Decoding Emotions: Deep Learning Facial Recognition

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Abstract: Computer vision's crucial role in facial expression detection has many practical applications. Facial expression recognition has been remarkably successful with deep learning techniques. We present a thorough review of cutting-edge deep learning-based face emotion identification methods in this research paper. We go over the many deep learning architectures utilised for this assignment the difficulties encountered and the solutions. We also provide a comparison of how different techniques performed on test datasets. We cover recent developments in the recognition of facial emotions, including transfer learning, multi-task learning, and models based on attention. Researchers, practitioners, and developers working on the subject of computer vision, particularly those with an interest in facial expression identification, may find the findings reported in this study to be helpful.

Keywords: Deep learning, Facial emotion, Recognition, Human sentiment.

I. INTRODUCTION

Facial emotion detection has gained significant attention in the field of computer vision and machine learning due to its numerous applications such as human-computer interaction, emotion-based marketing, and mental health diagnosis[1]. The ability to automatically detect emotions from facial expressions has been made possible by the advancements in deep learning algorithms and the availability of large-scale datasets. One such dataset is the FER 2013 dataset, which has been widely used in the research community for training deep-learning models for facial emotion detection.

The FER 2013 dataset was introduced in 2013 by Goodfellow et al. and contains 35,887 grayscale images of faces categorized into seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. The images were collected from the internet and labelled by crowdsourcing. The dataset has become a benchmark for evaluating facial emotion

recognition models and has been used in numerous studies in the field.

Deep learning has shown promising results in facial emotion detection using the FER 2013 dataset. Convolutional neural networks (CNNs) are one of the most popular deep learning architectures for facial emotion detection[1]. These networks can automatically learn hierarchical features from the input images, which helps detect the subtle changes in facial expressions that indicate different emotions.

There have been several studies that have utilized deep learning algorithms on the FER 2013 dataset to achieve state-of-the-art performance in facial emotion detection. For example, in a study by Mollahosseini et al., a CNN-based model was trained on the FER 2013 dataset and achieved an accuracy of 71.2% on the test set. In another study by Liu et al., a hybrid model combining CNN and long short-term memory (LSTM) was trained on the FER 2013 dataset and achieved an accuracy of 71.7% on the test set[1].

In conclusion, facial emotion detection using deep learning algorithms and the FER 2013 dataset has become an active research area in computer vision and machine learning. The availability of large-scale datasets like FER 2013 has made it possible to train deep-learning models that can accurately detect emotions from facial expressions[2]. There have been numerous studies that have demonstrated the effectiveness of deep learning algorithms on the FER 2013 dataset, and further research in this area is expected to lead to even more accurate and reliable facial emotion detection systems.

II. LITERATURE REVIEW

A. Studies made

Facial emotion detection using deep learning algorithms and the FER 2013 dataset has become a popular research area in the field of computer vision and machine learning. Several studies have utilized this dataset to train deep-learning models for facial emotion recognition. In this literature review, we will discuss some of the notable studies conducted in this area.

Mollahosseini et al. (2016) proposed a convolutional neural network (CNN) based model for facial emotion recognition on the FER 2013 dataset[21]. The authors trained the model on the training set of the dataset and evaluated it on the test set. The proposed model achieved an accuracy of 71.2% on the test set. The study showed that CNN-based models can achieve high accuracy in facial emotion recognition tasks.

Liu et al. (2018) proposed a hybrid model combining CNN and long short-term memory (LSTM) for facial emotion recognition on the FER 2013 dataset[22].

The authors used CNN for feature extraction from facial images and LSTM for temporal modelling of the extracted features. The proposed model achieved an accuracy of 71.7% on the test set, outperforming other state-of-the-art models on the same dataset.

Zhao et al. (2019) proposed a model based on multi-task learning for facial emotion recognition and face detection on the FER 2013 dataset[23]. The authors used a deep neural network architecture that jointly learned facial emotion recognition and face detection tasks. The proposed model achieved an accuracy of 71.6% on the test set for facial emotion recognition and 95.9% for face detection.

Luo et al. (2020) proposed a model based on an attention mechanism for facial emotion recognition on the FER 2013 dataset[24]. The authors used an attention mechanism to weigh the importance of different regions of the facial image for emotion recognition. The proposed model achieved an accuracy of 73.5% on the test set, outperforming other state-of-the-art models on the same dataset.

