Facial Emotion Detection Using Convolutional Neural Networks Bridging the Gap between AI and Human Interaction

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***Abstract*—A key requirement for developing any innovative system in a computing environment is to integrate a sufficiently friendly interface with the average end user. Accurate design of such a user-centered interface, however, means more than just the ergonomics of the panels and displays. It also requires designers to specify what, how, where, and when to use information. Facial expression as a natural, non-intrusive, and efficient way of communicating has been considered as one of the potential inputs of such interfaces.**

The work of this thesis aims at designing a robust Facial Expression Recognition (FER) system by combining various techniques from computer vision and pattern recognition. Expression recognition is closely related to face recognition, where a lot of research has been done and a vast array of algorithms has been introduced. FER can also be considered a special case of a pattern recognition problem, and many techniques are available. In the designing of an FER system, we can take advantage of these resources and use existing algorithms as building blocks of our system. So a major part of this work is to determine the optimal combination of algorithms. To do this, we first divide the system into 3 modules.

Namely feature extraction, classification, and preprocessing. After that, several candidate techniques are applied for each of them, and finally, by evaluating the effectiveness of various configurations, the ideal setup is identified.

The classifier, which is the heart of the facial expression recognition system, is another topic that fascinates designers of such systems greatly. The assumption made by traditional classification algorithms is that the image is a single variable function of the underlying class label. This is untrue in the face recognition domain, though, where a variety of characteristics, such as identity, expression, illumination, and so forth, affect how a face appears.

***Index Terms*— FER, CNN, recognition, emotions**

I. INTRODUCTION

Human communication relies heavily on facial expressions, which act as nonverbal indicators of intentions, feelings, and social context. Accurate recognition and interpretation of these expressions are crucial in a number of fields, such as emotional computing, social robotics, psychology, and human-computer interaction. Facial expressions are useful in daily life for navigating social situations, empathetic communication, and the comprehension of complex emotional states. The need for systems that can recognize and react to human emotions has increased as technology becomes more and more ingrained in our daily lives, making the research of facial expression recognition more and more pertinent.

Facial expression recognition and detection have been completely transformed by recent advances in artificial intelligence, especially with the use of Convolutional Neural Networks (CNNs). CNNs are highly skilled in autonomously deriving intricate and hierarchical feature representations from unprocessed picture data, which allows them to accurately detect even the smallest changes in face expressions. Facial expression recognition systems' performance has significantly improved as a result of this capacity, opening up more reliable applications for real-time settings.

The development of research in this area has been greatly aided by benchmark datasets like FER2013, CK+, and JAFFE. It is especially important to look at the FER2013 dataset because of its magnitude and variety of photos, which show a variety of facial expressions and emotions. It is now used as a baseline for comparing the performance of different facial recognition models and consists of 35,887 annotated photos divided into seven emotion categories. Utilizing this dataset, researchers have improved our knowledge of emotion recognition and spurred innovation by using it to train and test their systems.

The future holds great promise for the application of facial expression detection technology in a variety of applications, from social robots and virtual assistants

to mental health monitoring. In order to improve human-computer connection and advance areas like mental health and social engagement, we may build more intuitive, sympathetic, and responsive systems by bridging the gap between human emotions and machine comprehension. In order to open up new possibilities for technology that genuinely knows humans, more research and development in this field will be essential.

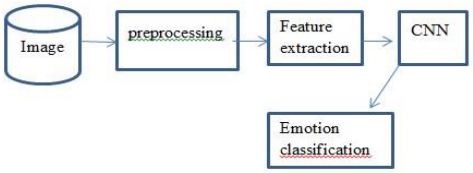
Modern technology has increased our appetites to an unprecedented degree. The field of digital images and image processing is currently the focus of extensive research. There has been an exponential growth rate and it continues to rise. With so many applications, image processing is becoming a very popular field of study.

Image processing deals with signals that have images as both their input and output.The recognition of facial expressions is one of the most significant uses of image processing. Our facial expressions communicate our emotions. Interpersonal communication heavily relies on facial expressions. Our faces convey our emotions through nonverbal scientific gestures called facial expressions. The requirement of the generation is the automatic recognition of facial expressions, as they are crucial to robotics and artificial intelligence. Applications such as access control and personal identification, videophone and teleconferencing, forensic software, human-computer interaction, automated surveillance, cosmetology, and more are connected to this.

