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Artificial Intelligent System for Automatic Depression Level Analysis Through Visual and Vocal Expressions

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Abstract: *Depression is the most predominant mind-set problem overall essentially affecting prosperity and usefulness, and significant individual, family and cultural impacts. The early and precise discovery of signs identified with despondency could have many advantages for the two clinicians and impacted people. The current work pointed toward creating and clinically testing a technique ready to distinguish visual indications of discouragement and backing clinician choices. Programmed sadness appraisal dependent on obvious signals is a quickly developing examination space. The present thorough survey of existing methodologies as detailed in north of sixty distributions during the most recent ten years centers around picture handling and AI calculations. Visual appearances of sadness, different methodology utilized for information assortment, and existing datasets are summed up. The survey diagrams techniques and calculations for visual component extraction, dimensionality decrease, choice techniques for classification and regression approaches just as various combination systems. A quantitative meta-examination of detailed outcomes, depending on execution measurements hearty to risk, is incorporated, distinguishing general patterns and key irritating issues to be considered in ongoing investigations of programmed sorrow evaluation using viewable prompts alone or in blend with obvious signals. The proposed work also carried out to predict the depression level according to current input of face images using deep learning.*

Keywords: Depression

I. INTRODUCTION

MENTAL health issues such as depression have been linked to deficits of cognitive control. It affects one in four citizens of working age, which can cause significant losses and burdens to the economic, social, educational, as well as justice systems [1], [2]. Depression is defined as "a common mental disorder that presents with depressed mood, loss of interest or pleasure, decreased energy, feelings of guilt or low self-worth, disturbed sleep or appetite, and poor concentration." [3]

Among all psychiatric disorders, major depressive disorder (MDD) commonly occurs and heavily threatens the mental health of human beings. 7.5% of all people with disabilities suffer from depression, making it the largest contributor [4], exceeding 300M people. Recent study [5] indicates that having a low income shows an increased chance of having major depressive disorders. It can also affect the major stages in life such as educational attainment and the timing of marriage. According to [6], majority of the people that obtain treatment for depression do not recover from it. The illness still remains with the person. This may be in the form of insomnia, excessive sleeping, fatigue, loss of energy or digestive problems. Artificial intelligence and mathematical modeling techniques are being progressively introduced in mental health research to try and solve this matter. The mental health area can benefit from these techniques, as they understand the importance of obtaining detailed information to characterize the different psychiatric disorders [7].

Emotion analysis has shown to been an effective research approach for modeling depressive states. Recent artificial modeling and methods of automatic emotion analysis for depression related issues are extensive [8], [9], [10], [11]. They demonstrate that depression analysis is a task that can be tackled in the computer vision field, with machine based

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automatic early detection and recognition of depression is expected to advance clinical care quality and fundamentally reduce its potential harm in real life. The face can effectively communicate emotions to other people through the use of facial expressions. Psychologists have modeled these expressions in detail creating a dictionary called the Facial Action Coding System (FACS). It contains the combination of facial muscles for each expression [12], and can be used as a tool to detect the emotional state of a person through their face. Another approach to classify emotion through facial expressions is using local and holistic feature descriptors, such as in [13].

Unlike FACS, these techniques treat the whole face the same and look for patterns throughout, and not just for certain muscles. However, the depression disorder is not limited to be expressed by the face. The perception of emotional body movements and gestures has shown it can be observed through a series of controlled experiments using patients with and without MDD [14]. Furthermore, EEG signals and brain activity using MRI imaging, are modalities recent to computer vision [15], [16]. Electrocardiogram (ECG) and electro-dermal activity (EDA) are also considered for depression analysis alongside the audio-visual modality [17]. All of this research is evidenced by the series of international Audio/Visual Emotion Recognition Challenges (AVEC2013 [1], AVEC2014 [18] and most recently AVEC2016 [17]). Each challenge provides a dataset that has rich video content containing subjects that suffer from depression. Samples consist of visual and vocal data, where the facial expressions and emotions through the voice have been captured carefully from the cognitive perspective.

The objective is to communicate and interpret emotions through expressions using multiple modalities. Various methods have been proposed for depression analysis [11], [19], [20], including most recent works from AVEC16 [21], [22], [23]. In order to create a practical and efficient artificial system for depression recognition, visual and vocal data are key as they are easily obtainable for a system using a camera and microphone. This is a convenient data collection approach when compared to data collection approaches that requires sensors to be physically attached to the subject, such as EEG and ECG data. For machines and systems in a noncontrolled environment, obtaining EEG and ECG can therefore be difficult to obtain. The depression data from the AVEC2013 and AVEC2014 datasets provide both visual and vocal raw data. However, AVEC2016 provides the raw vocal data but no raw visual data, for ethical reasons. Instead is provided a set of different features obtained from the visual data by the host. For this reason, the AVEC2014 dataset has been chosen in order to run experiments using raw visual and vocal data.

Deep learning is also a research topic that has been adopted towards visual modality, especially in the form of a Convolutional Neural Network (CNN). It has significantly taken off from its first big discovery for hand digit recognition [24]. Recently, the effectiveness of deep networks have been portrayed in different tasks such as face identification [25], image detection; segmentation and classification [26], [27] and many other tasks. The majority of these applications have only become achievable due to the processing movement from CPU to GPU. The GPU is able to provide a significantly higher amount of computational resources versus a CPU, to handle multiple complex tasks in a shorter amount of time. Deep networks can become very large and contain millions of parameters, which was a major setback in the past. Now there are a variety of deep networks available such as AlexNet [28] and the VGG networks [29]. These networks have been trained with millions of images based on their applications, and are widely used today as pre-trained networks. Pre-trained CNNs can be exploited for artificial image processing on depression analysis, mainly using the visual modality. However, the pre-trained CNN models such as VGGFace provide good features at the frame level of videos, as they are designed for still images. In order to adapt this across temporal data, a novel technique called Feature Dynamic History Histogram (FDHH) is proposed to capture the dynamic temporal movement on the deep feature space. Then Partial Least Square (PLS) and Linear regression (LR) algorithms are used to model the mapping between dynamic features and the depression scales. Finally, predictions from both video and audio modalities are combined at the prediction level.

Experimental results achieved on the AVEC2014 dataset illustrates the effectiveness of the proposed method. The aim of this paper is to build an artificial intelligent system that can automatically predict the depression level from a user's visual and vocal expression. The system is understood to apply some basic concepts of how parts of the human brain works. This can be applied in robots or machines to provide human cognitive like capabilities, making intelligent humanmachine applications. The main contribution of the proposed framework are the following:

1) A framework architecture is proposed for automatic depression scale prediction that includes frame/segment level feature extraction, dynamic feature generation, feature dimension reduction and regression

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2) Various features, including deep features, are extracted on the frame-level that captured the better facial expression information;
3) A new feature (FDHH) is generated by observing dynamic variation patterns across the frame-level features;
4) Advanced regressive techniques are used for regression. The rest of the paper is organized as follows.

II. RELATED WORKS

Recent years have witnessed an increase of research for clinical and mental health analysis from facial and vocal expressions [30], [31], [32], [33]. There is a significant progress on emotion recognition from facial expressions. Wang et al. [30] proposed a computational approach to create probabilistic facial expression profiles for video data. To help automatically quantify emotional expression differences between patients with psychiatric disorders, (e.g. Schizophrenia) and healthy controls. In depression analysis, Cohn et al. [34], who is a pioneer in the affective computing area, performed an experiment where he fused both the visual and audio modality together in an attempt to incorporate behavioral observations, from which are strongly related to psychological disorders. Their findings suggest that building an automatic depression recognition system is possible, which will benefit clinical theory and practice. Yang et al. [31] explored variations in the vocal prosody of participants, and found moderate predictability of the depression scores based on a combination of F0 and switching pauses. Girard et al. [33] analyzed both manual and automatic facial expressions during semi-structured clinical interviews of clinically depressed patients. They concluded that participants with high symptom severity tend to express more emotions associated with contempt, and smile less. Yammine et al. [35] examined the effects caused by depression to younger patients of both genders. The samples (n=153) completed the Beck Depression Inventory II questionnaire which indicated that the mean BDI II score of 20.7 (borderline clinically depressed), from the patients that were feeling depressed in the prior year. Scherer et al. [32] studied the correlation between the properties of gaze, head pose, and smile of three mental disorders (i.e. depression, post-traumatic stress disorder and anxiety). They discovered that there was a distinct difference between the highest and lowest distressed participants, in terms of automatically detected behaviors. The depression recognition sub-challenge of AVEC2013 [1] and AVEC2014 [18]; had proposed some good methods which achieved good results [19], [36], [37], [38], [39], [40], [41], [42], [43], [44], [11], [10]. From this, Williamson et al. [19], [20] was the winner of the depression sub-challenge for the AVEC2013 and AVEC2014 competitions. In 2013, they exploited the effects that reflected changes in coordination of vocal tract motion associated with Major Depressive Disorder. Specifically, they investigated changes in correlation that occur at different time scales across dormant frequencies and also across channels of the delta-mel-cepstrum [19].

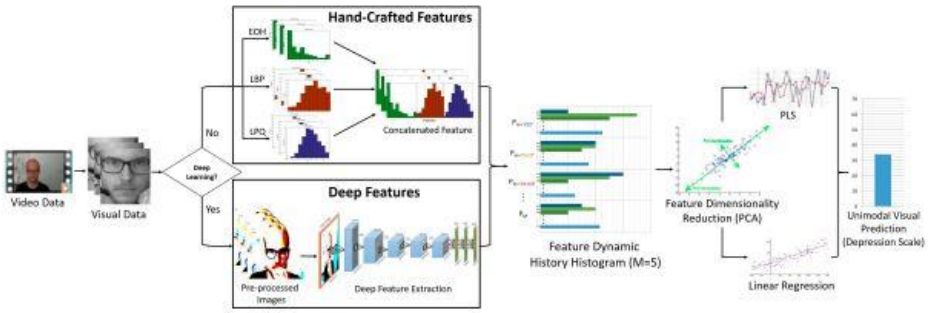

Fig. 1. Overview of the proposed automatic depression scale recognition system from facial expressions. The Video Data is broken down into visual frames. If deep learning is utilized, then deep features are extracted from the frames, otherwise a set of hand-crafted features are extracted. This is followed by FDHH to produce a dynamic descriptor. The dimensionality is reduced and a fusion of PLS and LR is used to predict the Depression Scale.

In 2014 they looked at the change in motor control that can effect the mechanisms for controlling speech production and facial expression. They derived a multi-scale correlation structure and timing feature from vocal data. Based on these two feature sets, they designed a novel Gaussian mixture model (GMM) based multivariate regression scheme. They referred this as a Gaussian Staircase Regression, that provided very good prediction on the standard Beck depression rating scale. Meng et al. [11] modeled the visual and vocal cues for depression analysis. Motion History Histogram (MHH) is used to capture dynamics across the visual data, which is then fused with audio features. PLS

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regression utilizes these features to predict the scales of depression. Gupta et al. [42] had adopted multiple modalities to predict affect and depression recognition. They fused together various features such as Local Binary Pattern (LBP) and head motion from the visual modality, spectral shape and MFCCs from the audio modality and generating lexicon from the linguistics modality. They also included the baseline features Local Gabor Binary Patterns - Three Orthogonal Planes (LGBP-TOP) [18] provided by the hosts. They then apply a selective feature extraction approach and train a Support Vector Regression (SVR) machine to predict the depression scales. Kaya et al. [41] used LGBP-TOP on separate facial regions with Local Phase Quantization (LPQ) on the inner-face. Correlated Component Analysis (CCA) and Moore-Penrose Generalized Inverse (MPGI) were utilized for regression in a multimodal framework. Jain et al. [44] proposed using Fisher Vector (FV) to encode the LBP-TOP and Dense Trajectories visual features, and LLD audio features. Perez et al. [39] claimed; after observing the video samples; that subjects with higher BDI-II showed slower movements. They used a multimodal approach to seek motion and velocity information that occurs on the facial region, as well as 12 attributes obtained from the audio data such as 'Number of silence intervals greater than 10 seconds and less than 20 seconds' and 'Percentage of total voice time classified as happiness'. The above methods have achieved good performance. However, for the visual feature extraction, they used methods that only consider the texture, surface and edge information.

