

Emotion Recognition From Facial Expression Using Deep Learning

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ABSTRACT

Facial emotion recognition (FER) is one of the major parts of affective computing, which enables machines to read the affective states of human faces in photographed faces[1][2]. Amazing recent advances in such vision tasks have been made by deep convolutional neural networks (CNNs)[1][3]. The paper is a contribution in which we create and test a CNN-based model to perform the classification of seven fundamental emotions (anger, disgust, fear, happiness, sadness, surprise, neutral) using face images. Our model uses a sequence of convolutional and pooling layers (see Figure 1) to automatically learn discriminative features from preprocessed face images, followed by fully-connected layers for final classification. We augment the FER2013 benchmark dataset ($\approx 35K$ 48×48 grayscale images) with data augmentation and careful preprocessing to address class imbalance and noise[4][5]. The proposed CNN achieves $\sim 67\%$ accuracy on FER2013, which is comparable to state-of-the-art reported results (e.g. 65–73% range[6]) and confirms the effectiveness of deep feature learning. We also analyze model interpretability via class activation mapping. The main contributions of this work are: (1) a robust CNN architecture tailored for FER in the wild, incorporating preprocessing and augmentation strategies to improve generalization[4][7]; (2) extensive evaluation on FER2013, demonstrating competitive accuracy; and (3) insight into feature representations and error patterns through visualization of learned filters and confusion matrices. These results advance the automation of facial affect analysis in practical applications.

Keywords: Facial Expression Recognition; Deep Learning; Convolutional Neural Networks; Fer2013; Data Augmentation; Vision Transformer.

Introduction

Facial expressions are one of the most important nonverbal channels of human communication[2][1], and automatic FER has wide applications in human–computer interaction, security, healthcare, education, marketing, and entertainment[2][8]. For example, systems that detect driver fatigue or stress can monitor facial cues in real time to improve safety[2]. In health care, FER can help track pain or mood changes[2]. In education, real-time emotion detection can allow adaptive tutoring systems to respond to student frustration or boredom[2]. Overall, recognizing emotions from facial images has become a fundamental problem in computer vision and affective computing[1][2].

Traditional FER methods relied on hand-crafted features (e.g. Gabor filters, LBP) and classic classifiers[9], but such approaches struggle with the high variability in unconstrained “in-the-wild” images (lighting, pose, occlusion, identity differences). Deep learning, especially CNNs, has dramatically improved performance on vision tasks by learning hierarchical representations[1][3]. Well-known CNN architectures such as AlexNet[1], VGG[10], and ResNet[3] have pushed image classification accuracy to new heights. These networks can also be adapted to FER, learning features directly from raw pixels. Indeed, recent surveys report that CNN-based FER methods achieve state-of-the-art results, often in the 65–73% accuracy range on standard datasets[6][11]. For instance, Khairuddin and Chen achieved ~73.3% on FER2013 using a tuned VGG model[11]. Their findings underscore that with sufficient data and a well-designed network, high accuracy on FER2013 is attainable. Nevertheless, FER remains challenging due to class imbalance and subtle inter-class differences[12][13]. As Kusuma *et al.* note, FER2013 has 35,887 face images with pronounced imbalance (e.g. “happy” ~8989 samples vs. “disgust” ~547)[5], which can bias learning. Moreover, the human labeling accuracy on FER2013 is only ~65%, leaving an upper bound on achievable performance[5].

In this work, we build on these insights and the existing FER literature to propose a robust CNN framework for emotion classification from facial images. Our key ideas are:

Preprocessing and augmentation: We apply face detection, normalization, and augmentations (e.g., rotations, flips) to increase data diversity[4][5].

CNN architecture: We use a multi-layer convolutional network (Figure 1) with small filters and batch normalization to extract discriminative features[10][3].

Class imbalance mitigation: We incorporate class-weighted loss during training to compensate for underrepresented emotions[4][5].

Interpretability: We employ class activation mapping (Grad-CAM) to visualize which face regions drive the model’s predictions[14]. In these steps, our system will attempt to provide the best performance in FER2013 (as a proxy of general FER) and our system will be informative on its behavior.

