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SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I6P110

Volume 10 Issue 6, 94-105, June 2023
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Original Article

Facial Emotion Recognition using a Modified Deep Convolutional Neural Network Based on the Concatenation of XCEPTION and RESNET50 V2

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Received: 10 April 2023 Revised: 21 May 2023 Accepted: 12 June 2023 Published: 30 June 2023

Abstract *- Facial emotion recognition has gained significant attention in modern years due to its wide applications in numerous fields, including human-computer interaction, market research and healthcare. This research focuses on improving facial emotion recognition accuracy by proposing a modified deep learning method based on the concatenation of Xception and ResNet50 architectures. The proposed approach aims to leverage the strengths of both Xception and ResNet50 networks to enhance facial expression representation and classification. Xception is known for its efficient feature extraction capabilities, while ResNet50 excels in capturing deeper and more complex patterns. By combining these architectures, the modified deep learning model can achieve higher emotion recognition accuracy. The research involves several stages. First, a large dataset of facial expressions is collected and preprocessed. The facial images are then fed into the modified deep-learning model, where feature extraction and classification occur. The model learns to recognize patterns and associations between facial expressions and specific emotions through a supervised learning process. Six distinct pre-trained DCNN models (ALEXNET, INCEPTIONV3, RESNET 50, VGG 16, XCEPTION and the concatenation of XCEPTION and RESNET50 V2) are used to validate the proposed system and with well-known datasets of FER2013, KDEF, CK+ JAFFE and with newly created custom Dataset-1 of 9K facial images. The proposed novel technique showed astounding accuracy, with a validation accuracy of 97.58% for a Softmax classifier, and it also recognized XCEPTION-RESNET V2 as the best network, with training and validation accuracy of 99.99% and 90%, respectively.*

Keywords *- Deep learning, FER, Classifiers, Nets, Dataset.*

1. Introduction

Facial emotion recognition is a technology that detects and interprets human emotions based on facial expressions. It is an interdisciplinary field that combines computer vision, machine learning, and psychology. Facial emotion recognition aims to develop algorithms and systems that can accurately identify and understand an individual's emotional state by analyzing facial features. Human emotions are expressed through various facial expressions, such as happiness, sadness, anger, fear, surprise, and disgust. These expressions involve movements of different facial muscles, which can be captured and analyzed using image or video data. Facial emotion recognition systems use this data to extract relevant features and patterns that correlate with specific emotions. The following steps are usually involved in the face-emotion recognition process:

- Face detection: The first step is to locate and detect faces in an image or video stream. This is done using computer vision techniques to identify facial landmarks and boundaries.
- Feature extraction: Once the faces are detected, key facial features are extracted, such as the position of the eyes, nose, mouth, and eyebrows. These features provide valuable information about the facial expressions.
- Feature representation: The extracted features are then transformed into a suitable format that can be used for analysis. Common representations include numerical vectors or feature descriptors.
- Emotion classification: Machine learning algorithms are trained using labelled data to classify the extracted features into different emotional categories. These algorithms learn to recognize patterns and associations between facial expressions and emotions.
- Model evaluation: The accuracy, precision, recall, and F1 score are among the evaluation metrics used to gauge the effectiveness of the face expression detection system. This aids in evaluating the model's efficiency and dependability.

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Facial emotion recognition has various applications across different fields, including human-computer interaction, market research, psychology, and healthcare. For example, it can enhance emotion-aware interfaces, develop personalized advertising, improve customer experience, or assist in diagnosing emotional disorders.

2. Literature Review

Li and Chen [7] proposed using physiological information collected from the body surface of several people to identify emotion. Four physiological signals, ECG, SKT, GSR, and respiration, rate-were used to extract recognition features. The pattern classifier used was canonical correlation analysis, and its accuracy rate is 85.3%. Fear, neutrality, and joy all had categorization rates of 76%, 94%, and 84%, respectively. The dataset is one of the success factors for accurate emotion detection using facial expressions.

Wfa Mellouk [4] lists existing datasets with their specifications. It also gives different deep learning architectures depending on the accuracy percentage with which it detects the emotion. This paper fails to mention real-time emotion recognition and also fails to differentiate between real and fake emotions. An inception network with transfer learning is used to detect facial emotions. Nithya Roopa, S. [10] has observed 35.6% accuracy in detecting real-time images. The work fails to achieve accurate results. Therefore, the model could have been more reliable with real-time images. In order to recognise facial emotions, DY Liliana [2] uses the Cohn Kanade (CK+) dataset. As a component of the facial action coding system, which symbolises human emotion, this work employs deep convolutional neural network technology to detect the presence of facial action units.

The performance reaches an accuracy of 92.81%. The work fails to differentiate between real and fake emotions and could have been more accurate in real-time. Salem Bin Saqer [3] Marri uses the FERC 2013, JAFFE, and RAVDESS databases. The paper uses fast R-CNN. It is trained using a high-quality video database. This has achieved 94% accuracy in real-time. The limitation of this work is that no accurate results are achieved when the resolution of the face is less, and it also fails to differentiate between real and fake emotions. Xuan-Phung Hujuhuses's [6] database from Chalear's LAP challenge for facial emotion recognition, an extended short-term memory technique with parametric bias, is used here to detect natural and fake emotions. Limitations of this work are that it detects facial emotions with 66.7% accuracy in real-time images.

