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A Deep Learning-based Framework for Emotion Recognition using Facial Expression

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Abstract- **Humans convey their message in different forms. Expressing their emotions and moods through their facial expression is one of them. In this work, to avoid the traditional feature extraction process (Geometry based method, Template based method, and Appearance based method), the CNN model is used as a feature extractor for emotion detection using facial expression. In this study, we also used three pre-trained models VGG-16, ResNet-50, and Inception-V3. This experiment is done on the Fer-2013 facial expression dataset and Cohn Extended (CK+) dataset. By using FER-2013 dataset the accuracy rates for CNN, ResNet-50, VGG-16 and Inception-V3 are 76.74%, 85.71%, 85.78%s, 97.93% respectively. Similarly, the experimental results using the CK+ dataset showed that the accuracy rates for CNN, ResNet- 50, VGG-16, and Inception-V3 are 84.18%, 92.91%, 91.07%, and 73.16%, respectively. The experimental results showed exceptional results for Inception-V3, with 97.93% using the FER-2013 dataset, and ResNet-50, with 91.92% using the CK+ dataset.**

Index Terms-- **Deep Learning, transfer Learning CNN, ResNet-50, VGG-16, and Inception-V3**

I. INTRODUCTION

Humans use a variety of communication styles to get their points across. One of them is conveying their thoughts, feelings, and attitudes through the expressions on their faces. A person's emotional state can be summed up by facial expressions, which are the total of various subtle muscle movements in the face. Eckman developed the facial action coding system (FACS) to classify facial actions. FACS was first widely used to measure and evaluate the movement of all small facial muscles. Face expression includes changes in muscles and the eye and head. His theory proposed seven universal emotions to all people: happiness, sadness, surprise, fear, anger, disgust, and contempt. Human-computer interaction is essential in deep learning models to recognize emotion detection through facial expressions. In technology, the computer is a primary source for understanding algorithms and identifying patterns. Although detecting human emotions through facial expression is challenging, exact prediction of human emotions is significant to respond appropriately in many fields such as medicine, monitoring, military, and e-learning. Emotion detection has a vital role in driver fatigue monitoring. In ATM booths, for security purposes,s we use the face encoding process to detect human emotions. This system allows happy faces to proceed with the transaction quickly over other emotions. This system enables happy faces to proceed with the transaction promptly over other emotions [1-6].

In past years, rapid development occurred in pattern recognition, machine learning, deep learning, and artificial intelligence. Face detection is the first and most important part of the recognition process. This phase is challenging and requires different techniques to detect the face from image sequences. To this day, there are many techniques for this approach. Various models and algorithms are designed to perform this task fast and accurately [7-12].

Many techniques detect the face, like Haar-cascade classifiers, Adaboost algorithm, and Histogram algorithm. After detecting the face, facial features are required to perform training. Features used for classification can be in the form of static images or video streams. According to the type of data input, the current feature extraction methods can be divided into two types: one is based on static images, and the other is based on a dynamic sequence. For static images, there are different methods, such as the Haar wavelet transform, Gabor wavelet transform, Local Binary Pattern (LBP), and Active Appearance Models (AAM). Dynamic-based input use time and motion information from sequences of images having facial expression. To escape from the traditional feature extraction process (Geometry based method, Template based method, and Appearance based method), the CNN model is used as a feature extractor for Emotion Detection using facial expression [13, 14]. But Convolutional neural network is not enough for emotion detection using facial expressions because these models take a long training time. Deep learning models are unable to learn multiple tasks sequentially (Catastrophic forgetting). Deep learning models are Vulnerable to adversarial inputs.

Deep learning models can't derive results in Cross-Domain boundary areas. The intelligence of these models depends on the training datasets because these models usually can't solve the problem that dynamically changes. Neural networks can produce wrong results from inaccurate and incomplete input data. Due to a lack of global generalization, these models can not imagine possible problems and provide solutions. To overcome these limitations, in this work, we proposed three pre-trained models, which are Resnet-50, Vgg-16, and inception-V3 [3, 5, 15-20].

