuracy varies across men and women due to the fact that women tend to convey emotions more vividly than males. All of these aspects will be taken into account when determining the intensity of emotions as well as the detection of emotions in real-world face recognition systems, and they may have a substantial impact on the performance of any technique.

5. CONCLUSION

This research developed a model for facial expression recognition using different appearance-based features, which was implemented in an experiment. In order to extract features, HOG and Gabor features were utilized, and SVM classification was

applied to recognize different facial expressions. The experimental findings revealed that the suggested framework outperformed various widely used algorithms on the FER 2013 database. This is in line with previous research. The majority of this article was devoted to the analysis of facial expressions in static photographs. In our future work, we will take into account more facial expressions from various databases, as well as calculation times for embedded systems.

REFERENCES

Abrahim A. R., Shafry M. Rahim M., & Sulong, G. (2019). *Splicing image forgery identification based on artificial neural network approach and texture features*, Cluster Computing, vol. 22, no. Supplement 1, p. 647–660.

Ashir, A. M., Eleyan, A., & Akdemir, B. (2020). *Facial expression recognition with dynamic cascaded classifier*. Neural Com- puting and Applications, vol. 32, no. 10, pp. 6295–6309.

Bakchy, S. C., Ferdous, M. J., Sathi, A. H., Ray, K. C., Imran, F., & Ali, M. M. (2017). *Facial expression recognition based on support vector machine using Gabor wavelet filter*. In 2017 2nd International Conference on Electrical & Electronic Engineering (ICEEE) (pp. 1-4). IEEE.

Bougourzi, F., Mokrani, K., Ruichek, Y., Dornaika, F., Ouafi, A., & Taleb-Ahmed, A. (2019). *Fusion of transformed shallow features for facial expression recognition*. IET Image Processing, vol. 13, no. 9, pp. 1479–1489.

Chen, J., Chen, Z., Chi, Z., & Fu, H. (2014). *Facial expression recognition based on facial components detection and hog features*. In International workshops on electrical and computer engineering subfields, pp. 884-888.

Dalal, N., & Triggs, B. (2005). *Histograms of Oriented Gradients for Human Detection*, in Computer Vision and Pattern Recognition. IEEE Conference on, 2005, pp. 886-893.

Ekman, P., Friesen, W.V. (1971). *Constants across cultures in the face and emotion*. Journal of Pers. Soc. Psychol., 17(2), pp. 124–129

Feng, X., Hadid, A., & Pietikäinen, M. (2004). *A coarse-to-fine classification scheme for facial expression recognition.* In Image Analysis and Recognition, pp. 668-675.

Hassan, M. M., Hussein, H. I., Eesa, A. S., & Mstafan, R. J. (2021). *Face Recognition Based on Gabor Feature Extraction Followed by FastICA and LDA*. CMC-COMPUTERS MATERIALS & CONTINUA, 68(2), 1637-1659.

Ibrahim, D. A., Zebari, D. A., Ahmed, F. Y., & Zeebaree, D. Q. (2021). *Facial Expression Recognition Using Aggregated Handcrafted Descriptors based Appearance Method.* In 2021 IEEE 11th International Conference on System Engineering and Technology (ICSET) (pp. 177-182). IEEE.

Khandait, S., Thool, R., & Khandait, P. (2012). *Automatic facial feature extraction and expression recognition based on neural network*. International Journal of Advanced Computer Science and Applications, vol. 2, pp. 113-118.

Kumar, P., Happy, S L, & Routray, A. (2016). *A Real-time Robust Facial Expression Recognition System using HOG Features.* International Conference on Computing, Analytics and Security Trends (CAST), pp. 289-293.

Łabędź, P., Skabek, K., Ozimek, P., & Nytko, M. (2021). *Histogram Adjustment of Images for Improving Photogrammetric Reconstruction*. Sensors, 21(14), 4654.

Lekdioui, K., Ruichek, Y., Messoussi, R., Chaabi, Y., & Touahni, R. (2017). *Facial expression recognition using face-regions*. International conference on advanced technologies for signal and image processing (ATSIP) (pp. 1-6). IEEE.

Liu, K., Zhang, M., & Pan, Z. (2016). *Facial expression recognition with CNN ensemble*, in: Proceeding of the International Conference on Cyberworlds (CW), IEEE, pp. 163–166.

Liu, Y., Li, Y., Ma, X., & Song, R. (2017). *Facial expression recognition with fusion features extracted from salient facial areas*. Sensors, vol. 17, no. 4, p. 712.

Mahmud, F., & Al Mamun, Md. (2017). *Facial expression recognition system using extreme learning machine*. International Journal of Scientific & Engineering Research, 8, (3), pp. 26–30.

