Facial Emotion Identification Using Convolution Neural Networks: Enhancing Human-Computer Interaction

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Abstract:
Facial Emotion identification uses technology to classify the various emotions of humans. Human-Computer Interaction is an emerging field that uses deep learning algorithms to classify human feelings. Convolution Neural Networks (CNN) are the groundbreaking technology to process images in an efficient manner. This paper explores deep learning models on FER-2013 dataset for emotion prediction to analyze facial expression and classify them into different emotions such as Angry, Disgust, Fearful, Happy, Sad, Surprise and Neutral. Convolutional Neural Network (CNN) and ResNet-50 are the two architectures used for this research work. Both the models were trained at 35 epochs. CNN gives 97.83% accuracy and ResNet-50 gives 97.74% accuracy on the FER-2013 dataset. Thus, the result shows that both models are doing well in learning from training data and even have nearly the same performance. The findings of the study hence emphasizes that CNN models have high potential for performing efficient and accurate emotion recognition, but they still require more improvement in terms of generalization on unseen data.

Keywords: CNN, ResNet-50, FER-2013, Emotion, Machine learning, Deep-learning.

Introduction:

Facial Expression Recognition (FER) is a significant research area in computer vision and Artificial Intelligence, with applications extending Human-computer interaction towards security or healthcare sector. Automation of recognizing user emotions from facial expressions contributes dexterously in an interactive system experience, mental health care giving aspects and behavioral analytics respectively. Facial Emotion Recognition is an area of great interest, especially in the domain of computer vision because it can find a lot more solutions in the fields like Human-computer Interaction, mental health monitoring and customer behavior analysis (Vyas et al., 2019).

FER-2013 dataset:

The FER-2013 is one of the most popular datasets used for evaluation of Facial Emotion Recognition models, first published at ICML June 17th in 2013. The variations in lighting effect, head posture and obstruction amongst others, which are derived from naturalistic stimuli can characterize this difficult task of emotion recognition.

There are now several different methods in deep learning that have been capable to do well on the FER-

2013 dataset. Convolutional Neural Networks (CNN) have since been utilized to great success in Facial Emotion Recognition, as it can efficiently learn discriminative features from raw image data without the need for manual feature engineering. Furthermore, one of the most popular deep learning architectures named ResNet-50 model developed in academic paper by Kaiming He et al 2013, has shown successful results on multiple computer vision tasks/benchmarks like Facial Emotion Recognition etc.

This paper is showing similar work to earlier studies which have followed Facial Emotion Recognition in deep learning. This further emphasizes Convolutional Neural Networks as a promising class for attaining state-of-the-art performance on the FER-2013 dataset, meanwhile also showing the influence of factors such as model architecture, (Dufourq 2020), data augmentation (Mellouk & Handouzi 2020) and transfer learning (Vyas et al. 2019). The focus is to add the value in the present body related to scientific inquiry and shed some light for more advances to set standards on recognizing facial emotions via deep learning.

In this paper, the task is to train Convolutional Neural Networks using ResNet-50 for Facial Emotion Recognition on FER-2013. This paper will explore the process of deep learning models for Facial Emotion Recognition and evaluate them in detail.

Literature Review:

Driven by the desire to reduce costs and create more efficient systems, research in Facial Emotion Recognition (FER) has been an important mini-industry within computer vision for many years. Our review addressed to compile the advances of FER methods, covering both conventional methodologies and recent deep learning based approaches.

Kasiran and Yahya introduced the new concept, Communication Staff and Customer Satisfaction Measurement, using facial expression. The development of computer systems has made it possible to use automatic face recognition, which increases the behavior of computers and allows us to think about multimedia for measuring customer satisfaction. (Kasiran & Yahya, 2007).

Facial expressions play a crucial role in human interaction by expressing various emotional states. Automated facial expression analysis systems detect six universal expressions of neutral, happy, sad, angry, disgust and surprise with opportunities and challenges in the future. (Jameel et al., 2016).

