International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(1s) 2026 pp. 1-13

https://doi.org/10.70917/ijcisim-2026-1962
Article

Deep Learning-Based Emotion Recognition from Facial Expressions

Santosh B. Dhekale[1], S. S. Nikam[2], D. K. Shedge[3]

[1] Department of E & TC Engineering, AISSMS Institute of Information Technology, Pune Affiliated to Savitribai Phule Pune University, Pune, AISSMS College of Engineering, Pune, INDIA
[2] Department of E & TC Engineering AISSMS College of Engineering, Pune, INDIA
[3] Department of E & TC Engineering AISSMS Institute of Information Technology, Pune, INDIA

Abstract: Artificial Intelligence, Human-Computer Interaction and Human Intelligence are some of the most relevant areas of study at the present time. Especially the facial emotion recognition system that detects human emotions based on human expressions and human facial features has drawn many people's attention due to its wide usage in healthcare, security measures, advertisement, user behavior analysis, and user interfaces.

There are seven major emotions that are commonly distinguished and recognized in humans: happiness, sadness, anger, fear, surprise, disgust, and neutral expression. Facial emotion recognition is based on the changes in facial muscles and emotions' identification based on this feature. Many companies study facial emotions to understand their customers' response to certain goods and services offered and increase the quality of their services.

Random Forest and SVM algorithms have been successfully applied to machine learning. They work well with classification problems but convolutional neural networks are considered to be more accurate and applicable to emotion recognition due to their ability to identify human facial features.

Due to the development in deep learning techniques, modern facial recognition models based on CNNs are able to detect facial expressions in both images and video streams.

In this project, the facial emotion recognition system will be implemented with the use of CNN algorithm in Python with the help of the OpenCV library. The system will be developed based on the CNN classification algorithm for detecting facial features and emotions expressed with the help of facial images.
Keywords: NA

1. Introduction

The significance of recognizing emotions through facial expressions has grown as artificial intelligence merges with human-computer interaction[1]. This connection is essential for understanding human feelings. Human emotions are key in communication. They influence relationships, opinions, and overall perceptions. People express these emotions in various ways, including body language, speech, gestures, and facial expressions[2- 4]. Facial expressions are quite effective for automated analysis in scenarios involving human-computer interaction[5,6]. They seem to be the simplest and most convenient cues for recognizing emotions.

Technological advancements in artificial intelligence, big data, and machine learning have significantly propelled emotion recognition technology to a new level[7-9]. Such progress grants us the capability of recording and interpreting human expressions more quickly and accurately. Here we have chosen a CNN-based method as our primary research comes from the previous deep learning labours in the field of emotion recognition. The study especially concentrates on the publication [5,10], which describes how Convolutional Neural Networks raise the precision and efficiency of the classification in real-time[11]. Deep learning methods, particularly CNNs, are designed to overcome the limitations of conventional machine learning algorithms[12-15]. They prove really good at extracting fine facial details for things like emotion classification [16-22]. This kind of technology finds practical uses in fields such as security. There, detecting emotions adds an extra check for verification. It also applies to marketing, where analyzing emotions in real time helps businesses gauge how customers respond to products and ads [12,24-27]. In this study, we introduce a deep learning-based model that employs a convolutional neural network architecture to classify into anger, disgust, fear, happiness, sadness, surprise, and neutrality. Thus, we aim to improve the accuracy and applicability of automated emotion recognition systems, gives the way for a more intuitive and empathetic human-computer interaction experience [16].

A. Traditional Methods for Emotion Recognition

The most traditional method for emotion recognition was the application of manual feature extraction and classical machine learning algorithms. These methods were based on extracting some particular facial features or action units from images and then applying standard classical machine learning algorithms to classify them. Such methods, although foundational, had severe limitations when handling the complexity of human emotions [17].

Feature-Based Methods:

Traditional approaches were primarily based on feature extraction, where specific facial landmarks or characteristics of the face were defined through human interpretation. From there, the features were interpreted to identify emotions [6].

Geometric-Based Feature Extraction:

Geometric-based methods try to identify and measure specific points in the face, including the positions of eyes, eyebrows, the mouth, and the nose. An analysis about distances, angles, or relative positioning can be used to determine expressions; for example, raised eyebrows together with distended eyes might suggest surprise [17].

Figure 1: Salient Points and Geometric Structure of Facial Expressions

In Figure 1, you can see the geometric mapping of facial expressions through the use of salient landmark points and the relations among them. Each of the mappings represents one particular emotional expression: neutral, surprise, happy, sad, fear, and angry. The mapping of the facial features clearly explains how changes in their relative distances lead to the identification of different emotions.

A. Traditional Machine Learning

Extract geometric or appearance-based features: Classical machine learning algorithms were applied for emotion classification using these features. These are the standard procedures for classification of the expression using the acquired features.

Support Vector Machines (SVM):

SVM was widely applied to affective computing for emotion recognition since they are good classification algorithms, especially in scenarios with limited or small datasets.

In emotion recognition, SVM performed well with geometric feature-based systems in which distances and relationships of facial landmarks could be used as input features for classification.

K-Nearest Neighbors (KNN):

KNN is an algorithm in which data points are classified by the majority class among the k-nearest data points. For emotion recognition, KNN would be useful in classifying emotions by comparing extracted features of a new face with previously labelled examples.

Simple and interpretable, KNN was limited to large diverse training data as it required a comprehensive database of features for successful classification.

Random Forest and Decision Trees:

The Random Forest is an ensemble of decision trees and has been applied for its ability to handle noise and to be robust. In emotion recognition, it was helpful to discover very complicated relations between facial features and emotions without the need of a linear relation.

A. *Limitations and Challenges by Traditional Techniques Hand-Crafted Feature Extraction:*

Traditional approaches relied on handcrafted feature extraction or selection based on expert knowledge to identify salient points or regions on the face. This was time-consuming and sensitive to noise, especially when handling large datasets or varying facial expressions. Manual feature extraction further restricted the capacity for capturing complex or subtle emotional expressions since they depended on predefined kinds of landmarks as well as certain facial features.

