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F2R Analyzer Using Machine Learning and Deep Learning

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Abstract - *The field of emotion recognition has advanced significantly, and it now has a significant impact on HCI. It is important to extract the facial features that may be used to detect the expression in order to do any Facial Expression Recognition. It details the range and uses of automatic emotion recognition systems across several industries. This study also examines a number of parameters that can improve the system's precision, security, and effectiveness. How photos can be recognised by computers in a similar way to how humans do. Handwriting is one that can be recognised from an image and is useful for processing handwritten forms and for human labour like check analysis. check analysis and processing of handwritten forms. The process of recognising the image in image recognition will be influenced by the angle of view, lighting, and clarity of the captured image. The method for offline handwritten digit recognition presented in this work is based on various machine learning techniques. The major goal of this study is to provide efficient and trustworthy methods for handwritten digit recognition.*

Key Words: **Facial emotion recognition (FER), feature extraction, deep learning , facial expressions, pattern recognition, handwritten recognition ,digit recognition, machine learning.**

1. INTRODUCTION

Visually perceptible human facial emotions are all around humans. They are organic cues that aid in their comprehension of the emotions of any subject in front of them or in pictures or movies. While these emotions are extremely complex and difficult for machines to comprehend, they are simple to comprehend for humans. Numerous human-computer interactions, including those involving smartphones, affective computing, intelligent control systems, psychological research, behavioural analysis, pattern searching, defence, social media, robotics, and other areas, have made extensive use of human facial emotion recognition. One might provide the highest level of user pleasure and feedback to enhance present technologies by evaluating these feelings. Only computer vision and deep learning can be used for this. To create several Facial Emotion Recognition (FER) systems that have been evaluated for encoding and transmitting Information from facial representations.

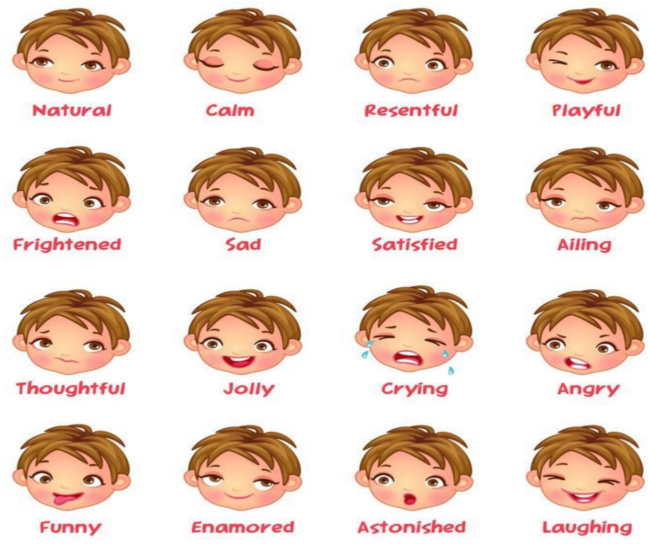


Figure-1: Different Expressions.

The OCR is a process of classifying the optical patterns present in a digital image to the corresponding characters. The character recognition is achieved through important steps of feature extraction and classification. OCR system simulates the human capability to recognize printed forms of text and it has become one of the most successful applications in the field of object recognition. Applications of OCR include identifying the vehicle registration number from the image of number plate which helps in controlling traffic, converting printed academic records into text for storing in an electronic database, decoding ancient scripture, automatic data entry by optical scanning of cards, bank checks, etc. The OCR systems save time and prevent typing errors. The usage of neural networks is possible for OCR. OCR has been the subject of extensive investigation during the last 30 years. As a result, document image analysis (DIA), multilingual, handwritten, and omni-font OCRs have become popular. Despite these considerable study efforts, the machine's capacity for accurate text reading is still far lower than that of the human. Therefore, contemporary OCR research focuses on enhancing OCR's accuracy and speed for documents printed in a variety of styles and written in unrestricted situations. No open source or paid software has ever been made accessible for difficult languages like Urdu, Sindhi, etc.

1.1 Motivation

Rapid shifts of visual attention between components of the current task and other context cues are caused by an eager incentive to prevent errors of omission (i.e., promotion focus). These quick adjustments in focus should make it easier to execute the usual task of recognising facial emotions. Our hypothesis, which is mostly based on the regulatory focus literature, is also consistent with the body of research on face emotion identification.

There are numerous OCR-based programmes that can extract text from images, but they are insufficiently accurate to perform the same purpose for handwritten writing. There are numerous OCR-based programmes that can extract text from images, but they are insufficiently accurate to perform the same purpose for handwritten writing.