In addition to the above studies, several other studies have been conducted in this area using the FER 2013 dataset. For example, Wang et al. (2018) proposed a model based on transfer learning for facial emotion recognition on the same dataset, while Wang et al. (2020) proposed a model based on adversarial training. These studies have demonstrated the effectiveness of deep learning algorithms for facial emotion recognition tasks using the FER 2013 dataset[25].

In conclusion, the FER 2013 dataset has become a benchmark dataset for facial emotion recognition using deep learning algorithms. Several studies have utilized this dataset to train models for facial emotion recognition and have achieved state-of-the-art performance. The studies discussed in this literature review have demonstrated the effectiveness of various deep learning algorithms such as CNN, LSTM, and attention mechanisms for facial emotion recognition on the FER 2013 dataset. Further research in this area is expected to lead to even more accurate and reliable facial emotion recognition systems.

B. Datasets and their reported results

Table 1 shows the reported results of facial emotion recognition on various datasets using deep learning algorithms. The FER 2013 dataset has been widely used for this task, and several studies have reported high accuracy on this dataset using different deep learning models. Mollahosseini et al. (2016) reported an accuracy of 71.2% using a CNN-based model, while Liu et al. (2018) achieved an accuracy of 71.7% using a hybrid CNN-LSTM model. Zhao et al. (2019) used a multi-task learning model to

achieve an accuracy of 71.6%, and Luo et al. (2020) reported the highest accuracy of 73.5% using an attention mechanism.

Other datasets such as CK+, JAFFE, AffectNet 2018, RAF-DB, and Oulu-CASIA have also been used for facial emotion recognition tasks using deep learning algorithms. Ismail et al. (2019) achieved an accuracy of 98.3% on the CK+ dataset using a CNN-based model, while Prasad et al. (2020) achieved an accuracy of 97.2% on the JAFFE dataset using a CNN-based model. Zhang et al. (2020) used a ResNet-50 model to achieve an accuracy of 90.8% on the AffectNet 2018 dataset, and Jin et al. (2020) achieved an accuracy of 86.4% on the RAF-DB dataset using a DenseNet-121 model. Bhattacharya et al. (2020) achieved an accuracy of 93.9% on the Oulu-CASIA dataset using a CNN-LSTM model.

Dataset	No. of classes	No. of images	Reported Accuracy	Model used	Reference
FER 2013	7	35,887	71.2%	CNN	Mollahosseini al. (2016)
FER 2013	7	35,887	71.7%	CNN-LSTM	Liu et al. (2018
FER 2013	7	35,887	71.6%	Multi-task learning model	Zhao et al. (20
FER 2013	7	35,887	73.5%	Attention mechanism	Luo et al. (202
CK+	6	981	98.3%	CNN	Ismail et al. (2(
JAFFE	7	213	97.2%	CNN	Prasad et al. (2020)
AffectNet 2018	8	1,035,135	90.8%	ResNet-50	Zhang et al. (2020)
RAF-DB	7	29,672	86.4%	DenseNet-121	Jin et al. (2020
Oulu-CASIA	6	480	93.9%	CNN-LSTM	Bhattacharya e (2020)

In conclusion, several datasets have been used for facial emotion recognition tasks using deep learning algorithms, and different models have been employed to achieve high accuracy. The FER 2013 dataset has been widely used for this task, and several studies have reported high accuracy on this dataset using different deep learning models. However, other datasets such as CK+, JAFFE, AffectNet 2018, RAF-DB, and Oulu-CASIA have also been used, and some studies have reported high accuracy on these datasets as well.

It is worth noting that the reported accuracy of facial emotion recognition using deep learning algorithms varies widely across different studies and datasets. This is due to various factors such as differences in the dataset size, quality, and imbalance of classes. Moreover, the performance of deep learning models can be affected by various factors such as the choice of hyperparameters, network architecture, and optimization techniques. Therefore, it is essential to carefully choose the dataset and deep learning model and optimize their parameters to achieve high accuracy in facial emotion recognition tasks.

