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Leveraging the Deep Learning Tools and Technique for Enhanced Biometrics and Facial Emotion Based Predictions for Customised Applications

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ABSTRACT

In today's society, the use of machines for various tasks is rising. Machines can perform a wide range of tasks when given perception. There are also very difficult ones, like elderly care. Understanding the interlocutor's intentions and surrounding environment is necessary for machine perception. In this regard, facial emotion recognition can be helpful. Images depicting facial emotions like happiness, sadness, anger, surprise, disgust, and fear were used in the development of this work with deep learning techniques. A pure convolutional neural network approach outperformed other authors' statistical methods, such as feature engineering, in this study. There is a learning function that can be used with convolutional networks. This seems promising for this job, where it takes time to define the functionality. Two distinct corpora were also used to evaluate the network. One was used to help define the network's architecture and fine-tune parameters during network training. Mimic emotions made up this corpus. The network with the highest classification accuracy results was tested on the second dataset. Even though the network was only trained on one corpus, when it was tested on another dataset with non-real facial emotions, it showed promising results. The obtained results needed to meet current standards. Evidence suggests that facial expression classification may benefit from deep learning. As a result, deep learning has the potential to enhance interaction between humans and machines. Because machines can develop cognition through the ability to learn new functions, the machine can respond more smoothly through perception, greatly enhancing the user experience.

INTRODUCTION

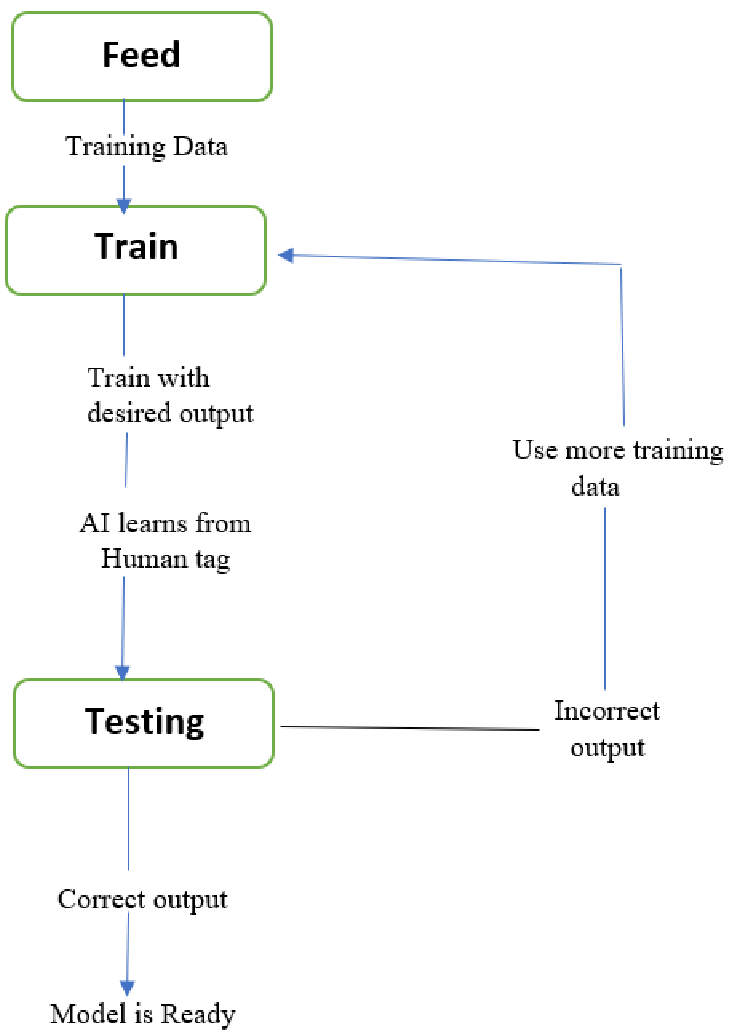
Automated emotion recognition is a significant and extensive field of study that focuses on two distinct issues: recognition of human emotions psychologically and artificial intelligence Information about human emotions, both verbal and nonverbal, can be gleaned from various sensors like B. Changes in facial expression, pitch, and physiological signs. Mehrabian demonstrated in 1967 that 55% of his emotional information was visual, 38% verbal, and 7% verbal. The first indications of an emotional state are facial changes during communication. As a result, this method piques the interest of most researchers. To improve classification, extracting features from different faces is challenging and delicate. Ekman and Friesen were the first pantomime enthusiasts to develop the FACS (Facial Action Coding System) in 1978. In this system, the action unit AU describes facial movements. The human face is broken up into 46 AU action units by them. Encoded in one or more muscles of the face. Philipp et al.'s statistics indicate that Researchers compare automated FER to other modalities.