1.2 Scope

In the age of artificial intelligence and the internet of things, emotion recognition is essential. It has enormous potential for behavioural modelling, robotics, healthcare, biometric security, and human-computer interface.

In the upcoming years, it is anticipated that the global market for optical character recognition would expand quickly. In 2021, the OCR market was estimated to be worth USD 8.93 billion. Between 2022 and 2030, a CAGR of 15.4% is anticipated for growth. The rising need for OCR across a range of end-use industries, including healthcare, automotive, and others, is what's fueling this expansion.

1.3. Problem Statement For Facial Emotion Recognition

These varyingly tiny yet complex signals in our facial expressions frequently reveal a wealth of information about how we are feeling. We can easily and inexpensively assess the effects that content and services have on audiences and users by using face emotion recognition.

1.4. Problem Statement For OCR Recognition

A well-known issue in artificial intelligence and machine learning is optical character recognition (OCR). The issue arises when the available data is somewhat vague and unregulated, which is precisely the case in handwritten text recognition, despite the fact that most people think the situation is clear-cut.

2. RELATED WORKS FOR FACIAL EMOTION RECOGNITION

Facial Emotion Recognition is a technology that analyses emotions from a variety of sources, including images and videos. It is a member of the group of technologies known as "affective computing," a multidisciplinary area of study on the capacity of computers to recognise and understand affective states and human emotions that frequently relies on Artificial Intelligence technology.

Human emotions can be inferred from facial expressions, which are a form of non-verbal communication. Decoding these emotional expressions has long been of interest to researchers in both the human computer interaction and psychology fields (Lang et al. 1993; Ekman and Friesen 2003). (Cowie et al. 2001; Abdat et al. 2011). The widespread use of cameras as well as recent advancements in machine learning, pattern recognition, and biometrics analysis have all been significant factors in the development of FER technology.

The fact that so many businesses, from corporate behemoths like NEC or Google to smaller ones like Affectiva or Eyeris, invest in the technology demonstrates its expanding significance. A number of programmes under the Horizon20201 EU research and innovation programme are investigating the use of the technology.

Face detection, facial expression detection, and expression classification to an emotional state make up the three steps of FER analysis. Based on an examination of facial landmark placements, emotion detection is possible (e.g. end of nose, eyebrows). Additionally, in recordings, variations in such postures are also examined in order to spot facial muscle contractions (Ko 2018). Faces can indicate fundamental emotions (such as anger, disgust, fear, joy, sadness, and surprise) or compound emotions (such as happily sad, happily surprised, happily disgusted, tragically afraid, sadly angry, sadly surprised), depending on the algorithm (Du et al. 2014). In other situations, the physiological or mental state of a person may be related to their facial expressions (e.g. tiredness or boredom).

Surveillance cameras, cameras near billboards in businesses, social media, streaming services, and personal devices are some of the sources of the photos and videos used as input by FER algorithms.

3. RELATED WORKS FOR OCR RECOGNITION

Early computer programmes could comprehend print handwriting with separated characters, but cursive handwriting with interwoven characters offered Sayer's Paradox, a character segmentation challenge. The first applied pattern recognition programme was created in 1962 by Shelia Guberman, who was living in Moscow.

Commercial illustrations came from organisations like IBM and Communications Intelligence Corporation. In the early 1990s, two companies – Paragraph International and Lexicus developed technologies that could recognise handwriting in cursive. While Ronjon Nag and Chris Kortge, two Stanford University students, established Lexicus, Paragraph was based in Russia and was founded by computer scientist Stepan Pachikov. The Lexicus Longhand system was made commercially accessible for the PenPoint and Windows operating systems, while the Paragraph CalliGrapher technology was implemented in the Apple Newton systems. After being purchased by Motorola in 1993, Lexicus went on to create for the company Chinese handwriting detection and predictive text technologies. The handwriting recognition team at Paragraph, which SGI purchased in 1997, later established the P&I division, which Vadem later acquired from SGI. In 1999, P&I purchased CalliGrapher handwriting recognition technology from Vadem, along with other digital ink technologies.

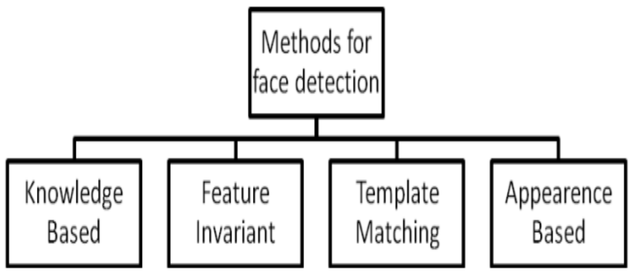
4. IMPLEMENTATION AND WORKING

4.1 FACIAL EMOTION RECOGNITION

The process of FER is a composite activity comprises different phases. These phases are as follows:

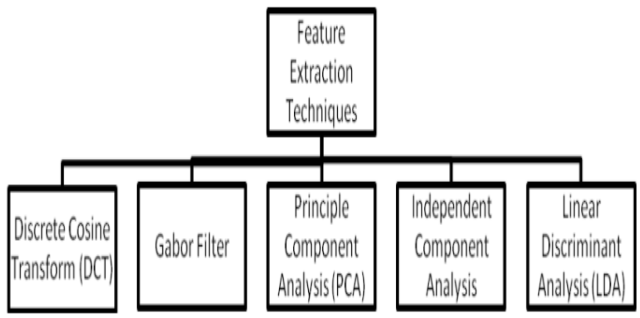
Typically, the face is made up of skin, facial muscles, and bones. These muscles contract, resulting in distorted face features. The quickest way to convey any type of information is through facial expressions. Facial expression detection software could result in a user-friendly human-machine interface. According to research by Ekman and Frisen from 1978, facial expressions function as a quick signal that changes with the contraction of facial features like the lips, eyes, cheeks, and brows, affecting the recognition accuracy. Additionally, happy, sad, fearful, disgusted, angry, and surprised are six universally recognised basic expressions. Face detection, feature extraction, and expression classification are the first three steps in the process of recognising facial expressions.

Face detection is the preliminary processing stage for facial expression recognition. To transform a picture into a normalised pure facial image for feature extraction, follow these steps: find the feature points, rotate the image to line them up, find the face region, and crop it using a rectangle in accordance with the face model. Face detection techniques entail finding faces in a single image.



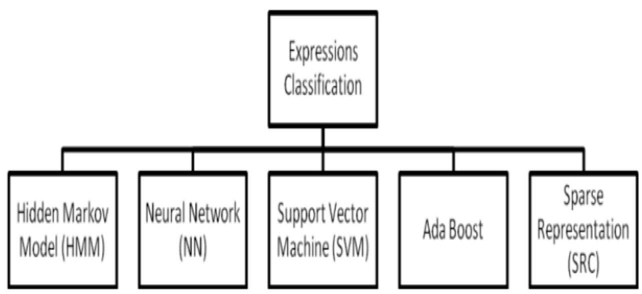
4.1.1 FEATURE EXTRACTION

The process of feature extraction transforms pixel data into a more complex representation of the face's or its components' shape, motion, colour, texture, and spatial arrangement. In general, feature extraction brings the input space's dimensions down. As a crucial task in a pattern recognition system, the reduction procedure should preserve critical information. Different methods can be used for feature extraction.



4.1.2 EXPRESSION CLASSIFICATION

A classifier that is connected to a decision process and frequently includes models of pattern distribution performs expression classification. Action units and prototypical facial expressions are the two primary classes Ekman identified for use in facial expression recognition. To extract expressions, a variety of categorization techniques are applied.



4.2 OPTICAL CHARACTER RECOGNITION

The process of OCR is a composite activity comprises different phases. These phases are as follows:

4.2.1 IMAGE ACQUISITION

The first step in OCR is called image acquisition, and it entails getting a digital image and putting it into a format that a computer can easily process. Both picture compression and quantization may be used in this. Binarization, which uses just two levels of the image, is a unique instance of quantization. The binary picture is usually sufficient to describe the image. There are two types of compression: lossy and lossless. There has been provided an overview of the various image compressing methods.

4.2.2 PRE- PROCESSING

Pre-processing follows image acquisition and seeks to improve the image quality. Thresholding is one of the pre-processing methods that seeks to binary the image depending on a certain threshold value. Both local and global settings are possible for the threshold value. You can use a variety of filters, including averaging, min and max filters. As an alternative, several morphological processes like erosion, dilatation, opening, and shutting can be carried out.

Finding the document's skew is a crucial step in pre-processing. Projections profiles, the Hough transform, and nearest neighbour methods are some of the skew estimating methods. Before applying following steps, the image is occasionally thinned as well. As a final step in the pre-processing stage, it is also possible to determine the text lines that are present in the document. This may be accomplished via pixel clustering or projections.

4.2.3 CHARACTER SEGMENTATION

Before moving on to the classification phase, the image is divided into characters in this stage. Segmentation can be done formally or inferentially as a result of the classification process. Additionally, the additional stages of OCR can assist in supplying contextual data beneficial for image segmentation.