The contributions of this paper are:

- The proposed system uses Big Data of emotion to train deep networks.
- We used the local binary pattern (LBP) image and the interlaced derivative pattern (IDP) image together with the grayscale image of key-frames in the three-dimensional CNN; this gives different informative patterns of key-frames.
- We used four deep-learning models in our experiments: CNN, Resnet-50, Vgg16, and Inception-V3 on two big datasets.
- The proposed framework shows that we achieved 97.93% accuracy by applying robust pre-processing techniques.

II. RELATED WORK

Here we will review some work on the local binary patterns approach for feature extraction. And we will discuss how deep models and transfer models can be feature extractors.

A. LOCAL BINARY PATTERN APPROACH

This study [1] presented cognition and mapped local binary patterns. They constructed pseudo-3-D and performed classifications on Basic Emotion Model and Circumplex Emotion Model. The experiment was done on Cohn–Kanade (CK +), and test datasets were collected manually. The circumplex emotion model achieved higher accuracy in facial expression recognition. This work [2] proposed an algorithm combining gentle boost decision trees and neural networks. Decision trees are trained to extract local binary features and jointly optimize through a shallow neural network architecture. The proposed method (LBF-NN) uses benchmark datasets: CK+, MMI, JAFFE, and SFEW 2.0 and compares admiringly with state-of-the-art algorithms while achieving magnitude improvement in execution time.

In this study [3] they proposed a 2D two-dimensional landmark feature map and integrated framework of convolutional neural network and long short-term memory LSTM. SMIC and CAMSE II datasets show 71 and 74 percent results, respectively. In this research [4] a concept of micro genetic algorithm is proposed to perform feature Optimization. Cohn Kanade and MMI benchmark databases are used for their study. Multiple classifiers are used for recognizing, but their algorithm achieved the best accuracy of 100% over 30 runs for the CK+ database and 94.66 for MMI evaluation. Currently, every well-known organization uses data mining and machine learning applications frequently to explore the meaningful hidden patterns from raw collected data [17-19]. Nowadays, machine learning is used in various aspects of life [20] to perform complex analyses and explore hidden patterns from data points [21].

The authors of [5] calculated the distance between each unique landmark and a nose peak to capture the changes. They implement an experiment done on 3 constraint video data sets. Their model approached an accuracy of 95.97 percent for AM-FED+ Dataset, 94.89 percent for the AFEW dataset, and 91.14 percent for MELD. In the same contrast, deep learning is currently used in most common image recognition tools [22], natural language processing (NLP) [23] and speech recognition software. These tools are starting to appear in applications as diverse as self-driving cars and language translation services.

B. DEEP LEARNING APPROACH

In this article [6], the author introduced a deep learning algorithm divided into three subnetworks. Each network is made of a convolutional neural network. The experiment is based on FER2013, JAFFE, and AffectNet databases. Their proposed algorithm achieved test accuracy of 71.91, 96.44, andv62.11 percent, respectively. In this paper [7], they proposed a CNN method that extracted the edge of each layer of the image. After this, by the maximum pooling method, dimensionality reduction is processed. They mixed up FER2013 and LFW datasets to verify this method's robustness. Their proposed method achieved an accuracy rate of 88.56%. This study [8] proposed a framework based on convolutional layers and residual blocks. The image passed from the Deep Neural Network model. They used two data sets which are Cohn Kanade CK+ and JAFFE. The outcomes of that proposed model have greater accuracy than state-of-the-art methods. This paper [9] uses a deep learning network architecture to perform feature learning tasks. Three datasets in this research are GENKI-4k, CK+, and KDEF. They compared their performances with state-of-the-art methods. Nowadays, computational technologies are being used in various domains of life, including healthcare [24], security [23] and also in safety purposes [21], and disaster [20, 23] as well.

C. TRANSFER LEARNING APPROACH.

In this study [10], to utilize the spatial-angular information, they presented a deep network by the combination of VGG and LSTM. Against nine state-of-the-art benchmarking methods, their model used two protocols. The proposed method with fusion framework, in subject independent, achieved an accuracy rate of 85.62 percent. This study [11] suggested a residual network in ResNet-50 as the model. They used their dataset containing 700 images. With 4 residual blocks, ResNet-50 performed a convolutional operation with 50 conv2D operations for the classification task. They achieved 95.39% accuracy, with is the highest as compared to State-Art-Method.