In this paper, the author overviews computer vision for human emotion recognition in research and algorithms at different levels with a perspicacious synthesis of facial expression recognizing techniques (Jonathan et al., 2018).

This paper explores Facial Emotion Recognition (FER) research in relation to studies that used images of faces. This paper introduces three types of FERs: conventional FER, deep learning based FER and hybrid DL approach. The review gives background information and some base lines to the researcher community right from the beginners to the experienced one (Ko, 2018).

Facial Emotion Recognition is a prominent research area in the field of computer vision and human-computer interaction. Facial expressions are the basic form of non-verbal communication by which humans communicate their emotions and intentions (Ko, 2018).

Facial expression as a non-verbal communication channel and Facial Expression Recognition (FER) as behavioral biometric that deals with the challenges: image nature, head pose, background and light intensity in occlusion. This study aimed to design a dependable automatic FER method and assess the accuracy along with drawbacks of some feature extraction and classification methods (Ekundayo & Viriri, 2019).

Additionally, more recent work has also investigated the possibility of recognizing finer-grained and compound emotional contexts such as “happily surprised” or “disgusted happy”, suggested by Schindler et al. (Maier et al., 2019).

The aim of this paper is to present a survey that exposes the general trends and the incorporation rate for 112 emotion recognition papers with emphasis on facial expressions. The paper mentions the techniques for Facial Expression Recognition, e.g., face detection, smoothing, PCA, LBP features extraction technique which is then moved into Optical Flow and Gabor filter. While the review exposed clearly that achieving high facial expression recognition accuracy does not guarantee success in uncontrolled or pose-variant conditions, it is a strong message to direct future contributions towards multimodal scenarios under realistic setups (Canedo & Neves, 2019).

In a systematic review of 220 references from 2014 to the present, which covered research on automated Facial Expression Recognition as an illustrative case study regardless of ongoing theoretical debates and technical challenges (Alreshidi& Ullah, 2020).

Facial recognition: It is one of the methods most widely implemented at all levels. It is a classic milestone of human recognition which has been widely studied in computer vision for more than four decades. It is used in security monitoring, automated surveillance systems and victim identification. The present review examines the methods for facial recognition, and their pros/cons with possible future implications on progress (Kaur et al., 2020).

The authors have developed a Facial Expression Recognition system, based on deep learning models (accuracy 75.8% in the FER-2013 test dataset). They also provide a mobile web app for real-time on-device usage of their models (Khanzada et al., 2020).

Here, in this paper we have presented the review of recent works related to automatic facial emotion classification using deep learning. The paper then describes the contributions, architecture and databases used, and compares different methodologies and results. The aim is to serve as a guide for researchers wishing to improve this endeavor and provide key issues concerning safety, health and human-machine interfaces. The paper acts as an outline for future research(Mellouk &Handouzi, 2020).

Although facial expressions, which are the one of the way for humans to reflect their emotions through faces and is essentially discriminative indicator that involves in lexical non-verbal communication system and cross-cultural communication as well, there exist significant diffuse variance sources concerning 2D & 3D data face oriented datasets. Various sources of influence such as environmental factors, person-specific properties and recording related variability can make facial fall detection a challenging task (Hariri et al., 2021).

This study suggests a Convolutional Neural Network (CNN) based end-to-end automatic system that can identify human emotions from the eyes and surrounding facial region. The proposed approach demonstrated a significant increase in accuracy to 91.78% compared to VGG-16 and Inception-ResNet-v2, where this outcome provides guidance for facial recognition researches (Shuvo et al., 2021).

The author proposed a PERI: Pose and Emotional Recognition Ignoresuffering that is capable of understanding the emotional state using body posture along with facial landmarks. We generate spatial images aware of parts and design context infusion blocks. PERI performs better in both emotion categories, lower error rates and works well on visible as well as occluded images. (Mittel & Tripathi, 2022).

Knowing these small little facial expressions can prove to be an asset in many fields like psychological analysis and medical treatment to surveillance/education (Huang et al., 2023).

