Facial Expression Detection

AIM97

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Contents

Chapter 1

CH1 - Introduction

1.1 Preface

1.1.1 Preface

<You expect employees to have high levels of emotional intelligence when interacting with customers. Now, thanks to advances in Deep Learning, you'll soon expect your software to do the same.>

<Companies have also been taking advantage of emotion recognition to drive business outcomes. For the upcoming release of Toy Story 5, Disney plans to use facial recognition to judge the emotional responses of the audience. Apple even released a new feature on the iPhone X called Animoji, where you can get a computer simulated emoji to mimic your facial expressions. It's not so far off to assume they'll use those capabilities in other applications soon.>

1.2 Image Processing

1.2.1 Brief

definition Image processing is the process of applying some operations to an image to reach an enhanced image that satisfies a certain goal depending on the application in hand. for example if we need to make an application that detects edges within an image we use an image processing technique that is capable of highlighting those edges and make them stand out. the result image is not necessarily a beautiful one from the perspective of a human, but it has to highlight the features of interest within the image that would be used for further processing.

impact Apart from the rule image processing plays in graphics enhancement to make image more visually appealing, Image processing is very important tool that is used for the specially preparation for computer vision and Machine learning, image processing a key preprocessing step to be taken before start in any of the two fields. the key difference between those two purposes is that when we want the image to be more visually appealing our target is a human, a human is the one who should view that image in the end. but when it comes to fields like computer vision or Machine Learning, the target is a computer that is programmed to act based on the content of input image. for this computer to do that it must be able to clearly extract feature of interest from the image, in order to make use of the image, we must have 2 main tasks for image processing:

1. noise removal: to remove the noise (like salt and pepper, or gauessian blur, ...etc) that we estimate to exist in the image so as to refine the features to be extracted from the image.
2. feature extraction: to highlight and evaluate features of interest that exist in the image to be used as input data for computer vision or Machine learning algorithms e.g. neural networks.

these two processes are the most common use cases for image processing, and we will go over them with more detail in next section.

1.2.2 How important is image processing?

The applications of image processing are many we will catch on some applications for noise removal and feature extraction.

Noise removal

this process is done to make features more clear to refine the quality of extracted features by removing different types of noise (see figure 1.1).
multiple filters exists to restore original image by removing noise as much as possible.

1. Max filter: the output at one pixel is the **maximum** value of the pixels around it.
2. Min filter: the output at one pixel is the **minimum** value of the pixels around it.
3. Median filter: the output at one pixel is the **median** value of the pixels around it.
4. Mean filter: the output at one pixel is the **mean** value of the pixels around it.
5. Gauessian filter: it applies a matrix with values with gaussian distribution(highest weight in the center and weight decreases as we go away from the center) to the current window and the result is assigned to current pixel.

these filters make use of the values of pixels around current pixel in order to detect abnormal changes within the image which is probably noise and based on the values of surrounding pixel a new value is assigned to current pixel which is estimated to be closest to the original value.
Some other filter are used for enhancement can be sharpening filter and.

Feature extraction

this process is done to highlight features of interest in an image

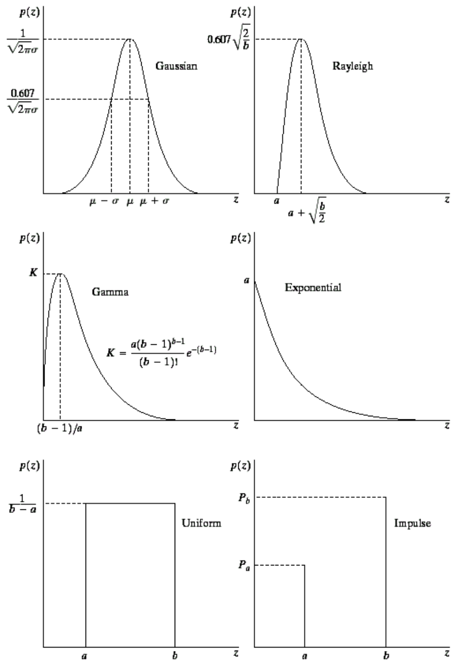

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Figure 1.1: examples for different types of noise

1.2.3 How is image processing important for our project

The purposes of our project is to recognize the facial expression from face image, for this task multiple image processing techniques have been applied to the input image before extracting features like face landmarks and HOG from the image.

Noise Removal

since we don't expect the input image to be particularly corrupted we only use median filter to remove white noise and salt and pepper noise a gaussian filter was being used at as well but it was inefficient in terms of time so the median filter took its place without a problem. we also use sharpening filter to make face features more clear for the landmark extraction process.