Recently, deep learning techniques have made significant progress on visual object recognition, using deep neural networks that simulate the humans vision-processing procedure that occurs in the mind. These neural networks can provide global visual features that describe the content of the facial expression. Recently Chao et al. [43] proposed using multitask learning based on audio and visual data. They used LongShort Term Memory (LSTM) modules with features extracted from a pre-trained CNN, where the CNN was trained on a small facial expression dataset FER2013 by Kaggle. This dataset contained a total of 35,886 48x48 grayscale images. The performance they achieved is better than most other competitors from the AVEC2014 competition, however it is still far away from the state-of-the-art. A few drawbacks of their approach are the image size they adopted is very small, which would result in downsizing the AVEC images and reducing a significant amount of spatial information. This can have a negative impact as the expressions they wish to seek are very subtle, small and slow. They also reduce the color channels to grayscale, further removing useful information. In this paper, we are targeting an artificial intelligent system that can achieve the best performance on depression level prediction, in comparison with all the existing methods on the AVEC2014 dataset. Improvement will be made on the previous work from feature extraction by using deep learning, regression with fusion, and build a complete system for automatic depression level prediction from both vocal and visual expressions. I

III. FRAMEWORK

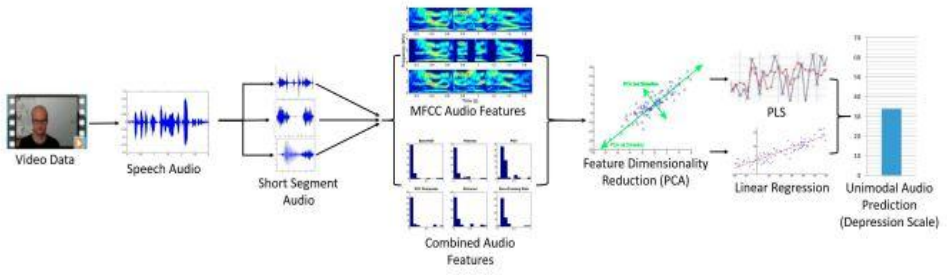

Fig. 2. Overview of the proposed automatic depression scale recognition system from vocal expressions. The Speech Audio is extracted from the Video Data, where short segments are produced. Then a bunch of audio features are extracted from each segment and averaged. These are reduced in dimensionality and a fusion of PLS and Linear regression is used to predict the Depression Scale.

Human facial expressions and voices in depression are theoretically different from those under normal mental states. An attempt to find a solution for depression scale prediction is achieved by combining dynamic descriptions within naturalistic facial and vocal expressions. A novel method is developed that comprehensively models the variations in visual and vocal cues, to automatically predict the BDI-II scale of depression. The proposed framework is an extension

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of the previous method [10] by replacing the hand-crafted techniques with deep face representations as a base feature to the system.

IV. LITERATURE REVIEW

Many studies have been conduced to recognize the exact looks that are identified with discouragement. A review has been led for discovering Action Units (AU) identified with various feelings showed by discouraged patients [1]. The presence of AU12 which is related with feeling grin was low in profoundly discouraged patients. The presence of AU14 identified with feeling scorn and AU10 identified with feeling disdain was likewise present alongside AU12. The video information for this review was gathered through clinical meetings of discouraged patients just as non-discouraged patients. The outcomes showed that AU14 identified with feeling scorn demonstrated generally precise for sorrow location.

Highlights identified with eye development to comprehend the eye action of the discouraged and elements identified with head present development to comprehend the head development conduct of the discouraged has been done in [2]. The characterization of the highlights identified with eye action showed higher importance in recognizing serious sadness. Location of gloom from facial elements should be possible by estimating 'Multi-Scale Entropy' (MSE) on the patient meeting video. [4] MSE assists with discovering the varieties that happen across a solitary pixel in the video. The entropy levels of exceptionally expressive, non-discouraged patients were high. The entropy level was low for discouraged patients who were less expressive of their feelings.

Another review introduced a strategy which utilizes examination of facial math alongside investigation of discourse for melancholy location [3]. This work says that the articulations related with melancholy are viewed as in lower frequencies in more modest span recordings. Consequently, longer time recordings should be caught for successful despondency location. Datasets are additionally made by catching recordings of patients while noting clinical meetings. Interviews recorded were for both for discouraged patients just as non-discouraged patients. Recordings are additionally recorded from the finding of sorrow till the patient has improved. [1][4]. Studies showed that there is a huge connection between facial elements and vocal conduct of the discouraged .

In specific investigations, patients were given wearable devises to screen their actual wellbeing, passionate conduct and social communication for distinguishing misery [6]. A few analysts have gathered datasets by showing people film-strips to catch the looks of subjects watching them. Information is additionally gathered by giving an undertaking of perceiving negative and positive feelings from various facial pictures [7]. Rather than investigating a video for sadness identification outline by outline, better outcomes have been got for location of wretchedness when the video is considered in general. [8] For this the patient's face locale is first instated physically. Then, at that point, KLT (KanadeTomasi-Lucas) tracker is utilized to follow the face all through the video. The KLT tracker removes shape data from a picture, for example for a miserable articulation the sides of the mouth would be calculated down. Video based methodology showed more precision as it sums up the face area all the more precisely thus the moment developments inside the face locale are additionally considered for melancholy recognition.

The understudies experiencing melancholy would show less mindfulness in homerooms. Assuming the understudies' feelings are planned to the exercises done in homeroom, their enthusiastic state can be seen if they are discouraged or not, and in light of this the educator can help the understudy by focusing harder on that specific understudy. [11] If various appearances in a similar scene show a similar positive or negative feeling, it would assist with understanding the entire circumstance of the scene, regardless of whether subjects in the scene are cheerful or whether something wrong is going on in the scene [12].

4.1 PROBLEM STATEMENT

A face recognition and voice based system Artificial Intelligent System for Automatic Depression Level Analysis Through Visual and Vocal Expressions

but it can be easily hacked if somebody uses video and audio of a person. As a solution, in addition to face recognition and voice detecting system is required.

4.2 OBJECTIVE

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1) To study existing audio and video recording system.
2) To design the system architecture for proposed system.
3) To implement the proposed system using machine learning and artificial intelligance.
4) To analyze and evaluate the design module

4.3 MOTIVATION

Automatic face recognition from video and audio recording has been a challenging task for the research community. It has been extensively adopted by the applications including biometrics, surveillance, security, identification, and authentication. Face recognition video and audio usually exploit high-dimensional information which makes it computationally intensive. The general public has immense need for security measures against spoof attack. Human facial expressions and voices in depression are theoretically different from those under normal mental states. An attempt to find a solution for depression scale prediction is achieved by combining dynamic descriptions within naturalistic facial and vocal expressions.

V. SYSTEM DEVELOPMENT

5.1 Design Methodology

5.1.1 Introduction

The proposed research to design and implement a system for depression level prediction using deep learning, the visual features has extracted from users face and predicts the scale of depression.

5.1.2 Proposed System

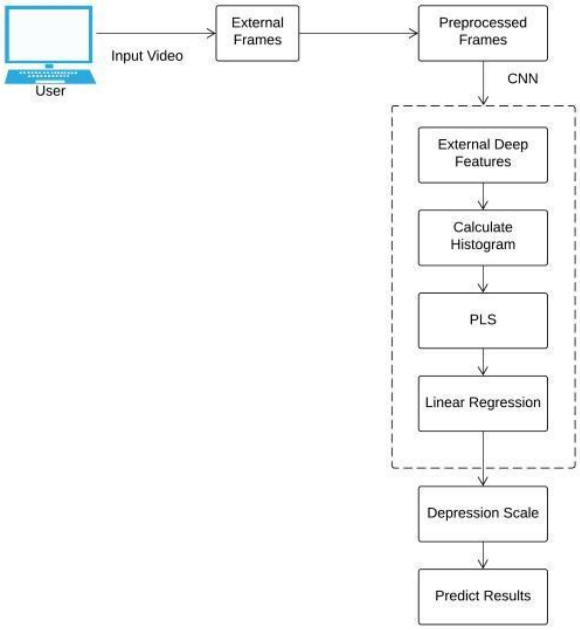

Fig. Architecture Diagram

Following is the methodology used in proposed system

- The image data were collected from Kaggle.
- The collected dataset is divided into 2 parts. i.e.:- 80% for training and 20% for testing
- Various Techniques like preprocessing, feature extraction is applied
- CNN was used for classification
- Web application is been developed using php and bootstrap for frontend and Python for backend.
- The user captured image is passed and captured images feature are extracted.

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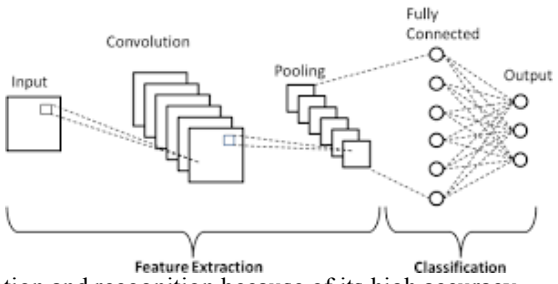
- Extracted Features will be matched with the trained model, depending on nearby match the predicted output isbeen obtained

5.2 Algorithm Used CNN
Why CNN?



CNNs are used for image classification and recognition because of its high accuracy.
The CNN follows a hierarchical model which works on building a network, like a funnel, and finally gives outa fully-connected layer where all the neurons are connected to each other and the output is processed.
Hence, we are using Convolutional Neural Network for proposed system

5.3 System Hardware and Software Requirement
Hardware Requirements:
• Processor – I3 / I5
• Speed – 2.6 GHz
• RAM – 4 GB(min)
• Hard Disk - 128 GB SSD
• Monitor – SVG

Software Requirements:
• Operating System - Windows / Linux
• Front End – python Django
• Database - My SQL 5.0

5.4 Image processing in Python
As the name says, image processing means processing the image and this may include many different techniques until we reach our goal.
The final output can be either in the form of an image or a corresponding feature of that image. This can be used for further analysis and decision making.
But what is an image?
An image can be represented as a 2D function F(x,y) where x and y are spatial coordinates. The amplitude of F at a particular value of x,y is known as the intensity of an image at that point. If x,y, and the amplitude value is finite then we call it a digital image. It is an array of pixels arranged in columns and rows. Pixels are the elements of an image that contain information about intensity and color. An image can also be represented in 3D where x,y, and z become spatial coordinates. Pixels are arranged in the form of a matrix. This is known as an RGB image.

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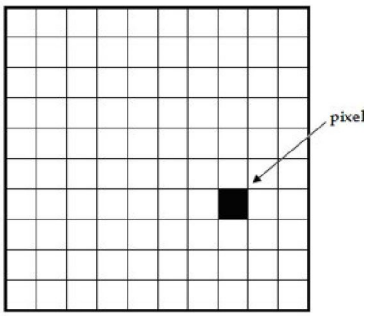
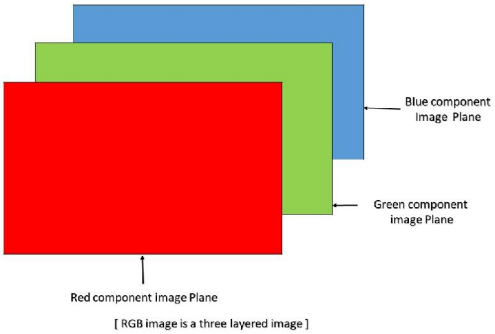


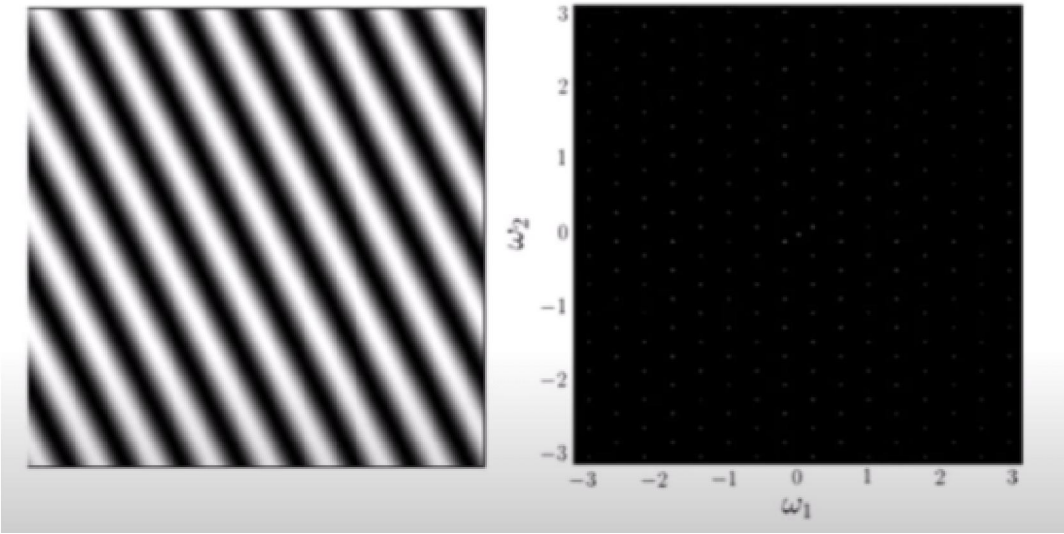


Source

There are various types of images:
RGB image: It contains three layers of 2D image, these layers are Red, Green, and Blue channels.
Grayscale image: These images contain shades of black and white and contain only a single channel.