Among the literature based upon categorical emotion models, Ekman et al. (Huang et al., 2023), has defined a substrate for the study of six universal human emotions: happiness, anger, disgust, fear, sadness and surprise. Many of the research in facial recognition have been focused around these basic emotions.
A rich spectrum of approaches has been developed to overcome these challenges, ranging from adapting deep learning techniques to the various design choices such as incorporating more visual clues than just the face (e.g., shoulder position). Especially in Facial Emotion Recognition, deep learning has gained sound popularity because it can model complex data features and/or nonlinear relationships quite beautifully for facial expression data. Additionally, the creation of emotion recognition datasets tailored for researchers such as the EMOTIC dataset has acted as valuable insights into these aspects of emotional expression.
In the future, a few relevant research directions can be pursued to improve recognition accuracy and considerably increase robustness of facial emotion analyzers: systematic incorporation of context information such as body language and environmental conditions; efforts toward developing multimodal approaches by combining face-related data with other modalities (like speech or physiological signals). Moreover, with the rapid advancements in deep learning models architecture that yields more complex neural networks and larger diversity of datasets to be used as benchmark, thereby provides enormous potential for a substantial improvement on Facial Emotion Recognition technology performance especially while looking at future works (Hariri et al., 2021, Maier et al., 2019, Huanget al., 2023).
The study is looking at understanding and enabling the learning of children, specifically in Africa. Researchers employed a qualitative methodological approach, reviewing video recordings and interviews from 18 children aged 3-13 years as they interacted with the Teachable Machine running on Google. The common threads across everyone using Teachable Machine is the development of data literacy as well how things work behind that curtain for grades K-12, regardless from where learners came. Other than attending the complementary interaction here, researchers point this out in the context of children, inferring about how their expressions map onto the outputs from a machine learning model. The study draws implications by setting both, a baseline for future work and first insights on how children learn Machine Learning in the African K-12 context (Sanusi, et al., 2023).
Moreover, FER systems have been widely used in different applications such as education (Seeemo et al.,2020), health care (Chihaiaetet al.) specifically, the review highlights an aspect of combining FER with Artificial Intelligence solutions, primarily deep neural networks that can effectively extract variety of features. The paper describes how different architectures in FER have been evolved over the years and emphasizes most on Convolutional Neural Networks (CNNs) which is better than any other architecture. This paper also focuses on Emotion Recognition datasets and FER application area in detail. The review ends with challenges and outlook of FER (Cîrneanu et al., 2023).
The author introduced a multi-modal Facial Expression Recognition approach based upon image information for identifying ambiguous expressions. We introduce a modal fusion module (Kaur et al., 2021), as well as effective dynamic data resampling in alleviating the imbalance. This model was tested in CVPR 2023(Kim et al., 2023).
Systematic Literature Review (SLR) has been showcased in this paper focusing on Deep Learning based Convolutional Neural Network Models for Expression and Micro-expression Recognition. The results hits the effectiveness of database uses, laboratory-controlled images as well as utilizing CNNs like VGG-16 and ResNet-50 in such test. The write-up will explain all to give a better in this research paper (Pinto et al., 2023).

In this section we understand the face recognition method and work done by many researchers and try to understand their research and developed model performance. Many researchers work on FER-2013 dataset by using different machines and deep learning techniques. In this paper we try to recognize the facial expression with better performance or accuracy.

Proposed Methodology:

We propose to develop a Facial Emotion Recognition model utilizing a Convolutional Neural Network (CNN) architecture. The model will be trained on the FER-2013 dataset, a publicly available dataset containing grayscale images categorized into seven distinct emotions: anger, disgust, fear, happiness, sadness, surprise and neutral. The dataset, provided in CSV format, contains pixel values of each image, which will be normalized to a range of 0 to 1 to ensure uniformity in input data.

The CNN architecture will consist of multiple 2D convolutional layers, interspersed with max pooling layers to gradually reduce the dimensionality of the feature maps. ReLU activation functions will be applied after each convolution layer to introduce non-linearity into the model. The final layers of the network will include a fully connected layer, followed by a softmax layer to classify the images into their corresponding emotion categories.