This study [12] proposed a Transductive deep Transfer Learning network. They used 4 datasets named RAF, SFEW, BU-3DEF, and Multi-PIE. Given the excellent performance of VGG-16 FaceNet, the Transductive Deep Transfer Learning Network achieved excellent accuracies than the state-of-the-art methods. In this research [13], they combined VGG-16 and ResNet-50. They suggested a combination of experiments on four benchmark datasets to evaluate the model. These datasets are AR, Oulu-CASIA, JAFFE, and CK+. The proposed model achieved advanced state-of-the-art recognition rates, 98.9, 96.8, 94.5, and 98.7%, respectively. This study [14] presented a model based on a Weighted Mixture of Deep Neural Networks. A partial VGG16 network is built to extract the facial features automatically. With initial parameters gained from ImageNet, they used fine-tuning to train the network. The ability to remove features automatically is much better than hand-crafts feature approaches. The accuracies they achieved in the benchmarking datasets JAFFEE, CK+, and Oulu-CASIA are 0.922, 0.970, and 0.923, respectively. In this paper [15], they released the iCV-MEFED dataset. This dataset contains 50 categories of compound emotions. Due to this challenging task, they conducted a challenge in this dataset and nominated misclassified emotion categories. So, the third winner used the Inception- V3 method. In this [16] study, they proposed an algorithm based on an active unit for emotion recognition. This algorithm's data processing is faster due to the reduced transfer process. They were using Raspberry Pi improved efficiency. The experiment was done on RAF-DB and Affect datasets. The model achieved 78.62 percent accuracy in RAF- DB and 50.13 in the Affect database.

III. METHODOLOGY

Our proposed framework for facial expression recognition is based on four classifiers: CNN, Resnet-50, Vgg16, and Inception V3. In our designed framework, we give an image to our classifier. We performed pre-processing on the target image. In our pre-processing phase, we resized the greyscale images and saved our target size of an image. After that, we designed our required and trained model on our training set. The trained models will give us the final prediction about the image. Our proposed model is shown in Fig. 1.

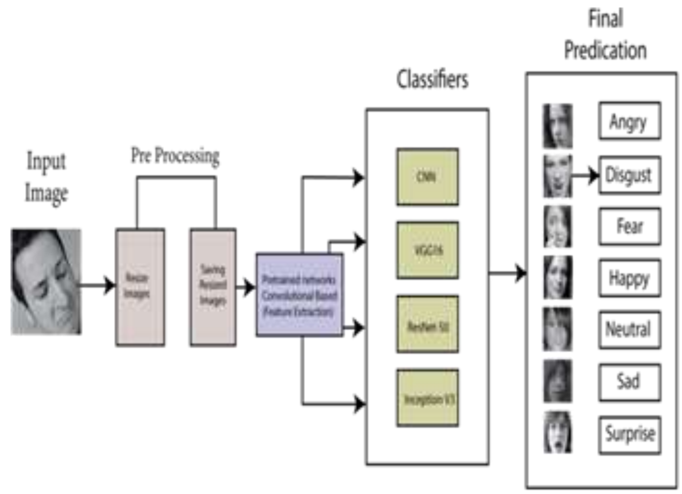

FIGURE 1: Proposed Model.

A. DATASETS

We used two different datasets, FER-2013 and Cohn Kanade (CK+) in this research work. The details of this dataset aregiven in the following sections.

a) FER-2013 DATASET

The first dataset used for this research work is FER-2013. It is available on Kaggle. It comprises 32,298 emotional images, further divided into training and testing samples. So, it has 28,709 images for the training sample and 3589 for testing data. These emotion images have 7 classes of emotions. The seven categories of emotions are angry, disgust, fear, happy, neutral, sad, and surprise. The dataset consists of 48x48 pixels grayscale images. The sample images from the dataset are displayed in Fig. 2.