VI. FOURIER TRANSFORM IN IMAGE PROCESSING

Fourier transform breaks down an image into sine and cosine components.
It has multiple applications like image reconstruction, image compression, or image filtering.
Since we are talking about images, we will take discrete fourier transform into consideration.
Let's consider a sinusoid, it comprises of three things:
Magnitude – related to contrast
Spatial frequency – related to brightness
Phase – related to color information
The image in the frequency domain looks like this:



Source

The formula for 2D discrete fourier transform is:

$$F(u, v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\, e^{-j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}$$

In the above formula, f(x,y) denotes the image.

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The inverse fourier transform converts the transform back to image. The formula for 2D inverse discrete fourier transform is:

$$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v)\, e^{j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}$$

VII. EDGE DETECTION IN IMAGE PROCESSING

Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness.

This could be very beneficial in extracting useful information from the image because most of the shape information is enclosed in the edges. Classic edge detection methods work by detecting discontinuities in the brightness.

It can rapidly react if some noise is detected in the image while detecting the variations of grey levels. Edges are defined as the local maxima of the gradient.

The most common edge detection algorithm is **sobel edge detection algorithm**. Sobel detection operator is made up of 3*3 convolutional kernels. A simple kernel Gx and a 90 degree rotated kernel Gy. Separate measurements are made by applying both the kernel separately to the image.

$$Gx = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} * Image\ matrix$$

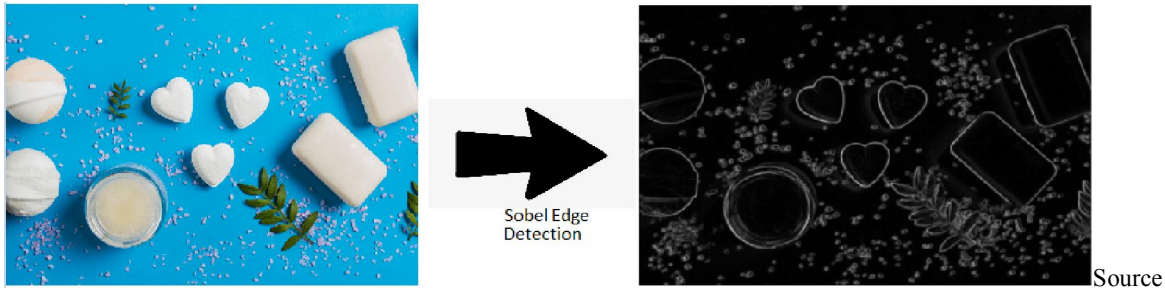
And,

$$Gy = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * Image\ matrix$$

* denotes the 2D signal processing convolution operation.

Resulting gradient can be calculated as:

$$G = sqrt(Gx^2 + Gy^2)$$



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7.1 Wavelet Image Processing

We saw a Fourier transform but it is only limited to the frequency. Wavelets take both time and frequency into the consideration. This transform is apt for non-stationary signals.

We know that edges are one of the important parts of the image, while applying the traditional filters it's been noticed that noise gets removed but image gets blurry. The wavelet transform is designed in such a way that we get good frequency resolution for low frequency components. Below is the 2D wavelet transform example:

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Image processing using Neural Networks

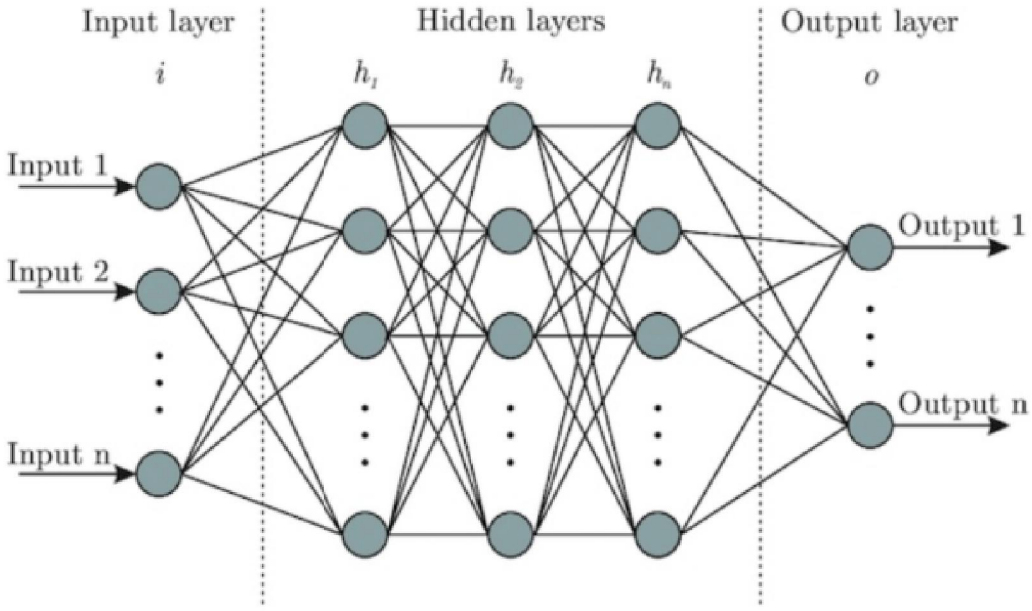
Neural Networks are multi-layered networks consisting of neurons or nodes. These neurons are the core processing units of the neural network. They are designed to act like human brains. They take in data, train themselves to recognize the patterns in the data and then predict the output.

A basic neural network has three layers:

Input layer

Hidden layer

Output layer



Basic neural network | Source

The input layers receive the input, the output layer predicts the output and the hidden layers do most of the calculations. The number of hidden layers can be modified according to the requirements. There should be atleast one hidden layer in a neural network.

The basic working of the neural network is as follows:

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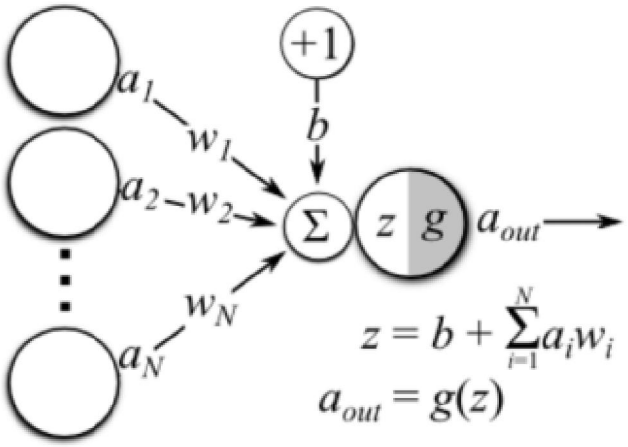
Let's consider an image, each pixel is fed as input to each neuron of the first layer, neurons of one layer are connected to neurons of the next layer through channels.
Each of these channels is assigned a numerical value known as weight.
The inputs are multiplied by the corresponding weights and this weighted sum is then fed as input to the hidden layers.
The output from the hidden layers is passed through an activation function which will determine whether the particular neuron will be activated or not.
The activated neurons transmits data to the next hidden layers. In this manner, data is propagated through the network, this is known as Forward Propagation.
In the output layer, the neuron with the highest value predicts the output. These outputs are the probability values.
The predicted output is compared with the actual output to obtain the error. This information is then transferred back through the network, the process is known as Backpropagation.
Based on this information, the weights are adjusted. This cycle of forward and backward propagation is done several times on multiple inputs until the network predicts the output correctly in most of the cases.
This ends the training process of the neural network. The time taken to train the neural network may get high in some cases.
In the below image, **ai's** is the set of inputs, **wi's** are the weights, **z** is the output and **g** is any activation function.



Operations in a single neuron |

Here are some guidelines to prepare data for image processing.
More data needs to be fed to the model to get the better results.
Image dataset should be of high quality to get more clear information, but to process them you may require deeper neural networks.
In many cases RGB images are converted to grayscale before feeding them into a neural network.
Types of Neural Network
Convolutional Neural Network
A convolutional neural network, ConvNets in short has three layers:
Convolutional Layer (*CONV*): They are the core building block of CNN, it is responsible for performing convolution operation.The element involved in carrying out the convolution operation in this layer is called the **Kernel/Filter (matrix).** The kernel makes horizontal and vertical shifts based on the **stride rate** until the full image is traversed.

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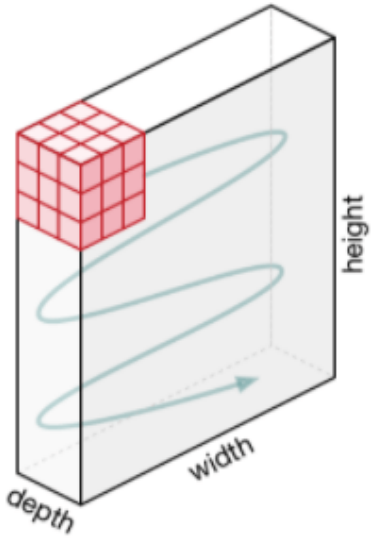
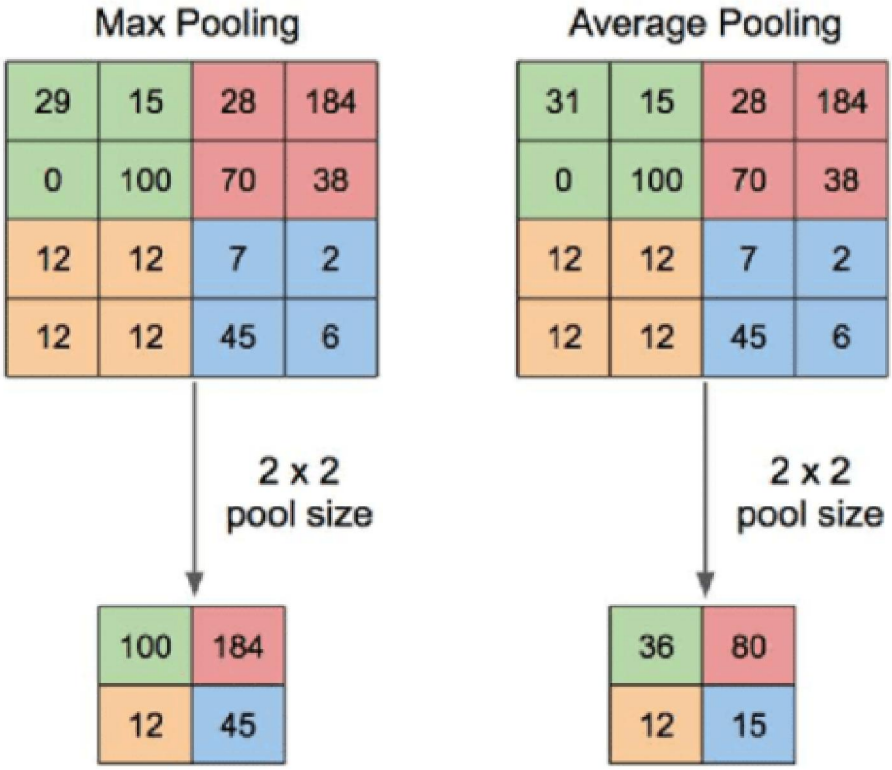


Movement of the kernel |

Pooling Layer (*POOL*): This layer is responsible for dimensionality reduction. It helps to decrease the computational power required to process the data. There are two types of Pooling: Max Pooling and Average Pooling. Max pooling returns the maximum value from the area covered by the kernel on the image. Average pooling returns the average of all the values in the part of the image covered by the kernel.