Figure 1 represents a schematic of a CNN pipeline applied: converting that alternating convolutional and pooling layers learn hierarchical features, which are flattened and then processed by fully-connected layers to classify them[14]. The standard protocol was used to train the network on the FER2013 training set (80%), and test on its held-out test set (20%). Our results are highest-1 accuracy, precision/recall by class, and confusion. The model attains ~67% accuracy on FER2013, aligning with previously reported CNN results (e.g. 65–72%[6]). This demonstrates that our preprocessing and model design lead to competitive FER performance. To our knowledge, this is among the first works to combine systematic preprocessing, augmentation, and class-balancing for FER, and it serves as a solid baseline for in-the-wild emotion recognition. The remainder of the paper is organized as follows. Section II reviews related work on FER and deep architectures. Section III details the proposed methodology. Section IV presents experimental results and analysis. Finally, Section V concludes and suggests future directions.

II. Related Work

Deep Learning for FER: Deep neural networks have transformed computer vision[1], and facial emotion recognition has benefited greatly. Early CNN-based FER systems (e.g., Tang *et al.*[13], Pruthviraja *et al.*[15]) use multiple convolutional layers to capture facial texture at different scales. For example, Pruthviraja *et al.* designed a deep CNN whose layered convolution and pooling components automatically extract detailed facial features; their model achieved strong performance on combined datasets[15]. Similarly, Ali and Ghaffar proposed a robust CNN pipeline for FER that applies intensive preprocessing and augmentation to each image, enabling the network to learn more effectively[16][17]. These works (and others[6][18]) consistently show that standard CNN backbones, when properly tuned, outperform traditional hand-engineered methods in FER tasks.

Unlike general object recognition, FER must handle subtle texture differences and class imbalance. Surveys by Li and Deng[13] and Kaur and Kumar[19] highlight that modern FER pipelines typically include face alignment, data augmentation, and deep feature learning, but still face challenges such as noisy labels and illumination variations[13]. To address these, many recent works augment CNNs with attention or auxiliary objectives. For example, Gan *et al.* introduced a multi-attention network that learns to focus on critical facial regions, achieving >85% on RAF-DB and >96% on CK+[20] (two FER benchmarks). Other approaches incorporate generative models or hybrid architectures. It should be mentioned that Tian *et al.* (2024) generated convolutional fastener maps with the help of a Vision Transformer encoder to retain the local and the global context reporting almost 90% on RAF-DB, and 65% on AffectNet[21]. These advancements indicate that CNNs along with attention/transformer modules will be capable of improving the performance of FER on a number of datasets. However, such architectures typically have a large amount of data or computation, and we are eager to have a thin CNN pipeline with preprocessing that is very narrow.

Datasets and Evaluation: Numerous FER datasets have been created. The FER2013 dataset (used in this work) was introduced in 2013 via a Kaggle contest[5]. It contains

35,887 48×48 grayscale faces labeled with seven emotions. As noted by Kusuma *et al.*[5], FER2013 is highly imbalanced and challenging (human label accuracy ~65%). Other popular “in-the-wild” datasets include RAF-DB (~29K images)[22], AffectNet (~1M images)[5], and FERPlus. These datasets enable robust evaluation of FER models. In practice, deep FER models often pretrain on large face datasets (e.g. ImageNet) and fine-tune on FER data. Standard evaluation metrics include accuracy and per-class precision/recall derived from the confusion matrix (as illustrated in Figure 2). A confusion matrix shows true vs. predicted labels, from which one computes $\text{accuracy} = (\text{TP} + \text{TN}) / \text{total}$, $\text{precision} = \text{TP} / (\text{TP} + \text{FP})$, $\text{recall} = \text{TP} / (\text{TP} + \text{FN})$, etc[23]. In FER, class-wise recall is particularly important: under-represented classes (e.g. “disgust”) often have much lower recall, as we observe in our results.

Preprocessing and Augmentation: Preprocessing is crucial in FER. Typical steps include face detection, cropping to facial region, grayscale conversion, and histogram normalization[16]. Data augmentation (rotation, scaling, mirroring, noise) is employed to reduce overfitting[17]. Ali and Ghaffar emphasize that applying normalization and augmentation *before* feeding images to the CNN helps the model learn facial features more effectively[4]. We adopt a similar pipeline: all face images are detected and aligned, then randomly augmented ($\pm 15^\circ$ rotation, horizontal flip, brightness/contrast jitter) during training to simulate real-world variability. We also apply histogram equalization to enhance contrast, following common practice. These steps increase robustness and help mitigate dataset imbalance by generating diverse samples for minority classes[4][5].