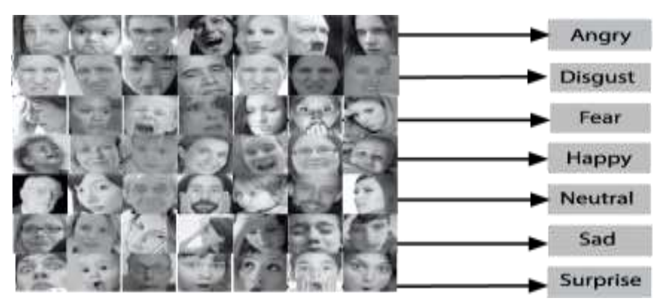

FIGURE 2: Sample of FER-2013 dataset

b) COHN-KANADE (CK+)

This dataset contains a resolution of either 640x490 or 640x480 pixels. 123 different fields are involved in 293 video series. This dataset contains seven expression classes: anger, contempt, disgust, fear, happiness, sadness, and surprise. The sample images from this dataset are shown in Fig. 3.

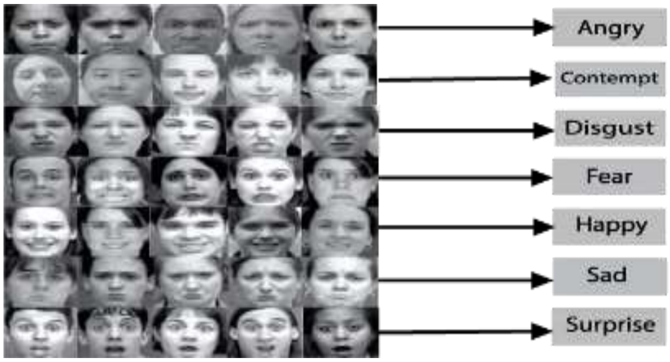

FIGURE 3: Sample of Cohn Extended (CK+) dataset

B. DEEP LEARNING MODELS

This research used the neural network model and three pre-trained models named Resnet-50, VGG-16, and inception-V3.

1) Convolutional Neural Network

Convolutional Neural Networks are feed-forward artificial neural networks whose structure is similar to the visual cortex. Using convolutional neural networks, we can classifytexts, audio, videos, and images.

The other architecture of CNN is described below:

A. Convolutional layer

In convolutional neural networks, the most critical layer is the convolutional layer. This layer consists of a feature detector. This feature detector creates a feature map. The image is passed to a feature map.

B. Pooling Layer

Two techniques for making a pooled map. Max pooling and average pooling. Max pooling is the most popular method.

1. Max Pooling

It picks the leading item that belongs to the feature map.

2. Average Pooling

It calculates the average for each region of the feature map

C. Flatten Layer

Flatten layer converts the output data into a 1-dimensional array. The output of the flattened layer is used to create a single feature vector.

D. Fully Connection

After the flattened layers, it is connected to the final classification model, a fully connected layer.

2) Resnet-50

ResNet-50 is one of the fine-tuned models of deep learning. ResNet-50 consists of 50 layers. In ResNet-50, convolutional and pooling layers are related to the Standard convolutional neural network. Its function is to make the bond between actual and predicted values. For this model, we found 22972 images for testing belonging to 7 classes, 5741 images for validation belonging to 7 classes, and 7208 images for testing belonging to 7 classes. We expand the dimension of the image by using Keras pre-processing (48, 48, 3) to (1, 48, 48, 3). In thismodel, 16 layers are employed and trained on 50 epochs. The Resnet-50 model holds five phases with identity and convolution blocks. 224*224 is its input size, and it belongs to three channels. Each convolution and each identity block has three convolution layers. After these five phases, the upcoming is average pooling layer fully connected to 1000 neurons.

3) VGG-16

One of the mighty deep models with a convolution neural net (CNN) architecture is VGG-16. The most distinguishing feature of VGG-16 is that it focuses on having convolution layers of a *3x3* filter with a stride one and always uses the same padding and max pool layer of a *2x2* filter with a stride 2. It maintains the convolution and max pool layer arrangements throughout the design. It has two FC (completely connected) layers in the final stage, followed by a softmax for output. The 16 in VGG16 is the part of it that has 16 layers with different weights. It has 138 million or such. For both training and testing data, we utilized Image Data Generator, passing the folder containing the training data to the object train data and the folder containing the testing data to the object test data. Image Data Generator will automatically label all 7 emotion classes. This technique prepares data for transmission to a neural network. Initializing the sequential model came first. After initializing themodel, we added 4 dense Layers, and the kernel-initializer used in 3 dense layers is He-Uniform, and the activation function is ReLU, but in last dense layer used a softmax activation layer. We used RELU activation for two thick layers of 32 units. The architecture of VGG-16 is reported in Fig. 4.