3. Methodology

This work initially aims at creating a database, which is the critical step in building an accurate model. There are two main steps to developing a standard FER model: Training the created dataset and classification of the test image. Any CNN model has seven layers that make up the training phase: input, convolution, reLU, max pooling, batch normalisation, dropout, and fully connected layers. Depending on the number of times these layers are repeated, they are categorised as different NETS. Every NET is tested for performance accuracy, and the results are recorded. The best classifier is validated using the trained CNN-NET model. The dataset and the NET are kept constant while the classifiers are run on the image to be classified, and each classifier's detection accuracy is recorded. The best classifier is determined to be the one that correctly detects the test image. The outcomes produced by the top classifier are noted. A conventional modified CNN model is produced by enhancing the dataset, NET, and classifier.

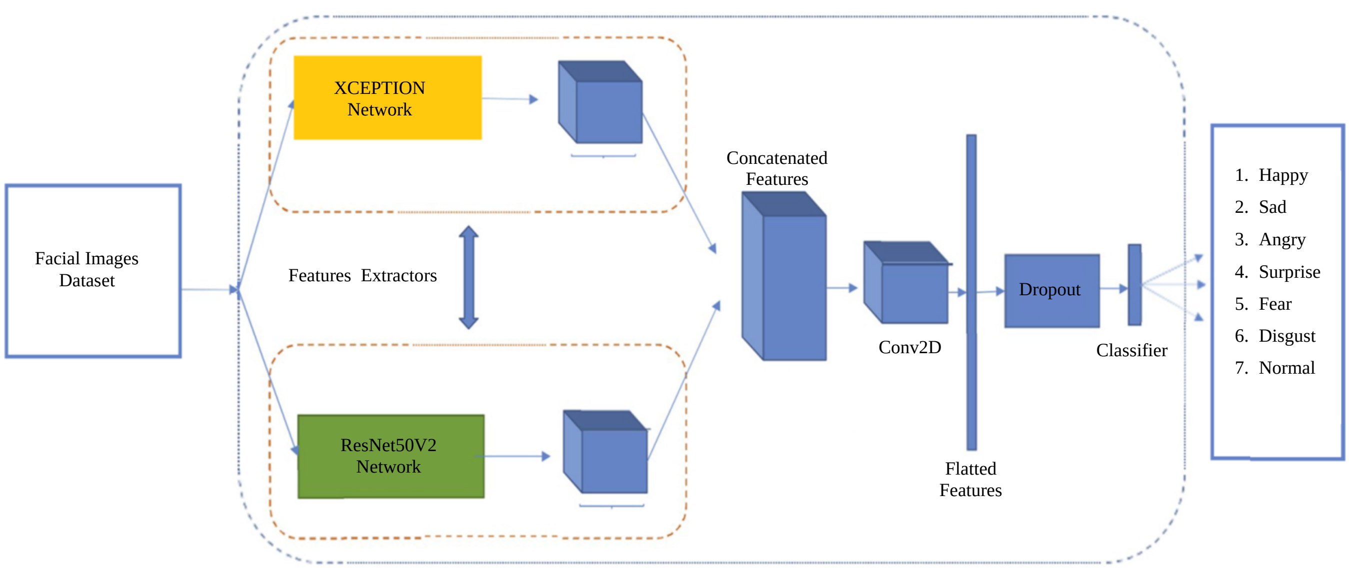


Fig. 1 Framework for the proposed methodology

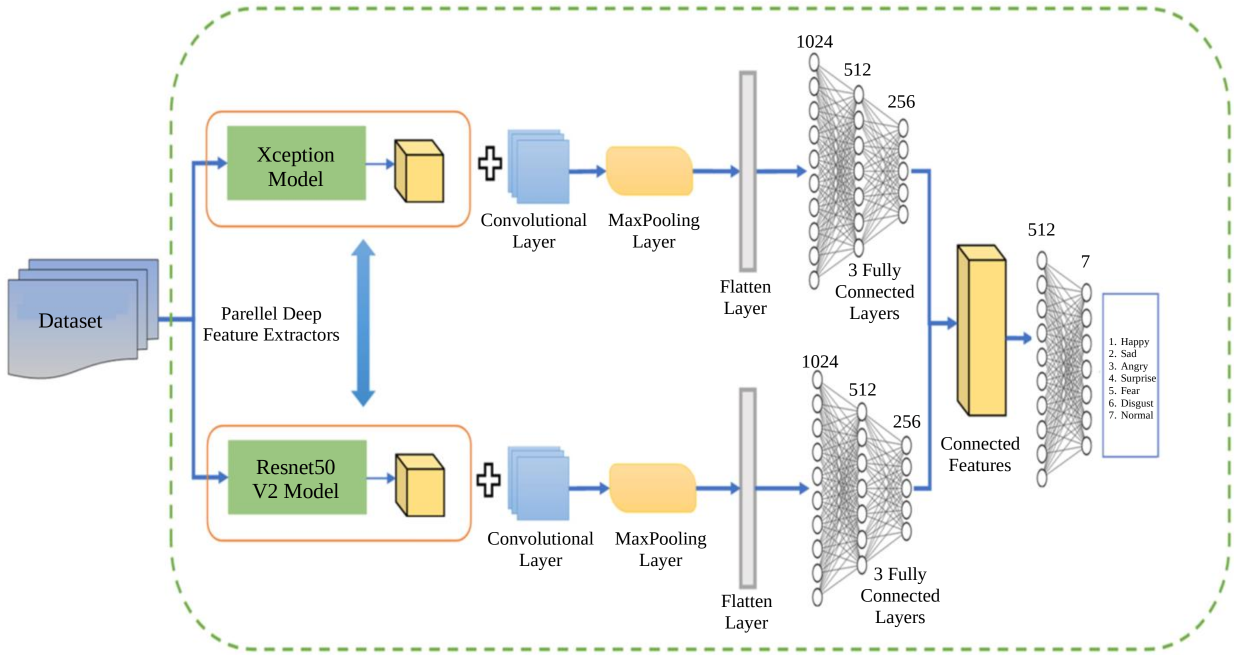


Fig. 2 Proposed architecture of the concatenated network

Table 1. Datasets

Dataset	Number of Images	Emotion Labels	Image Resolution
CK+	593	Anger, Contempt, Disgust, Fear, Happiness, Sadness, Surprise	640x480 pixels
FER2013	35,887	Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral	48x48 pixels
JAFFE	213	Anger, Contempt, Disgust, Fear, Happiness, Sadness, Surprise	256x256 pixels
KDEF	4,900	Anger, Disgust, Fear, Happy, Sadness, Surprise, Neutral, Contempt	Various resolutions
*Custom Dataset-1	9000	Angry-1449, Disgust-1013, Fear-1304, Happy-1617, Sad-1482, Surprise-1461, Normal-1449	75x75 pixels

4. Design and Implementation

4.1. Dataset Description and Data Preprocessing

The dataset combines several existing datasets, including CK+, FER2013, Jaffe, and KDEF. Along with this, a customized dataset was created using Google photographs of Indian faces to boost the dataset's robustness; we gathered a total of over 9,000 pictures for the seven classes, collectively known as Database 1.

The existing dataset has already been preprocessed, whereas the Indian faces are manually selected and preprocessed by using proper preprocessing techniques tailored explicitly for facial emotion recognition; possible results can be achieved by enhancing the quality and relevance of the data, reducing noise and bias, and improving the model's ability to recognize and classify facial expressions of emotions accurately. Here are some critical steps and techniques commonly used in preprocessing to achieve possible results:

Data Cleaning: This step involves handling missing values, outliers, and noise in the data. Missing values can be imputed or removed, outliers can be detected and corrected or removed, and noise can be reduced through techniques like smoothing or filtering.

Data Integration: If the data comes from multiple sources or different formats, it is integrated into a consistent and unified dataset. This may involve resolving inconsistencies, merging duplicate records, or aligning data with a standard schema.

