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FACIAL EXPRESSIONS AND EMOTION RECOGNITION

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ABSTRACT- *The results of recognizing seven emotional states (neutral, joy, sadness, surprise, anger, fear, and disgust) based on facial expressions are provided in this article. As features, six participants' coefficients representing aspects of face expressions were used. For a three-dimensional facial model, the features were estimated.The classification of features was performed using k-NN classifier and MLP neural network.*

I. INTRODUCTION

Recognizing human expressions and emotions has piqued researchers' interest, as the ability to recognize one's expressions aids in human-computer interaction, the creation of appropriate advertising campaigns, and the culmination of augmented and enhanced human communication, all while improving human emotional intelligence ("EQ"). The recognition of human expressions can be tested in a variety of ways, including facial expressions, body posture, voice tone, and so on. We focused on face expression recognition in this work. Facial Emotion Recognition (FER) is a flourishing study topic in which many breakthroughs are being made in industries, such as automatic translation systems and machine-to-human contact. The study, on the other hand, concentrates on surveying and reviewing numerous facial extractions.

The following is a breakdown of the paper's structure. The second section provides background information on expression recognition, emotion recognition systems, and emotion recognition applications. The methods for feature selection and image optimization are explained in Section 3. The fourth section examines and contrasts several facial emotional databases. Section 5 discusses various classifier techniques for categorizing photographs based on the identified phrase.

II. LITERATURE REVIEW

A detailed study on the facial emotion recognition is discussed in which exposes the properties of dataset, facial emotion recognition study classifier. Visual features of image are examined and some of the classifier techniques are discussed in which is helpful in the further inspection of the methods of emotion recognition. This paper examined the prediction of the future reactions from images based on the recognition of emotions, using different classes of classifiers. Some of the classification algorithms like K-Nearest Neighbor, Random Forest are applied in to classify emotions. Neural network arises tremendously which attempts to solve problems in data science. Deep RNN like LSTM, Bi-directional LSTM modeled for audio visual features are used in Various range of CNN , modeled and trained for facial emotion recognition are evaluated in .Facial emotion Recognition is drawing its own importance in the research field. Facial emotion recognition is inspected and analyzed on all research areas. Emotion is identified from facial images using filter banks and Deep CNN which gives high accuracy rate with which we had an inference that deep learning can also be used for emotion detection. Facial emotion recognition can be also performed using image spectrograms with deep convolutional networks which is implemented in .All the above methods mentioned used some of the conventional methods of feature selection from MFCC's, wave parameters such as pitch are used in the paper. This paper studies different database used for facial emotion recognition, features selected from facial expression images, classifiers used to classify different classes of emotions. As the amount of data array is taken and the method of bottleneck is used, Long Short-term Memory (LSTM) is used for Facial emotion recognition. Though speech emotion recognition is done and desired results are shown, research real time facial emotion is still ongoing. Real-time facial emotion recognition is done through RGB image classification using transfer learning methodologies in which knowledge gained from solving one problem and that is implemented for the another problem [19].

Emotion has been recognized from facial expressions using hidden markov models and deep belief networks with unweighted average recall (UAR) of about 56.36 %. Different image types and emotions were examined for detecting expressions from the facial expressions using different classifiers such as KNN, HMM, GMM, SVM. This paper explains about learning significant features such as convolutional neural network, local invariant feature learning, and salient discriminative feature analysis for facial emotion recognition. Various significant features are examined and trained to detect emotions using Convolution neural networks in which dataset is obtained from various emotional databases such as SAVEE, Emo-DB, DES, MES. This paper describes Facial emotion recognition using Deep neural Networks .Although Probabilistic method of identifying emotion is conventional ,that is used to recognize emotion changes.

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III. EXISTING SYSTEM

Support vector machines (SVMs), which are supervised learning models with associated learning algorithms that examine data for classification and regression analysis, are used in the current system. An SVM model is a representation of the examples as points in space, mapped so that the examples of the different categories are separated by a large distance. New instances are then mapped into the same space and assigned to a category based on which side of the gap they land on.