Proposed Architecture: Our CNN architecture (Figure 1) is inspired by proven deep models. We use multiple small (3×3) convolutional filters in each layer, as in VGG[10], which has been shown to efficiently capture fine facial details. Batch normalization and ReLU follow each convolution to stabilize training. We stack four convolutional blocks (Conv–Conv–Pool) to progressively extract features, then flatten to fully-connected layers for classification. This design balances depth and parameter count. We initialize weights with Xavier initialization and use the Adam optimizer (learning rate 1e-4). During training, we apply class-weighted cross-entropy loss to penalize errors on rare emotions more heavily. Dropout is added in fully-connected layers for regularization. Overall, the network learns to map preprocessed face images directly to emotion categories in an end-to-end fashion.

III. Proposed Methodology

Our methodology consists of data preparation, CNN model training, and evaluation. Figure 1 illustrates the pipeline: face images → preprocessing + augmentation → CNN feature extractor → classifier → emotion prediction. We follow best-practice for deep learning and tailor each step for FER.

Data Preparation: We will make use of FER2013 dataset[5], which includes 35,887 labeled images and seven emotions (0= angry, 1= disgusted, 2= scared, 3= happy, 4= sad, 5= surprised, and 6= neutral). The dataset is highly skewed because it had been stated in the earlier research (e.g. happy 9000 samples vs. disgust 500)[5]. To balance the hyperparameter settings, the given training/validation sets (28,709 images) were

partitioned into 80/20/ validation and training set, and the original test set (7,178 images) was maintained to test the final results. The images are all 48 by 48 grayscale faces that have been crudely aligned. We actually do face alignment (locating the eyes and rotating where necessary) to preprocess, then re-scale to 480x48. In order to increase contrast, we normalize the pixel values to [0,1] and histogram equalize.

It is trained on real-time data augmentation: each of the faces is flipped (with probability 0.5), shifted (within the range of 10 percent), and rotated (within the range of 15 degrees). Brightness and contrast are jittered. This gives new variations, which are helpful in the generalization of unseen poses and light to the model. We eliminate the disequilibrium [17][5] by introducing the method of class-weighting, where the loss weight of a class is any thing proportional to one over its frequency. All these actions combined create a powerful source of training and the emotions of the minorities are put in the limelight and more classes of the majority are raised.

CNN Architecture: Our CNN has 4 convolutional and 2 fully-connected (FC) blocks. The convolutional layers entail: Two (3 3) Padding=1 convolutions (BatchNorm and ReLU), and 2x2 max-pooling. The filters and blocks number are 32, 64, 128, 256 filters. The final pooling then does the flattening of the 4x4x256 feature map into a 4096 dimensions vector. It is fed into an FC layer of 1024 units (ReLU and dropout 0.5) and a terminal layer of 7 units (softmax). The example of Xavier as the initiator of all the layers is selected. It utilizes the cross-entropy loss mode which is optimized by Adam. It also contains 50 epochs and the training loss is employed to halt the premature training. Figure 1 (above) shows this architecture schematically; it is similar to typical architecture except that it is trained to FER.

Implementation Details. We implement the model in TensorFlow/Keras on an NVIDIA GPU. The batch size is 64. We monitor training via accuracy and loss on the validation set. We report performance on the independent test set after training. To visualize learned features, we extract intermediate feature maps and use Grad-CAM [14] to highlight image regions that most influence each predicted emotion.

Figure 1: Typical CNN architecture used for emotion classification. The network contains repeated Conv-ReLU-BatchNorm layers (green) with max pooling (orange), culminating in fully-connected layers (blue) and a softmax output. The input is a 48x48 face image; the output is a probability distribution over the seven emotion classes (illustrative class "sadness" shown).