4.2.4 FEATURE EXTRACTION

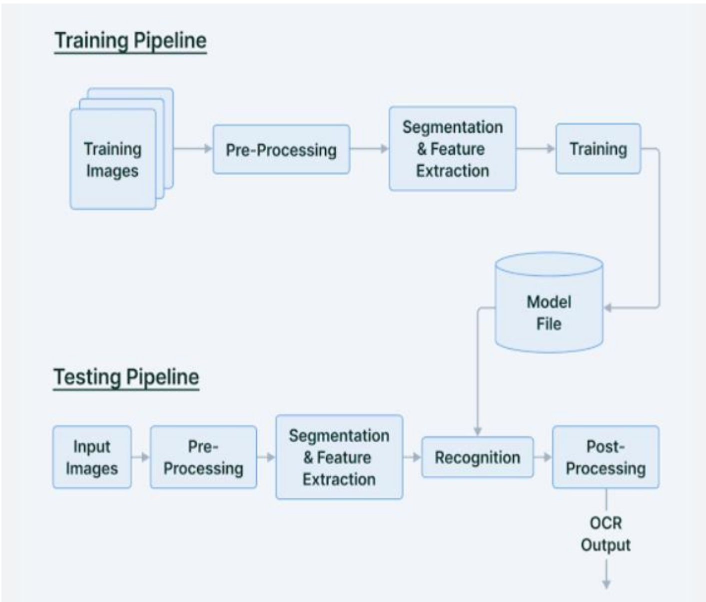
Various character traits are extracted at this level. Characters can only be identified by these traits. An important research question is how to choose the best features and how many characteristics should be employed overall. It is possible to use a variety of features, including the image itself, geometric features (loops, strokes), and statistical features (moments). Finally, a variety of methods, including principal component analysis, can be employed to reduce the image's dimensionality.

4.2.5 CLASSIFICATION

The process of placing a character in the right category is what it is described as. Based on relationships found in picture component relationships, the structural method to classification. The statistical methods rely on the classification of the image using a discriminating function. The Bayesian classifier, decision trees, neural networks, closest neighbour classifiers, and others are examples of statistical classification methods. Finally, there are classifiers that use a syntactic approach, which implies the use of a grammatical technique to build a picture from its constituent parts.

4.2.6 POST PROCESSING

There are several methods that can be utilised to increase the accuracy of OCR findings once the character has been classified. Using more than one classifier to categorise an image is one strategy. The classifier can be applied in a hierarchical, parallel, or cascade manner. After that, multiple methods can be used to integrate the classifiers' output. Contextual analysis can also be done to enhance OCR outcomes. Error chances can be decreased by taking into account the geometrical structure and document context of the image. OCR results can be enhanced by lexical processing based on Markov models and dictionaries.



5. FUTURE SCOPE

Profiles of individuals can also be produced using FER technology in a variety of circumstances. It could be used to determine whether someone accepts a certain product, advertisement, or idea. It can also be used to categorise workplace productivity and fatigue resistance. The risk comes from the possibility that the target of the targeting may not be aware of it and may get uncomfortable once they learn about it. Erroneous profiling or assumptions made merely on the basis of an association with a certain set of people who share the same feelings can have additional ramifications.

Last but not least, FER can affect behavioural modifications if a person is conscious of the technological exposure (known as Reactivity in psychology). People may modify their routines or stay away from particular locations where the technology is used in an effort to self-sensor and protect themselves. If non-democratic administrations employed such technology to infer residents' political attitudes, one may picture the chilling impact it could have on a society and the feeling of unease among citizens.

In this study, an effective method for handwritten character recognition is proposed. The handwritten numerals were recognised by a deep network model in the proposed work. By introducing the new kernel approaches, the low identification rate of the three numbers 3, 7, and 9 can be raised. A pattern of overlap among them may be the cause. However, by introducing a quad-tree based structure, which can even deep grasp each digit pattern at a coarser-grain level, the identification rate can be increased. In order to increase accuracy, modern methods can be utilised to investigate topological properties.

6. CONCLUSION

On the front end, the system uses both FER and OCR technologies equally, however the back end uses different technologies.

The review of the framework for facial expression recognition has been presented in this research. and provides a review of the literature on the various methods used to identify facial expressions. Based on their rate of recognition, these techniques are evaluated.

The recognition reading is still negative even though the training and input set were compiled using a third-party image processing programme with noise-free images. This test compares two sets of distinct people's handwriting, hence the outcome is predicted to be unremarkable in terms of matching and recognition. Numerous factors contribute to the inadequate recognition, some of which are given below:

• The possibility that two sets of input and training files represent the handwriting of two different people. Even if we assume that the same individual contributed both sets, there is very little likelihood that the letters will be identical to those that were previously provided. Therefore, it is anticipated that the recognition using crossed-set will be poor. Despite receiving a poor score for recognition, some letters can still be accurately identified even after being crossed-tested. These letters include the letters "T" and "E," which have little to no curvature.

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