Pooling operation |

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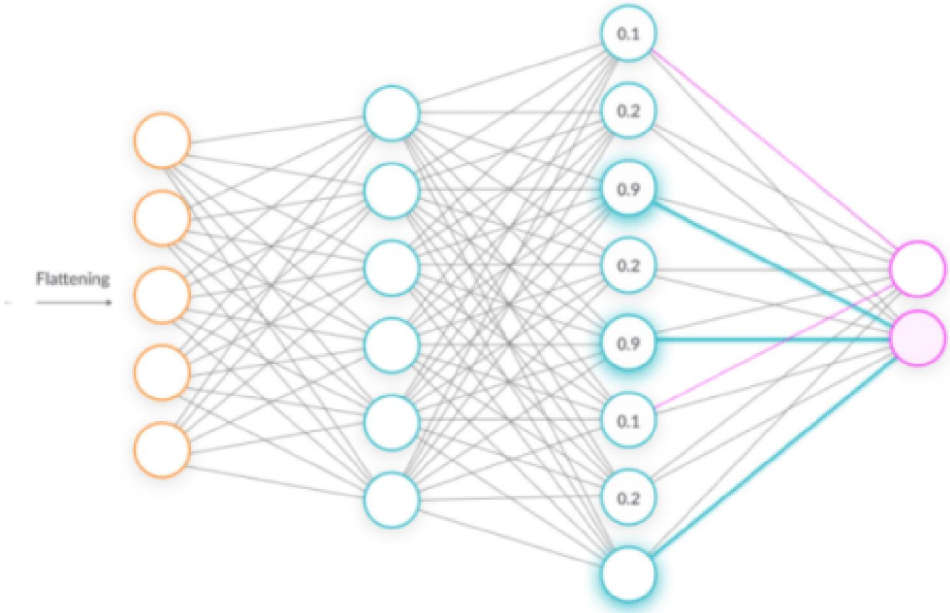
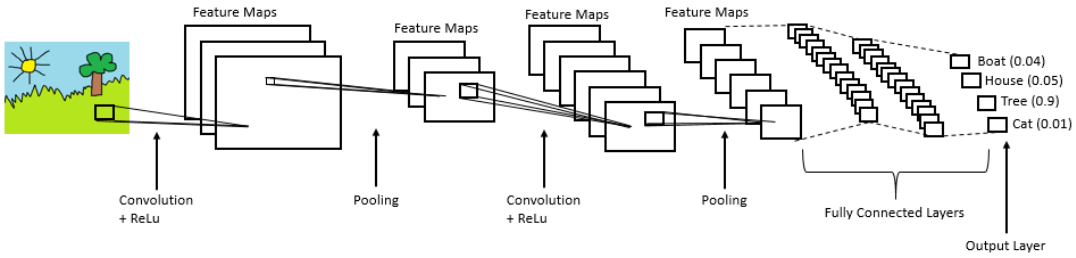
Fully Connected Layer (*FC*): The **fully connected layer** (**FC**) operates on a flattened input where each input is connected to all neurons. If present, **FC layers** are usually found towards the end of **CNN** architectures.



Fully connected layers |

CNN is mainly used in extracting features from the image with help of its layers. CNNs are widely used in image classification where each input image is passed through the series of layers to get a probabilistic value between 0 and 1.



Generative Adversarial Networks

Generative models use an unsupervised learning approach (there are images but there are no labels provided).

GANs are composed of two models **Generator** and **Discriminator.** *Generator* learns to make fake images that look realistic so as to fool the discriminator and *Discriminator* learns to distinguish fake from real images (it tries not to get fooled).

Generator is not allowed to see the real images, so it may produce poor results in the starting phase while the discriminator is allowed to look at real images but they are jumbled with the fake ones produced by the generator which it has to classify as real or fake.

Some noise is fed as input to the generator so that it's able to produce different examples every single time and not the same type image. Based on the scores predicted by the discriminator, the generator tries to improve its results, after a certain point of time, the generator will be able to produce images that will be harder to distinguish, at that point of time, the user gets satisfied with its results. Discriminator also improves itself as it gets more and more realistic images at each round from the generator.

Popular types of GANs are Deep Convolutional GANs(DCGANs), Conditional GANs(CGANs), StyleGANs, CycleGAN, DiscoGAN, GauGAN and so on.

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GANs are great for image generation and manipulation. Some applications of GANs include : Face Aging, Photo Blending, Super Resolution, Photo Inpainting, Clothing Translation.

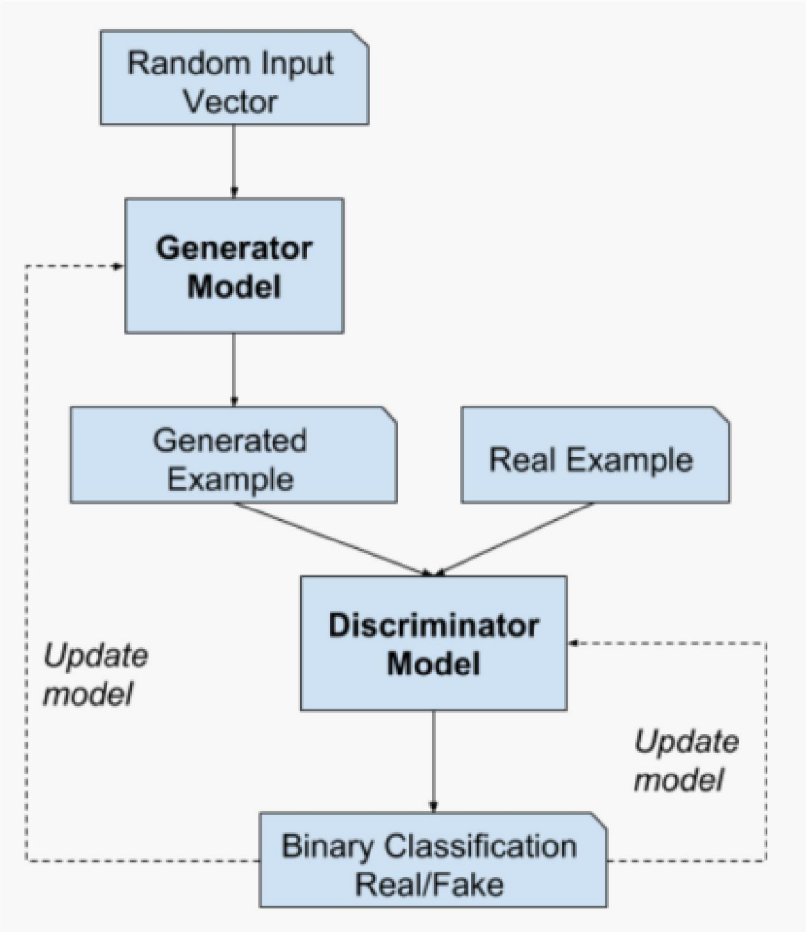

Image processing tools

1. OpenCV

It stands for Open Source Computer Vision Library. This library consists of around 2000+ optimised algorithms that are useful for computer vision and machine learning. There are several ways you can use opencv in image processing, a few are listed below:

Converting images from one color space to another i.e. like between BGR and HSV, BGR and gray etc.
Performing thresholding on images, like, simple thresholding, adaptive thresholding etc.
Smoothing of images, like, applying custom filters to images and blurring of images.
Performing morphological operations on images.
Building image pyramids.
Extracting foreground from images using GrabCut algorithm.
Image segmentation using watershed algorithm.

2. Scikit-image

It is an open-source library used for image preprocessing. It makes use of machine learning with built-in functions and can perform complex operations on images with just a few functions.

It works with numpy arrays and is a fairly simple library even for those who are new to python. Some operations that can be done using scikit image are :

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To implement thresholding operations use **try_all_threshold()** method on the image. It will use seven global thresholding algorithms. This is in the **filters** module.
To implement edge detection use **sobel()** method in the **filters** module. This method requires a 2D grayscale image as an input, so we need to convert the image to grayscale.
To implement gaussian smoothing use **gaussian()** method in the **filters** module.
To apply histogram equalization, use **exposure** module, to apply normal histogram equalization to the original image, use **equalize_hist()** method and to apply adaptive equalization, use **equalize_adapthist()** method.
To rotate the image use **rotate()** function under the **transform** module.
To rescale the image use **rescale()** function from the **transform** module.
To apply morphological operations use **binary_erosion()** and **binary_dilation()** function under the **morphology** module.

VIII. WORKING

Related Works

Recent years have witnessed an increase of research for clinical and mental health analysis from facial and vocal expressions [30]–[33]. There is a significant progress on emotion recognition from facial expressions. Wang *et al.* [30] proposed a computational approach to create probabilistic facial expression profiles for video data. To help automatically quantify emotional expression differences between patients with psychiatric disorders, (e.g., Schizophrenia) and healthy controls.
In depression analysis, Cohn *et al.* [34], who is a pioneer in the affective computing area, performed an experiment where he fused both visual and audio modality together in an attempt to incorporate behavioral observations, from which are strongly related to psychological disorders. Their findings suggest that building an automatic depression recognition system is possible, which will benefit clinical theory and practice. Yang *et al.* [31] explored variations in the vocal prosody of participants, and found moderate predictability of the depression scores based on a combination of F0 and switching pauses. Girard *et al.* [33] analyzed both manual and automatic facial expressions during semistructured clinical interviews of clinically depressed patients. They concluded that participants with high symptom severity tend to express more emotions associated with contempt, and smile less. Yammine *et al.* [35] examined the effects caused by depression to younger patients of both genders. The samples (n=153) completed the Beck depression inventory II (BDI-II) questionnaire which indicated that the mean BDI-II score of 20.7 (borderline clinically depressed), from the patients that were feeling depressed in the prior year. Scherer *et al.* [32] studied the correlation between the properties of gaze, head pose, and smile of three mental disorders (i.e., depression, post-traumatic stress disorder, and anxiety). They discovered that there was a distinct difference between the highest and lowest distressed participants, in terms of automatically detected behaviors.
The depression recognition subchallenge of AVEC2013 [1] and AVEC2014 [18]; had proposed some good methods which achieved good results [10], [11], [19], [36]–[44]. From this, Williamson *et al.* [19], [20] were the winner of the depression subchallenge (DSC) for the AVEC2013 and AVEC2014 competitions. In 2013, they exploited the effects that reflected changes in coordination of vocal tract motion associated with MDD. Specifically, they investigated changes in correlation that occur at different time scales across dormant frequencies and also across channels of the delta-mel-cepstrum [19]. In 2014, they looked at the change in motor control that can effect the mechanisms for controlling speech production and facial expression. They derived a multiscale correlation structure and timing feature from vocal data. Based on these two feature sets, they designed a novel Gaussian mixture model-based multivariate regression scheme. They referred this as a Gaussian staircase regression, that provided very good prediction on the standard Beck depression rating scale.
Meng *et al.* [11] modeled the visual and vocal cues for depression analysis. Motion history histogram (MHH) is used to capture dynamics across the visual data, which is then fused with audio features. PLS regression utilizes these features to predict the scales of depression. Gupta *et al.* [42] had adopted multiple modalities to predict affect and depression recognition. They fused together various features such as local binary pattern (LBP) and head motion from the visual modality, spectral shape, and mel-frequency cepstral coefficients (MFCCs) from the audio modality and generating lexicon from the linguistics modality. They also included the baseline features local Gabor binary patterns—three

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orthogonal planes (LGBP-TOP) [18] provided by the hosts. They then apply a selective feature extraction approach and train a support vector regression machine to predict the depression scales.

Kaya *et al.* [41] used LGBP-TOP on separate facial regions with local phase quantization (LPQ) on the inner-face. Correlated component analysis and Moore–Penrose generalized inverse were utilized for regression in a multimodal framework. Jain *et al.* [44] proposed using Fisher vector to encode the LBP-TOP and dense trajectories visual features, and low-level descriptor (LLD) audio features. Pérez Espinosa *et al.* [39] claimed; after observing the video samples; that subjects with higher BDI-II showed slower movements. They used a multimodal approach to seek motion and velocity information that occurs on the facial region, as well as 12 attributes obtained from the audio data such as "*number of silence intervals greater than 10 s and less than 20 s*" and "*percentage of total voice time classified as happiness*."

The above methods have achieved good performance. However, for the visual feature extraction, they used methods that only consider the texture, surface, and edge information. Recently, deep learning techniques have made significant progress on visual object recognition, using deep neural networks that simulate the humans vision-processing procedure that occurs in the mind. These neural networks can provide global visual features that describe the content of the facial expression. Recently, Chao *et al.* [43] proposed using multitask learning based on audio and visual data. They used long short-term memory modules with features extracted from a pretrained CNN, where the CNN was trained on a small facial expression dataset FER2013 by Kaggle. This dataset contained a total of 35886 48×48 grayscale images. The performance they achieved is better than most other competitors from the AVEC2014 competition, however, it is still far away from the state-of-the-art. A few drawbacks of their approach are the image size they adopted is very small, which would result in downsizing the AVEC images and reducing a significant amount of spatial information. This can have a negative impact as the expressions they wish to seek are very subtle, small and slow. They also reduce the color channels to grayscale, further removing useful information.

In this paper, we are targeting an artificial intelligent system that can achieve the best performance on depression level prediction, in comparison with all the existing methods on the AVEC2014 dataset. Improvement will be made on the previous work from feature extraction by using deep learning, regression with fusion, and build a complete system for automatic depression level prediction from both vocal and visual expressions.

Framework

Human facial expressions and voices in depression are theoretically different from those under normal mental states. An attempt to find a solution for depression scale prediction is achieved by combining dynamic descriptions within naturalistic facial and vocal expressions. A novel method is developed that comprehensively models the variations in visual and vocal cues, to automatically predict the BDI-II scale of depression. The proposed framework is an extension of the previous method [10] by replacing the hand-crafted techniques with deep face representations as a base feature to the system.