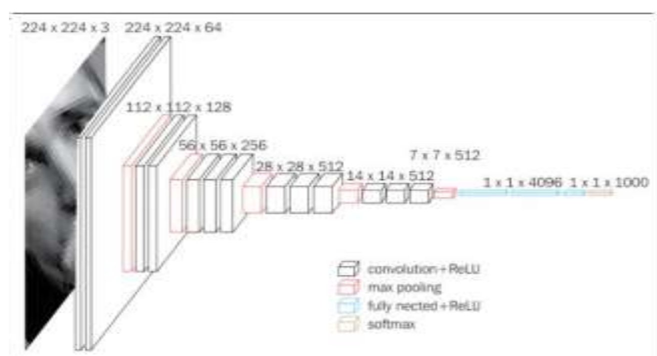

FIGURE 4: Architecture of VGG-16

4) Inception-V3

Inception-V3 is a convolutional neural network that has a depth of 50 layers. This model was created and trained by Google. The pre-trained version of Inception-V3 can classify up to 1000 objects with the ImageNet weights. The image input size of the InceptionV3 network was 299x299 pixels, which is larger than the VGG-19 network.

Furthermore, the complete hyperparameters details of all four models are reported in Table I.

TABLE I: Implementation Parameters of our Models

Parameters	CNN	ResNet-50	Vgg-16	Inception-V3
Model Type	Sequential	Sequential	Sequential	Sequential
Input shape	(48,48,1)	(48,48,3)	(48,48,3)	(48,48,3)
Trainable-params	2,134,407	1,335,815	7,099,399	689,223
Epochs	30	60	30	30
Batch Size	64	64	64	64
Optimizer	Adam	Adam	Adam	Adam
Activation	ReLU	ReLU	ReLU	ReLU
Dropout	(None,32)	(None,32)	(None,32)	(None,32)
Dense	(None,7)	(None,7)	(None,7)	(None,7)
Classification n-function	Softmax	Softmax	Softmax	Softmax
Loss function	Categorial cross entropy	categorical cross entropy	Categorical cross entropy	Categorical cross entropy

IV. RESULTS AND DISCUSSION

For emotion detection using facial expression, we obtained images from two different datasets, which are FER-2013 and CK+, as we mentioned above in the dataset section. For these two datasets, we used one deep learning model called CNN and 3 Pre-trained models, which are Resnet-50, VGG-16, and Inception V3. By experimenting on FER-2013, we achieved accuracy results for CNN, Resnet-50, VGG-16, and Inception V3 are 76.74%, 85.71%, 85.78%, and 97.93%, respectively. Conversely, the Cohn Extended (CK+) dataset reported that the accuracy rates for CNN, ResNet-50, VGG-16, and Inception-V3 are 84.18%, 92.91%, 91.07%, and 73.16%, respectively. Figure 5 reported the compared accuracies of our four models on two different datasets named FER-2103 and CK+.