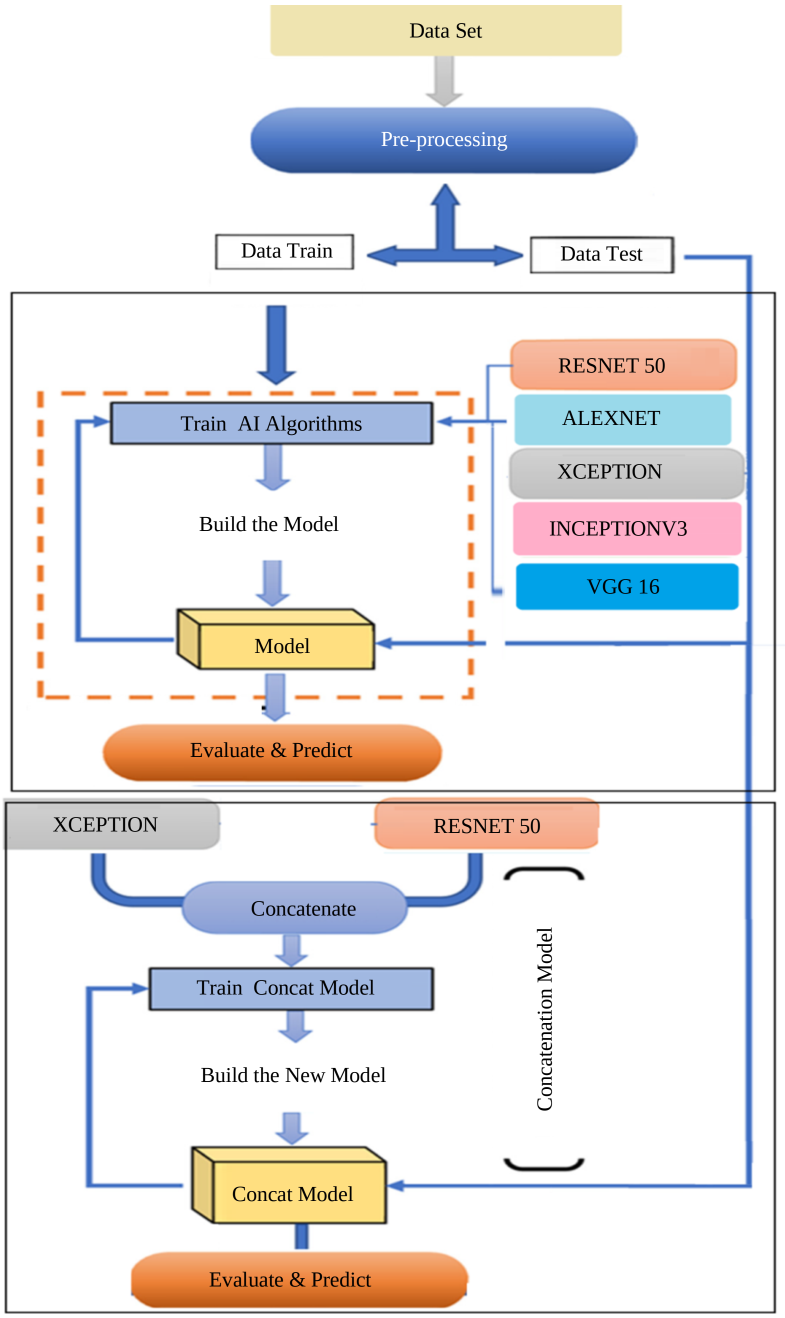


Fig. 3 Flow chart of overall concatenated algorithm

Data Transformation: In this step, data is transformed to meet the assumptions of the modelling algorithms. Common transformations include scaling or normalizing numerical features to a specific range and transforming skewed distributions using techniques like logarithmic or power transformations.

4.2. Model Architecture and Development

Deep learning techniques, particularly CNN neural networks, have significantly advanced recently. Training costs a lot since data models are so complex. In addition, the use of deep learning requires expensive GPUs. The fact that computing restrictions have loosened and better technology is more widely accessible represents a significant advancement. Publicly accessible high-performance models can be successfully modified and utilized as a foundation for the classification of emotions. We broadened this technique by changing the architecture of two models, XCEPTION and RESNET V2 NET, which are subsequently used for classifying based on confidence fusion. This thorough study of several model combinations revealed that the selected models had the most significant evaluation metrics.

The second fully connected layer supports the Softmax activation function, which produces a vector of categorical probabilities for each class. Both models' output vectors are employed in the confidence fusion process that classifies the image. The confidence vectors that both models may offer for every successful sample. To evaluate the proposed technique's prediction performance, Precision, Recall, and F-score, we used the K-Folds cross-validation (k=5) technique. Additionally, it aids in preventing bias in data selection. To maintain the proportion of samples for every class, eighty percent are employed for training, and the other twenty percent are used for testing. This provides a simple method to interpret observations that are not from samples. The concatenation of the Xception and ResNet50 algorithms can be beneficial in some cases, but it also has certain limitations.

Xception is a deep convolutional neural network (CNN) architecture that aims to improve the efficiency and performance of traditional CNNs. It employs depth-wise separable convolutions, which split the standard convolution into two separate operations: a depth-wise convolution and a point-wise convolution. This separation allows the model to capture spatial and channel-wise information more effectively. ResNet50 is a CNN architecture that introduced the concept of residual connections. Residual connections enable the network to bypass certain layers and directly propagate information from earlier layers to the last layers.

