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Face Recognition using Efficient Net

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Abstract— *Face recognition is a biometric technique that detects a person's facial characteristics. People snap pictures of one other's faces, which are then automatically analyzed by facial recognition software. The paper covers a wide range of facial recognition experiments. The article discusses the stages of facial recognition development as well as the technology that support it. Face recognition is a critical component of video surveillance systems because it allows users to examine and identify persons who appear in a scene acquired by a network of cameras. The recognition of persons from photos has piqued the scientific community's interest, both because of the potential uses and because of the obstacles that artificial vision algorithms face.They must deal with a variety of face characteristics and shooting scenarios (pose, lighting, haircut, expression, background). Face recognition has emerged as a promising future development technique with extensive applications. The motive of this is to study a Convolutional Neural Network-based facial recognition application for a biometric system. It uses a Deep Learning model structure to provide more precision and processing speed.*
Keywords—*Machine Learning; Neural Networks; Deep Learning; Face Recognition; EfficientNet; Convolution Neural Network (CNN); Deep Learning.*

I. INTRODUCTION

Since 1960, face recognition has been a creative breakthrough, and it is a technology that is constantly evolving with a range of real-world applications. To increase the accuracy of face recognition, several calculations and techniques have been devised. Deep learning for desktop apps has gotten a lot of press recently. Convolutional Neural Networks may be used to extract important facial highlights. These high points might be used to reflect on how they seem to one another. The system may be programmed to recognize a group of individuals. We demonstrate several Face Recognition-based apps that may be created. The goal of this study is to see how effective deep CNN architectures are in recognizing faces in photographs under various barrier conditions and with varied proximity estimations.

Face recognition [1] is a technique for allowing a computer system to detect and recognize human faces in pictures or videos rapidly and reliably. To increase the performance of face recognition models, several methodologies and tactics have been devised. For computer vision applications, deep learning has lately gotten a lot of interest. The human brain is capable of automatically detecting and recognizing several faces. On the other hand, doing all of the difficult actions on a computer is impossible at the level of the human brain. Biometrics includes face recognition. Biometrics connects fundamental human features to contemporary data. The present approach models are improved by retrieving and implementing facial features utilizing efficient methods. Computers that recognize and identify faces might be utilized in a variety of applications, including criminal identification, security systems, and identity verification. In general, a face recognition system [1, 2] comprises two steps:

- Face Detection - in this scenario, the input image is scanned for faces, and then image processing is performed to clean up the facial image so it can be recognized more easily.
- Face recognition — determining a person's identity by comparing a detected and processed face to a database of known faces. Face detection differs from face recognition in that we need to know if there is a face in the image, whereas recognition requires us to know who it is. Face features are retrieved and compared to faces in the datasets [1] and [2] that have been similarly processed.

In general, face recognition algorithms may be divided into two types:

- Facial representation approaches — these techniques employ whole-face or part-face images with holistic texture properties.

- Feature-based methods — these strategies make use of geometric face traits (mouth, eyes, brows, and other facial features) and their geometric linkages [3].

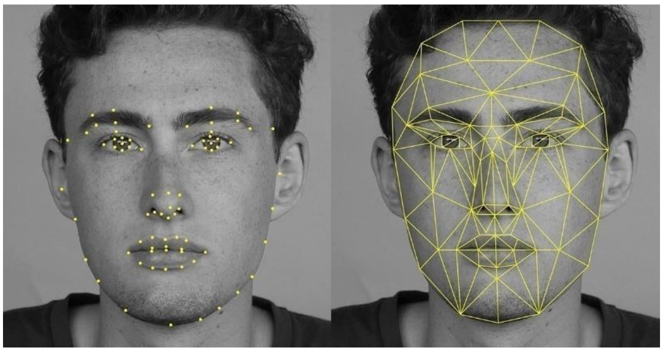

Figure 1: Face Recognition using facial features

Although there are various approaches for improving facial emotion identification accuracy, a rethinking of the training framework and image pre-processing can help applications outperform other algorithms. One difficulty is that, due to the influence of light and other factors, image characteristics may fluctuate at times when the camera snaps photographs quickly. Changes like this might result in incorrect facial expression recognition as shown in Figure 1. To solve this problem for smooth system functioning and maintenance of recognition speed, we introduce adjustments to picture attributes during high-speed capture [3]. The proposed approach relates to the starting picture for averaging rather than the immediate output as a reference to ease recognition. In this method, visual elements can be eliminated as a source of distraction.When compared to merely employing a convolution neural network, the testing results show that using this technique significantly enhances overall resilienceand accuracy of facial emotion recognition (CNN).