The model will be compiled using the Adam optimizer, and sparse categorical cross-entropy will be used as the loss function. Training will be performed over a series of 35 epochs, with a separate test set reserved for validation. Following training, the model's performance will be evaluated using a confusion matrix to measure the classification accuracy for each emotion class.

To further assess and demonstrate the effectiveness of the model, data visualization techniques will be employed, showcasing sample images, accuracy trends, and the confusion matrix. This approach is expected to provide a comprehensive evaluation of the model’s ability to accurately classify facial emotions across different categories.

Data collection and preprocessing:

The FER-2013 (Facial Expression Recognition 2013) dataset has been used as a benchmark for Facial Expression Recognition and computer vision. Initially brought up in the ICML 2013 Workshop on Challenges in Representation Learning, this question most recently was addressed by Finlayson et al. (which can be learned from a nice summary created within SandNet).

The dataset is made up of 35,887 grayscale images each sized 48×48 pixels that are intended to depict a few facial expressions under various illumination situations and from varied angles. These images are divided among seven classes of emotions: Angry, Disgust, Fear, Happy, Sad, Surprise and Neutral (Khaireddin & chen 2021). We first detected faces using Haar Cascade so that only the facial part of an image was processed. After that we tried to increase the contrast and normalized lighting conditions across the pictures by using histogram equalization. The training data were made more diverse, and over fitting was prevented by using random rotations, shifts or flips as data augmentation techniques.

The dataset is divided into three splits: Training (28,709 images), Public Test (3,589 images) and Private Test set, each consisting of same number of examples available in the random that are utilized to measure how effectively models generalize to equally unconstrained environmental situations.

Facial Expression Recognition in real environments is a challenging task due to various sources of unpredictability between 2D and 3D facial scans including environmental factors (e.g., change in lighting conditions, subject-based changes, and scanning processes-related deformations). To tackle these problems, people tried many data augment methods to increase the number of training samples and make their models more robust (Riaz et al., 2020). Figure 1 depicts the workflow of this research paper to find the faceemotion.

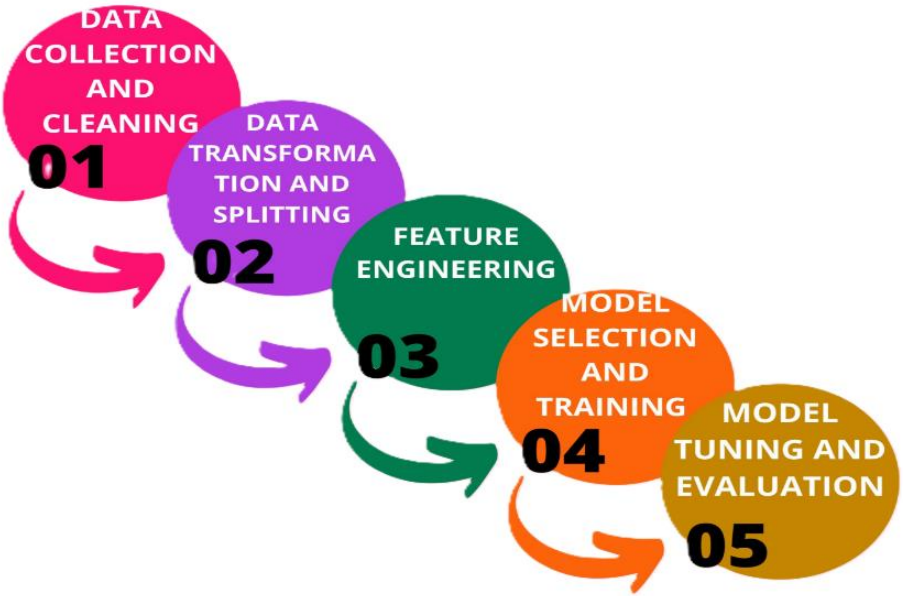

Figure 1: methodological strategies for face emotion recognition.