Developed in the most extensively researched but challenging because each person presents their emotions. Head posture, brightness, age, gender, background changes, occlusion issues caused by sunglasses, scarves, skin diseases, and other factors cannot be ignored in this field. Facial feature extraction employs conventional techniques like geometric and texture features, Gabor wavelets, the local binary pattern LBP, the facial action unit FAC, and the local directional pattern LDA. Deep learning has become a very effective and successful strategy in recent years.

B. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Why did researchers start using this method to find out how people feel? I've tried in various ways. An overview of recent developments in emotion recognition through facial expression recognition using various deep-learning architectures is provided in this article.

METHODOLOGY

The proposed system is capable of automatically recognizing seven universal emotions that are believed to be shared by all cultures: disapproval, rage, anxiety, joy, sadness, neutrality, and surprise. I can manage it. These systems look at facial images and make computer-generated predictions about how people will look. An automatic face recognition module is incorporated into this strategy, which generates a neural network from a training dataset.



How to increase precision:

It is possible to use deep convolutional neural networks. This network adapts and trains three distinct neural network architectures for a variety of classification tasks. The network receives image data from the input, generates return values for the output layer from the performance matrix of the final model, and determines the maximum value from the matrix. This value represents the current sentiment of the input.

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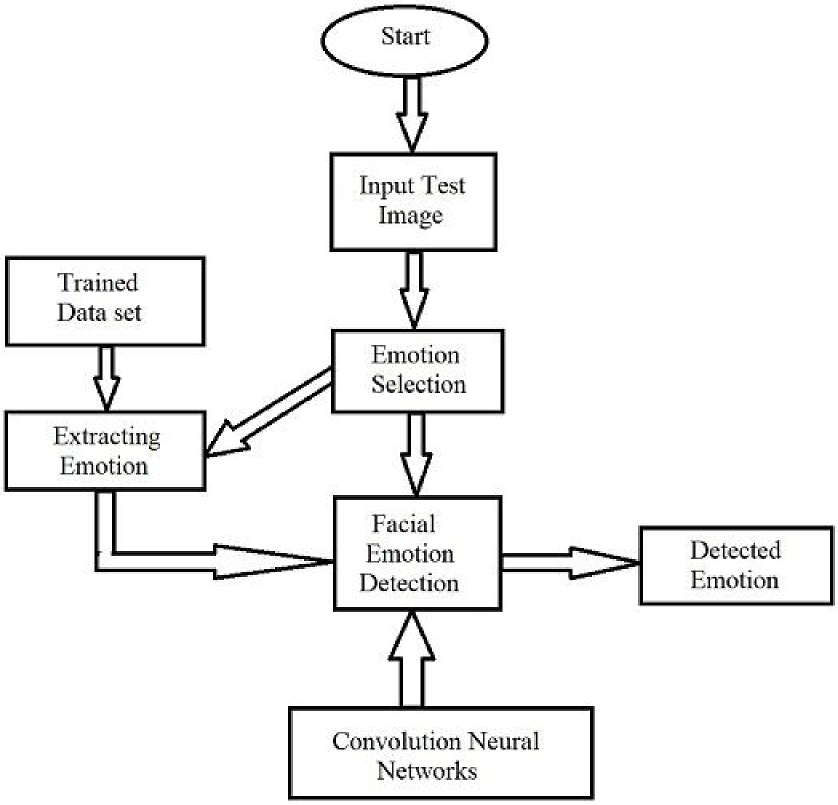
MODELING AND ANALYSIS