Majumder, A., Behera, L., & Subramanian, V.K. (2018). *Automatic facial expression recognition system using deep network-based data fusion*. IEEE Trans on Cybern. 48 (1) 103–114

Mandal, J. K., & Mukhopadhyay, S. (2013). *Adaptive Median Filtering Based on Unsupervised Classification of Pixels*. In Handbook of Research on Computational Intelligence for Engineering, Science, and Business (pp. 273-296). IGI Global.

Meena, H. K., Sharma, K. K., & Joshi, S. D. (2020). *Effective cur- velet-based facial expression recognition using graph signal processing*. Signal, Image and Video Processing, vol. 14, no. 2, pp. 241–247.

Mollahosseini, A., Chan, D., & Mahoor, M.H. (2016). *Going deeper in facial expression recognition using deep neural networks*. In Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV), Lake Placid, NY, USA, 7–10; pp. 1–10.

Nigam, S., Singh, R., & Misra, A. K. (2018). *Efficient facial ex- pression recognition using histogram of oriented gradients in wavelet domain*. Multimedia Tools and Applications, vol. 77, no. 21, pp. 28725–28747.

Niu, B., Gao, Z., & Guo, B. (2021). *Facial expression recognition with LBP and ORB features*. Computational Intelligence and Neuroscience.

Qi, C., Li, M., Wang, Q., Zhang, H., Xing, J., Gao, Z., & Zhang, H. (2018). *Facial expressions recognition based on cognition and mapped binary patterns*. IEEE Access, 6, 18795-18803.

Ryu, B., Rivera, A. R., Kim, J., & Chae, O. (2017). *Local directional ternary pattern for facial expression recognition*. IEEE Transactions on Image Processing, vol. 26, no. 12, pp. 6006–6018.

Shah, S. K., & Khanna, V. (2015). *Facial expression recognition for color images using Gabor, log Gabor filters and PCA*. International Journal of Computer Applications, 113(4).

Shan, C., Gong, S., & McOwan, P. W. (2009). *Facial expression recognition based on Local Binary Patterns: A comprehensive study*. Image and Vision Computing, vol. 27, pp. 803-816.

Taher, K. I., Abdulazeez, A. M., & Zebari, D. A. (2021). *Data Mining Classification Algorithms for Analyzing Soil Data*. Asian Journal of Research in Computer Science, 17-28.

Tsai, H.-H., & Chang, Y.-C. (2018). *Facial expression recognition using a combination of multiple facial features and support vector machine*. Soft Computing, vol. 22, no. 13, pp. 4389–4405.

Turan, C., & Lam, K.-M. (2018). *Histogram-based local descriptors for facial expression recognition (FER): a comprehensive study*. Journal of Visual Communication and Image Repre- sentation, vol. 55, pp. 331–341.

Xiang, J., & Zhu, G. (2017). *Joint face detection and facial expression recognition with MTCNN*, in: Proceedings of the 4th International Conference on Information Science and Control Engineering (ICISCE), IEEE, pp. 424–427.

Zebari, D. A., Abrahim, A. R., Ibrahim, D. A., Othman, G. M., & Ahmed, F. Y. (2021). *Analysis of Dense Descriptors in 3D Face Recognition*. In 2021 IEEE 11th International Conference on System Engineering and Technology (ICSET) (pp. 171-176). IEEE.

Zebari, D. A., Haron, H., Zeebaree, S. R., & Zeebaree, D. Q. (2019). *Enhance the mammogram images for both segmentation and feature extraction using wavelet transform*. In 2019 International Conference on Advanced Science and Engineering (ICOASE) (pp. 100-105). IEEE.

Zebari, D. A., Zeebaree, D. Q., Abdulazeez, A. M., Haron, H., & Hamed, H. N. A. (2020). *Improved threshold based and trainable fully automated segmentation for breast cancer boundary and pectoral muscle in mammogram images*. IEEE Access, 8, 203097-203116.

Zebari, G. M., Zebari, D. A., Zeebaree, D. Q., Haron, H., Abdulazeez, A. M., & Yurtkan, K. (2021). *Efficient CNN Approach for Facial Expression Recognition*. In Journal of Physics: Conference Series (Vol. 2129, No. 1, p. 012083). IOP Publishing.

Zeng, G., Zhou, J., Jia, X., Xie, W., & Shen, L. (2018). *Hand-crafted feature guided deep learning for facial expression recognition*, in: Proceedings of the 2018 13th IEEE International Conference on Automatic Face Gesture Recognition (FG 2018), pp. 423–430.

Zhang, L., & Tjondronegoro, D. (2011). *Facial expression recognition using facial movement features*. Affective Computing, IEEE Transactions on, vol. 2, pp. 219-229.