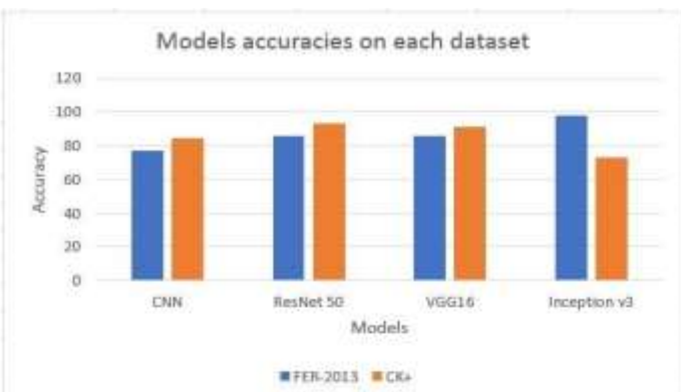

FIGURE 5: Comparative accuracies of proposed models

According to our results, the highest accuracy by using FER-2013 dataset is achieved by Inception-v3, which is 97.93%, while using Cohn Extended (CK+) dataset, we achieved the highest accuracy from Resnet-50, which is 92.91%. The classification task was to classify the seven emotions into seven different classes. Moreover, we plotted a confusion matrix to represent our highest accuracy model's performances. To illustrate the representation of statistical results through experiments, confusion matrices are most frequently used in machine learning and deep learning classification issues. Figure 6 reports the confusion matrix using the Inception-V3 on the FER-2013 dataset. Similarly, Fig. 7 reported the Confusion Matrix of Resnet-50 using CK+ dataset.

FIGURE 6: Confusion Matrix of Inception V3 using the FER-2013 dataset

FIGURE 7: Confusion Matrix of Resnet-50 using CK+ dataset

The performance of a classifier is evaluated from the accuracy, precision, recall, and f-measure parameters as given by,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - measure = 2x \frac{Precision\ x\ Recall}{Precision\ x\ Recall} \quad (4)$$

The precision F1-score curve is another metric to assess the performance of a classification model. In classification, precision only measures true class prediction, while F1-score combines precision and recall into a single metric by calculating their harmonic means. Figure 8 reported the F1-score of the Resnet- 50 models on the CK+ dataset. Similarly, Fig. 9 reported the precision of the Resnet-50 model on the CK+ dataset.

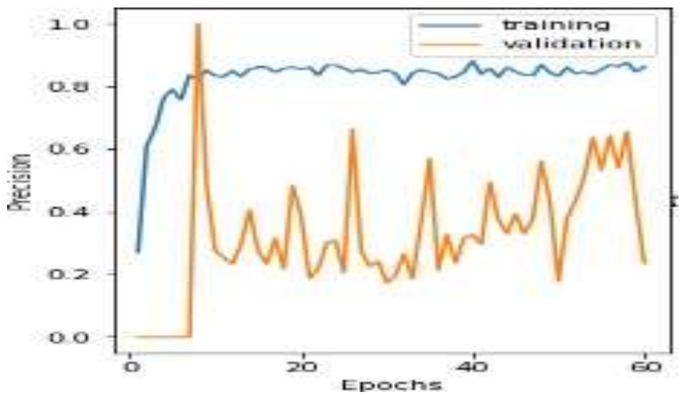

FIGURE 8: F1-measure of Resnet-50 using Cohn Extended CK+ dataset

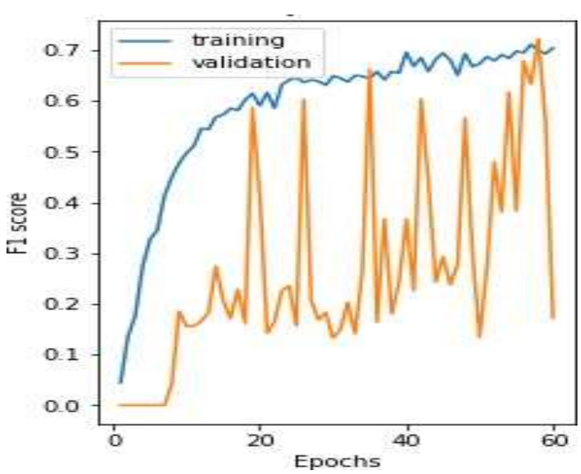

FIGURE 9: Precision of Resnet-50 using Cohn Extended CK+ dataset

IV. CONCLUSION

This research presented a deep learning-based framework for emotion recognition using facial expressions. According to the findings of our experiments, the performance of our deep learning framework is superior to that of the most cutting-edge approaches for emotion recognition when employing well-known emotion corpora. We used two datasets in our experiments. Utilizing the FER-2013 dataset, the experimental results demonstrate that Inception-V3 achieves excellent results with 97.93%, and ResNet-50 achieves remarkable results with 91.92% when using the Cohn Extended (CK+) dataset.

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CONFLICTS OF INTEREST

The authors declare they have no conflicts of interest to report regarding the present study.

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