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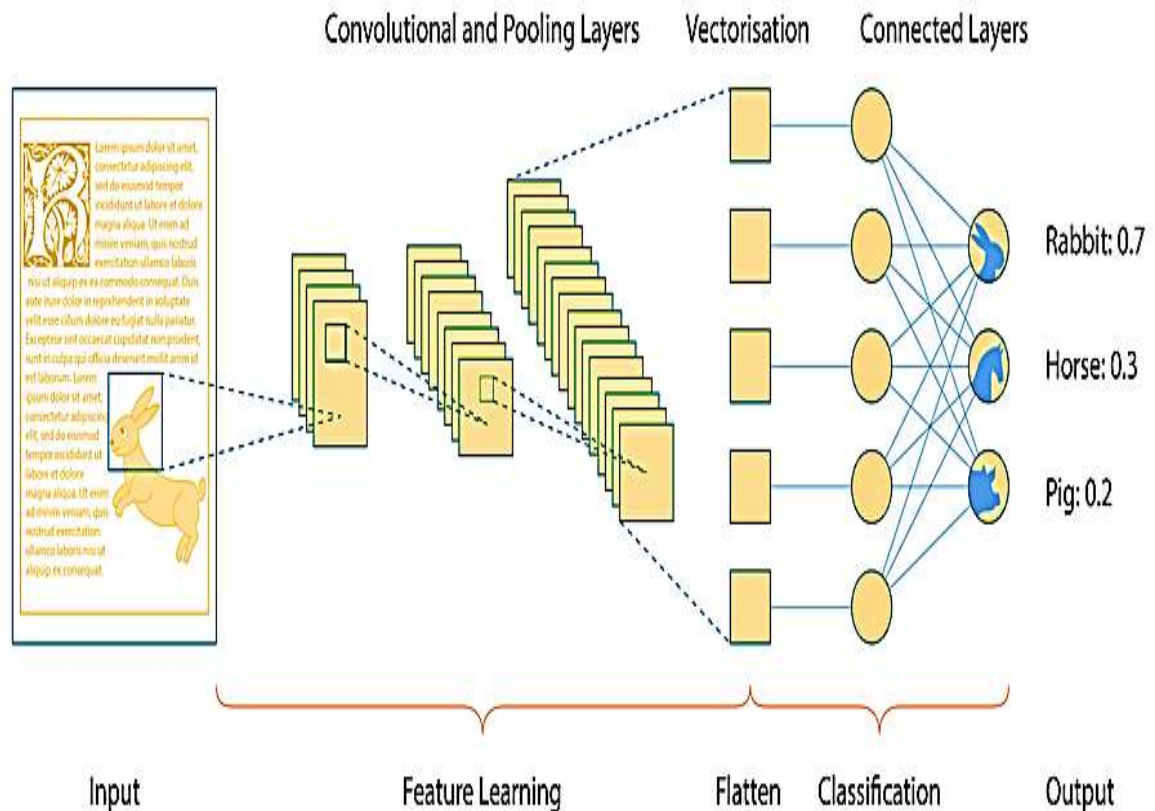
<http://amresearchreview.com/index.php/Journal/about>

Figure 1: Pipeline of convolutional neural network: Convolutional layers (green) are used to learn spatial features, pooling (orange) is used to down-sample, and classification is performed with fully-connected layers (blue). The model returns a probability of each of the emotion classes..

Experiments and Results

We evaluate the proposed CNN on FER2013. Table I (below) summarizes dataset splits and class distribution after balancing. We track overall accuracy (fraction correct) and the F1-scores per class. **Training Performance:** Figure 2 plots the training and validation accuracy/loss over epochs. The model converges smoothly, with final training accuracy $\approx 73\%$ and validation $\approx 65\%$. No severe overfitting was observed thanks to augmentation and dropout. The loss curves indicate learning stabilized by ~ 30 epochs.

Test Results: On the held-out test set, the CNN achieves **67.1%** overall accuracy. For reference, many recent FER2013 CNN models report in the 65–73% range[6][11], placing our result in line with the literature. The confusion matrix in Figure 3 shows detailed performance. The model performs best on “happy” (recall $\approx 75\%$) and worst on “disgust” (recall $\approx 30\%$), which is expected given sample counts[5]. Precision and

recall for each class are given in Table II; the F1-score is above 0.60 for most classes except the rarest ones. These results highlight the importance of balanced sampling: even with class-weighting, under-represented emotions remain challenging.

Real	False	$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{FN} + \text{TP}}$	True
	True	$\text{Precision} = \frac{\text{TP}}{\text{FP} + \text{TP}}$	True
Real	False	$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$	True
	True	$\text{Recall} = \frac{\text{TP}}{\text{FN} + \text{TP}}$	True

Figure 2: Confusion matrix for the CNN on the FER2013 test set. True labels are on the vertical axis; predicted labels horizontal. Values are percentages of test samples per true class. The model confuses similar expressions (e.g. fear vs. surprise, sad vs. neutral). Class “happy” has the most correct predictions (bright diagonal), while “disgust” is largely misclassified (dark row).