This helps alleviate the vanishing gradient problem and allows for the training of intense networks. When concatenating the Xception and ResNet50 architectures, one common approach is to use the output feature maps from both models and concatenate them before passing them through additional layers for further processing. This can potentially leverage the strengths of both architectures and improve overall performance. However, there are a few limitations increased computational complexity, potential overfitting and limited interpretability.

4.3. Tools and Programming Language Used for CNN Model Training

To obtain the original relevant models and apply the suggested modified-based models based on the modified CNN approach, the Tensorflow 2.1 toolbox was employed. The standard API package for Python was used. Models are built using the Keras. We created the concatenation function in Python to combine the model's performances, and we used the Jupyter Framework Library to assess the outcomes swiftly. We also used the free Google Colab platform to train our modified algorithms and proposed concatenation models. Google Colab is a cloud service that leverages the Jupyter Notebook framework to train and study ML and DL algorithms.

5. Results and Discussion

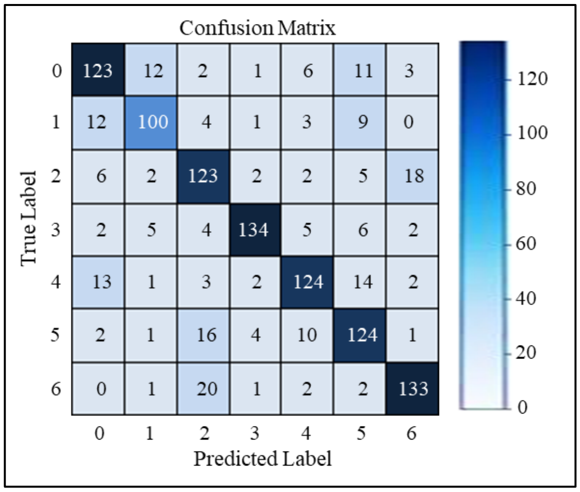
Before discussing the outcomes, we begin by going through several fundamental performance evaluation approaches frequently used to evaluate the ML models during each phase of training as well as testing. We start by computing a few metrics and creating a confusion matrix to evaluate the models' classification. This section presents the parameters and experimental results the studied models acquired. Every class in multiclass classification represents one of the three data types: True Positive (TP), False Positive (FP), and False Negative (FN). True positives show images that have been successfully categorised. False Positive refers to samples mistakenly assigned to the group under consideration, while False Negative refers to samples from the current class that were mistakenly assigned to a different class. Using the qualities mentioned above, several performance measures offer various evaluations. The effectiveness of our suggested methods is assessed using the four metrics listed below:

- Precision: In all samples that were predicted to belong to a certain class, it is the percentage of True classification. Precision=TP/(TP+FP)
- Recall: It speaks of the percentage of genuinely favourable results that were appropriately detected. Recall=TP/(TP+FN)
- F1-Score/F1-Measure: This statistic integrates the concerns about recall and precision into one by providing a single value of the weighted average of both. F−score=(2×Precision×Recall)/(Precision+ Recall)
- Accuracy: Out of all the samples, it is the percentage of correctly categorised samples.