Robustness to Environmental Factors:

Traditional methods failed with lighting variability, facial pose, and occlusions such as glasses or hats, which degraded the quality of features extracted. Minor lighting variations could significantly vary appearance-based features, while changes in pose could warp geometric relations between facial landmarks.

Limited Adaptability and Scalability:

Classical algorithms such as SVMs and KNNs were successfully applied on small, controlled datasets but cannot scale up for large, varied datasets. They have not been capable enough to generalize complex datasets with diverse subjects, ethnicities, or age groups [23]. Most importantly, the choice of features was sensitive, and it was not easy to adapt such an algorithm towards subtlety of emotions without considerable amount of personalization.

B. *Shift of Traditional methods to CNN*

While good starting points for developing automated emotion recognition, these traditional approaches also had some significant shortcomings when it came to dealing with real-world variability and complexity. The need for laborious hand-extracted features, fragility toward environmental conditions, and lack of adaptability make for a capability that fails miserably in terms of the reliable and accurate classification of emotions in any but the best controlled or dynamically static settings. These limits have given birth to deep learning techniques, like Convolutional Neural Networks (CNNs), which can automatically learn features from the data and adapt to the variety of conditions in order to make a fantastic splash in emotion recognition.

2. Methodology And Proposed Work

This project deals with designing a real-time emotion recognition system using CNN. It analyses images & live feeds with face expressions. Below, we have described the dataset, pre-processing steps, CNN architecture, model training, and the real-time detection pipeline.

A. Dataset Source

We used an existing dataset of facial expression which is publicly accessible or any other dataset that had labelled pictures of various expressions through a human face. These pictures were classified based on emotions, including the state of happiness, sadness, anger, surprise, and neutrality. We then analysed these various datasets amongst which the FER2013 was most reliable dataset.

Classes of Emotion: The provided dataset has seven key emotions: Happy, Sad, Angry, Surprise, Disgust, Fear, and Neutral for the classification and analysis of facial expressions.

Dataset Splitting: All the data was divided into a training set at 70%, and then 15% each for validation and test set that will actually be used for training and tuning and evaluation of the performance of various models.

B. Pre-processing

Image Standardization: The detected face is cropped using background subtraction method where the foreground image is subtracted from the background image and the facial part is cropped effectively and the image is rescaled for 48 x 48 pixels [17]. The input of all these images is also in grayscale because the color0020information of those images is not at all necessary for emotion detection, and also with the grayscale input; it would make the input and reduce computational loads on the processor.

Normalization: The pixel values were normalized to the range [0,1] using 255. It further accelerates the convergence of the model as inputs end up being uniformly distributed.

Data Augmentation: We have improved the size of our dataset and better the generalization of our model by using horizontal flipping, slight rotations, and brightness adjustments. This kind of augmentation would enable the network to learn robust features for simulating in real-life scenarios.

C. Feature Extraction using CNN

Automatic Feature Learning: The system automatically learns to identify edges, corners, and textures-all the features that would be necessary for distinguishing various emotions from facial images-using a CNN model. Therefore, the architecture of the CNN model is suited for emotion classification from facial images, as it may capture the spatial hierarchies.

Face Detection: In our real-time implementation, we used OpenCV's Haar Cascade Classifier, and we cropped the faces from live video frames before they went into the CNN model. This ensured that the network was interested only in the region concerned with a face, thus increasing the accuracy and efficiency of the prediction.

D. Model Architecture

Convolutional Neural Network Design:

The CNN architecture utilizes different layers of convolution and max pooling followed by a ReLU activation function in order to introduce non-linearity and enhance feature extraction.

Convolutional Layers: The three layers of convolutions in the CNN model are using filter sizes progressively increased for capturing complex patterns, like 32, 64, and 128.

Pooling Layers: A max pooling is applied after the activation function following each convolutional layer. It will reduce spatial dimensions, which help in making a model less computationally complex and less prone to overfitting.

Flatten and Dense Layers: The flattened output from the final pooling layer is then passed through the dense layers. These layers merge features which eventually come into play for classification.

Output Layer: SoftMax activation in the output layer is used, giving the probabilities to each one of the seven emotion classes, meaning that the model will classify each input image into one of its emotion classes.

E. Training and Evaluation

Training Configuration:

Optimizer: Used is the Adam optimizer. This has adaptive learning rates that help improve convergence speed. Loss Function: The categorical cross-entropy loss function was chosen because it applies best for multi-class classification problems.

Training Parameters: The model is trained for 30 epochs while maintaining a batch size of 32, along with tracking the validation loss to avoid overfitting.

Evaluation Metrics: The effectiveness of the model is monitored using accuracy, precision, recall, and F1-score; these helps to determine each emotion that the model has identified correctly.

This is derived from the testing set so that the model has a good view of unseen data.

F. Real-Time Emotion Detection Pipeline

Face Detection in Video Feed: It uses a live webcam feed where faces are being detected through Haar cascades. Their presence is located and cropped for each frame with pre-processes tailored towards the requested input format the CNN model requires.

Emotion Prediction and Display:

For each face, he resizes to 48x48 pixels, converts to grayscale, and feeds into the CNN model.

Each face will be associated with a prediction emotion, and the result will be rendered in real-time with an accompanying bounding box and its predicted emotion label above the person's face.

Optimized for low latency, this system ensures live video frames are processed in real-time with accurate emotion detection in changing environments.

3. Results And Discussion

In our research, we observed that the emotion images in the FER 2013 dataset were not proportionally balanced across all seven emotion categories.