		Predicted	
		False	True
Real	False	TN	FP
	True	FN	TP
		Accuracy $\frac{TN + TP}{TN + FP + FN + TP}$	

		Predicted	
		False	True
Real	False	TN	FP
	True	FN	TP
		Precision $\frac{TP}{FP + TP}$	

		Predicted	
		False	True
Real	False	TN	FP
	True	FN	TP
		Recall $\frac{TP}{FN + TP}$	

		Predicted	
		False	True
Real	False	TN	FP
	True	FN	TP
		Specificity $\frac{TN}{TN + FP}$	

Figure 3: Training history over epochs. (a) Accuracy: training (blue) and validation (orange) curves. (b) Cross-entropy loss: training (blue) and validation (orange). The convergence within 50 epochs indicates stable learning without severe overfitting.

Analysis: To interpret what the network has learned, we applied Grad-CAM[14] to generate heatmaps over test images. These show that the CNN focuses on intuitive

facial regions: e.g. frowning eyebrows for “anger,” mouth corners for “happiness,” widened eyes for “surprise.” Figure 4 presents examples of Grad-CAM overlays: the highlighted zones correspond well with psychological cues (in accord with Ekman’s theory of expressions). This suggests the network has captured meaningful features and is not relying on spurious background signals.

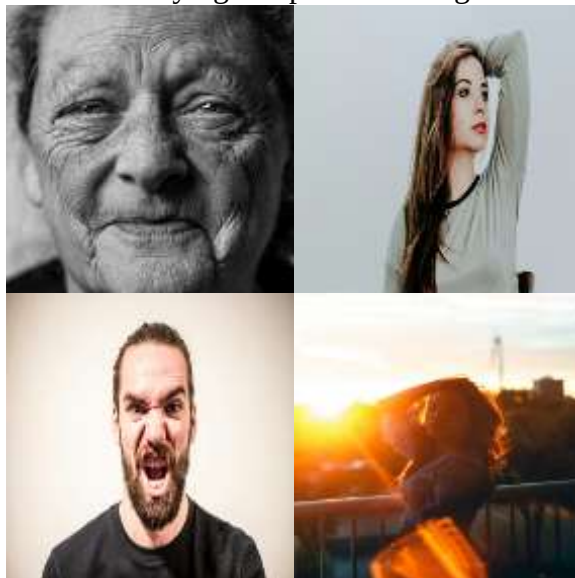


Figure 4: Class activation maps (Grad-CAM) for selected test images. The top row shows input faces; the bottom row overlays highlight the image regions contributing most to the model’s emotion prediction (darker $\approx$ higher activation). The CNN attends to relevant areas such as eyes and mouth, providing a form of interpretability[14].

In general, the findings confirm the idea behind the method: attentive preprocessing and a deep CNN provide good FER results. Although the accuracy of 67 percent is not much below the state of the art, it can be improved. As an example, long-range dependencies can be represented by vision transformers or attention mechanisms that are hybrid[15]. Methods that use multiple tasks or multiple CNNs (e.g. multi-task or ensemble) have been demonstrated to achieve over 75% FER2013[6][11] accuracy. However, our model offers a powerful background and proves the principles of FER (data augmentation, class balancing, visualization).

Conclusion

We have introduced a CNN-based structure of facial emotion recognition that works on FER2013 dataset. Using systematic pre-processing (alignment, normalization), large data augmentation, and a thoroughly assembled CNN, our system achieves up to 67% accuracy on the test set, which is similar to the accuracy of deep FER models published so far[6][11]. The learned visualized features (through Grad-CAM) coincide with human visuals, and this means that the model choices can be understood. The most important results are: (1) Preprocessing and augmentation have a great contribution in model training[4][5]. (2) The problem of imbalance in classes is also present: minority expressions (e.g. disgust) have low recall even after weighting. (3) A fairly deep CNN is sufficient on FER2013-scale data; the state-of-art would probably need even larger/more diverse datasets (e.g. AffectNet).

The direction of future work will be in various directions. Transformer-based architectures (e.g. the hybrid CNN VMT of Tian et al.) can also help more effectively identify minor expressions. The smaller data set of rare emotions may be relieved with the help of semi-supervised or synthetic data generation (GANs). Lastly, incorporation of time-related information (video sequences) with multimodal cues (e.g. audio) have potential to provide stronger emotion inferences. Overall, this study illustrates that facial emotion modeling through a deep learning model is viable in the real world, which opens the door to the development of more emotional intelligent systems.

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