A. System Overview

Fig. 1 illustrates the process of how the features are extracted from the visual data using either deep learning or a group of hand-crafted techniques. Dynamic pattern variations are captured across the feature vector, which is reduced in dimensionality and used with regression techniques for depression analysis. Fig. 2 follows a similar architecture as Fig. 1, but is based on audio data. The audio is split into segments and two sets of features are extracted from these segments. Then one of these sets are reduced in dimensionality and used with regression techniques to predict the depression scale.

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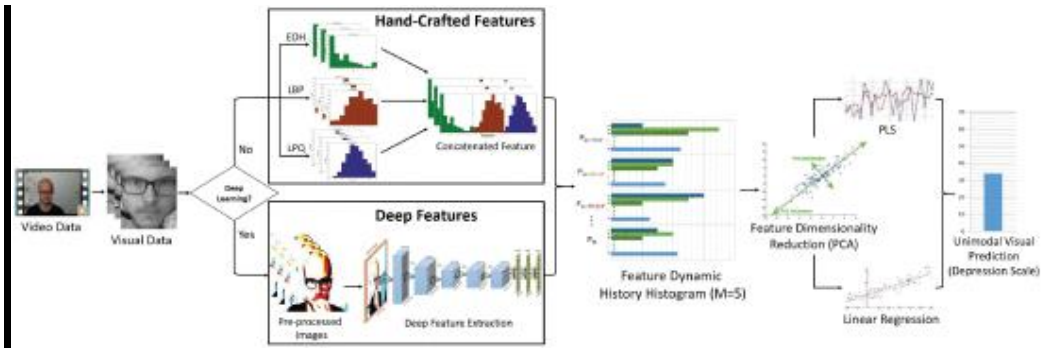

Fig. 1.

Overview of the proposed automatic depression scale recognition system from facial expressions. The video data is broken down into visual frames. If deep learning is utilized, then deep features are extracted from the frames, otherwise a set of hand-crafted features are extracted. This is followed by FDHH to produce a dynamic descriptor. The dimensionality is reduced and a fusion of PLS and LR is used to predict the depression scale.

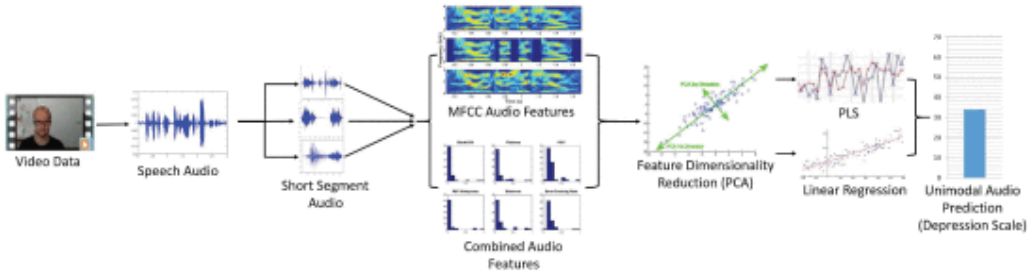

Fig. 2.

Overview of the proposed automatic depression scale recognition system from vocal expressions. The speech audio is extracted from the video data, where short segments are produced. Then a bunch of audio features are extracted from each segment and averaged. These are reduced in dimensionality and a fusion of PLS and LR is used to predict the depression scale.

For the deep feature process, the temporal data for each sample is broken down into static image frames which are preprocessed by scaling and subtracting the given mean image. These are propagated forward into the deep network for high level feature extraction. Once the deep features are extracted for a video sample, it is rank normalized between 0 and 1 before the FDHH algorithm is applied across each set of features per video. The output is transformed into a single row vector, which will represent the temporal feature of one video.

Both frameworks are unimodal approaches. The efforts are combined at feature level by concatenating the features produced by each framework just before principal component analysis (PCA) is applied. This gives a bimodal feature vector, which is reduced in dimensionality using PCA and is rank normalized again between 0 and 1. It is applied with a weighted sum rule fusion of regression techniques at prediction level, to give the BDI-II prediction.

B. Visual Feature Extraction

This section looks at the different techniques and algorithms used to extract visual features from the data.

1) Hand-Crafted Image Feature Extraction:

Previously [10], the approach was based on investing in hand-crafted techniques to represent the base features. These were applied on each frame, similar to the deep face representation, with three different texture features LBP; edge orientation histogram (EOH) and LPQ.

LBP looks for patterns of every pixel compared to its surrounding 8 pixels [45]. This has been a robust and effective method used in many applications including face recognition [46]. EOH is a technique similar to histogram of oriented gradients [47], using edge detection to capture the shape information of an image. Applications include hand gesture recognition [48], object tracking [49], and facial expression recognition [50]. LPQ investigates the frequency domain,

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where an image is divided into blocks where discrete Fourier transform is applied on top to extract local phase information. This technique has been applied for face and texture classification [51].

2) Architectures for Deep Face Representation:

In this section, different pretrained CNN models are introduced, detailing the architectures and its designated application. Two models are then selected to be testing within the system for the experiments.

3) VGG-Face:

Visual Geometry Group have created a few pretrained deep models, including their *very deep networks*. These networks are VGG-S, VGG-F, and VGG-M [52] networks which represent slow, fast, and medium, respectively. VGG-D and VGG-E are their very deep networks, VGG-D containing 16 convolutional layers and VGG-E containing 19 [29]. These networks are pretrained based on the ImageNet dataset for the object classification task [53]. VGG-Face is a network which they train on 2.6M facial images for the application of face recognition [25]. This network is more suited for the depression analysis task as it is trained mainly on facial images, as opposed to objects from the ImageNet dataset.

The VGG-Face [25] pretrained CNN contains a total of 36 layers, where 16 are convolution layers and 3 are fully connected layers. The filters have a fixed kernel size of 3×3 and as the layers increase, so does the filter depth which varies from 64 to 512. The fully connected layers are of 1×1 kernel and have a depth of 4096 dimensions, with the last layer having 2622. The remaining 20 are a mixture of rectified linear activation layers and max pooling layers, with a softmax layer at the end for probabilistic prediction. The full architecture is shown in Fig. 3, along with how the high and low level features look like throughout the network. It can be seen how certain filter responses are activated to produce edges and blobs that over the network they combine to remake the image.

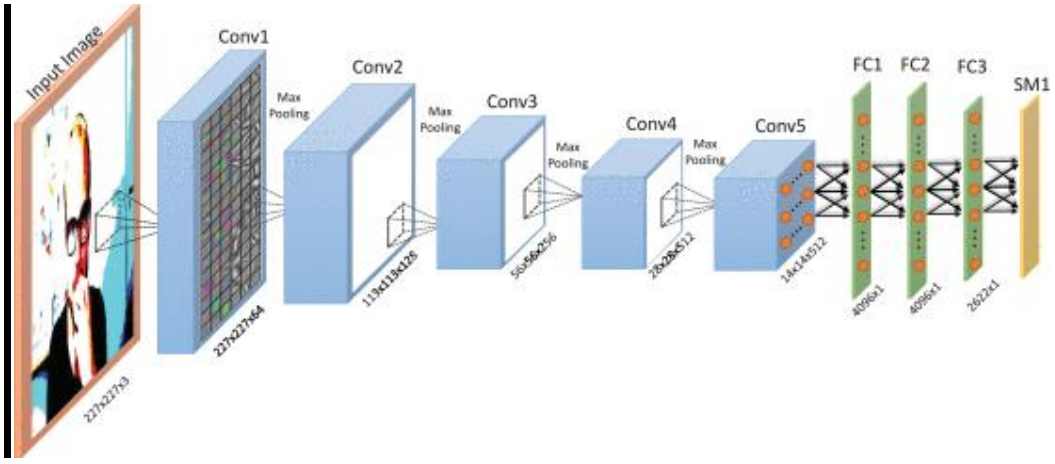

Fig. 3.

VGG-Face architecture visualizing low to high-level features captured as a facial expression is propagated through-out the network, stating the dimensions produced by each layer.

This network is designed to recognize a given face between 2622 learned faces, hence the 2622 filter responses in the softmax layer. However, the task is more to observe the facial features that are learned by the convolutional layers. The early to later convolution layers (Conv1–Conv5) contain spatial features from edges and blobs, to textures and facial parts, respectively. Their filter responses can be too big to be used directly as a feature vector to represent faces. Therefore, the fully connected layers are looked upon to obtain a plausible feature vector to describe the whole input facial image. In these experiments, the feature at the three fully connected layers FC1–FC3 were acquired and used.

4) AlexNet:

AlexNet, created by Krizhevsky *et al.* [28], is another popular network, which was one of the first successful deep networks used in the ImageNet challenge [53]. This pretrained CNN contains 21 layers in total. The architecture of AlexNet varies from the VGG-Face network in terms of the depth of the network and the convolution filter sizes. The targeted layers for this experiment are 16 and 18, which are represented as FC1 and FC2, respectively. This network is designed for recognizing up to 1000 various objects, which may result in unsuitable features when applied with facial

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images. However, it will be interesting to see how it performs against VGG-Face, a network designed specifically for faces.

C. Audio Feature Extraction

For audio features, the descriptors are derived from the set provided by the host of the AVEC2014 challenge. They include spectral LLDs and MFCCs 11–16. There are a total of 2268 features, with more details in [18]. These features are further investigated to select the most dominant set by comparing the performance with the provided audio baseline result. The process includes testing each individual feature vector with the development dataset, where the top eight performing descriptors are kept. Then, each descriptor is paired with every other in a thorough test to find the best combination. This showed Flatness, Band1000, PSY Sharpness, POV, Shimmer, and ZCR to be the best combination, with MFCC being the best individual descriptor. Fig. 2 shows the full architecture using the selected audio features, where two paths are available, either selecting the MFCC feature or the combined features.

D. Feature Dynamic History Histogram

MHH is a descriptive temporal template of motion for visual motion recognition. It was originally proposed and applied for human action recognition [54]. The detailed information can be found in [55] and [56]. It records the grayscale value changes for each pixel in the video. In comparison with other well-known motion features, such as motion history image [57], it contains more dynamic information of the pixels and provides better performance in human action recognition [55]. MHH not only provides rich motion information, but also remains computationally inexpensive [56].

MHH normally consists of capturing motion data of each pixel from a string of 2-D images. Here, a technique is proposed to capture dynamic variation that occurs within mathematical representations of a visual sequence. Hand-crafted descriptors such as EOH, LBP, and LPQ model the mathematical representations from the still images, which can be interpreted as a better representation of the image. Furthermore, fusion of these technical features can provide a combination of several mathematical representations, improving the feature as demonstrated in [13]. Several techniques have been proposed to move these descriptors into the temporal domain in [58]–[61]. They simply apply the hand-crafted descriptors in three spatial directions, as they are specifically designed for spatial tasks. This ideally extends the techniques spatially in different directions rather than dynamically taking the time domain into account.

A solution was proposed to obtain the benefits of using hand-crafted techniques on the spatial images, along with applying the principals of temporal-based motion techniques. This was achieved by capturing the motion patterns in terms of dynamic variations across the feature space. This involves extracting the changes on each component in a feature vector sequence (instead of one pixel from an image sequence), so the dynamic of facial/object movements are replaced by the feature movements. Pattern occurrences are observed in these variations, from which histograms are created. Fig. 4 shows the process of computing FDHH on the sequence of feature vector, the algorithm for FDHH can be implemented as follows.

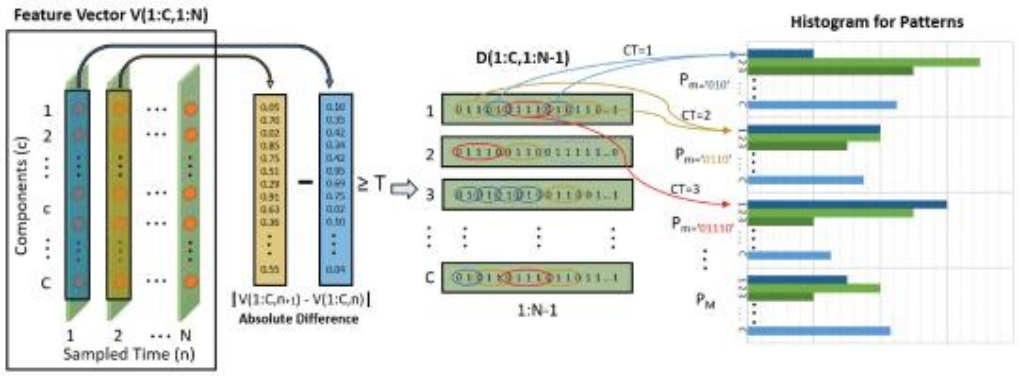

Fig. 4.

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Visual process of computing FDHH on the sequence of feature vectors. The first step is to obtain a new binary vector representation based on the absolute difference between each time sample. From this, binary patterns Pm are observed throughout each components of the binary vector and a histogram is produced for each pattern.