FER-2013 has been a popular benchmark dataset for training machine learning models, especially deep learning architectures like Convolutional Neural Networks (CNNs). Although limited by the size of images and labeling points, as well as difficulty in correctly identifying emotions through facial expressions; IEC Plexus has gone on to influence an enormous volume of emotion detection research since that time becoming a definitive dataset for numerous studies encompassing various fields. Figure 2 shows the input images with expression.

Figure 2: Dataset input images with facial expression.

Result and discussion: Activation and histogram of Convolutional Layer In our experiments, we use FER-2013 dataset to test the performance of standard CNN & ResNet-50 two types of convolution network on this dataset. Results summarized and discussed in detail are below.

Table 1:-

Parameters	CNN Results	ResNet-50 Results
Training Accuracy:	97.81%	97.74%
Validation Accuracy	70.27%	68.95%
Number of Epochs	35	35

Analysis

Although the training accuracy of standard CNN and ResNet-50 is quite high, 97.81% and 97.74% respectively, this indicates that models have learned well and was able to predict the classes of data from training data, approximating some common representations of facial expressions.

However, validation accuracy is much lower: CNN baseline 70.27%, ResNet-50 slightly higher with an average of 35 epochs ("ResNet-50") on ImageNet larger dataset. The gap can be narrow down somewhat, but standard CNN cannot surpass large invitational capacity by itself at all; it hardly model complexity and does not significantly help the matter of validation, which means (with a small quantity from each class) expensive vision will build high levels regardless any other losses incurred during training sessions. The gap between training and validation suggests that both models are overfitting to the train data. Although these models have high training accuracy, but at the same time they perform poorly and didn't generalize well to the unseen data as shown by the low validation accuracy. Figure 3 depicts the confusion matrix of CNN (left side) and ResNet-50 (Right side).