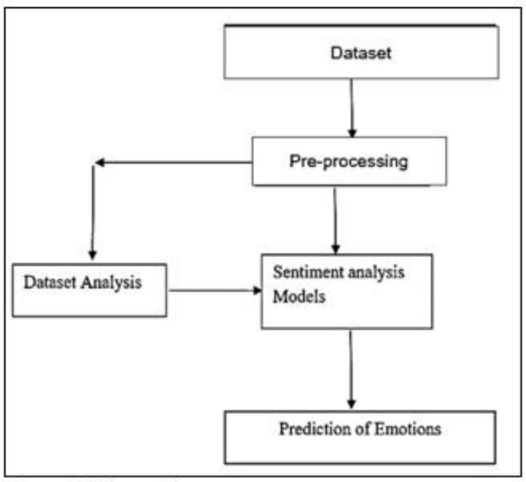


Figure 2: Flow Chart

Figure 3: Labelled Dataset of various image

For increasing the learning capacity and performance of the model, the dataset was modified such that there is more balanced distribution of the emotions in it. The flow chart for the suggested approach is shown in Figure 2 and depicts the step-wise process starting from acquisition of the data to processing, sentiment classification, and emotion detection. In addition to that, Figure 3 shows the annotated data set utilized for training, where facial expressions are shown along with confidence levels.

After training our CNN model on this refined dataset, we achieved following results:

CNN:

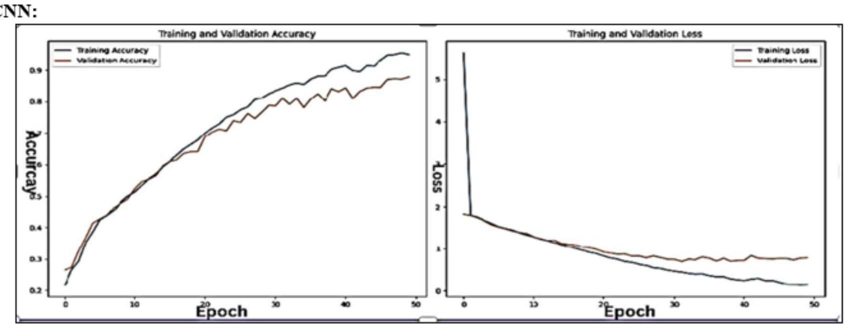


Figure 4: Model Accuracy and Loss

Figure 4 depicts the curves of training and validation accuracy of the CNN model, which are presented in the left panel. The right panel displays the corresponding loss values. With the CNN accuracy going up gradually with the epochs, it is evidently consistent performance improvement of the model. Validation accuracy at the very end of training fluctuates to a very small extent, thus, it can be assumed that overfitting is still under control. Although the loss curve looks more downward than upward, the small fluctuations are still visible. The same patterns come from the mentioned research and confirm that the CNN is a proper tool working with this dataset.

	precision	recall	f1-score	support
angry	0.92	0.94	0.93	793
disgusted	1.00	1.00	1.00	812
fearful	0.93	0.94	0.93	865
happy	0.93	0.90	0.92	770
neutral	0.92	0.90	0.91	794
sad	0.91	0.87	0.89	743
surprised	0.95	0.98	0.97	723
accuracy			0.94	5500
macro avg	0.93	0.93	0.93	5500
weighted avg	0.94	0.94	0.94	5500

Figure 5: Model Performance Metrics

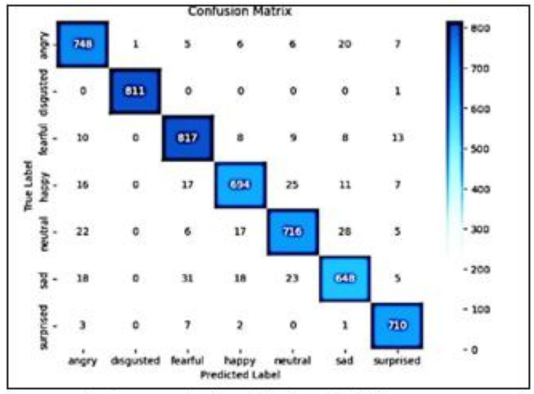


Figure 6: Confusion Matrix

Figure 5 displays the key performance metrics of the CNN, i.e., precision, recall, and F1-score, for each emotion category. The scores stay high in all categories proving that the CNN is good at distinguishing the different emotions. These results corroborate with [27]. The model is the most effective for the "disgust" category where the F1-score of 1.00 is achieved, and then for the "surprise" category with an F1-score of 0.98. Figure 6 explains the CNN performance with the help of a confusion matrix. The rows are the true classes from the dataset, and the columns are the classes predicted by the model. The diagonal elements are the samples that have been correctly classified, and the higher values along the diagonal show stronger accuracy of the emotion categories.

RNN:

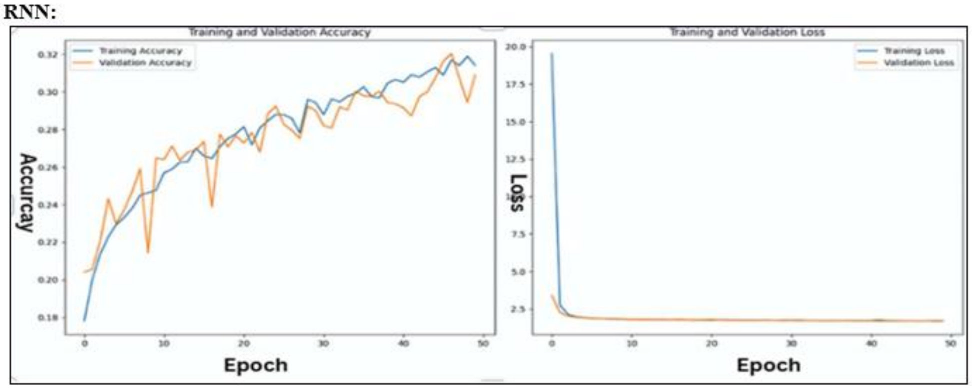


Figure 7: Model Accuracy and Los.