The dataset is maintained constant for the following analysis while several models and classifiers vary.

The various NETS utilized for validation are displayed in Table 2. The dataset, SOFTMAX classifier, and epochs are kept fixed while the model network is varied during validation, and the following findings are noted. Accuracy of Training, Accuracy of Validation, Accuracy of Training Loss, Accuracy of Validation Loss, Strained Parameter, MB, and LR.

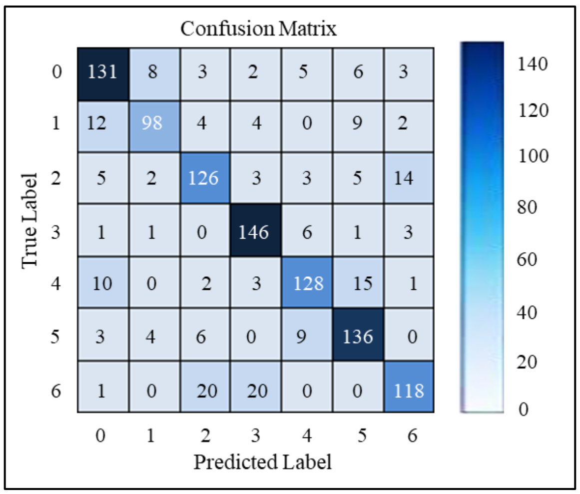
Therefore, XCEPTION-RESNET V2, which has a validation accuracy of 90% and a training accuracy of 99.99%, is the best NET for recognizing facial emotions. Table 3 presents the accuracy results for the different classifiers used for validation. Throughout the validation procedure, the dataset and CNN are kept unchanged. Therefore, the most accurate classifier for distinguishing facial expression is Softmax, which has a validation accuracy of 97.49% with a training accuracy of 99.5%



test accuracy: 79.7961 %

	precision	recall	f1-score	support
0	0.78	0.78	0.78	158
1	0.82	0.78	0.80	129
2	0.72	0.78	0.75	158
3	0.92	0.85	0.88	158
4	0.82	0.78	0.80	159
5	0.73	0.78	0.75	158
6	0.84	0.84	0.84	159
accuracy			0.80	1079
macro avg	0.80	0.80	0.80	1079
weighted avg	0.80	0.80	0.80	1079

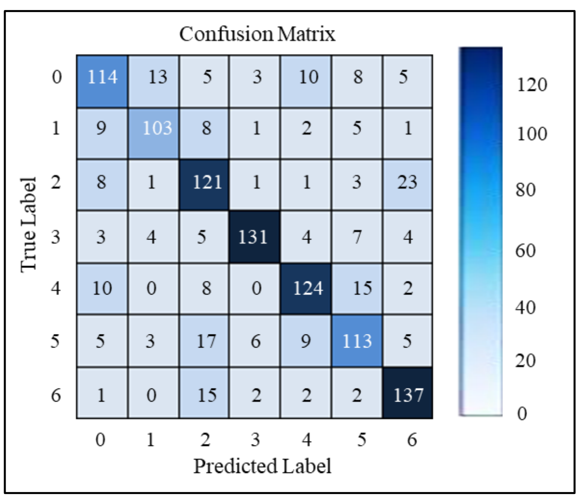
Fig. 4 Confusion matrix and precision, recall, f1-score accuracy of ALEXNET model



test accuracy: 81.835 %

	precision	recall	f1-score	support
0	0.80	0.83	0.82	158
1	0.87	0.76	0.81	129
2	0.78	0.80	0.79	158
3	0.82	0.92	0.87	158
4	0.85	0.81	0.83	159
5	0.79	0.86	0.82	158
6	0.84	0.74	0.79	159
accuracy			0.82	1079
macro avg	0.82	0.82	0.82	1079
weighted avg	0.82	0.82	0.82	1079

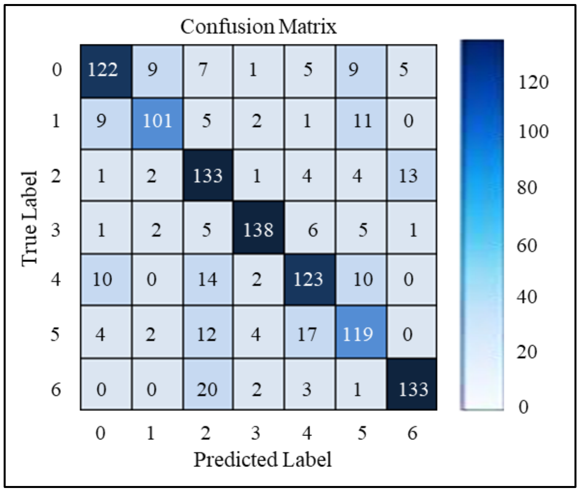
Fig. 5 Confusion matrix and precision, recall, f1-score accuracy of INCEPTION V3 model



test accuracy: 78.1279 %

	precision	recall	f1-score	support
0	0.76	0.72	0.74	158
1	0.83	0.80	0.81	129
2	0.68	0.77	0.72	158
3	0.91	0.83	0.87	158
4	0.82	0.78	0.80	159
5	0.74	0.72	0.73	158
6	0.77	0.86	0.82	159
accuracy			0.78	1079
macro avg	0.79	0.78	0.78	1079
weighted avg	0.79	0.78	0.78	1079