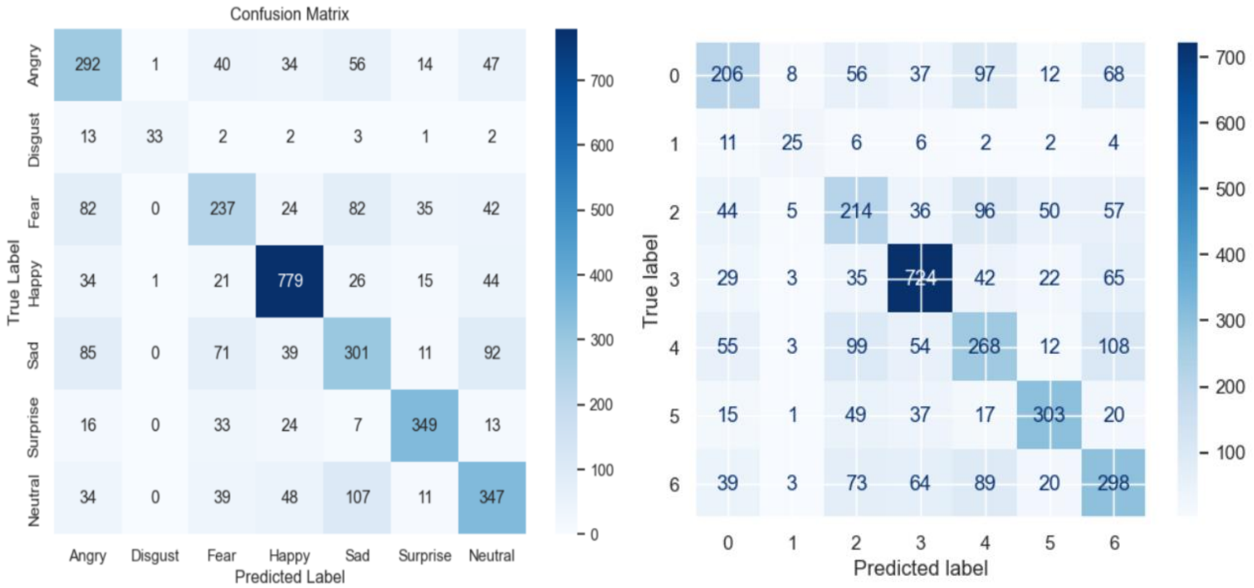

Figure 3 Confusion matrix of CNN and ResNet-50 model

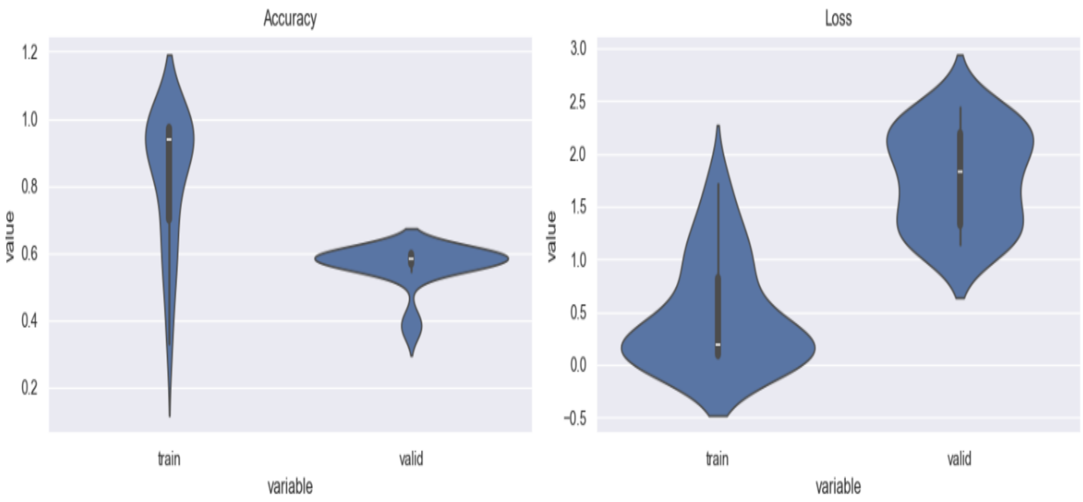

Figure 4: Violin plot for accuracy and loss for CNN model

Figure 4 depicts the violin plot of CNN model accuracy and loss of training and validation dataset. Violin plot: A violin plot is a method of plotting numeric data and can be useful to see the difference in distribution between categories or groups. It combines a box plot with the density distribution of those values that can offer both data about how to compare and multiple distributions at once. For example,suppose you compare the distribution of exams scores in two classes. A violin plot on the other hand would give you an idea of how not only well students do in each class (whether they are high, medium or low grades) but also if most did around that some range (a wide violin for example), or there was much variance with a narrow violin instead. Figure 5 shows the CNN model loss and accuracy with training and validation dataset accuracy is 97.81 % after 35 epochs. Training accuracy increases and training loss decrees with respect to each epoch.