	precision	recall	f1-score	support
angry	0.46	0.17	0.25	818
disgusted	0.79	0.96	0.87	844
fearful	0.29	0.36	0.32	814
happy	0.23	0.35	0.28	735
neutral	0.35	0.17	0.23	767
sad	0.32	0.37	0.35	798
surprised	0.45	0.45	0.45	724
accuracy			0.41	5500
macro avg	0.41	0.41	0.39	5500
weighted avg	0.42	0.41	0.40	5500

Figure 8: Model Performance Metrics

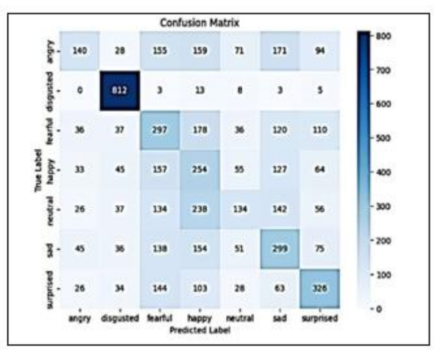


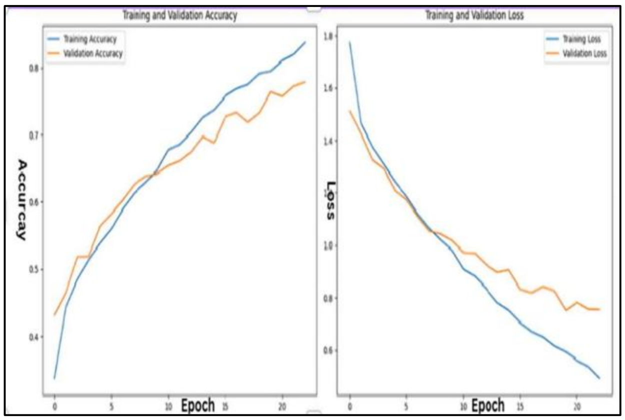
Figure 9: Confusion Matrix

Figure 7 depicts the curves of training and validation accuracy of the RNN model, which are presented in the left panel. The right panel displays the corresponding loss values.

Figure 8 displays the key performance metrics of the RNN, i.e., precision, recall, and F1-score, for each emotion category. The scores stay high in all categories proving that the RNN is good at distinguishing the different emotions.

Figure 9 explains the RNN performance with the help of a confusion matrix. The rows are the true classes from the dataset, and the columns are the classes predicted by the model. The diagonal elements are the samples that have been correctly classified, and the higher values along the diagonal show stronger accuracy of the emotion categories

Resnet50:



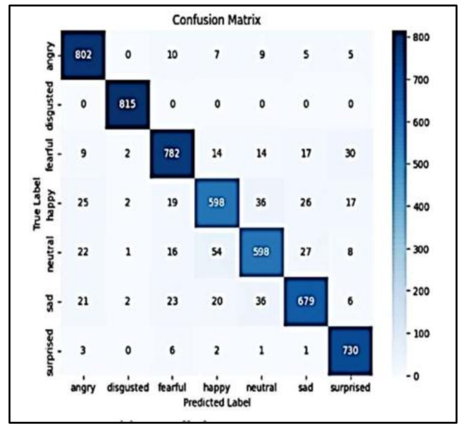


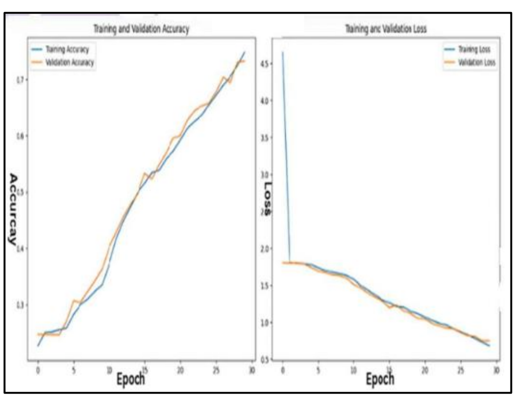
Figure 10: Model Accuracy and Loss

Figure 11: Confusion Matrix

Figure 10 depicts the curves of training and validation accuracy of the **Resnet50** model, which are presented in the left panel. The right panel displays the corresponding loss values.

Figure 11 explains the **Resnet50** performance with the help of a confusion matrix. The rows are the true classes from the dataset, and the columns are the classes predicted by the model. The diagonal elements are the samples that have been correctly classified, and the higher values along the diagonal show stronger accuracy of the emotion categories

VGG-16:



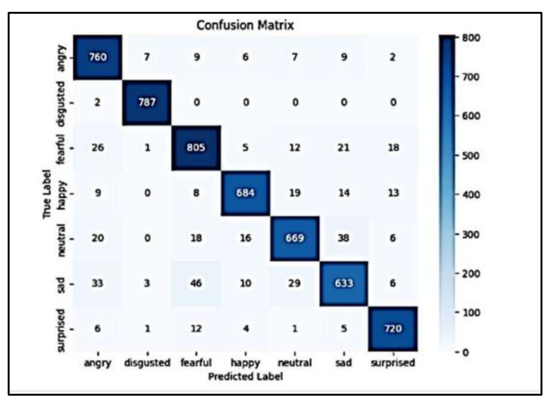


Figure 12: Model Accuracy and Loss **Figure 13:** Confusion Matrix

Predicted Label

	precision	recall	f1-score	support
angry	0.56	0.75	0.64	439
disgusted	0.90	0.44	0.59	43
fearful	0.57	0.44	0.49	511
happy	0.92	0.90	0.91	889
neutral	0.72	0.72	0.72	609
sad	0.59	0.63	0.61	620
surprised	0.84	0.76	0.80	389
accuracy			0.71	3500
macro avg	0.73	0.66	0.68	3500
weighted avg	0.72	0.71	0.71	3500

Figure 14: Model Performance Metrics

Figure 12 depicts the curves of training and validation accuracy of the VGG-16 model, which are presented in the left panel. The right panel displays the corresponding loss values.

Figure 13 displays the key performance metrics of the VGG-16, i.e., precision, recall, and F1-score, for each emotion category. The scores stay high in all categories proving that the RNN is good at distinguishing the different emotions.