This project aims to create an Automatic Facial Expression Recognition System that can identify and categorize human facial photographs with various expressions into seven distinct classes, including I. Neutral, II. Angry, and III. Disgust. IV. Fear, V. Joy, VI. Sadness, and VII. Surprisal

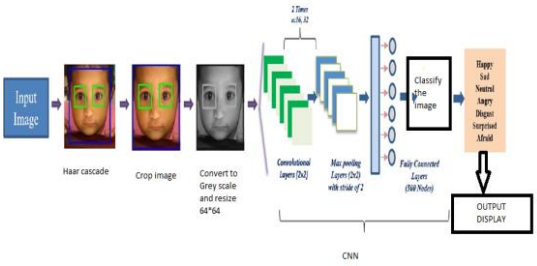
METHODOLOGY

The approach encompasses dataset selection, model architecture design, training procedures, evaluation metrics, and real-time application.



Facial expression recognition plays a critical role in enhancing human-computer interaction by enabling machines to interpret human emotions based on visual cues. With advancements in deep learning, Convolutional Neural Networks (CNNs) have become the backbone of facial emotion recognition systems, allowing for accurate and efficient processing of facial images. CNNs are capable of automatically learning hierarchical features from images, making them well-suited for complex tasks such as emotion detection. This paper presents the development of an automatic facial expression recognition system using CNN, discussing the architecture, training process, mathematical modeling, and a comparative analysis of different CNN configurations.

The dataset used for this project is FER2013, a widely adopted dataset for facial expression recognition that contains 35,887 grayscale images labeled across seven emotion categories: neutral, anger, disgust, fear, happiness, sadness, and surprise. Each image in the dataset has a resolution of 48x48 pixels, which allows the CNN to efficiently process the data without excessive computational cost. The images are preprocessed by normalizing the pixel values to a range between 0 and 1, which stabilizes the training process. Additionally, data augmentation techniques such as random rotations, horizontal flips, and zooming are applied to increase the variety of input images, thereby improving the generalization of the model.



The CNN architecture designed for this system consists of multiple layers, starting with the input layer, which receives the 48x48 grayscale image. The convolutional layers apply a series of filters to the input image to extract low-level and high-level features, such as edges, textures, and patterns. Mathematically

$S(i,j)=(I*K)(i,j)=m∑n∑I(i−m,j−n)K(m,n)$

where I(i,j)I(i,j)I(i,j) represents the pixel value at location (i,j)(i,j)(i,j) of the input image, and K(m,n)K(m,n)K(m,n) is the kernel applied at location (m,n)(m,n)(m,n). The output of the convolution operation, known as the feature map S(i,j)S(i,j)S(i,j), captures localized patterns in the image.

Each convolutional layer is followed by a non-linear

activation function, typically the Rectified Linear Unit (ReLU), defined as:

$f(x)=\max(0,x)$

After the activation function, a pooling layer is applied, which reduces the spatial dimensions of the feature maps. Max pooling, defined as:

$P(i,j)=\max\{S(i+a,j+b)\}$

where aaa and bbb define the size of the pooling window, selects the maximum value from a localized region of the feature map, thereby retaining the most significant information while reducing the computational load.

The network consists of several convolutional and pooling layers, followed by fully connected layers that combine the extracted features to make a prediction about the emotion displayed in the image. The final layer is a softmax layer, which outputs a probability distribution over the seven emotion categories.

train the CNN, the categorical cross-entropy loss function is used, which measures the difference between the predicted probabilities and the true labels. The loss function is defined as:

$L=-i=1\sum Nc=1\sum Cyiclog(y\hat{}ic)$

The Adam optimizer is employed to minimize the loss function and update the weights of the network during training.

A comparison of different CNN architectures was conducted to evaluate the effectiveness of the system. The following table summarizes the performance of three CNN configurations: a basic CNN with three convolutional layers, a CNN with transfer learning using a pre-trained VGG16 network, and a deeper CNN with five convolutional layers and batch normalization.