Let {V(c,n),c=1,…,C,n=1,…,N} be a feature vector with C components and N frames, and a binary sequence {D(c,n),c=1,…,C,n=1,…,N−1} of feature component c is generated by comprising and thresholding the absolute difference between consecutive frames as shown in (1). T is the threshold value determining if dynamic variation occurs within the feature vector. Given the parameter M=5 , we can define the pattern sequences PM as Pm(1≤m≤M) , where m represents how many consecutive "1"s are needed to create the pattern, as shown in Fig. 4. The final dynamic feature can be represented as {FDHH(c,m),c=1,…,C,m=1,…,M}

D(c,n)={1,0,if {|V(c,n+1)−V(c,n)|≥T}otherwise.(1)

Equation (1) shows the calculation for the binary sequence D(c,n) . The absolute difference is taken between the sample n+1 and n , which is then compared with a threshold to determine if the sequence should be a 1 or "0." A counter is then initialized to CT=0 , which is used to search for patterns of 1s in a sequence D(1 : C,1 : N−2)

CT= FDHH(c,m)={CT++,0,if {D(c,n+1)=1}a pattern P1:M found, reset CT{ FDHH(c,m)+1, FDHH(c,m),if {Pm is found}otherwise.(2)(3)

When observing a component from a sequence D(c,1 : N) , a pattern of Pm(1≤m≤M) is detected by counting the number of consecutive 1s, where CT is updated as shown in (2). This continues to increment for every consecutive 1 until a 0 occurs within the sequence, and for this case the histogram FDHH is updated as shown in (3), followed by the counter CT being reset to 0.

Equation (3) shows the FDHH of pattern m is increased when a pattern Pm is found. This is repeated throughout the sequence for each component until all the FDHH histograms are created for the desired patterns 1 : M . There are two special cases that have been dealt with. These are the case where CT=0 (consecutive 0s), none of the histograms are updated and where CT>M , the histogram for PM is incremented. The full algorithm can be seen in Fig. 5.

Algorithm (FDHH)

Input: Feature Vector *V(c,n)*, component $c=1,...,C$, frame $n=1,...,N$
Initialisation: Patterns $m=1,...,M$,
FDHH (1:*C*,1:*M*) = 0,
D(1:*C*,1:*N*-1) = 0,
CT =0
For n=1 to N-1 **(For N1)**
Compute $D(1:C,n) = |V(c,n+1) - V(c,n)| \geq T$ (Binary Output)
End (For N1)
For c=1 to C **(For C)**
For n=1 to N-2 **(For N2)**
If (D(c,n+1)==1) **(If 1)**
Update: CT++
ElseIf(CT>0 & $CT \leq M$)
Update: $FDHH(c,CT)$++
Update: CT=0
ElseIf($CT>M$)
Update: $FDHH(c,M)$++
Update: CT=0
End (If 1)
End (For N2)
End (For C)
Output: $FDHH(1:C,1:M)$

Fig. 5.

FDHH algorithm.

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E. Feature Combination and Fusion

Once the deep features are extracted, FDHH is applied on top to create M feature variation patterns for each deep feature sequence. The resulting histograms provide a feature vector that contains the information of the dynamic variations that occur throughout the features. The audio features are then fused with the dynamic deep features by concatenating them together, producing one joint representational vector per sample, which is normalized between [0, 1]. For testing purposes, the normalization is based on the training set. Equation (4) shows how the features are ranked within the range of the training data

Xi^=Xi−αminαmax−αmin(4)

where Xi is the training feature component, αmin and αmax are the training minimum and maximum feature vector values, and Xi^ is the normalized training feature component. PCA is performed on the fused feature vector to reduce the dimensionality and decorrelate the features. Doing this reduces the computational time and memory for some regression techniques such as LR. The variance within the data is kept high to about 94% by retaining dimensions L=49 . After PCA is applied, the feature is once again normalized between [0, 1] using the training data.

F. Alternate Feature Extraction Approach

For comparison purposes, another approach (APP2) is undergone to apply the original MHH [54] on the visual sequences, that was used similarly in the previous AVEC2013 competition by Meng *et al.* [11]. Their approach has been extended here by using deep features. MHH is directly applied on the visual sequences to obtain M motion patterns MHH(u,v,m) and {u=1,…,U,v=1,…,V,m=1,…,M} , where {u,v} are the frames for 1 : M motion patterns. The frames are treated as individual image inputs for the deep CNNs and are forward propagated until the softmax layer. This approach closely resembles the main approach to allow for fair testing when evaluating and comparing them together.

The 4096-dimensional features are extracted from similar layers to the main approach, resulting in a deep feature vector of M×4096 per video sample. These features are then transformed to a single vector row from which it is fused with the same audio features used in the main approach. They are then rank normalized between [0, 1] using the training data range before the dimensionality is reduced using PCA to L=49 , and finally the reduced feature vector is rank normalized again between [0, 1] using the training data range.

G. Regression

There are two techniques adopted for regression. PLSs regression [62] is a statistical algorithm which constructs predictive models that generalize and manipulates features into a low-dimensional space. This is based on the analysis of relationship between observations and response variables. In its simplest form, a linear model specifies the linear relationship between a dependent (response) variable, and a set of predictor variables.

This method reduces the predictors to a smaller set of uncorrelated components and performs least squares regression on these components, instead of on the original data. PLS regression is especially useful when the predictors are highly collinear, or when there are more predictors than observations and ordinary least-squares regression either produces coefficients with high standard errors or fails completely. PLS regression fits multiple response variables in a single model. PLS regression models the response variables in a multivariate way. This can produce results that can differ significantly from those calculated for the response variables individually. The best practice is to model multiple responses in a single PLS regression model only when they are correlated. The correlation between feature vector and depression labels is computed in the training set, with the model of PLS as

S=W=KGK+EUHK+F(5)

where S is an a×b matrix of predictors and W is an a×g matrix of responses. K and U are two n×l matrices that are, projections of S (scores, components or the factor matrix) and projections of W (scores); G , H are, respectively, b×l and g×l orthogonal loading matrices; and matrices E and F are the error terms, assumed to be independent and identical normal distribution. Decompositions of S and W are made so as to maximize the covariance of K and U .

LR is another approach for modeling the relationship between a scalar dependent variable and one or more explanatory variables in statistics. It was also used in the system along with PLS regression for decision fusion. The prediction level fusion stage aims to combine multiple decisions into a single and consensus one [63]. The predictions from PLS and LR are combined using prediction level fusion based on the weighted sum rule.

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IX. EXPERIMENTAL RESULTS

A. AVEC2014 Dataset

The proposed approaches are evaluated on the AVEC2014 dataset [18], a subset of the audio-visual depressive language corpus. This dataset was chosen over the AVEC2013 dataset as it is a more focused study of affect on depression, using only 2 of the 14 related tasks from AVEC2013. The dataset contains 300 video clips with each person performing the two human–computer interaction tasks separately whilst being recorded by a web-cam and microphone in a number of quiet settings. Some subjects feature in more than one clip. All the participants are recorded between one and four times, with a period of two weeks between each recording. Eighteen subjects appear in three recordings, 31 in 2, and 34 in only one recording. The length of these clips are between 6 s to 4 min and 8 s. The mean age of subjects is 31.5 years, with a standard deviation of 12.3 years and a range of 18–63 years. The range of the BDI-II depression scale is [0, 63], where 0–10 is considered normal, as ups and downs; 11–16 is mild mood disturbance; 17–20 is borderline clinical depression; 21–30 is moderate depression; 31–40 is severe depression; and over 40 is extreme depression. The highest recorded score within the AVEC14 dataset is 45, which indicates there are subjects with extreme depression included.

B. Experimental Setting

The experimental setup has been followed by the AVEC2014 guidelines which can be found in [18]. The instructions are followed as mentioned in the DSC, which is to predict the level of self-reported depression; as indicated by the BDI-II that ranges of from 0 to 63. This concludes to one continuous value for each video file. The results for each test are evaluated by its the mean absolute error (MAE) and root mean squared error (RMSE) against the ground-truth labels. There are three partitions to the dataset, these are training, development, and testing. Each partition contains 100 video clips, these are split 50 for "Northwind" and 50 for "Freeform." However, for the experiments the *Northwind* and *Freeform* videos count as a single sample, as each subject produces both videos with what should be the same depression level.

The MatConvNet [64] toolbox has been used to extract the deep features. This tool has been opted for the experiments as it allows full control over deep networks with access to data across any layer along with easy visualization. They also provide both AlexNet and VGG-FACE pretrained networks.

1) Data Preprocessing:

In order to obtain the optimal features from the pretrained networks, a set of data preprocessing steps were followed, as applied by both Parkhi *et al.* [25] and Krizhevsky *et al.* [28] on their data. For each video, each frame was processed individually to extract its deep features. Using the meta information, the frames were resized to 227×227×3 representing the image height, width, and color channels. AlexNet has the same requirement of 227×227×3 image as an input to the network. The images were also converted into single precision as required by the MatConvNet toolbox, followed by subtracting the mean image provided by each network. The next stage was to propagate each preprocessed frame through the networks and obtain the features produced by the filter responses at the desired layers.

2) Feature Extraction:

For each video clip, the spatial domain is used as the workspace for both approaches. With AlexNet, the 4096-dimensional feature vector is retained from the 16th and 18th fully connected layers. The decision to take the features at the 16th layer is in order to observe if the first 4096 dimension fully connected layer produces better features than the second (layer 18). For the VGG-Face network, the 4096-dimensional feature vectors are extracted at the 35th, 34th, and 32nd layers. The 34th layer is the output directly from the fully connected layer, the 35th is the output from the following rectified linear unit (ReLU) activation function layer and the 32nd layer is the output from the first fully connected layer.

The initial convolution layers are bypassed as the parameter and memory count would have been drastically higher if they were to be used as individual features. After observing the dimensions for AlexNet, there were around 70K versus 4096 when comparing the initial convolution layer versus the fully connected layers, and staggering 802K versus 4096 for VGG-Face. The connectivity between filter responses are responsible for the dramatic decrease in dimensions

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at the fully connected layers. The fully connected layer is observed using (6), where yj is the output feature by taking the function f(x) of the given input xi from the previous layer. The function calculates the sum over all inputs xi multiplied by each individual weight (j=1 : 4096) of the fully connected layer plus the bias bj

$$yj=f(\sum i=1mxi\cdot wi,j+bj).(6)$$

The role of a ReLU layer can be described with (7), where xi is the input filter response and y(xi) is the output

$$yj=max(0,xi).(7)$$

For testing purposes, the decision to investigate the effects of a feature vector before and after a ReLU activation layer (layers 34 and 35) had been taken into account. As the activation function kills filter responses that are below 0, it was assumed that the resulting feature vector will become sparse with loss of information.

When extracting the dynamic variations across the deep features, the parameter M is set to M=5 , capturing five binary patterns across the feature space. Based on a sample feature visualization of the binary pattern histograms, M=5 was chosen as beyond this results to histograms with a low count. Given that the deep feature data ranges from [0, 1], the optimized threshold value for FDHH has been set to 1/255 = 0.00392, after optimization on the training and development partitions. This will produce five resulting features with 4096 components each, making a total of feature dimension count of $5\times4096=20480$ per video sample. As there are two recordings per ground truth label, (*Northwind* and *Freeform*), the 20 480 features are extracted from both recordings and concatenated together to make a final visual feature vector of 40 960 dimensions.

The features that are extracted using AlexNet and FDHH are denoted as A16_FD and A18_FD, representing the deep features extracted from the 16th and 18th layer, respectively. For VGG-Face, the feature vectors are denoted as V32_FD, V34_FD, and V35_FD, representing the deep features extracted from the 32nd, 34th, and 35th layer, respectively.

Due to the nature of feature extractors used, it is difficult to pinpoint which parts of the face contributes the most. The movement of these facial parts play a big role in the system, and the FDHH algorithm is designed to pick up these facial movements that occur within the mathematical representations. This approach has been denoted as APP1. The whole system was tested on a Windows machine using MATLAB 2017a with an i7–6700K processor @ 4.3 GHz, and a Titan X (Pascal) GPU. For 6-s video clip, it will take less than 3.3 s to process.

3) Alternate Approaches for Feature Extraction:

An Alternate approach, denoted as APP2, started by extracting MHH of each visual sequence, for both Northwind and Freeform. The parameter M is set to M=6 to capture low to high movement across the face, this results in six motion pattern frames. Each of these frames are then propagated through AlexNet and VGG-Face, however, as there are no color channel for the pattern frames, each frame is duplicated twice making three channels in total to imitate the color channels. The output of the CNNs will produce 6×4096 features, which is transformed into a single row to make 24 576 features, and 49 152 features when both Northwind and Freeform are concatenated. These features will be denoted as MH_A16, MH_A18, MH_V32, MH_V34, and MH_V35.