Figure14 explains the VGG-16 performance with the help of a confusion matrix. The rows are the true classes from the dataset, and the columns are the classes predicted by the model. The diagonal elements are the samples that have been correctly classified, and the higher values along the diagonal show stronger accuracy of the emotion categories

Figure 15 to Figure 22 We also evaluated our model using the original FER-2013 dataset and achieved the following results: After testing with the modified dataset, we applied RNN, CNN, ResNet-50, and VGG16 algorithms to the original FER-2013 dataset for further analysis.

CNN:

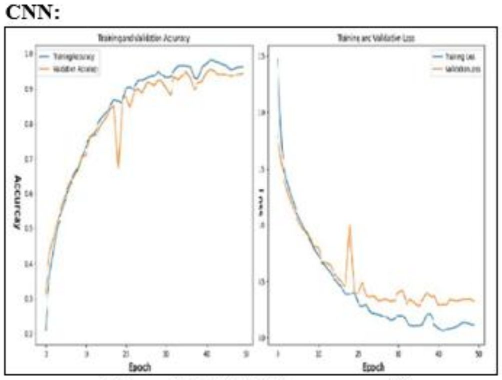


Figure 15: Model Accuracy and Loss

RNN:

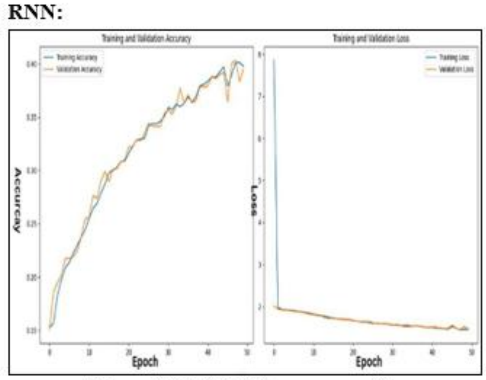


Figure 16: Model Accuracy and Loss

Resnet50:

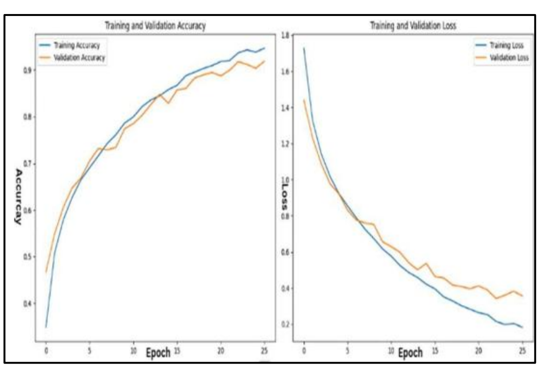


Figure 17 Model Accuracy and Loss

VGG-16:

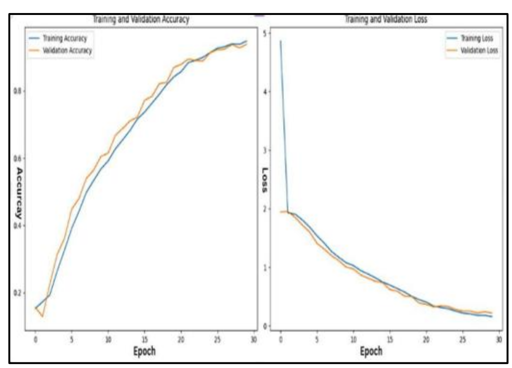
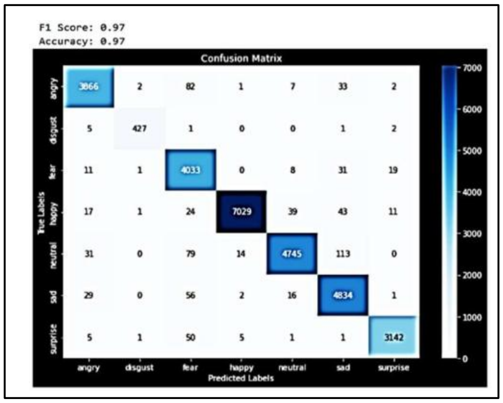


Figure 18: Model Accuracy and Loss



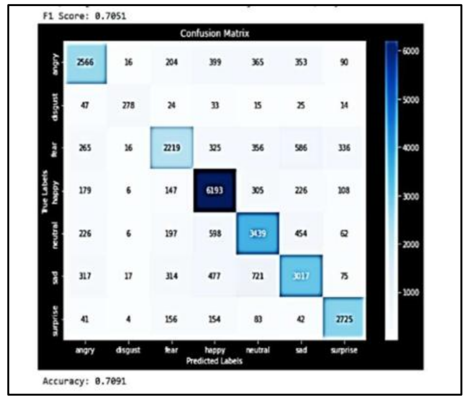
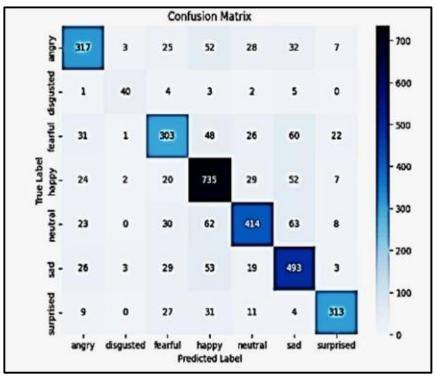


Figure 19: CNN Confusion Matrix

Figure 20: RNN Confusion Matrix



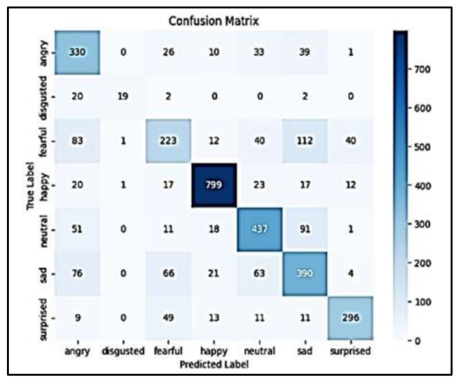


Figure 21: ResNet Confusion Matrix

Figure 22: VGG-16 Confusion Matrix

```
Found 18360 files belonging to 7 classes.
Class names: ['angry', 'disgusted', 'fearful', 'happy', 'neutral', 'sad', 'surprised']
37/37 ━━━━━━━━━━━━━━━━━━━━ 14s 351ms/step - accuracy: 0.8924 - loss: 0.5744
New Test Loss: 0.5626
New Test Accuracy: 89.53%
```