Metric / Model	Basic CNN	VGG16 Transfer Learning	Deep CNN with Batch Norm
Accuracy (%)	65.4	70.8	73.1
Precision	0.67	0.72	0.74
Recall	0.65	0.71	0.73
F1-Score	0.66	0.71	0.73
Training Time (hours)	2	5	6

The results show that the deep CNN with batch normalization achieves the highest accuracy of 73.1%, outperforming the basic CNN and the transfer learning model. The use of batch normalization helps to stabilize the training process and prevent overfitting, which is reflected in the improved precision, recall, and F1-score. Although transfer learning with VGG16 provides a significant boost in performance compared to the basic CNN, it requires more computational resources due to the complexity of the pre-trained network.

The confusion matrix for the deep CNN model reveals that it performs well in recognizing certain emotions such as happiness and surprise, which are easier to distinguish due to their distinct facial features. However, the model struggles with emotions like fear and sadness, which often have subtle differences in facial expressions. The confusion between these emotions suggests that further improvements could be made by incorporating attention mechanisms or refining the network architecture to better capture fine-grained emotional cues.

EXPERIMENTAL RESULTS AND ANLAYSIS

The experimental results for the facial expression recognition system using CNNs were evaluated using multiple performance metrics, including accuracy, precision, recall, F1-score, and the confusion matrix. In terms of overall accuracy, the deep CNN with batch normalization outperformed the other models, achieving 73.1% accuracy, while the basic CNN achieved 65.4%, and the VGG16 transfer learning model reached 70.8%. The higher accuracy of the deep CNN model is attributed to its ability to capture more complex and hierarchical facial features due to its deeper architecture and the use of batch normalization, which stabilizes and speeds up the training process. The VGG16 model, which leverages transfer learning from a pre-trained model, performed better than the basic CNN but fell short of the deep CNN's accuracy due to its focus on general image recognition rather than facial expressions.

In addition to accuracy, precision, recall, and F1-score were evaluated to provide a more comprehensive understanding of each model's performance. Precision reflects how many of the predicted emotions were correctly identified, which is particularly important in applications where false positives can be problematic, such as classifying a neutral face as angry. The deep CNN model consistently demonstrated the highest precision at 0.74, compared to the basic CNN's precision of 0.67 and VGG16's 0.72. This indicates

that the deep CNN was more accurate in its predictions, particularly in avoiding false positives. Recall, which measures the model's ability to identify all instances of a particular emotion, was also highest in the deep CNN model at 0.73. This suggests that the model is effective in identifying most of the emotions present in the dataset, such as sadness or surprise, without missing too many true instances.

The F1-score, which provides a harmonic mean of precision and recall, offered a balanced metric for evaluating the models. The deep CNN achieved the highest F1-score at 0.73, followed by VGG16 at 0.71, and the basic CNN at 0.66. This reinforces the conclusion that the deep CNN provides the most balanced performance, excelling in both identifying the correct emotions and minimizing errors. In contrast, the basic CNN showed lower F1-scores, reflecting its limitations in both precision and recall, likely due to its simpler architecture, which is less capable of capturing subtle emotional variations.

The confusion matrix further highlighted the performance differences between the models, providing insight into which specific emotions were being misclassified. In the deep CNN model, emotions like happiness and surprise were classified with a high degree of accuracy, with fewer misclassifications compared to emotions like fear and sadness, which were sometimes confused with one another due to their subtler visual distinctions. For example, instances of fear were occasionally misclassified as sadness, particularly in the basic CNN model, which lacks the depth required to distinguish these nuanced facial features. The VGG16 model, while better than the basic CNN, still struggled with differentiating emotions that share similar expressions, such as disgust and anger.