Previous research [10] worked in the spatial domain to produce local features using EOH, LBP and LPQ. These features are extracted frame by frame to produce 384-, 944-, and 256-dimensional histograms, respectively, for each frame. FDHH was used to capture the dynamic variations across the features to produce M=3 vectors of temporal patterns. The features are denoted as EOH_FD, LBP_FD, and LPQ_FD and are reshaped producing 1152, 2835, and 768 components, respectively, which were concatenated to produce a vector of 4755 components. These components are produced for both Northwind and Freeform videos and were also concatenated together producing a total of 9510 components per video sample, which is denoted as (MIX_FD). The experiments were run on the concatenated features MIX_FD, as well as their individual feature performance. The vectors EOH_FD, LBP_FD, and LPQ_FD had been tested with the development set before they were concatenated, to provide a comparison from its individual and combined benefits.

Furthermore, modeling the temporal features of facial expressions in the dynamic feature space was explored, similar to [11]. First, MHH was applied on the video to produce five (M=5) frames. Then, the local features (EOH, LBP, and LPQ) was extracted from each motion histogram frame. Finally, all the feature vectors were concatenated and denoted as (MH_MIX).

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The baseline audio features (2268) are provided by the dataset. The short audio segments (short) were used, which were a set of descriptors that extracted features every 3 s of audio samples. The mean of the segments were taken to provide a single vector of 1×2268 per sample and it was denoted it (audio). The combined audio features of Flatness, Band1000, POV, PSY Sharpness, Shimmer, and ZCR were used, containing 285 of the 2268 features and was denoted as (Comb). MFCC was also investigated as a sole feature vector, and was denoted as (MFCC). For all the dynamic features from visual and vocal modalities, the dimensionality was reduced with PCA to L=49 components, and the depression analyzed by the PLS and LR.

C. Performance Comparison

Starting with the hand-crafted features LBP, LPQ, and EOH, Table I demonstrates the individual performance of the three hand-crafted feature extraction methods that are combined with FDHH. The depression scales were predicted using the two regression techniques separately and fused. It is clear that using PLS for regression was better than LR in all tests. However, when they were fused with a weighting more toward PLS, the results were improved further. LBP was shown to be the weakest amongst the three and LPQ the strongest.

TABLE I Performance of Depression Scale Prediction Using the Dynamic Visual Feature FDHH (FD) Measured Both in MAE and RMSE Averaged Over All Sequences in the Development Set

Partition	Methods	MAE	RMSE
Develop	EOH_FD_PLS	**8.87**	**11.09**
Develop	EOH_FD_LR	9.92	12.39
Develop	EOH_FD_(PLS+LR)	9.14	11.39
Develop	LBP_FD_PLS	9.34	11.16
Develop	LBP_FD_LR	9.86	12.68
Develop	LBP_FD_(PLS+LR)	**9.18**	**11.15**
Develop	LPQ_FD_PLS	8.79	10.88
Develop	LPQ_FD_LR	9.73	11.49
Develop	LPQ_FD_(PLS+LR)	**8.70**	**10.63**

Table II contains results of both approaches, with APP1 combining the efforts of the individual hand-crafted features, and demonstrates the effectiveness of the deep features using the FDHH algorithm. APP2 applies MHH before the hand-crafted and deep features. Three of the best results from each part have been highlighted in bold. MIX_FD has shown a significant improvement over the individual performances in Table I. However, it is clear from this that the deep features perform consistently better than the individual and combined hand-crafted features. The AlexNet deep features with FDHH (A16_FD) have shown a good performance on the development subset, closely followed by VGG-Face deep features with FDHH (V32_FD). The overall performance of APP2 can be viewed as inferior when compared to our main approach APP1, with all performances projecting a worse result than its respective main approach feature, e.g., MH_V34_PLS versus V34_FD_PLS. Second, we can see that the deep learning approaches have performed better than hand-crafted features using both approaches.

TABLE II Performance of Depression Scale Prediction Using FDHH (FD) After MIX (EOH, LBP, LPQ, and Deep) Visual Features are Shown Under APP1 and MHH (MH) Before MIX (EOH, LBP, LPQ, and Deep) Visual Features are Shown in APP2, Measured Both in MAE and RMSE Averaged Over All Sequences in the Development Set

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Methods	Develop		Methods	Develop	
APP1	MAE	RMSE	APP2	MAE	RMSE
MIX_FD_PLS	7.72	9.68	MH_MIX_PLS	8.91	10.78
MIX_FD_LR	7.52	10.05	MH_MIX_LR	10.59	12.71
A16_FD_PLS	**6.66**	**9.02**	MH_A16_PLS	**7.42**	**9.58**
A16_FD_LR	**6.96**	**9.52**	MH_A16_LR	7.41	9.73
A18_FD_PLS	7.19	9.36	MH_A18_PLS	**7.33**	**9.46**
A18_FD_LR	7.23	9.43	MH_A18_LR	**7.41**	**9.56**
V32_FD_PLS	7.25	9.52	MH_V32_PLS	8.06	10.13
V32_FD_LR	**6.90**	**9.32**	MH_V32_LR	7.75	9.70
V34_FD_PLS	7.08	9.52	MH_V34_PLS	8.53	10.46
V34_FD_LR	7.09	9.53	MH_V34_LR	8.56	10.55
V35_FD_PLS	7.44	9.43	MH_V35_PLS	9.47	13.17
V35_FD_LR	7.50	9.44	MH_V35_LR	9.48	12.86

A subexperiment was to investigate the features before and after a ReLU layer. This would supposedly introduce sparsity by removing negative magnitude features, which would result in a bad feature. This was tested by observing the features at the 34th and 35th layer of the VGG-Face network. From the individual performance evaluation on both approaches, it is clear that there is a higher RMSE and MAE for V35 using either regression techniques.

In Table III, the audio features for short segments were tested. From the 2268 audio features (audio), the combined features (Comb) and MFCC features have been taken out to be tested separately. The individual tests show the audio and MFCC features performing well on the development subset, with MFCC showing great performance on the test subset. When compared to visual features, they fall behind against most of them.

TABLE III Performance of Depression Scale Prediction Using Complete Audio, Comb Features, and MFCC. Measured Both in MAE and RMSE Averaged Over All Sequences in the Development and Test Subsets

Methods	Develop		Test	
	MAE	RMSE	MAE	RMSE
Comb_short_PLS	9.31	11.52	8.52	10.49
Comb_short_LR	9.42	11.64	10.33	12.99
Audio_short_PLS	**8.25**	**10.08**	8.42	10.46
Audio_short_LR	**8.39**	**10.21**	8.45	10.73
MFCC_short_PLS	8.86	10.70	**8.04**	**10.42**
MFCC_short_LR	8.86	10.92	**8.07**	**10.28**

Features from both audio and visual modalities were combined as proposed in the approach, to produce bimodal performances that can be found in Table IV. This table demonstrates that the fusion of the two modalities boosts the overall performance further, especially on the test subset. VGG deep features have once again dominated the test subset, with AlexNet performing better on the development subset. A final test has been on fusing the performances of the regression techniques using the best features observed in Table IV. This involved using a weighted fusion technique on the PLS and LR predictions, the performance are detailed in Table V.

TABLE IV Performance of Depression Scale Prediction Using FDHH on Various Spatial Features. Measured Both in MAE and RMSE Averaged Over All Sequences in the Development and Test Subsets

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Methods	Develop		Test	
	MAE	RMSE	MAE	RMSE
MIX_FD+MFCC_PLS	7.41	9.30	7.28	9.15
MIX_FD+MFCC_LR	7.69	9.57	7.11	8.98
A16_FD+MFCC_PLS	7.40	9.21	6.58	8.19
A16_FD+MFCC_LR	7.14	8.99	6.87	8.45
A18_FD+MFCC_PLS	**6.92**	**8.79**	6.44	7.96
A18_FD+MFCC_LR	**6.66**	**8.67**	7.10	8.57
V32_FD+MFCC_PLS	7.35	9.54	**6.17**	**7.44**
V32_FD+MFCC_LR	**7.07**	**9.34**	**6.31**	**7.59**
V34_FD+MFCC_PLS	7.08	9.35	**6.14**	**7.56**
V34_FD+MFCC_LR	7.16	9.44	6.51	7.80
V35_FD+MFCC_PLS	7.20	9.24	8.34	10.43
V35_FD+MFCC_LR	6.90	9.06	8.12	10.15

TABLE V System Performance Using Weighted Fusion of Regression Techniques, PLS and LR, on Selected Features for the Development and Test Subsets

Partition	Methods	MAE	RMSE
Develop	V32_FD+MFCC_(PLS+LR)	7.06	9.35
Test	V32_FD+MFCC_(PLS+LR)	**6.14**	**7.43**
Develop	A18_FD+MFCC_(PLS+LR)	**6.58**	**8.65**
Test	A18_FD+MFCC_(PLS+LR)	6.52	8.08

The best performing unimodal feature based on the test subset has been V32_FD, producing 6.68 for MAE and 8.04 for RMSE. Both achieving the state-of-the-art when compared against other unimodal techniques. The best overall feature uses the fusion of the audio and visual modalities, along with the weighted fusion of the regression techniques (V32_FD+MFCC)_(PLS+LR). This feature produced 6.14 for MAE and 7.43 for RMSE, beating the previous state-of-the-art produced by Williamson *et al.* [19], [20] who achieved 6.31 and 8.12, respectively. The predicted values of (V32_FD+MFCC)_(PLS+LR) and actual depression scale values on the test subset are shown in Fig. 6. Performance comparisons against other techniques including the baseline can be seen in Table VI.

TABLE VI Performance Comparison Against Other Approaches on the Test Partition, Measured in RMSE and MAE. Modality for Each is Mentioned and Grouped for Comparison (A = Audio and V = Visual)

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Method	Modality	MAE	RMSE
Ours	Unimodal (V)	**6.68**	**8.01**
Kaya [41]	Unimodal (V)	7.96	9.97
Jain [44]	Unimodal (V)	8.39	10.24
Mitra [40]	Unimodal (A)	8.83	11.10
Baseline [18]	Unimodal (V)	8.86	10.86
Perez [39]	Unimodal (V)	9.35	11.91
Ours	Bimodal (A+V)	**6.14**	**7.43**
Williamson [20]	Bimodal (A+V)	6.31	8.12
Kaya [41]	Bimodal (A+V)	7.69	9.61
Chao [43]	Bimodal (A+V)	7.91	9.98
Senoussaoui [38]	Bimodal (A+V)	8.33	10.43
Perez [39]	Bimodal (A+V)	8.99	10.82
Kachele [37]	Multimodal	7.28	9.70
Gupta [42]	Multimodal	-	10.33

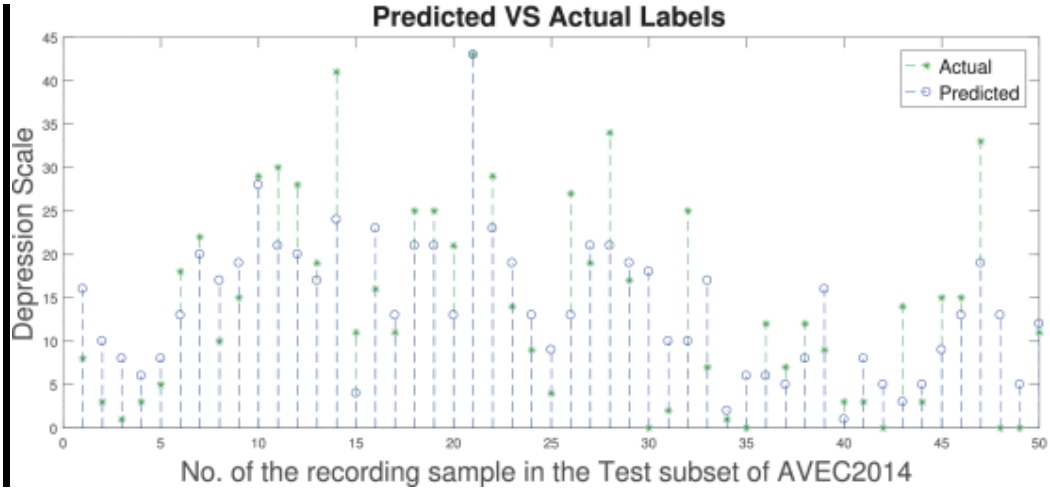

Fig. 6.
Predicted and actual depression scales of the test subset of the AVEC2014 dataset based on audio and video features with regression fusion.