When data is unlabeled, supervised learning is impossible, hence an unsupervised learning strategy is necessary, in which the data is clustered naturally into groups and new data is mapped to these groups. The support-vector clustering [2] technique was developed by HavaSiegelmann and Vladimir Vapnik to categorise unlabeled data using support vector statistics obtained in the support vector machines algorithm. It is one of the most extensively used clustering algorithms in industrial applications.

A support-vector machine, in more technical terms, creates a hyperplane or set of hyperplanes in a high- or infinite-dimensional space that can be used for classification, regression, or other tasks such as outlier detection. [3] Intuitively, the hyperplane with the greatest distance to the nearest training-data point of any class (so-called functional margin) achieves a decent separation, because the larger the margin, the lower the classifier's generalization error.

3.1 LIMITATIONS IN EXISTING SYSTEM

SVM’s requires full labeling of input data. Uncalibrated class membership probabilities—SVM stems from Vapnik's theory which avoids estimating probabilities on finite data. The SVM is only directly applicable for two-class tasks. Therefore, algorithms that reduce the multi-class task to several binary problems have to be applied; see the multi-class SVM section.Parameters of a solved model are difficult to interpret.

IV. PROPOSED SYSTEM

Proposed system is using method of Convolution Neural Network (CNN). A convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.

In comparison to other image classification methods, CNNs require very little pre-processing. This means that the network learns the filters that were previously hand-engineered in traditional techniques. This feature design independence from prior knowledge and human effort is a significant benefit.

Convolution is a type of linear operation that is specialised. Convolutional networks are simple neural networks with at least one layer that uses convolution instead of ordinary matrix multiplication.

When programming a CNN, the input is a tensor with shape (number of images) x (image height) x (image width) x (image depth). Then after passing through a convolutional layer, the image becomes abstracted to a feature map, with shape (number of images) x (feature map height) x (feature map width) x (feature map channels). A convolutional layer within a neural network should have the following attributes:

- Convolutional kernels defined by a width and height (hyper-parameters).
- The number of input channels and output channels (hyper-parameter).
- The depth of the Convolution filter (the input channels) must be equal to the number channels (depth) of the input feature map.

4.1 ADVANTAGES OF PROPOSED SYSTEM

- Convolutional neural networks provide an advantage over feed-forward networks because they are capable of considering locality of features.
- Convolutional Neural Network has the ability to handle large unstructured data.
- CNN are more powerful than machine learning algorithms and are also computationally efficient.
- For a completely new task / problem CNNs are very good feature extractors. This means that you can extract useful attributes from an already trained CNN with its trained weights by feeding your data on each level and tune the CNN a bit for the specific task.
- CNN is designed to automatically and adaptively learn spatial hierarchies of features through back propagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers
- Weight sharing is an essential aspect of a convolution operation: kernels are shared across all picture positions. Convolution operations include the following properties as a result of weight sharing: (1) allowing local feature patterns extracted by kernels to be translation b invariant as kernels travel across all image positions and detect learned local patterns, (2) learning spatial hierarchies of feature patterns by down sampling in conjunction with a pooling operation, resulting in capturing an increasingly larger field of view, and (3) increasing model efficiency by reducing the number of parameters to learn in comparison to fully connected neural networks.

V. SYSTEMIMPLEMENTATION

Figure 5.1: System Architecture

The system design model is tested functionally in four different levels

- Building a dataset to classify emotion using convolution neural network layer. The free dataset used is proposed work is represented in the link (http://www.kdef.se/) given. The KDEF data set as in figure 8 had 4900 pictures where 1999 pictures were removed as they were inside postures and trained the dataset with 2901 pictures by splitting and training the dataset in to 70 % and 30% respectively. Similarly with my images own dataset was also created with 100 images.