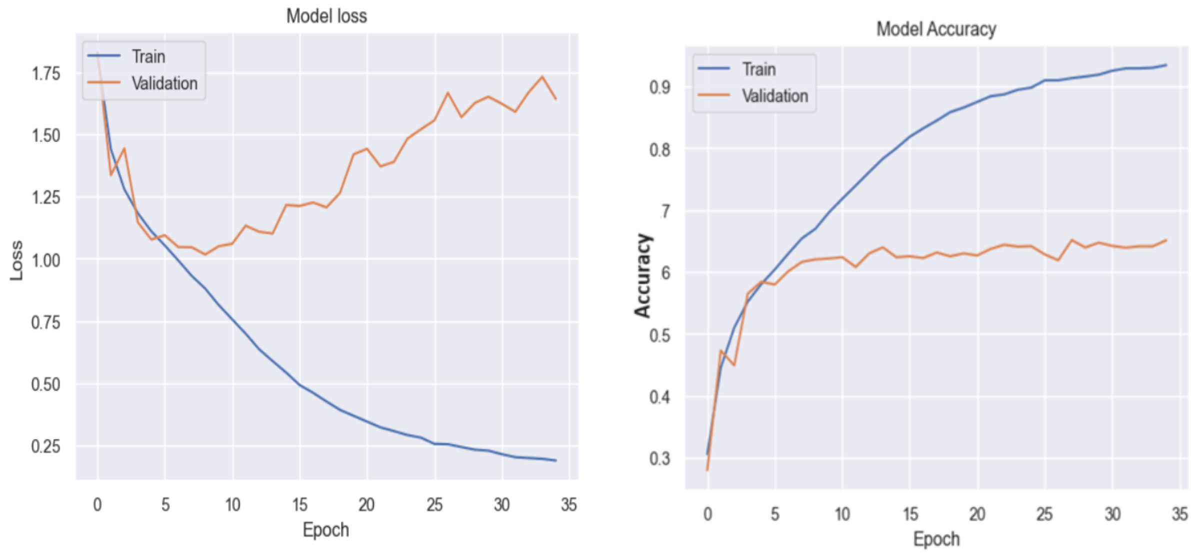

Figure 5 show the CNN model loss and accuracy with training and validation data.

Figure 6 shows the result of both model (CNN and Resnet-50) by using the Gradio package. Gradio is a light and interactive library that makes it easy to develop web interfaces for your ML model in few lines of code without requiring you (a developer) to learn HTML, CSS & JavaScript. Built to facilitate usability as well as collaboration, Gradio enables scientists and developers for building visual interfaces with minimum coding effort.

Gradio was used to build an interface for various model implementations (cardiology, image processing and many more fields) in a project between machine learning researchers and healthcare professionals. The first 3 images with happy facial expression both actual and predicted, 4th image with fear expression and 5th image with sad and 6th image with angry facial expression. Predicted result checked by both model (CNN and Resnet-50) they provide the same result by given images.