III. METHODOLOGY

The final model was trained using sets without the emotions of disgust and fear. Hence, the dataset was shrunk to 24282 pictures in the train set and 5937 images in the test set.

6043 photos make up the test set, and the validation set.

A.Data preprocessing

Data preprocessing is an essential step in facial emotion detection using deep learning with the FER 2013 dataset. The preprocessing step involves preparing the dataset for training the deep learning model by applying various transformations to the images.

The first step in data preprocessing is resizing the images to a fixed size, typically 48x48 pixels, which is the size used in the FER 2013 dataset. Resizing ensures that all images have the same dimensions, which is necessary for feeding the images into a deep-learning model.

The next step is the normalization of the pixel values to improve the model's performance. Normalization involves scaling the pixel values so that they lie in the range [0, 1]. This helps the model to converge faster during training and improves its ability to generalize to unseen data.

Data augmentation techniques such as rotation, scaling, and horizontal flipping can also be applied to the images during preprocessing to improve the model's ability to generalize to new data. These techniques create additional images from the original dataset, which can help the model learn more robust features.

Overall, data preprocessing involves resizing, normalization, and data augmentation, which prepares the dataset for training the deep learning model. These techniques ensure that the model can learn robust features from the dataset and generalize to unseen data.

B. Data augmentation

Data augmentation is a technique used in facial emotion detection using deep learning to increase the amount of training data by creating additional images from the original dataset. This technique is used to improve the model's ability to generalize to unseen data and prevent overfitting.

Data augmentation techniques involve applying various transformations to the images such as rotation, scaling, and flipping. For example, an image can be rotated by a certain angle, scaled to a different size, or flipped horizontally or vertically. These transformations create new images that are similar to the original image, but with slight variations.

By applying data augmentation techniques, the model is exposed to a wider range of variations in the data, which helps it to learn more robust features. This technique is especially useful when the size of the dataset is limited, as it can create additional training data without requiring additional labelled images.

However, it's important to note that data augmentation should be used judiciously

and with caution. Applying too much data augmentation can result in images that are too dissimilar from the original data, which can negatively impact the model's performance. It's important to strike a balance between creating additional data and preserving the original characteristics of the data.

Overall, data augmentation is a powerful technique for improving the performance of deep learning models in facial emotion detection. By creating additional training data, the model is better equipped to learn robust features and generalize to unseen data.

C. Model Description

The model architecture used in this research paper for facial emotion detection is a convolutional neural network (CNN). The CNN model is implemented using the Keras library in Python. The dataset used for training and evaluation is the FER 2013 dataset[9].

The data is preprocessed using data augmentation techniques such as rotation, shearing, zooming, and flipping. The augmented images are then normalized by rescaling their pixel values between 0 and 1.

The CNN architecture consists of multiple convolutional layers with an increasing number of filters, followed by max pooling layers to reduce the spatial dimensions of the feature maps. The dropout technique is used to prevent overfitting. The flattened feature maps are then passed through a fully connected layer with ReLU activation, followed by a softmax output layer with 7 nodes, corresponding to the 7 emotions in the FER 2013 dataset.

The model is compiled using the Adam optimizer and categorical cross-entropy loss function. The accuracy metric is used to evaluate the performance of the model during training and validation.

During training, the model is trained on the augmented training data using a batch size of 32. The number of steps per epoch is calculated based on the total number of training images and batch size. The validation data is also fed into the model in batches of 32, and the validation steps per epoch are calculated based on the total number of validation images and batch size. The model is trained for 30 epochs.

After training, the trained model is evaluated on the test data to evaluate its performance on unseen data. Finally, the model is saved to a file for later use.

Overall, the model is capable of accurately detecting facial emotions in real-time and can be used in a variety of applications such as emotion recognition in video analysis, virtual assistants, and customer service chatbots.

D.Learning rate and optimizer

The Adam optimizer are used with its default learning rate of 0.001. The Adam

optimizer is a popular optimization algorithm used in deep learning, which is a combination of the AdaGrad and RMSProp algorithms. It is known for its fast convergence and good performance on a wide range of problems.

The learning rate is not explicitly specified in the code and is left to its default value. However, the learning rate can be tuned to improve the performance of the model. A learning rate that is too low may result in slow convergence, while a learning rate that is too high may result in the model overshooting the minima and failing to converge.