Figure 23: CNN New Testing Accuracy

```
Found 18360 files belonging to 7 classes.
Class names: ['angry', 'disgusted', 'fearful', 'happy', 'neutral', 'sad', 'surprised']
37/37 ━━━━━━━━━━━━━━━━━━━━ 13s 331ms/step - accuracy: 0.2858 - loss: 1.6595
New Test Loss: 1.6587
New Test Accuracy: 29.01%
```

Figure 24: RNN New Testing Accuracy

```
Found 18360 files belonging to 7 classes.
Class names: ['angry', 'disgusted', 'fearful', 'happy', 'neutral', 'sad', 'surprised']
37/37 ━━━━━━━━━━━━━━━━━━━━ 10s 137ms/step - accuracy: 0.8947 - loss: 0.4457
New Test Loss: 0.4528
New Test Accuracy: 89.42%
```

Figure 25: RsNet50 New Testing Accuracy

```
Found 18360 files belonging to 7 classes.
Class names: ['angry', 'disgusted', 'fearful', 'happy', 'neutral', 'sad', 'surprised']
37/37 ━━━━━━━━━━━━━━━━━━━━ 6s 134ms/step - accuracy: 0.7922 - loss: 0.6575
New Test Loss: 0.6700
New Test Accuracy: 78.43%
```

Figure 26: VGG-16 New Testing Accuracy

After testing the first model, which is VGG-16, for seven epochs, it finished with a 54% accuracy rate. The second model got up to 69% accuracy, but that took about 40 epochs [26]. On the FER2013 dataset, the CNN model did even better overall. It managed to reach 74% accuracy [26]. That score really topped VGG-16, since the pre-trained one only hit 55.6% on the same dataset [17]. In the end, these results show that custom CNN approaches tend to handle emotion recognition tasks more effectively than something like VGG-16.

Table 1. From Reference [17]

Classification Accuracy using Lib SVM(RBF) on JAFFE Dataset								
Facial Expression	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise	Classification accuracy (%)
Angry	25	0	3	0	0	2	0	83.33
Disgust	2	24	1	0	0	2	0	82.75
Fear	1	2	25	0	2	2	0	78.12
Happy	0	0	0	27	2	0	2	87.09
Neutral	0	1	0	0	28	1	0	93.33
Sad	0	1	0	0	3	25	0	80.64
Surprise	2	2	0	4	0	0	22	73.33
Overall Accuracy								82.65

Table 1 depicts the results of classification accuracy of the facial emotion recognition using the support vector machine based on the radial basis function kernel for the JAFFE database. As can be seen from the data, the classification of facial emotion depends on the types of emotions being classified, where the most accurate classification corresponds to the neutral emotions of 93.33%, whereas happy emotions have the second-highest classification accuracy of 87.09%. Also, the classification accuracy of surprise and fear emotions was 73.33% and 78.12%, respectively.

Table 2. From CNN NEW MODEL

Classification Accuracy using Lib SVM(RBF) on JAFFE Dataset								
Facial Expression	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise	Classification accuracy (%)
Angry	748	1	5	6	6	20	7	91.71
Disgust	0	811	0	1	2	0	0	99.14
Fear	10	0	817	8	9	8	13	94.22
Happy	16	0	7	694	25	11	7	91.06
Neutral	22	0	0	12	716	28	5	92.68
Sad	18	0	0	31	18	648	5	87.84
Surprise	3	0	7	2	0	1	710	98.47
Overall Accuracy								93.16

Accuracy for the CNN model when applied to the JAFFE database is shown in Table 2. It shows that there is a significant increase in the recognition rates for the emotions over that provided by other models such as SVM. Very high recognition rates were observed for all the emotions except sadness, which scored lower, although still much better than before. The accuracy rate was almost perfect for emotions like disgust, which was 99.14%. Surprise was also very high at 98.47%. Fear was at 94.22%. For emotions the computer was correct 92.68% of the time. Happiness was recognized 91.06% of the time. On average the computer was correct 93.16% of the time, for all emotions.

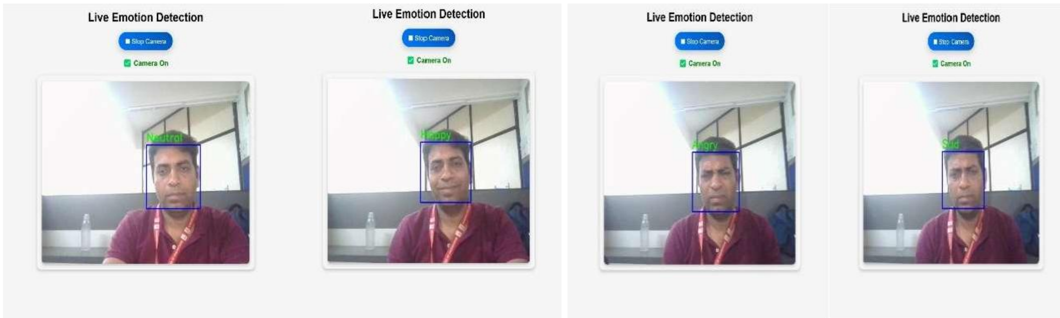


Figure 27: Web UI

The Fig 27 shows the web-based GUI that has been created for detecting the emotions in real-time. The application captures the facial images from the live webcam stream and detects emotions by adding bounding boxes to the faces and finally displaying the emotion detected right on the web interface.

Table 3: Comparison Table- We achieved more accurate results in modified datasets.