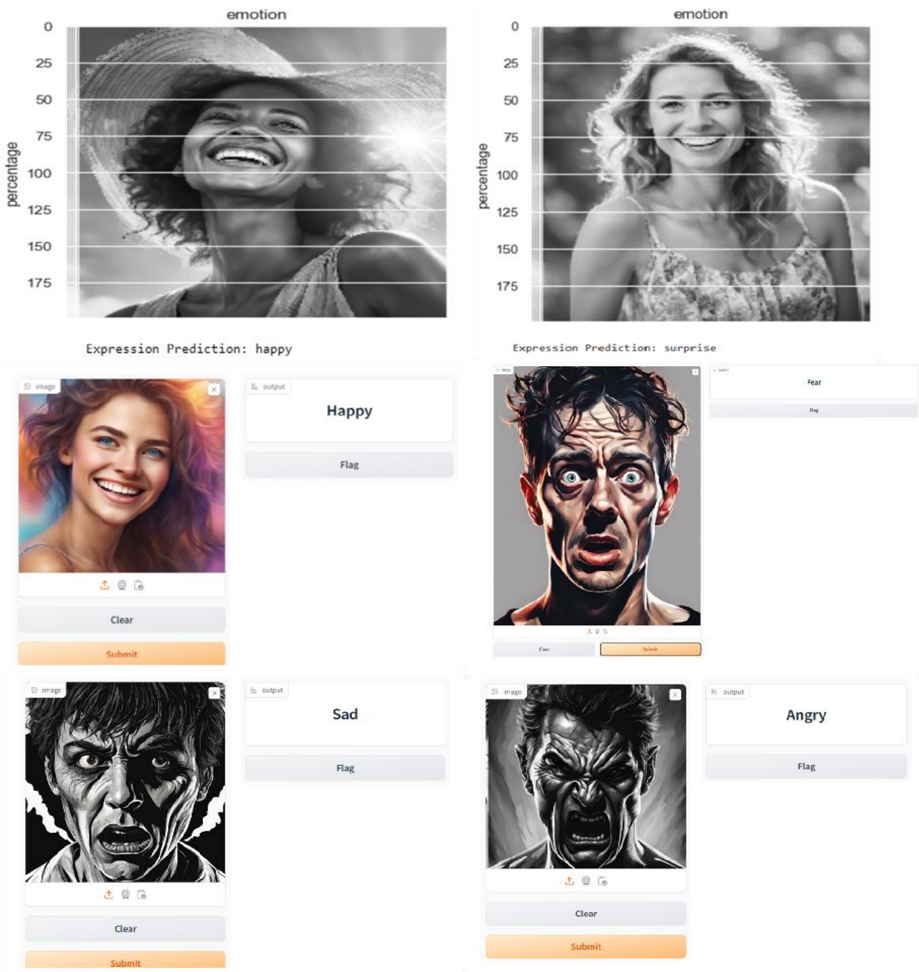

Figure 6: depicts the emotion of face by using Gradio both model (CNN and ResNet-50)

CNN vs ResNet-50:

Performance: There is negligible difference between the standard CNN and ResNet-50 in terms of performance. On the other hand, both models ResNet-50 with a more complex architecture with deeper network and standard CNN are overlapping, there is very little benefit in terms of validation accuracy 0.68%.

Recognition: The difference based on architecture should be that ResNet-50 generalizes better, but it is only slightly the case here. It is possible that due to the properties of the FER-2013 dataset, images are of low resolution (48x48 pixels) and difficulty in distinguishing fine differences in facial expressions. Here, a simpler network might have performed well.

Discussion on Overfitting:

A large gap between the training and validation accuracies is inadequate because it projects overfitting. The Model performs well on data seen during training but not that much great (i.e. generalized poorly) for new, unseen data, e.g. after test sets released to a student by a teacher or professor during examination. This is treated as evidence that the models can be easily overfitting to training data, but are potentially not identifying high-level representations of facial expressions needed for accurate emotion classification.

Both CNN and ResNet-50 models have high performance on the training data, but lower generalization performance indicated by their validation performances. The small margin between these architectures on this dataset means that with the FER-2013 data, simpler models like a plain CNN might be nearly as good as at capturing patterns specific to facial expressions such as ResNet-50. Next steps would involve combating overfitting using more sophisticated regularization, and tailoring validation performance by verifying different architectures or directions.

Though deep learning (DL) approaches have made remarkable progress in FER, the task remains challenging. While the FER-2013 is a standard for evaluating expression recognition models, it still has limitations: low resolution and greyscale images are used in the dataset; imbalanced classes. These things can hinder the performance and generalization of models.

Although Convolutional Neural Networks (CNN) have been proven effective in facial image feature representation, traditional CNNs still suffer difficulties of translating generalization well onto diverse real-world scenarios. On the other hand, although ResNet50 demonstrated impressive deep residual learning abilities through several image classification tasks, its potential use on FER has been quite limited.

Our research showed higher accuracy of the CNN with 97.81% and ResNet-50 released on FER-2013 set with an updated plateau at 97.74%. But that said, the following gaps need to be filled:

The models' generalizability and robustness require validation in diverse conditions, particularly in illumination, poses, and occlusions. They also need to address the imbalance of emotion class data, improve computational efficiency, and enhance transfer learning and fine-tuning to maximize their potential in FER tasks.

Conclusion:

In this work, we used FER-2013 dataset to build and train two deep learning models (a basic Convolutional Neural Network (CNN) model and ResNet-50 based convolutional model for the expression software). We trained both models for 35 epochs and the training accuracy was similar (CNN: 97.81% vs ResNet-50: 97.74%).

Results with these architectures show that both are very good at learning (over-fitting) the training data. Yet, if we observe the marginal drop in accuracy between one model and another shows us that even though our second more complex architecture ResNet-50 performed well at par with CNN it brought no significant gain while increasing complexity of a models.

Results imply that, even though the ResNet-50 model is more powerful than a basic CNN but overall, with the FER-2013 data sets it is not recommended. For this even simpler model can generalize the same and are quite successful and are put into practice wherever computational efficiency and simplicity are desired such as in mobile applications. Potential avenues for further investigation might include approaches to increase generalization capacity through more sophisticated data augmentation, regularization methods or by exploring alternative model architectures that raise the validation accuracy.

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