Due to the rise in security concerns and humanity's value in law enforcement and industrial applications, the face detection and recognition (FR) technology has been proclaimed an important area of study in recent years [3, 4]. There are two ways of operation in FR. One-to-one matching is the confirmation mode in biometrics. The operational confirmation mode picks a face from a large database of faces to determine if the face information belongs to a certain individual. One-to-many matching is the second method of identification. Authentication entails comparing a person's features to a list of possible IDs. Facial recognition, realignment, modelling (facial expression collection), and classification are the four steps of the FR method.The key problem with the FR system is the data augmentation strategy for identifying and extracting for a certain biometric feature utilizing the best way of description. One of the most crucial processes in picture categorization is the extraction of features. During the feature extraction phase, the most important data is kept for categorization. Independent component analysis is a kind of principal component analysis. Local binary sequences and the distribution technique [4] are two feature extraction algorithms that have been promoted for use in biometric systems.

Convolutional neural networks, a kind of deep learning, have recently risen to prominence as the most popular feature extraction method in FR. CNN provides a diverse set of services. The first step is to learn everything there is to know about the design. The datasets are utilized to train the model, and the pre-trained model's structure is employed in this situation. When the information is large, the second option is to use pre-trained CNN features for action recognition.Furthermore, CNN may be used for transfer learning by keeping the multilayer base in its original structure and sending its findings to the predictor [4, 5]. When there is minimal data or perhaps the problem to be classified is identical, the pre-trained model is used as a static feature extraction technique [4]. The goal of this study was to look into recognition rate by looking at FR performance with pre-trained CNN (EfficientNet Architecture) for extracting features, support vector machine (SVM) [5,] for feature extraction, and eventually transfer learning with CNN (AlexNet model) for both feature extraction and classification.

II. LITERATURE REVIEW

S. Shojaeilangari [6] discusses the use of extreme sparse learning to recognise facial expressions, which is one of the most rapidly increasing and intriguing areas in the next years. Human-computer interaction, automated tutoring systems, picture and video retrieval, smart surroundings, and driver warning systems are just a few of the possible uses. Due of uncontrollable motions, facial emotion is a difficult endeavour. Due to its ability to expose significant data, sparse representation is a well-built tool for reconstructing, representing, and compressing high- dimensional noisy data of images/videos and features. The face representation was proposed utilising the regional covariance matrix. A person-specific approach for rationalising diverse facial expressions was presented using a variable-intensity template. Because of the proposed paper's findings, the suggested emotion recognition system is clearly defined as stable.

In the connection between man and computer, R. Ghasemi

[7] asserts That Recognition of facial expressions is crucial and strong. As a result, the methods were divided into six categories: anger, disgust, fear, happiness, sorrow, and surprise. There are three crucial elements in the face expression process. Face detection and picture pre- processing, feature extraction and feature selection, and classification are the three steps. The eyes, brows, and mouth are the most essential features of a person's face. These regions are automatically achieved by utilising an integral projection curve. As a result, the suggested study improves face emotion identification accuracy while also saving time.

Human emotions, according to S.Mohseni[8] are a major source of facial movements. Human facial expressions contain a lot of information, and fundamental emotions like anger, pleasure, sorrow, surprise, fear, and contempt are crucial facial movements. To show the efficiency of the suggested strategy, it was tested on three distinct classifiers, with an accuracy of 87.7%.

According to B. Yang [9], the major difficulty in facial expression recognition enabling robots to recognise human emotional changes is face detection.The identification performance of hand-crafted features is less reliant on face expression recognition. The basic categories of features employed in FER techniques include appearance, geometry, and motion characteristics. Deep learning, according to G. Yolcu [10], is a subdomain of machine learning that use hierarchical structures to learn high-level abstractions from data. CNN is one of the machine learning courses. Deep learning approaches have made progress in facial emotion identification. In the initial structure of CNN, a face component such as the mouth, eye, and brow regions are cascaded from the rest of the picture in a trained to segment. Segmentation is a binary classification task in which each of the image's 16 16 blocks is classified as a face component. The block's coverage of either face component is greater than 80%. As a result, the suggested paper has a face expression detection accuracy of 93.43 percent.

Client engagements using commercial products and applications are evolving, according to F. Ahmed [11]. Monitoring, interpersonal behavior, information graphics, collaborative drones, even interactive gadgets are all examples of applications. The process is completed by applying rudimentary treatments to the picture. The suggested paper presents GP-based spatial feature extraction integration for face expression recognition. Comparing it against physical attribute characteristics in databases like the CK and JAFFE databases determines the capacity.