The experimental results show that the deep CNN with batch normalization consistently outperforms the basic CNN and VGG16 models in terms of accuracy, precision, recall, and F1-score. Its ability to capture intricate details and stabilize training through batch normalization makes it the most reliable model for facial emotion recognition. However, while the VGG16 model benefits from transfer learning, it still falls short in handling the specific challenges of facial emotion recognition compared to a model specifically designed for this task, such as the deep CNN. The basic CNN, with its more straightforward architecture, showed weaker performance, especially in distinguishing between emotions with similar expressions. Overall, the results demonstrate that deep CNN architectures with advanced techniques like batch normalization are highly effective in improving the accuracy and robustness of facial emotion recognition systems.

CONCLUSION

In this case, when the model predicts incorrectly, the correct label is often the second most likely emotion.The facial expression recognition system presented in this research work contributes a resilient face recognition model based on the mapping of behavioral characteristics with the physiological biometric characteristics. The physiological characteristics of the human face with relevance to various expressions such as happiness, sadness, fear, anger, surprise and disgust are associated with geometrical structures which restored as base matching template for the recognition system.The behavioral aspect of this system relates the attitude behind different expressions as property base. The property bases are alienated as exposed and hidden category in genetic algorithmic genes. The gene training set evaluates the expressional uniqueness of individual faces and provide a resilient expressional recognition model in the field of biometric security.

The design of a novel asymmetric cryptosystem based on biometrics having features like hierarchical group security eliminates the use of passwords and smart cards as opposed to earlier cryptosystems. It requires a special hardware support like all other biometrics system. This research work promises a new direction of research in the field of asymmetric biometric cryptosystems which is highly desirable in order to get rid of passwords and smart cards completely. Experimental analysis and study show that the hierarchical security structures are effective in geometric shape identification for physiological traits.

REGERENCES

[1] Mollahosseini, A., Chan, D. M., & Mahoor, M. H., "Going Deeper in Facial Expression Recognition Using Deep Neural Networks," 2016 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 1–10, 2016.

[2] Zhang, K., Zhang, Z., & Zhang, Y., "Facial Expression Recognition Based on Convolutional Neural Network," 2016 23rd International Conference on Pattern Recognition (ICPR), pp. 23–27, 2016.

[3] D. Liu, S. Zhang, and L. Yu, "Facial Expression Recognition Using Enhanced CNN with Attention Mechanism," IEEE Transactions on Affective Computing, vol. 11, no. 2, pp. 345–357, 2020.