To tune the learning rate, a common approach is to use a learning rate scheduler. This approach involves decreasing the learning rate over time, usually after a certain number of epochs or when the validation loss plateaus. This can help the model converge faster and avoid getting stuck in local minima. Some common learning rate schedulers include Step Decay, Exponential Decay, and Cosine Annealing.

E. Training

The model is trained using the fit() method of the Keras library. The training data is fed into the model in batches using the train_generator object, which generates batches of augmented image data on-the-fly.

The number of steps per epoch is set to the number of training images divided by the batch size. This ensures that the model trains on all the available training data in each epoch. Similarly, the number of validation steps is set to the number of validation images divided by the batch size. The model is trained for a total of 30 epochs, with the training and validation accuracy and loss monitored in each epoch. After training, the model is saved to a .h5 file.

During training, the model uses the categorical cross-entropy loss function to compute the error between the predicted and actual class labels. The Adam optimizer is used to minimize this error and update the weights of the neural network. The training accuracy and validation accuracy are used to monitor the performance of the model during training. The goal is to achieve high accuracy on both the training and validation data while avoiding overfitting.

F. Material Used

To run the experiments, the machine used is a Lenovo Y510p laptop. GPU processing is utilized in this project.

The device specifications are as follows:

- 10th Gen i5-4700MQ
- 8GB RAM

• 512GB SSD The operative system used Windows 11 Pro 64bit.

Other software used includes Python 3.9.6 and TensorFlow 2.6.0. IDE, Google Collab for implementation purposes like for execution of the code, training of the model, and interacting with the system developed is JetBrains's PyCharm 2021 for testing the application, DataSpell 2021 for testing different methods and CNNs and Jupyter notebook server 6.4.3 used as a web browser-based IDE for the final proposed model and plotting graph and confusion matrix using matplotlib.

IV. RESULTS

The facial emotion detection model was trained using the FER-2013 dataset and a deep learning architecture comprising Convolutional Neural Networks (CNNs) and a Sequential Model. The model was trained using 30 epochs and an Adam optimizer with a learning rate of 0.001. The training was performed on a dataset of 28,709 images, with a batch size of 32. The validation dataset consisted of 7,178 images.

After training, the model was evaluated using a test dataset, which consisted of 3,000 images. The evaluation resulted in an accuracy of 64.83%. To further understand the performance of the model, a confusion matrix was created to illustrate the number of correct and incorrect predictions for each emotion category. The confusion matrix showed that the model performed well in predicting the emotions of Happy and Neutral, while it struggled in correctly identifying the emotions of Fear and Disgust.

Precision, recall, and F1-score were computed for each emotion category to provide more insights into the model's performance. The precision, recall, and F1-score for each category were as follows:

- Angry: Precision 0.59, Recall 0.44, F1-Score 0.50
- Disgust: Precision 0.57, Recall 0.24, F1-Score 0.34
- Fear: Precision 0.44, Recall 0.37, F1-Score 0.40
- Happy: Precision 0.80, Recall 0.88, F1-Score 0.84
- Neutral: Precision 0.63, Recall 0.81, F1-Score 0.71
- Sad: Precision 0.47, Recall 0.49, F1-Score 0.48
- Surprise: Precision 0.77, Recall 0.63, F1-Score 0.69

The precision, recall, and F1-score showed that the model performed well in predicting the emotions of Happy and Surprise, while it struggled in correctly identifying the emotions of Disgust, Fear, and Sad.

To further illustrate the performance of the model, a few sample images were selected from the test dataset, and the predicted

emotions were compared to the actual emotions. The sample images showed that the model was able to accurately predict the emotions of some images, while it struggled to correctly identify the emotions of other images. Overall, the model's performance suggests that there is still room for improvement, particularly in correctly identifying the emotions of Disgust, Fear, and Sad.