N. Song [12] uses facial expressions and sign language to create an emotional speech conversion approach that helps persons with speech impairments and healthy people communicate more effectively. Sign language and facial expression characteristics are highlighted using a deep neural network (DNN) model.According to S. Kim, the facial recognition paradigm has lately gained a lot of popularity. This is because picture capture technology is becoming more and more inexpensive every day. An increasing number of smartphones now come with a camera capable of capturing extremely detailed photographs [13]. As a result, the authors have proposed a unique approach for identifying facial emotion using the facial action coding unit using the deep learning paradigm in this study. The proposed approach has undergone considerable testing and has shown encouraging results. The key disadvantage of the suggested technique is the system's increased computingcomplexity.

According to T. Shen, the paradigm of facial expression recognition has gotten a lot of attention lately. A growing number of academics and researchers are conducting studies and using this technology to a variety of applications, including medical evaluation and HCI (Human-Computer Interface) [14]. As a result, the authors of this paper have proposed a unique face expression detection approach based on the usage of a depth map generated by a Light Field Camera. The results of the experiments show that the suggested methodology greatly improves previous methodologies. The authors have not improved the estimation of light in the depth map, which is a fundamentalflaw in their suggested technique.

S. Gaglio goes into detail about the process of recognising human-like behaviours. RGB-D cameras, such as those used in the Microsoft Kinect, are used to recognise actions. The Hidden Markov Model, Support Vector Machines, and K Mean Clustering [15] were all used by the authors in this research. To create a motion or an activity, the suggested approach uses changes in a human's body positions and joint bending. The suggested approach has been tested for performance evaluation purposes, and the results have been satisfactory. The authors did not enhance the posture

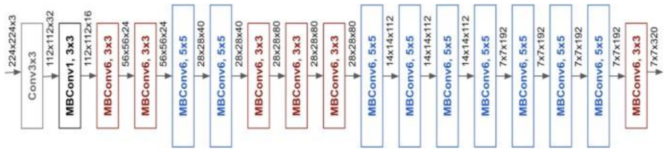

Figure 2: Architecture of baseline network of EfficientNet

estimation procedure, which is the fundamental disadvantage of the suggested approach.

According to S. Happy, the extraction of facial expression elements using a variety of methodologies is the paradigm. Facial feature recognition is useful in a variety of contexts and applications. As a result, the authors of this study have suggested an excellent method for automatically extracting face characteristics using prominent facial patches. These patches make it possible to identify a wide range of facial traits and build landmarks that make face recognition simple and effective [16]. To get successful outcomes, the recommended approach has been thoroughly tested. The key disadvantage of the suggested approach is the observed increased spatial complexity.

According to K. Zhang, one of the most demanding and problematic implementations is facial expression recognition, which is because identifying facial expression characteristics is a very complicated operation [17]. As a result, the authors of this paper present a unique approach for extracting face emotion using PHRNNs (Part based hierarchical Bidirectional Recurrent Neural Networks). The suggested strategy has been tested to see how well it performs, and the results show that it outperforms existing ways. The authors have not used strong structures to describe the mobility of face features, which is the fundamental shortcoming of the suggested approach.

III. EFFICIENTNET ALGORITHM FOR FACE RECOGNITION

The neural network architecture is used to handle various facial attribute recognition problems. To improve the accuracies, discontinuous features among the tasks are leveraged. Initially, the traditional technique is employed as the foundation. CNN is pre-trained on facial recognition using the dataset, immense in number. The 224x224 zone in the center of each shot is traditionally utilized as a pre- processing.

In 1999, Google proposed EfficientNet, a very efficient network concept. EfficientNet can extract features from a deeper neural network by borrowing the residual network to improve the depth of the neural network's depth. EfficientNet can also modify the number of feature layers for each layer to achieve additional feature extraction layers to obtain more features [24]. Finally, the input image's resolution can be enhanced to allow the network to learn and represent more data, improving accuracy. EfficientNet achieves a solid combination of accuracy and efficiency by scaling each dimension using ratios, such as composite scaling, which improves accuracy and speed.