RESULTS AND DISCUSSION

```
model_path = "model1.h5"
loaded_model = keras.models.load_model(model_path)

import matplotlib.pyplot as plt
import numpy as np
import cv2
from PIL import Image

image = cv2.imread("/content/drive/MyDrive/train/Fear/myvideo_frames0_jpg.rf.0464fbcd88f1307929b67d72c8432f6f.jpg")

img= Image.fromarray(image, 'RGB')
resize_image = img.resize((128, 128))
expand_input = np.expand_dims(resize_image,axis=0)
input_data = np.array(expand_input)
input_data = input_data/255

pred = loaded_model.predict(input_data)
result = pred.argmax()
result
```

```
1/1 [==============================] - 0s 87ms/step
2
```

Output => 2 indicates that 'Fear'

```
1/1 [==============================] - 0s 87ms/step
2
```

```
training_set.class_indices
```

```
{'Anger': 0,
 'Disgust': 1,
 'Fear': 2,
 'Happiness': 3,
 'Sadness': 4,
 'Surprise': 5}
```

CONCLUSION

This project developed deep learning methods for static facial image classification and research on facial emotion. Numerous approaches have been used to address this difficult issue. Despite his success with feature engineering, this project concentrated on one of DL's promises: attribute learning. The outcomes were not cutting-edge but slightly superior to those of other feature engineering methods. Given sufficient labelled examples, this indicates that DL techniques can finally resolve this issue. Today, feature engineering is used in facial emotion recognition software. Image pre-processing improves classification accuracy without requiring feature engineering.

The result is that the input data contain less noise. A trait-learning-based solution still needs to catch up with her due to her one major limitation, which is the requirement of large emotional datasets.

On larger data sets, networks with better feature learning capabilities can be implemented. For instance, the ImageNet competition uses datasets containing numerous images. This way, sentiment can be categorized using deep learning techniques.

REFERENCES

[1] Y.-L. Tian, T. Kanade, and J. F. Cohn, (2001), Recognizing action units for facial expression analysis, *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. CVPR 2000* Cat NoPR00662, vol. 1, no. 2, pp. 1–19.

[2] F. De la Torre and J. F. Cohn, (2011), Facial expression analysis, *Vis. Anal. Hum.*, pp. 377–410.

[3] A. Gudi, H. E. Tasli, T. M. Den Uyl, and A. Maroulis, (2015), Deep Learning based FACS Action Unit Occurrence and Intensity Estimation, *11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*

[4] Z. Ming et al., (2015), Facial Action Units Intensity Estimation by the Fusion of Features with Multi-kernel Support Vector Machine To cite this version : Facial Action Units Intensity Estimation by the Fusion of Features with Multi-kernel Support Vector Machine, *11TH IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*

[5] R. S. Smith and T. Windeatt, (2015), Facial action unit recognition using multi-class classification, *Neurocomputing*, vol. 150, pp. 440–448.

[6] S. Taheri, Qiang Qiu, and R. Chellappa, (2014), Structure-preserving sparse decomposition for facial expression analysis., *IEEE Trans. Image Process. Publ. IEEE Signal Process. Soc.*, vol. 23, no. 8, pp. 3590–603.

[7] Y. Wu and Q. Ji, (2015), Discriminative Deep Face Shape Model for Facial Point Detection, *Int. J. Computer. Vision.*, vol. 113, no. 1, pp. 37–53.

[8] M. F. Valstar and M. Pantic, (2012), Fully automatic recognition of the temporal phases of facial actions, *IEEE Trans. Syst. Man Cybern. Part B Cybern.*, vol. 42, no. 1, pp. 28–43.

[9] L. Wang, R. Li, and K. Wang, (2014), A Novel Automatic Facial Expression Recognition Method Based on AAM, *J. Comput.*, vol. 9, no. 3, pp. 608–617.