Feature Extraction

unlike CNN (convolutional neural network) model which extracts the features it needs from the image directly, one of the approaches we took requires pre-processing to extract some features from input image we needed two types of features in particular:

1. HOG (Histogram of Oriented Gradients) : feature descriptor which means that it generalize the object in a way that the same object (in this case a person) produces as close as possible to the same feature descriptor when viewed under different conditions.

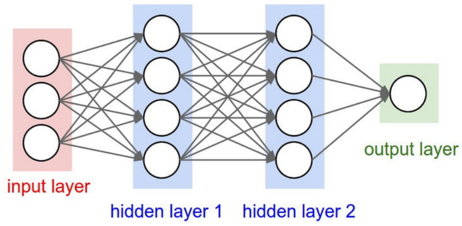

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Figure 1.2: Neural network

2. Face Landmarks : those are points in the face that represent the face main features and we need those to estimate the emotion as well.

1.3 Neural Networks

1.3.1 Breif

What is Neural Networks? Artificial neural networks are one of the main tools used in machine learning. As the "neural" part of their name suggests, they are brain-inspired systems which are intended to replicate the way that we humans learn. Neural networks consist of input and output layers, as well as (in most cases) a hidden layer consisting of units that transform the input into something that the output layer can use. They are excellent tools for finding patterns which are far too complex or numerous for a human programmer to extract and teach the machine to recognize.

While neural networks (also called "perceptrons") have been around since the 1940s, it is only in the last several decades where they have become a major part of artificial intelligence. This is due to the arrival of a technique called "backpropagation," which allows networks to adjust their hidden layers of neurons in situations where the outcome doesn't match what the creator is hoping for — like a network designed to recognize dogs, which misidentifies a cat, for example.

Another important advance has been the arrival of deep learning neural networks, in which different layers of a multilayer network extract different features until it can recognize what it is looking for.

1.3.2 Basics of Neural Networks.

a basic idea of how a deep learning neural network learns, imagine a factory line. After the raw materials (the data set) are input, they are then passed down the conveyer belt, with each subsequent stop or layer extracting a different set of high-level features. If the network is intended to recognize an object, the first layer might analyze the brightness of its pixels.

The next layer could then identify any edges in the image, based on lines of similar pixels. After this, another layer may recognize textures and shapes, and so on. By the time the fourth or fifth layer is reached, the deep learning net will have created complex feature detectors. It can figure out that certain image elements (such as a pair of eyes, a nose, and a mouth) are commonly found together.

Once this is done, the researchers who have trained the network can give labels to the output, and then use backpropagation to correct any mistakes which have been made. After a while, the network can carry out its own classification tasks without needing humans to help every time.

Beyond this, there are different types of learning, such as supervised or unsupervised learning or reinforcement learning, in which the network learns for itself by trying to maximize its score

1.3.3 Why Neural networks are important?

ANNs (Artificial Neural Networks) have some key advantages that make them most suitable for certain problems and situations:

1. ANNs have the ability to learn and model non-linear and complex relationships, which is really important because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex.

2. ANNs can generalize ,After learning from the initial inputs and their relationships, it can infer unseen relationships on unseen data as well,thus making the model generalize and predict on unseen data.

3. Unlike many other prediction techniques, ANN does not impose any restrictions on the input variables (like how they should be distributed). Additionally, many studies have shown that ANNs can better model heteroskedasticity i.e. data with high volatility and non-constant variance, given its ability to learn hidden relationships in the data without imposing any fixed relationships in the data.

1.3.4 Types of neural network

There are multiple types of neural network, each of which come with their own specific use cases and levels of complexity.

1. The most basic type of neural net is something called a feedforward neural network, in which information travels in only one direction from input to output.

Chapter 2

CH2 - Review

2.1 Overview About Our Work

2.2 Previous Work

in this section, we start making a review of the most common techniques usually used in Facial Expression Detection, highlight methodological differences, discuss the reported performances and the dataset used.

Based on CNN and Fer 2013 Dataset

CNN has enabled significant performance improvements in related tasks specifically those dealing with images using CNN help in feature extraction and inference.

FER2013 is a large, publicly available Facial Expression Detection dataset consisting of 35,887 face crops. The dataset is challenging as the depicted faces vary significantly in terms of person age, face pose, and other factors, reflecting realistic conditions. The dataset is split into training, validation, and test sets with 28,709, 3,589, and 3,589 samples, respectively. Basic expression labels are provided for all samples. All images are grayscale and have a resolution of 48 by 48 pixels. The human accuracy on this dataset is around 65.5%.