Model	Original Dataset (Accuracy)	Updated Dataset (Accuracy)
CNN	Training - 95.5%	Training - 96.48%
	Validation - 87.8%	Validation - 94.44%
	Testing – 84.54%	**Testing – 89.53%**
RNN	Training - 31.70%	Training - 39.70%
	Validation - 30.92%	Validation - 39.58%
	Testing – 22.91%	Testing – 29.01%
ResNet50	Training - 83.23%	Training - 94%
	Validation - 77.80%	Validation - 91.8%
	Testing – 76.87%	Testing – 89.42%
VGG-16	Training - 76.30%	Training - 94.48%
	Validation - 73.24%	Validation - 93.82%
	Testing – 78.43%	Testing – 84%

Table 3:

The comparison between the accuracy of different deep learning models using both datasets is presented in Table 3 below. As can be seen from the results presented in Table 3, the updated dataset helped increase accuracy for each model. CNN had the best testing accuracy rate, which went up to 89.53% as compared to 84.54% for the original dataset. Other models, such as ResNet50 and VGG 16 also showed improvement in terms of their testing accuracy rate by 89.42% and 84%, correspondingly. The least accurate model, RNN, had an accuracy rate of 29.01% after using the updated dataset as compared to 22.91% in the case of the original dataset. Effect size analysis revealed that CNN makes much improvement over VGG-16.

4. Conclusion

We have developed a reliable emotion detection system in this research, which uses CNNs (Convolutional Neural Networks) to detect the emotion someone is experiencing based on their facial expressions. By employing CNNs, we have produced a system that significantly outperforms many existing ML systems built on traditional techniques, and at the same time is far more adaptable to complex real-world situations that may involve changing lighting conditions, changing head poses and/or items blocking parts of an image that could interfere with emotion detection. Furthermore, the strength of this model depends upon how well we preprocess our data prior to feeding it into our neural network, which includes normalizing our data and applying augmentation techniques to compensate for changing environmental conditions. Multimodal media (MM) also helps a lot in this scenario. Things like speech patterns or physiological signals might reveal even more about human emotions. They could provide better insights for real-time applications too.

ACKNOWLEDGMENTS: Not applicable.

FUNDING INFORMATION: Not applicable.

AUTHOR CONTRIBUTIONS STATEMENT *(mandatory)* (10 PT)

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Santosh B. Dhekale	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Dr. S. S. Nikam		✓		✓		✓		✓	✓	✓	✓	✓		
Dr. D. K. Shedge	✓		✓	✓			✓				✓		✓	✓

CONFLICT OF INTEREST STATEMENT*:* Authors state no conflict of interest.

DATA AVAILABILITY: The data that support the findings of this study are available from the corresponding author, upon reasonable request.

BIOGRAPHIES OF AUTHORS (10 PT)

Mr. Santosh B. Dhekale received his BE(Electronics) from Walchand College of Engineering of Engineering Sangli and ME(E&TC) from Sinhgad Academy of Engineering, Pune from Savitribai Phule Pune University, Pune. He is having teaching experience of 17 years and 04 years of Industry Experience. He is associates with AISSMS College of Engineering since 2010. Email ID: sbdhekale@aissmscoe.com

Dr. Shobha S. Nikam received her BE (E&TC) degree from University of Pune, Maharashtra, India in 2007, ME (E&TC - Microwaves) from Savitribai Phule Pune University, Pune in 2012 and Ph.D from AISSMS's Institute of Information Technology affiliated to Savitribai Phule Pune University, Pune in 2022. She has teaching experience of 17 years and research experience of 1.5 years; currently she is associated with AISSMS Institute of Information Technology, Pune as an Assistant Professor in Electronics and Telecommunication Engineering. She has published papers in 29 international journals and presented papers in 7 international conferences. She was principal investigator of ISRO-UOP sponsored research project. She is a life member of ISTE and IETE and member of IEEE. Email ID: shoba.nikam@aissmsioit.org

Dr. D K Shedge is having total 35 years of teaching experience. He Worked as Professor and Head of Department in Department of E&TC, AISSMS Institute of Information Technology affiliated to Savitribai Phule Pune University Pune, Maharashtra, India. He has published papers in 34 international journals and presented papers in 11 international conferences. His area of specialization is CMOS Analog CMOS Design. He worked as BoS member in Savitribai Phule Pune University, Pune. Email ID: shedgedk@gmail.com

References

1. B. J. D. Kalyani, K. P. Sai, N. M. Deepika, S. Shahanaz, and G. Lohitha, "Smart Multi-Model Emotion Recognition System with Deep learning," Int. J. Recent Innov. Trends Comput. Commun., vol. 11, no. 1, pp. 139–144, 2023, doi: 10.17762/ijritcc.v11i1.6061.
2. J. G. Jyothi, J. Kalomika, and T. Manasa, "Detection and Recognition of Human Emotion using Machine Learning," Int.
3. J. Sci. Res. Sci. Technol. (IJSRST), vol. 10, no. 2, pp. 962–965, Jun. 2023.
4. B. K. Kumar, K. Swaroopa, and T. R. Balaga, "Facial Emotion Recognition and Detection Using CNN," Turk. J. Comput. Math. Educ. (TURCOMAT), vol. 12, no. 14, pp. 5960–5968, 2022.
5. R. Deshmukh and V. Jagtap, "A comprehensive survey on techniques for facial emotion recognition," Int. J. Eng. Res.
6. Technol., vol. 6, no. 3, pp. 1–6, 2017