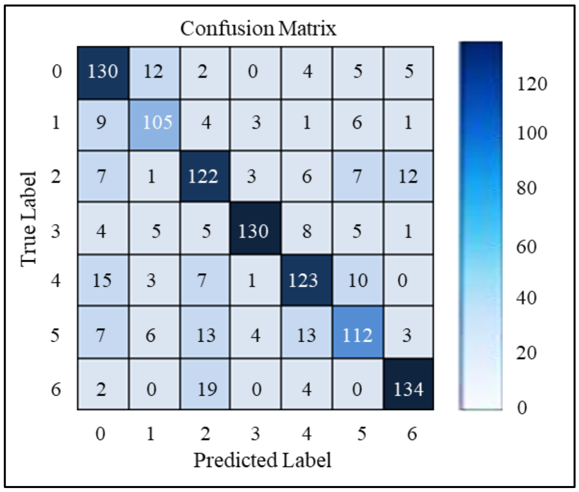
Fig. 6 Confusion matrix and precision, recall, f1-score accuracy of RESNET model



test accuracy: 80.5375 %

	precision	recall	f1-score	support
0	0.83	0.77	0.80	158
1	0.87	0.78	0.82	129
2	0.68	0.84	0.75	158
3	0.92	0.87	0.90	158
4	0.77	0.77	0.77	159
5	0.75	0.75	0.75	158
6	0.88	0.84	0.86	159
accuracy			0.81	1079
macro avg	0.81	0.80	0.81	1079
weighted avg	0.81	0.81	0.81	1079

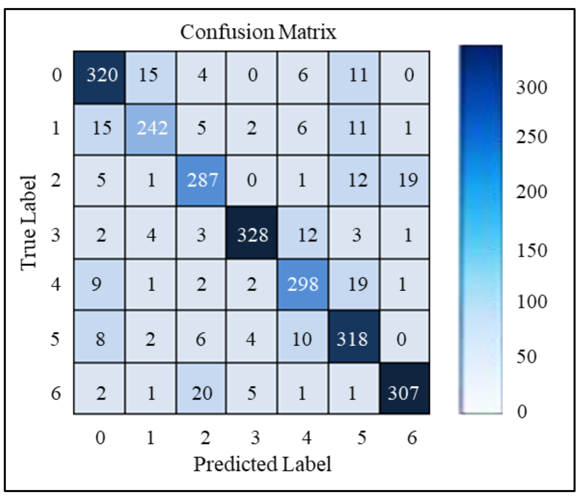
Fig. 7 Confusion matrix and precision, recall, f1-score accuracy of VGG16 NET model



test accuracy: 79.3327 %

	precision	recall	f1-score	support
0	0.75	0.82	0.78	158
1	0.80	0.81	0.80	129
2	0.71	0.77	0.74	158
3	0.92	0.82	0.87	158
4	0.77	0.77	0.77	159
5	0.77	0.71	0.74	158
6	0.86	0.84	0.85	159
accuracy			0.79	1079
macro avg	0.80	0.79	0.79	1079
weighted avg	0.80	0.79	0.79	1079

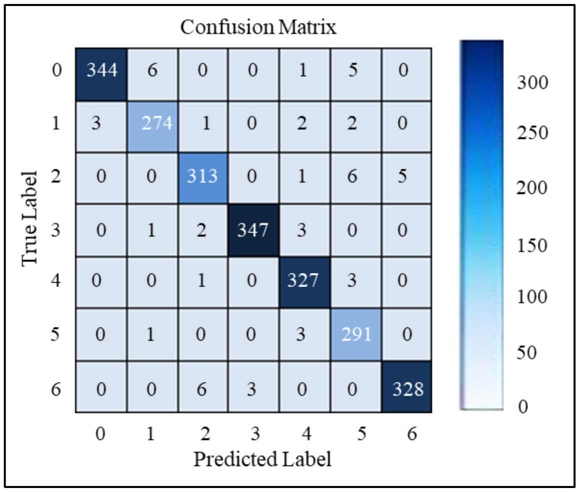
Fig. 8 Confusion matrix and precision, recall, f1-score accuracy of XCEPTION NET model



test accuracy: 79.0129 %

	precision	recall	f1-score	support
0	0.89	0.90	0.89	356
1	0.91	0.86	0.88	282
2	0.88	0.88	0.88	325
3	0.96	0.93	0.95	353
4	0.89	0.90	0.89	332
5	0.85	0.91	0.88	348
6	0.93	0.91	0.92	337
accuracy			0.90	2333
macro avg	0.90	0.90	0.90	2333
weighted avg	0.90	0.90	0.90	2333