EfficientNet's essential building piece, as indicated in Figure 2, is the mobile inverted bottleneck MBConv, which was initially presented in MobileNetV2. We effectively reduce processing by roughly a factor of k2 when compared to conventional layers by instantly employing shortcut between bottlenecks, which link a significantly lesser number of connections than extension layers, and insight separable convolution. Where k is the kernel size, which defines the size ofthe two-dimensional (2D) convolution window's height and breadth. The key advantage of the EfficientNet model is that it uses a composite scaling approach to scale up CNN in a more structured manner,

As illustrated in Figure 3, the CNN architecture is employed to obtain differentiating face characteristics in the densely integrated layer of CNN, while the SoftMax predictor is used to identify faces. The amount of convolutional and tightly coupled layers, as well as whether batch normalization, dropout, and max-pooling layers are present in the developing model, are all selectable by the user. Many other aspects of the face vary often; thus, the facial traits utilized for face recognition should stay constant. As a result, the facial features gained by CNN trained on an identification job, according to this research [25], cannot be used directly for face recognition. Because higher feature representations have been uncovered in the literature, internal layers of Inception Module C are presumed to be part of the InceptionV3 CNN architecture in this recommended approach. By integrating the feature map from Inception Module C's internal layer with its final feature vector, a multi-feature fusion approach is used.

Figure 4: Images from Dataset

V. FACE RECOGNITION USING IMAGES

As illustrated in Figure 5, a multi-task neural network [26,27] is investigated in this article to address multiple face attribute identification challenges. To improve accuracies, discontinuous characteristics among the jobs are leveraged. As illustrated in Figure 3, the CNN architecture is employed to obtain differentiating face characteristics in the densely integrated layer of CNN, while the SoftMax predictor is used to identify faces. The user may choose the number of which will assist in the feature extraction process for consistently categorizing emotions, as illustrated in Figure
3. Another notable aspect of this model is that it works well with higher-resolution images [24, 25].

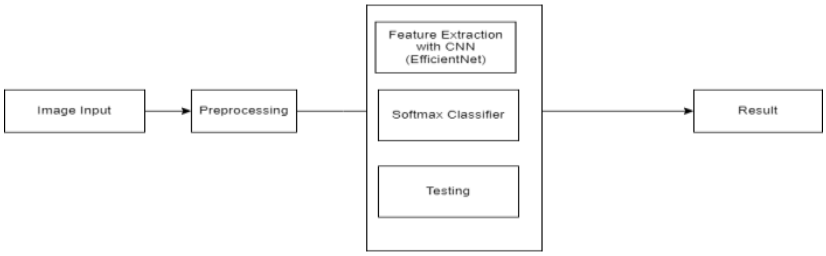

Figure 3: Steps involved in Face Recognition using EfficientNet algorithm.

Module C's internal layers will be evaluated to see which one performs better throughout the fusion process.

IV. DATASET STUDIED

Figure 4 shows 70,000 high-quality PNG photographs with a size of 1024 × 1024 pixels from the collection, which span a wide range of age, ethnicity, and image backdrop. With 59.3 percent males and a range of 80 to 843 photos per identity, the collection is generally gender-balanced, with an average of 362.6 images. A few photos from the dataset are shown in the diagram. As can be shown, a large original dataset can provide a wealth of visual information for the human face recognition task [26]. Unfortunately, in real- world applications, such a perfect database is hard to find. Using the alteration of facial images, a small picture collection may be dramatically expanded to become a large one. As a result, more image attributes could be extracted to train the classifier, resulting in improved face recognition. convolutional and closely linked layers in the developing model, as well as whether batch normalisation, dropout, and max-pooling layers are present. Many other parts of the face change often; as a result, the facial characteristics used for face identification should remain consistent. As a result, the facial features gained by CNN trained on a classification assignment [25], cannot be used directly for face recognition.