7. G. P. Nam, H. Choi, J. Cho, and I. J. Kim, “PSI-CNN: A Pyramid-Based Scale-Invariant CNN Architecture for Face Recognition Robust to Various Image Resolutions,” Applied Sciences, vol. 8, no. 9, Art. no. 1561, 2018, doi:10.3390/app8091561
8. M. F. Ali, M. Khatun, and N. A. Turzo, "Facial Emotion Detection Using Neural Network," International Journal of Scientific & Engineering Research, vol. 11, no. 8, pp. xx-xx, Aug. 2020, ISSN: 2229-5518.
9. V. Hosur and A. Desai, “Facial Emotion Detection Using Convolutional Neural Networks,” in 2022 IEEE 2nd Mysore Sub- section International Conference (MysuruCon), Oct. 2022, pp. 1–4, doi:10.1109/MysuruCon55714.2022.9972510.
10. S. Depuru, S. Sivanantham, K. Amala, V. Akshaya, M. Sakthivel and P. S. Kusuma, “Empirical Study of Human Facial Emotion Recognition: A Deep Learning,” in Proceedings of the 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1–6, doi: 10.1109/ICCCI56745.2023.10128492.
11. A. K. Talele and B. Chourasia, “Student’s Emotions Identification Using CNN,” International Journal of Advanced Research in Engineering and Technology, vol. 11, no. 11, pp. 1426–1434, Nov. 2020, doi:10.34218/IJARET.11.11.2020.130
12. K. Balasaranya, P. S. Rani, P. A. Sriya, S. K. R. Taj, and N. Anu Reethika, “Real-Time Emotion Recognizer and Classifier for Facial Expressions Based on Machine Learning Approach,” Turkish Journal of Computer and Mathematics Education, vol. 12, no. 10, pp. 1958–1964, 2021. ISSN: 1309-4653.
13. S. Penchala Reddy, J. V. S. Sai Varshini, A. Mounika, T. Vineela, V. Sunil, and O. Prameela, “Facial Emotion Detection Using Deep Learning,” International Journal of Emerging Technologies and Innovative Research (JETIR), vol. 11, no. 5,
14. pp. b779–b782, May 2024, ISSN: 2349-5162.
15. P. Angusamy, S. Inba, K. S. Pavithra, M. Ameer Shathali, and M. Athibarasakthi, “Human Emotion Detection using Machine Learning Techniques,” SSRN Electronic Journal, Jan. 2020, doi:10.2139/ssrn.3591060.
16. B. J. D. Kalyani, K. Praneeth Sai, N. M. Deepika, S. Shahanaz, and G. Lohitha, “Smart Multi-Model Emotion Recognition System with Deep Learning,” International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 1, pp. 139–144, 2023, doi:10.17762/ijritcc.v11i1.6061.
17. J. G. Jyothi, J. Kalomika, and T. Manasa, “Detection and Recognition of Human Emotion using Machine Learning,” International Journal of Scientific Research in Science and Technology (IJSRST), vol. 10, no. 2, pp. 962–965, Mar.–Apr. 2023.
18. X. Lu, “Deep Learning Based Emotion Recognition and Visualization of Figural Representation,” Frontiers in Psychology, vol. 12, Art. no. 818833, Jan. 2022, doi:10.3389/fpsyg.2021.818833.
19. V. G., K. S., H. B., and J. V., “Emotion Detection Using Machine Learning,” NCICCT 2020, vol. 8, no. 08, IJERT, 15 May 2020.
20. S. M. Gowda and H. N. Suresh, “Facial Expression Analysis and Estimation Based on Facial Salient Points and Action Unit (AUs),” International Journal of Electrical and Electronics Research vol. 10, no. 1, pp. 7–17, Mar. 30, 2022, doi:10.37391/IJEER.100102.
21. R. Vamshi N. and B. Raja S., “Facial Expression Recognition using Deep Learning,” arXiv, Jun. 7, 2020.
22. N. Yadav, O. Kudale, S. Gupta, A. Rao, and A. Shitole, “Twitter Sentiment Analysis Using Machine Learning For Product Evaluation,” in Proc. IEEE International Conference on Inventive Computation Technologies (ICICT), Feb. 2020, pp. 181–185, doi: 10.1109/ICICT48043.2020.9112381.
23. A. Maiden and B. Nakisa, “Complex Facial Expression Recognition Using Deep Knowledge Distillation of Basic Features,” arXiv, Aug. 11, 2023.
24. K. R. V. Raj and R. Gododagi, “Fingerprint Recognition using Ordinal Measures,” in Proc. ICESMART 2015, International Journal of Engineering Research & Technology (IJERT), vol. 3, no. 19, 2015.
25. V. Suma Avani, S. G. Shaila, and A. Vadivel, “Geometrical features of lips using the properties of parabola for recognizing facial expression,” Cognitive Neurodynamic, vol. 15, pp. 481–499, June 2021, doi:10.1007/s11571-020-09638-X.
26. V. Andrearczyk and P. F. Whelan, “Texture segmentation with Fully Convolutional Networks,” arXiv:1703.05230, Mar. 15, 2017.
27. A. T. Sahlol, M. Abd Elaziz, A. Tariq Jamal, R. Damaševičius, and O. F. Hassan, “A Novel Method for Detection of Tuberculosis in Chest Radiographs Using Artificial Ecosystem-Based Optimisation of Deep Neural Network Features,” Symmetry, vol. 12, no. 7, Art. no. 1146, 2020, doi:10.3390/sym12071146.
28. B. N. Narayanan, R. C. Hardie, M. S. De Silva, and N. K. Kueterman, “Hybrid machine learning architecture for automated detection and grading of retinal images for diabetic retinopathy,” J. Med. Imaging, vol. 7, no. 3, Art. no. 034501, 2020, doi:10.1117/1.JMI.7.3.034501.
29. C. Sathya and P. Dhatchana, “Facial Expression-Based Emotion Detection for Adaptive Teaching in Educational Environments,” Int. J. Innov. Sci. Res. Technol., vol. 10, no. 1, Jan. 2025, doi:10.5281/zenodo.14613833.
30. A. J. Shawon, A. Tabassum, and R. Mahmud, “Emotion Detection Using Machine Learning: An Analytical Review,”
31. Malaysian J. Sci. Adv. Technol., vol. 4, no. 1, pp. 32–43, Jan. 2024, doi:10.56532/mjsat.v4i1.195.