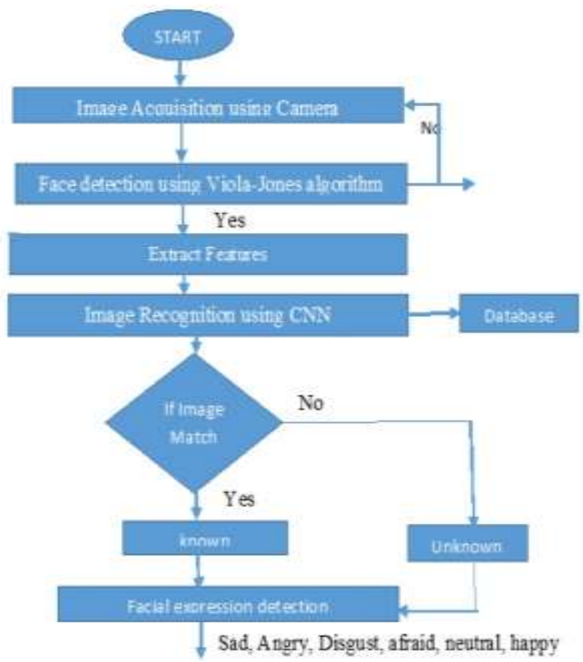

Figure 5.2: Data flow diagram

- Creating database with open CV library and other resources.

a) First make a folder and name it and then create two python files such as face_recognize.py and create_data.py. The code is copied in the resultant source file and executed to check the errors. Similarly copy the xml file in to project directory to support the face features. The file to be copied is haarcascade_frontalface_default.xml.

b) Dlib: It is cross platform library programmed using C++. It is used for face recognition and supports the face features using linear SVM and Histogram of oriented gradients (HoG).

c) Get-pip, numpy and Pandas: This is open source library tool used as installation package in python programming language.

d) open CV, sciPy, SVM and pickle: These are open source library for computer vision, computation operations and feature vectors. Imported library functions for python 3.5

- Training procedure for recognition and classification

The training and testing data is splitted into two models where VGG caffe model builds feature vector with support vector machine to train the emotion classification. The size of the image used is 224x 224 which is preprocessed as rescaling and extracted as feature vector to train the classifier

- Building all the files to Python 3.5 and Anaconda 3-4.2.0 software platform
- 4. Experimental Results

The results are followed in three phases as face detection, Face recognition and Face classification..

Objects, landscapes, and backgrounds are all part of the human face detection process. Facial recognition is built using the CNN model, which extracts and classifies facial features according to the VGG 16 model. The classification of a human face includes expressions such as contempt, sadness, happiness, fear, and neutral.

Matching is displayed on the LCD panel based on the classified expression. The task is divided into three steps, the first of which involves reading the image and capturing it using the openCVhaar cascade detection and viola jones technique. The RGB image was collected and processed for facial recognition using a database of extracted features. The image is transformed into a matrix with values ranging from 0 to 255. The database features training model is put to the test to detect the human face, with the image resolution lowered from 1024*1024*3 to 227*227*3 in order to conduct matrix manipulations using the CNN model.

Face detection: In the first step testing of the face is detected with 1024 x 1024 resolution using viola jones Algorithm

Face Recognition: is carried out with support of dataset built. The real time images are compared with trained model of dataset. The images are named if they are recognized on comparison with dataset built. In order to perform recognition images-data.csv and train.py is required.

Face Classification where the trained model is further classified to recognize the facial emotion and classify each expression with VGG 16 and svc_FER_linear_2.sav model. The face encodings are generated by convolution neural network (CNN) with knearestneighbor as clf. All the models are classified based on their weights to recognize the facial expression of human face in python main_FER_V2.py. Finally the program is run in different phases to load KDEF model to recognize the facial emotion expression.

VI. CONCLUSION

The goal of this project is to create a real-time system that can detect, recognize, and classify human faces. As indicated in the above data, the categorized expressions are represented in seven states. Anaconda and Python 3.5 are the software's that were utilized to test the functionality. The viola jones and haar cascade algorithms were employed to detect faces. For face recognition and classification, the KDEF dataset and VGG 16 were utilized in conjunction with a convolutional neural network model. The CNN model, which has an accuracy of 88 percent, is used to validate the performance measurements. The results, on the other hand, show that the network architecture designed outperforms previous techniques. This programme is widely utilized in a variety of fields, including education, industry, medicine, and electronics.

VII. FUTURE ENHANCEMENT

This system will have a wide range of uses in the future. Intelligent assistants and home automation can both benefit from this technology. This system has been improved and is now utilized in automation as well as other disciplines. Emotion recognition can be used in stores to determine customer feedback on products. It's used in virtual gaming to improve the overall experience.

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