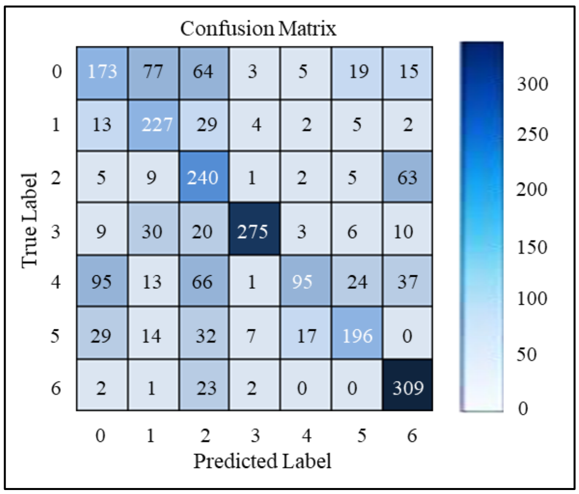
Fig. 9 Confusion matrix and precision, recall, f1-score accuracy of XCEPTION-RESNET V2 net with SOFTMAX



test accuracy: 97.5867 %

	precision	recall	f1-score	support
0	0.99	0.97	0.98	356
1	0.97	0.97	0.97	282
2	0.97	0.96	0.97	325
3	0.99	0.98	0.99	353
4	0.97	0.99	0.98	331
5	0.95	0.99	0.97	295
6	0.98	0.97	0.98	337
accuracy			0.98	2279
macro avg	0.98	0.98	0.98	2279
weighted avg	0.98	0.98	0.98	2279

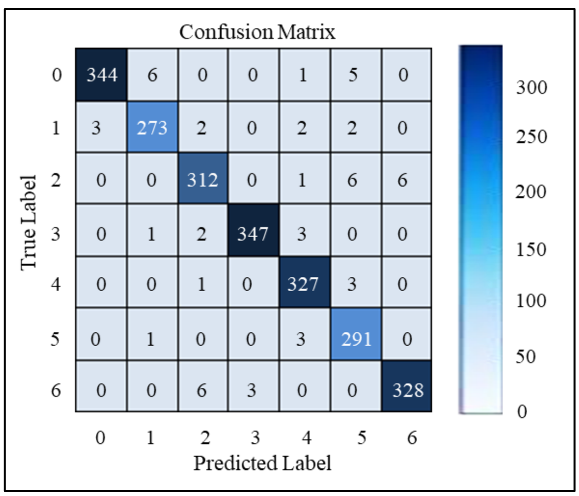
Fig. 10 Confusion matrix and precision, recall, f1-score accuracy of SOFTMAX classifier



test accuracy: 66.4765 %

	precision	recall	f1-score	support
0	0.53	0.49	0.51	356
1	0.61	0.80	0.70	282
2	0.51	0.74	0.60	325
3	0.94	0.78	0.85	353
4	0.77	0.29	0.42	331
5	0.77	0.66	0.71	295
6	0.71	0.92	0.80	337
accuracy			0.66	2279
macro avg	0.69	0.67	0.65	2279
weighted avg	0.69	0.66	0.65	2279

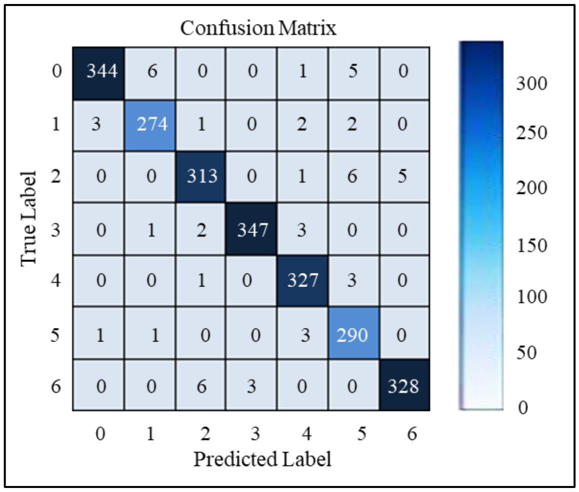
Fig. 11 Confusion matrix and precision, recall, f1-score accuracy of SVM classifier



test accuracy: 97.4989 %

	precision	recall	f1-score	support
0	0.99	0.97	0.98	356
1	0.97	0.97	0.97	282
2	0.97	0.96	0.96	325
3	0.99	0.98	0.99	353
4	0.97	0.99	0.98	331
5	0.95	0.99	0.97	295
6	0.98	0.97	0.98	337
accuracy			0.97	2279
macro avg	0.97	0.98	0.97	2279
weighted avg	0.98	0.97	0.98	2279

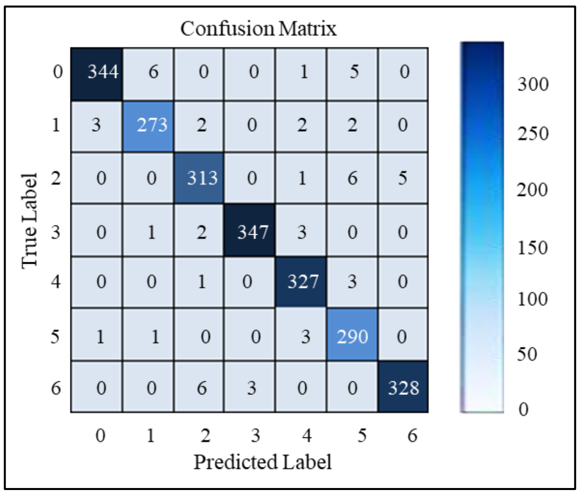
Fig. 12 Confusion matrix and precision, recall, f1-score accuracy of KNN classifier with K = 5



test accuracy: 97.5428 %

	precision	recall	f1-score	support
0	0.99	0.97	0.98	356
1	0.97	0.97	0.97	282
2	0.97	0.96	0.97	325
3	0.99	0.98	0.99	353
4	0.97	0.99	0.98	331
5	0.95	0.98	0.97	295
6	0.98	0.97	0.98	337
accuracy			0.98	2279
macro avg	0.97	0.98	0.98	2279
weighted avg	0.98	0.98	0.98	2279