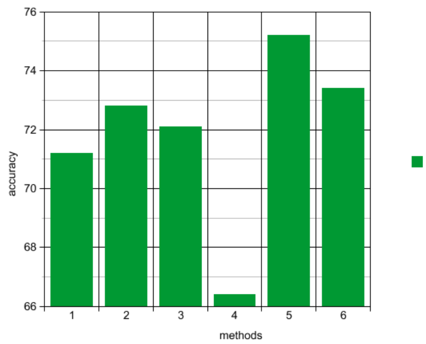
Facial Expression Recognition using Convolutional Neural Networks: State of the Art paper[1] get with only CNN 75% testing accuracy. also in this paper[1] a detailed review of six models we only mention there Architecture and accuracy here. in table 2.2.1.

the biggest bottleneck here according to paper is the dataset as it has an only 35k image with a lot of noise and needs too much

Table 2.1: CNN ARCHITECTURES. C, P, N, I, AND F STANDS FOR CONVOLUTION,POOLING,NORMALIZATION,INCEPTION AND FULLY CONNECTED LAYERS, RESPECTIVELY.

Method	**Architecture**
method 1[2]	CPCPFF
method 2[3]	CPCPCPFF
method 3[4]	PCCPCCPCFFF
method 4[5]	CPCPIIPIPFFF
method 5[6]	CPNCPNCPCFF
method 6[7]	CPCPCPFF

Fig. 2.2.1. Reported FER2013 test results.



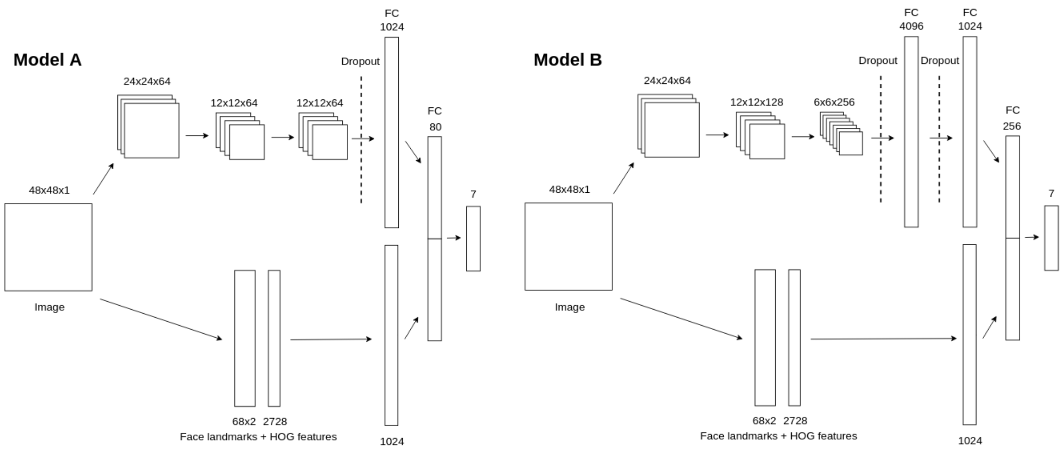
preprocessing the quick solution for it is appling data augmentation with different attributes.

another model build over state of art try to overcome its discussed problem is applied the model on tensorflow and CNN also work on fer13 . it defines a similar method to the final methods with some addition to help improve dataset performance adding Dropout and normalization Layers and it uses landmarks and a sliding window Hog as feature extraction.
Also we found an implementation using SVM, it depends actually on extraction features using landmarks and Hog and feeds them to a multi-class SVM classifier.here we can find the different architecture and accuracy of two models based on CNN and SVM model.

we try this model with this architecture (model B), the same preprocessing and on the same dataset but we get only 50% testing accuracy.

Table 2.2: 3. Classification Results (training on 5 expressions)

Experiments	SVM	Model A	Model B
CNN (on raw pixels)	——	72.4%	73.5%
CNN + Face landmarks	46.9%	73.5%	74.4%
CNN + Face landmarks + HOG	55.0%	68.7%	73.2%
CNN + Face landmarks + HOG + sliding window	**59.4%**	**71.4%**	**75.1%**



Chapter 3

CH3 - Proposed System

3.1 System Architecture

3.2 Preprocessing

3.3 Model

3.4 Library

Chapter 4

CH4 - Results

Chapter 5

CH5 - Conclusion

Chapter 6

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