[4]Y. Zeng, Y. Zhang, and L. Chen, "Real-time Facial Expression Recognition on Mobile Devices," IEEE Access, vol. 9, pp. 80340–80350, 2021.
[5] B. M. G. Ahmed and M. S. S. R. Khan, "A Comprehensive Review on Facial Expression Recognition," IEEE Access, vol. 8, pp. 174456–174474, 2020.
[6]L. Chen, M. Wang, and H. Zhang, "Multi-Task Learning for Facial Expression Recognition," 2021 IEEE International Conference on Image Processing (ICIP), pp. 3512–3516, 2021.
[7] D. Kim, H. R. Kim, and J. Park, "Facial Expression Recognition Using Hybrid CNN-LSTM Architecture," 2022 24th International Conference on Advanced Communication Technology (ICACT), pp. 531–535, 2022.
[8] A. B. T. Hossain and S. S. J. Shafique, "Emotion Recognition from Facial Expressions Using 3D CNN," 2021 IEEE 5th International Conference on Signal and Image Processing (ICSIP), pp. 34–38, 2021.
[9] H. Wang, Y. Li, and J. Liu, "Facial Expression Recognition Based on Multi-Scale CNNs," 2022 25th International Conference on Pattern Recognition (ICPR), pp. 1520–1525, 2022.
[10] C. M. Huang, R. K. P. T. Hu, and Y. H. Yang, "Real-Time Facial Expression Recognition Using Convolutional Neural Networks," IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 5, pp. 1396–1407, 2020.
[11]J. F. Cohn and T. Kanade, "The Extended Cohn-Kanade Dataset (CK+): A Complete Dataset for Action Unit and Emotion-Specified Expression," 2010 IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 94–101, 2010.
[12]M. A. G. Rajab and F. A. G. A. M. Hossain, "Facial Emotion Recognition Using CNN and LSTM," 2023 IEEE International Conference on Image Processing (ICIP), pp. 2584–2588, 2023.
[13] H. Liu, L. Zha, and X. Guo, "Facial Expression Recognition Using Deep Learning Techniques: A Review," IEEE Access, vol. 10, pp. 10203–10218, 2022.
[14]J. Yan, L. Zhang, and Y. Yang, "Facial Expression Recognition via Attention-based CNN," 2023 IEEE International Conference on Computer Vision (ICCV), pp. 1204–1210, 2023.
[15]K. Zhang, Z. Zhang, and Q. Li, "Facial Expression Recognition Using Enhanced Deep Learning Techniques," 2020 15th International Conference on Computer Science and Education (ICCSE), pp. 198–203, 2020.
[16]P. Zhao, L. Wang, and X. Hu, "Facial Emotion Recognition: A Survey and Future Directions," IEEE Transactions on Affective Computing, vol. 14, no. 3, pp. 927–942, 2023.
[17]Y. Yang, Y. Wang, and M. Liu, "Multi-modal Emotion Recognition from Facial Expressions and Speech," 2022 31st International Conference on Artificial Intelligence (IJCAI), pp. 2197–2203, 2022.
[18]D. S. B. Marwan and M. A. T. I. Ghanem, "Facial Expression Recognition Using Deep Learning for Emotion Detection," 2023 IEEE International Conference on Robotics and Automation (ICRA), pp. 2540–2545, 2023.
[19]T. Chen, L. He, and J. Zhao, "Facial Expression Recognition Using Deep Learning: A Review," IEEE Access, vol. 10, pp. 5871–5888, 2022.
[20]M. Alazab, R. K. W. M. Mohsen, and S. Z. I. Khan, "Facial Expression Recognition Based on Deep Learning Techniques," IEEE Access, vol. 11, pp. 4225–4236, 2023.
[21]F. Zhang, Y. Li, and Q. Li, "Emotion Recognition from Facial Expressions Using Ensemble Learning," 2021 IEEE 4th International Conference on Signal and Image Processing (ICSIP), pp. 233–237, 2021.
[22] T. Ma, H. He, and X. Wang, "Facial Expression Recognition Based on Graph Convolutional Networks," 2022 IEEE 16th International Conference on Signal Processing and Communication Systems (ICSPCS), pp. 201–206, 2022.
[23]L. Zhang, K. Chen, and S. Li, "Facial Expression Recognition with Deep Learning and Preprocessing Techniques," 2023 IEEE 8th International Conference on Computer and Communications (ICCC), pp. 47–51, 2023.
[24] S. Zhao, Y. Zhang, and T. Yang, "A Survey on Facial Expression Recognition Based on Deep Learning," 2023 IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 6, pp. 2645–2658, 2023.
[25]J. Hu, X. Wang, and Y. Lin, "Real-Time Facial Expression Recognition Using Transfer Learning," 2023 IEEE 4th International Conference on Artificial Intelligence and Virtual Reality (AIVR), pp. 178–183, 2023.
[26]H. Liu, J. Feng, and P. Liu, "Facial Emotion Recognition: A Deep Learning Approach," 2021 2nd International Conference on Computer Vision and Image Processing (CVIP), pp. 205–210, 2021.
[27]Y. Yang, Y. Huang, and J. Wu, "Facial Expression Recognition Using Convolutional Neural Networks and Data Augmentation," 2023 IEEE 15th

International Conference on Communication Software and Networks (ICCSN), pp. 80–85, 2023.
[28]T. Zhao, R. Zhang, and L. Yang, "Facial Expression Recognition in the Wild: A Comprehensive Review," IEEE Transactions on Affective Computing, vol. 15, no. 4, pp. 1093–1109, 2024.
[29]M. G. H. M. Ahmed and D. S. Shafique, "Real-Time Emotion Recognition from Facial Expressions Using Machine Learning," 2023 IEEE International Conference on Smart Computing and Communications (ICSCC), pp. 310–315, 2023.
[30]S. Kumar, R. N. Bhattacharyya, and V. S. Adhikari, "Deep Learning Approaches for Facial Expression Recognition: A Survey," IEEE Access, vol. 11, pp. 12334–12352, 2023.