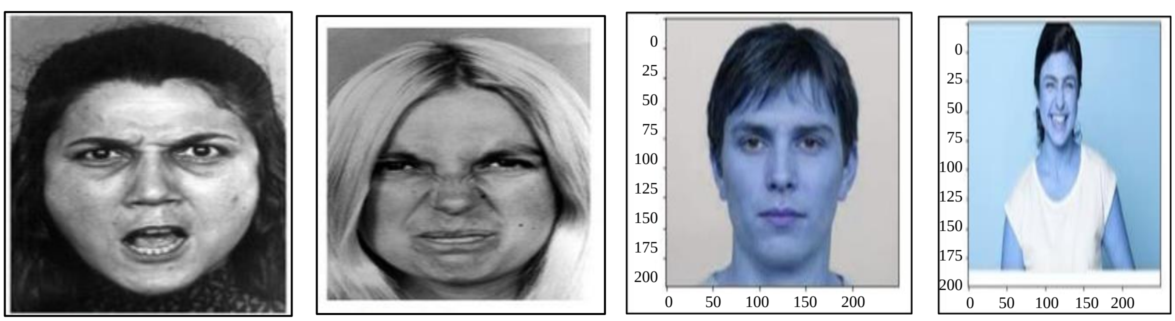
Fig. 13 Confusion matrix and precision, recall, f1-score accuracy of random forest classifier



test accuracy: 97.4989 %

	precision	recall	f1-score	support
0	0.99	0.97	0.98	356
1	0.97	0.97	0.97	282
2	0.97	0.96	0.96	325
3	0.99	0.98	0.99	353
4	0.97	0.99	0.98	331
5	0.95	0.98	0.97	295
6	0.98	0.97	0.98	337
accuracy			0.97	2279
macro avg	0.97	0.97	0.97	2279
weighted avg	0.98	0.97	0.98	2279

Fig. 14 Confusion matrix and precision, recall, f1-score accuracy of SOFTMAX + SVM classifier



Angry Disgusted Normal Happy

Fig. 15 Simulation results of emotion recognition using XCEPTION-RESNET V2 with "SOFTMAX" classifier

The generated dataset is used to evaluate different networks and classifiers. The findings indicate that the most accurate network currently operating is XCEPTION-RESNET V2. Similarly to this, it has been found that Softmax is the best classifier for determining facial expressions. In order to create the standard model, the XCEPTION- RESNET V2 and Softmax classifier are employed. This model's training accuracy for the generated dataset is 99.99%, and its validation accuracy is 90%. The confusion matrix and prediction accuracy of the CNN-produced model are shown in Figures 4 to Figures 14, respectively. The results of seven simulations of different emotions, including happy, sad, angry, disgust, normal, surprise, and fear, are shown in Figure 15.

Table 2. Comparative analysis of models

Nets	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Parameter Strained	Epochs	MB	LR
ALEXNET	0.948	0.7979	0.2494	0.6845	28873219	100	32	0.0005
INCEPTIONV3	0.958	0.8183	0.1127	3.4558	23908135	100	32	0.0005
RESNET 50	0.964	0.7813	0.1132	1.0198	23602055	100	32	0.0005
VGG 16	0.983	0.8054	0.0497	3.4285	33625927	100	32	0.0005
XCEPTION	0.972	0.7933	0.0803	0.9082	21387823	100	32	0.0001
XCEPTION – RESNET V2	0.999	0.9	0.0031	0.8348	41236958	100	32	0.0001

Table 3. Validation and training accuracy of different Classifiers

Classifiers	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Epochs	MB	LR
SOFTMAX	0.9995	0.975867	0	0.024133	70	64	0.0001
SVM	0.9634	0.664765	0	0.335235	70	64	0.0001
KNN	0.9995	0.974989	0	0.025011	70	64	0.0001
RANDOM FOREST	0.9995	0.975428	0	0.024572	70	64	0.0001
SOFTMAX + SVM	0.9995	0.974989	0	0.025011	70	64	0.0001

6. Conclusion

Facial emotion recognition using a modified deep learning method based on the concatenation of XCEPTION and RESNET50 provided promising results in terms of accuracy. This combination of two powerful convolutional neural network architectures can leverage their respective strengths and enhance the overall performance of the emotion recognition system. The XCEPTION network is known for its efficient and accurate feature extraction capabilities, while RESNET50 has demonstrated its effectiveness in capturing deeper and more complex patterns. By combining these architectures, the model potentially benefited from both local and global features, improving the representation of facial expressions and leading to higher accuracy in emotion classification.

The accuracy achieved by this modified deep learning approach depends on various factors, including the quality and size of the training dataset, the preprocessing techniques used, the optimization of hyperparameters, and the overall architecture design. This work includes a significant variety of nationalities in the created 9k dataset to handle these variations and thereby increase the robustness of the model. This work validates the best NET for facial emotion recognition as XCEPTION-RESNET V2, which has 99.99% training accuracy and 90% validation accuracy out of all the existing models, which includes ALEXNET, RESNET 50, INCEPTION V3, VGG16, and XCEPTION models. This work also validates the best classifier for facial emotion recognition as SOFTMAX, which has 99.95% training.

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