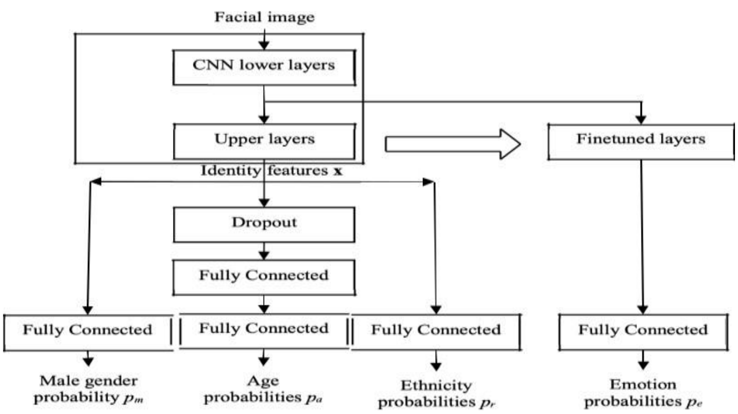

Figure 5: Face Recognition using Images

Using a basic classifier, such as one densely integrated (FC) layer, these characteristics can be used to predict stable properties for a given individual, such as racial socialization. The age of an issue does not remain constant over time, though it does fluctuateslowly [27]. Many other parts of the face change frequently, so the facial characteristics used for face identification should remain stable despite these changes. For example, the intra-class difference between different people who make the same physical expression should be much smaller than the inter- class distance between feature extraction attributes of the same person who has mixed emotions [28].As a result, according to this study, the facial characteristics produced by CNN trained on a recognition job cannot be used directly for expression recognition. Unlike CNN trained on unrelated datasets such as ImageNet, such CNN's bottom layers contain characteristics such as edges and corners, which may be preferable for the latter job. As a result, the face recognition CNN in this study is fine-tuned to either use crucial information about facial features or anticipate facial variables unrelated to classification using the emotion dataset.

VI. RESULT ANALYSIS

The performance of CNNs is seen in Table 1. The time it took to evaluate the mood of one face photo on the MSI GP63 8RE laptop [29] was measured. Although ResNet-18 operates at a comparablepace, the computational complexityand operating length of trained CNNs are both short, as projected.

TABLE I. PERFORMANCE OF EMOTION RECOGNITION MODELS FOR FACE RECOGNITION

ConvolutionalNeural Network	CPU Runningtime, Ms	Parameter count,MB
VGG-16	224.7	134.3
ResNet-18	58.7	11.7
Inception-v3	160.4	19.7
NFNet-F0	621.1	66.4
SENet-50	128.4	25.5
MobileNet-v1	40.6	3.2
EfficientNet-B0	54.8	4.3

The MTCNN was used to recognize the face areas in each picture. When there are several faces in a frame that are element is chosen [29, 30]. Table 2 shows the testing results of individual models.

TABLE II. VALIDATION ACCURACY OF SINGLE VIDEO-ONLY MODELS FORFACE RECOGNITION

Method Used	Accuracy (%)
Noisy student with iterative training [18]	55.17
Noisy student w/o iterative training[18]	52.49
DenseNet-161 [17]	51.44
Frame attention network (FAN) [25]	51.18
VGG-Face [26]	49.00
VGG-Face + LSTM [27]	48.60
DSN-HoloNet[28]	46.47
LBP-TOP (baseline) [16]	38.90
MobileNet-v1	55.35
EfficientNet-B0	59.27

As can be shown, the studied approach has the highest efficiency. After thorough and ongoing pre-training on the body language dataset, the MobileNet is 0.18 percent more effective than the ResNet-18. The EfficientNet-B0 architecture, which is more powerful, improves accuracy by 4%. Even though owing to face recognition mistakes, the entire verification set is not processed, the ensemble classifier approaches its best-known accuracy (59.27 percent). EfficientNet-B0 has accuracy of 59.27 percent, when just 379 validation videos including faces are analysed. It's worth noting that the EfficientNet-based technique is the most often used linear model for this dataset. The winner's DenseNet-121 face model, for example, is 2-4 percent more accurate.In addition, increased face detection can predict huge gains in group-level emotion categorization. The total accuracy for MobileNet and EfficientNet-B0 climbs to 70.31 percent and 68.29 percent, respectively, when only 741 validation films with at least one recognised face are used to test the models. Third, in this challenge, MobileNet features outperform EfficientNet-B0 by 2%, suggesting that both models have benefits in a range of emotion detection tasks.

VII. CONCLUSION

The performance of the EfficientNet method was evaluated experimentally in this work. Various numbers of training and test photographs were used to compute the overall results. So far, the best results have come from convolutional neural networks. When employing sophisticated structures, accuracy rates of approximately 98 percent are possible. Despite this great outcome, CNNs are identified, the face with the biggest structural unable to function without inflicting harm to others. Large training datasets result in a great amount of compute load and memory use, necessitating the use of a lot of computing capacity. This research looks at a novel training strategy for compact neural networks that results in state-of-the-art precision in facial emotion identification in photos and videos for a variety of datasets. It was demonstrated that, as compared to previous models, the facial feature extractor provides more resilience to face extraction and orientation, as evidenced by pre-training the facial feature extractor for Facial expression and features identification using multi- task learning. Faces were sliced with no margins, depending on the areas supplied by face detectors. As a result, there's a lot of precision (Table 4), as well as a lot of speed and model size (Table 3). Consequently, the suggested technique's estimated parameters might be employed inintegrated devices, such as mobile expert machines, to make quick choices. More complex classifiers on top of extracted features, such as graph convolutional networks or transformers, as well as frame/channel-level attention, will be required in the future to improve the standard of facial characteristics and emotion identification.

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