X. RESULT AND CONCLUSION

In this paper, an artificial intelligent system was proposed for automatic depression scale prediction. This is based on facial and vocal expression in naturalistic video recordings. Deep learning techniques are used for visual feature extraction on facial expression faces. Based on the idea of MHH for 2-D video motion feature, we proposed FDHH that can be applied to feature vector sequences to provide a dynamic feature (e.g., EOH_FD, LBP_FD, LPQ_FD, deep feature V32_FD, etc.) for the video. This dynamic feature is better than the alternate approach of MHH_EOH that was

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used in previous research [11], because it is based on mathematical feature vectors instead of raw images. Finally, PLS regression and LR are adopted to capture the correlation between the feature space and depression scales.

The experimental results indicate that the proposed method achieved good state-of-the-art results on the AVEC2014 dataset. Table IV demonstrates the proposed dynamic deep feature is better than MH_EOH that was used in previous research [11]. When comparing the hand-crafted versus deep features shown in Table II, deep features taken from the correct layer shows significant improvement over hand-crafted. With regards to selecting the correct layer, it seems that features should be extracted directly from the convolution filters responses. Generally the earliest fully connected layer will perform be the best, although the performances are fairly close to call. Audio fusion contributed in getting state-of-the-art results using only the MFCC feature, demonstrating that a multimodal approach can be beneficial.

There are three main contributions from this paper. First is the general framework that can be used for automatically predicting depression scales from facial and vocal expressions. The second contribution is the FDHH dynamic feature, that uses the idea of MHH on the deep learning image feature and hand-crafted feature space. The third one is the feature fusion of different descriptors from facial images. The overall results on the testing partition are better than the baseline results, and the previous state-of-the-art result set by Williamson *et al.* [19], [20]. FDHH has proven it can work as a method to represent mathematical features, from deep features to common hand-crafted features, across a temporal domain. The proposed system has achieved remarkable performance on an application that has very subtle and slow changing facial expressions by focusing on the small changes of pattern within the deep/hand-crafted descriptors. In the case that a sample contains other parts of the body; has lengthier episodes; or reactions to stimuli, face detection and video segmentation can adapt the sample to be used in our system.

There are limitations within the experiment that can affect the system performance. The BDI-II measurement is assessed on the response of questions asked to the patients. The scale of depression can be limited by the questions asked, as the responses may not portray their true depression level. The dataset contains patients only of German ethnicity; who are all Caucasian race. Their identical ethnicity may affect the robustness of a system when validated against other ethnicities. Another limitation can be the highest BDI-II recording within the dataset, which is 44 and 45 for the development and testing partitions, respectively. All these things can be considered for further improvement of the system.

Further ideas can be investigated to improve the system performance. The performance may improve if additional facial expression images are added into the training process of the VGG-Face deep network. The raw data itself can be used to retrain a pretrained network, which can be trained as a regression model. For the vocal features, a combination of descriptors have been tested. However, other vocal descriptors should also be considered to be integrated in the system, or even adapting a separate deep network that can learn from the vocal data. Other fusion techniques can also be considered at feature and prediction level that would improve the performance further.

XI. SUMMARY

11.1 ADVANTAGES

Following are some advantages of bank locker security system:

1. Provides high security.
2. Low cost.
3. Easy to implement.
4. No hack or crack to system.
5. Easy to use.
6. Fully automatic system.

11.2. LIMITATIONS

1) Lack of interactivity.
2) Internet must.
3) Totally online system

11.3. APPLICATIONS

This system can be used in following areas:

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1. In Medical.
2. In identification
3. All that places when unique identity & high security is required.

11.4 Future Scope

1. The System can be implemented in embedded processors such as raspberry PI
2. Additional facilities can be used such as facial recognition
3. The System can be further extended to other medical services

REFERENCES

[1]. Shaikh Awesh, Gund Suraj, Tipule Pratap, Bhusari Pratiksha , "Depression Detection By Social MediaAnalyzing", International Research Journal Of Engineering And Technology , 2021

[2]. Bhushan Parkar, Sahil Lanjekar , Arbaz Mulla, Vivek Patil ,"Depression Detection Using Nlp Algorithm On Youtube Data", International Research Journal Of Engineering And Technology,2021

[3]. Meenakshi Garg, Heramb Shankar Patil, "Comparative Study on Ai in Mental Health and Wellbeing – CurrentApplications and Trends", International Research Journal of Engineering and Technology, 2021

[4]. Suyash Dabhane, "Depression Detection On Social Media Using Machine Learning Techniques: A Survey",International Research Journal Of Engineering And Technology, 2020

[5]. Mrunal Kulkarni, "Depression Prediction System Using Different Methods", International Research Journal OfEngineering And Technology, 2019

[6]. R Shilkrot, J Huber, R Boldu, Pmaes and S Nanayakka "FingerReader: A Finger-Worn Assistive Augmentation"Springer Nature Singapore Pte Ltd. 2018

[7]. Pampouchidou, A., O. Simantiraki, C-M. Vazakopoulou, C. Chatzaki, M. Pediaditis, A. Maridaki, K. Marias et al." Facial geometry and speech analysis for depression detection." In Engineering in Medicine and Biology Society (EMBC), 39th Annual International Conference of the IEEE, pp. 1433-1436. IEEE, 2017.

[8]. Harati, Sahar, Andrea Crowell, Helen Mayberg, Jun Kong, and Shamim Nemati." Discriminating clinical phases of recovery from major depressive disorder using the dynamics of facial expression." In Engineering in Medicine and Biology Society (EMBC), 38th Annual International Conference of the, pp. 2254- 2257. IEEE, 2016.

[9]. Tasnim, Mashrura, RifatShahriyar, NowshinNahar, and Hossain Mahmud." Intelligent depression detection and support system: Statistical analysis, psychological review and design implication." In e-Health Networking, Applications and Services (Healthcom), 18th International Conference on, pp. 1-6. IEEE, 2016.

[10]. A. Jan, H. Meng, Y. F. A. Gaus, F. Zhang and S. Turabzadeh, "Automatic depression scale prediction using facial expression dynamics and regression", *Proc. 4th Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 73-80, 2014.

[11]. H. Meng et al., "Depression recognition based on dynamic facial and vocal expression features using partial least square regression", *Proc. 3rd ACM Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 21-30, 2013.

[12]. P. Ekman and W. V. Friesen, Facial Action Coding System, Palo Alto, CA, USA:Consulting Psychol. Press, 1978.

[13]. A. Jan and H. Meng, "Automatic 3D facial expression recognition using geometric and textured feature fusion", *Proc. 11th IEEE Int. Conf. Workshops Autom. Face Gesture Recognit. (FG)*, vol. 5, pp. 1-6, May 2015.

[14]. M. Kaletsch et al., "Major depressive disorder alters perception of emotional body movements", *Front. Psychiatry*, vol. 5, pp. 4, Jan. 2014.

[15]. J. Han et al., "Video abstraction based on fMRI-driven visual attention model", *Inf. Sci.*, vol. 281, pp. 781-796, Oct. 2014.

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ISSN (Online) 2581-9429
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[16]. J. Han et al., "Learning computational models of video memorability from fMRI brain imaging", *IEEE Trans. Cybern.*, vol. 45, no. 8, pp. 1692-1703, Aug. 2015.

[17]. M. Valstar et al., "AVEC 2016: Depression mood and emotion recognition workshop and challenge", *Proc. 6th Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 3-10, 2016.

[18]. M. F. Valstar et al., "AVEC 2014: 3D dimensional affect and depression recognition challenge", *Proc. Int. Conf. ACM Multimedia Audio/Vis. Emotion Challenge Workshop*, pp. 3-10, 2014.

[19]. J. R. Williamson et al., "Vocal biomarkers of depression based on motor incoordination", *Proc. 3rd ACM Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 41-48, 2013.

[20]. J. R. Williamson, T. F. Quatieri, B. S. Helfer, G. Ciccarelli and D. D. Mehta, "Vocal and facial biomarkers of depression based on motor incoordination and timing", *Proc. 4th ACM Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 41-47, 2013.

[21]. X. Ma, H. Yang, Q. Chen, D. Huang and Y. Wang, "Depaudionet: An efficient deep model for audio based depression classification", *Proc. 6th Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 35-42, 2016.

[22]. M. Nasir, A. Jati, P. G. Shivakumar, S. N. Chakravarthula and P. Georgiou, "Multimodal and multiresolution depression detection from speech and facial landmark features", *Proc. 6th Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 43-50, 2016.

[23]. R. Weber, V. Barrielle, C. Soladié and R. Séguier, "High-level geometry-based features of video modality for emotion prediction", *Proc. 6th Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 51-58, 2016.

[24]. Y. L. Cun et al., "Handwritten digit recognition with a back-propagation network", *Proc. Adv. Neural Inf. Process. Syst.*, pp. 396-404, 1990.

[25]. 25.O. M. Parkhi, A. Vedaldi and A. Zisserman, "Deep face recognition", *Proc. Brit. Mach. Vis. Conf.*, pp. 1-12, 2015.

[26]. K. He, X. Zhang, S. Ren and J. Sun, "Deep residual learning for image recognition", *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 770-778, 2016.

[27]. J. Long, E. Shelhamer and T. Darrell, "Fully convolutional networks for semantic segmentation", *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 3431-3440, 2014.

[28]. A. Krizhevsky, I. Sutskever and G. E. Hinton, "ImageNet classification with deep convolutional neural networks", *Proc. Adv. Neural Inf. Process. Syst.*, pp. 1097-1105, 2012.

[29]. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition", *Proc. ICLR*, pp. 1-14, 2015.

[30]. P. Wang et al., "Automated video-based facial expression analysis of neuropsychiatric disorders", *J. Neurosci. Methods*, vol. 168, no. 1, pp. 224-238, 2008.

[31]. Y. Yang, C. Fairbairn and J. F. Cohn, "Detecting depression severity from vocal prosody", *IEEE Trans. Affect. Comput.*, vol. 4, no. 2, pp. 142-150, Apr. 2013.

[32]. S. Scherer et al., "Automatic behavior descriptors for psychological disorder analysis", *Proc. IEEE Int. Conf. Autom. Face Gesture Recognit.*, pp. 1-8, 2013.

[33]. J. M. Girard, J. F. Cohn, M. H. Mahoor, S. Mavadati and D. P. Rosenwald, "Social risk and depression: Evidence from manual and automatic facial expression analysis", *Proc. IEEE Int. Conf. Autom. Face Gesture Recognit.*, pp. 1-8, 2013.

[34]. J. F. Cohn et al., "Detecting depression from facial actions and vocal prosody", *Proc. Int. Conf. Affective Comput. Intell. Interact. Workshops*, pp. 1-7, 2009.

[35]. L. Yammine, L. Frazier, N. S. Padhye, J. E. Sanner and M. M. Burg, "Two-year prognosis after acute coronary syndrome in younger patients: Association with feeling depressed in the prior year and BDI-II score and Endothelin-1", *J. Psychosom. Res.*, vol. 99, pp. 8-12, Aug. 2017.

[36]. L. Wen, X. Li, G. Guo and Y. Zhu, "Automated depression diagnosis based on facial dynamic analysis and sparse coding", *IEEE Trans. Inf. Forensics Security*, vol. 10, no. 7, pp. 1432-1441, Jul. 2015.

[37]. M. Kächele, M. Schels and F. Schwenker, "Inferring depression and affect from application dependent meta knowledge", *Proc. 4th Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 41-48, 2014.

IJARSCT
ISSN (Online) 2581-9429
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International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
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Volume 4, Issue 2, March 2024

[38]. M. Senoussaoui, M. Sarria-Paja, J. F. Santos and T. H. Falk, "Model fusion for multimodal depression classification and level detection", *Proc. 4th Int. Workshop Audio/Vis. Emotion Challenge*, pp. 57-63, 2014.

[39]. H. Pérez Espinosa et al., "Fusing affective dimensions and audio-visual features from segmented video for depression recognition: INAOE-BUAP's participation at AVEC'14 challenge", *Proc. 4th Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 49-55, 2014.

[40]. V. Mitra et al., "The SRI AVEC-2014 evaluation system", *Proc. ACM Int. Conf. Multimedia*, pp. 93-101, 2014.

[41]. H. Kaya, F. Çilli and A. A. Salah, "Ensemble CCA for continuous emotion prediction", *Proc. 4th ACM Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 19-26, 2013.

[42]. R. Gupta et al., "Multimodal prediction of affective dimensions and depression in human–computer interactions categories and subject descriptors", *Proc. 4th ACM Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 33-40, 2014.

[43]. L. Chao, J. Tao, M. Yang and Y. Li, "Multi task sequence learning for depression scale prediction from video", *Proc. Int. Conf. Affective Comput. Intell. Interact. (ACII)*, pp. 526-531, 2015.

[44]. V. Jain, J. L. Crowley, A. K. Dey and A. Lux, "Depression estimation using audiovisual features and Fisher vector encoding", *Proc. 4th ACM Int. Workshop Audio/Vis. Emotion Challenge (AVEC)*, pp. 87-91, 2014.

[45]. T. Ojala, M. M. Pietikäinen and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, pp. 971-987, Jul. 2002.