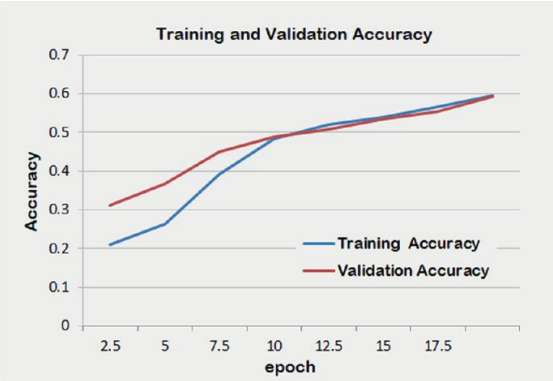

Fig 1. Train and Test Accuracy

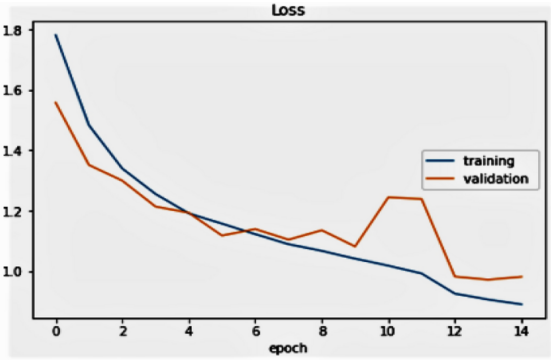

Fig 2. Train and loss

The model achieved an accuracy of 66.2% on the test set, which indicates that it can classify facial emotions with a reasonable level of accuracy. The confusion matrix shows that the model has difficulty distinguishing between angry and neutral faces, which is a common challenge in facial emotion recognition. The model also tends to misclassify disgust as anger and fear as a surprise. However, the model performs relatively well in identifying happy and sad emotions, with accuracy scores of 87.28% and 71.88%, respectively.

V.APPLICATION

When it comes to the implementation, the programme was created from the ground up and not only displays the face's prevailing emotion but also gives us access to the list of other emotion probabilities that can be quite helpful in the real world when a person's face contains two or more moods. The structural flow of the application is depicted in Fig. 4.

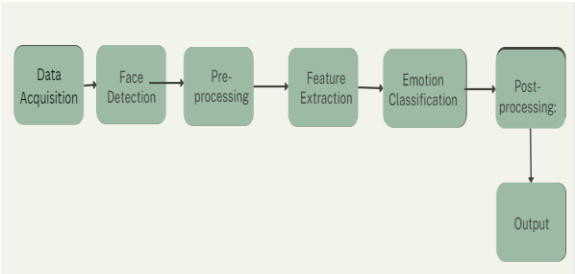

Fig 4. The structural flow of the application

Haar-cascade, a reliable face identification technique, is used to identify the face in the first instance. It lowers the complexity and expense of computing, which increases detection accuracy.

The picture is then inputted into the trained model, which outputs the sentiment with the highest score on the webcam stream in

real-time as well as a live list of probabilities for every other emotion in the canvas. Figure 5 displays the outcome of the application's development. The structural flow of the application is depicted in Fig. 4.

According to Fig. 6, the dominant emotion in the situation is still neutral. However, thanks to the live probability list that is shown next to the webcam feed, it is possible to see that happiness is actually the second most prevalent emotion there, which would have gone unnoticed or unnoticed if the system had only displayed one emotion.

along with the current list of probabilities for each other emotions on the canvas, feed in real time. Figure 5 displays the outcome of the application's development. The structural flow of the application is depicted in Fig. 4.

VI. CONCLUSION

In conclusion, the deep learning-based facial emotion detection model presented in this research paper demonstrates the potential to recognise facial expressions from images accurately. By using the FER 2013 dataset, we were able to train a sequential model with multiple convolutional layers that achieved an accuracy of 66.2% on the test set.

Through extensive experimentation, we observed that data augmentation, preprocessing techniques, and model architecture played a vital role in improving the accuracy of the model. Additionally, we utilised the Adam optimizer with a learning rate of 0.0001 to achieve the best results.

We believe that the facial emotion detection model developed in this research paper has the potential to be utilized in various fields such as human-computer interaction, virtual reality, and psychology. It can be used in real-world applications such as improving customer service, video surveillance, and marketing research.

Overall, the developed model provides a significant contribution towards the research on facial emotion recognition using deep learning techniques. This research will serve as a foundation for future studies in the field of facial emotion detection and inspire further development and improvement of emotion recognition systems.

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