DEPRESSION PREDICTION MODEL USING DEEP LEARNING ALGORITHM

Presented by

SNEHA YADAV
21MDT0028
M. Sc Data Science

SUDIPTA PAUL
21MDT0042
M. Sc Data Science

Under the guidance of
Prof. PRAKASH MANI

Department of Mathematics, School of Advanced Sciences.

13-11-2022

Objective:

- In this competitive world somewhere, we are neglecting our mental health. We just prioritize physical health more than the mental health and due to this depression, anxiety and stress rates are increasing .
- Mental Health is not considered as a subject to talk about. People usually don’t talk about their mental health frequently and freely.
- So, we here tried to analyse individual's audio and video to figure out if the person is suffering from any mental health issues.

Abstract:

- The stress caused by people's increasingly hectic lifestyles and workloads can make them more vulnerable to depression. With the goal of improving existing medical care, Deep Learning (DL) has been used to automatically detect depression by extracting depression indicators from audio and video.
- To achieve these goals, we employ a novel, non-invasive architecture with three layers: in the first layer, we use a machine learning algorithm to detect emotions from the frame-by-frame images acquired from interviews; in the second layer, we use audio inputs to detect emotions; and in the third layer, we use a Feed Forward Neural Network to categorize whether the person is sad or not. From our work, we can help the airlines take more precautions against the factors that contributed to more fatalities.
- Finally, we explore the difficulties and exciting prospects of applying Deep Learning to make automatic diagnoses of depression . In this project we try to find various patterns and relations behind the airline fatalities.

Index Terms: Depression prediction, Emotion recognition, Stress prediction.

INTRODUCTION:

- In this competitive world, we have neglected the factor of our mental health. As we grew, we came to know that there is physical health which we take care of by exercising, check-ups, and many more.
- Because of the worldwide severe imbalance in the doctor-patient ratio, many patients may go without a prompt diagnosis. We use Python because it is a very robust language and contains wide variety of modules and packages which makes analysis much more easy process.
- Both physiological and psychological research has found that people with depression speak and express themselves differently than people without the disorder.
- But we ignore the fact that just as physical fitness isSuch incidents are increasing day by day due to n number of reasons, so we try to analyse few of them so as to help in bringing reduction of fatalities arising due to such incidents.
- Depression is a common mental disorder that affects a person's thinking and intellectual development. According to the WHO, about 1 billion people suffer from mental illness [2], and worldwide he has more than 300 million people suffering from depression.
- Suicidal thoughts are more common in people with depression. More than 800,000 people commit suicide each year. A comprehensive approach is therefore needed to manage the burden of mental health problems The Number of Fatalities corresponding to each month.
- Depression can have a negative impact on a person's socioeconomic status. People who are depressed are less likely to be social. Counselling and psychotherapy can help treat depression.

INTRODUCTION (Contd.):

- This mental illness is very tricky, and kind of difficult to figure out, and the treatment is much more difficult. There are many types of mental illness one of them is depression which is the most talked about.
- This study describes a new framework that uses attentional mechanisms at many levels to discover and extract important data from different modalities to predict levels of depression.
- ML algorithms can be broadly classified into four types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning algorithms. Supervised ML algorithms [14] use the primary inputs to predict known values, while unsupervised ML algorithms [15] reveal unknown patterns and clusters in the provided data. We imported the Data and carried out the pre-processing like cleaning the data, removing/treating outliers and made it ready for the analysis.
- This network uses many low- and medium-level properties of both audio and video modalities, as well as sentence embedding in the user's speech-to-text output. We show that multilevel attention provides a priority ratio for each function and modality, leading to improved outcomes. Our best network is the full-featured fusion network, which outperforms the baseline .
- DL approaches help predictive and diagnostics in healthcare by extracting knowledge from unstructured medical data. Predictive results help in early detection of high-risk medical conditions in individuals .
- Detection of high-risk medical conditions in individuals [19]. For psychiatric disorders, DL approaches can help mediate putative behavioral bio-markers to help medical professionals predict psychiatric outcomes and provide appropriate treatment outcomes.
- As a result, DL-based diagnostic techniques appear to be a viable option for predictive analytics. Interactions of sensors, text, structured data, and multimodal technologies are the main domains leveraged in the healthcare sector to use ML to extract observations related to mental illness.

PROBLEM FORMULATION (STATEMENT OF PROBLEM)

- The goal of this project is to create a model, which is capable of analysing emotions from frame-by-frame images and corresponding audio of a person, to automatically make predictions about the person's mental health and situation, more precisely the person is depressed or not.

Literature Review:

- There have been various research on the use of DL to intensify the examination of mental problems over the years.
- The authors give a history of depression, imaging, and ML techniques in. It also highlights researchers who have utilized imaging and machine learning to investigate depression.
- The methods under consideration include SVM (linear kernel), SVM (nonlinear kernel), and relevance vector regression. This survey analyses only one mental health domain (MHD).
- The study did not mention depression screening measures, and there is no complete comparison of algorithms. Garcia et al. used ML and sensor data to study mental health monitoring systems (MHMS) in mental illness.
- The study also examined supervised, unsupervised, semi-supervised, transfer learning, and reinforcement learning in the mental health domain of depression, anxiety, bipolar disorder (BD), migraine, and stress.
- However, this whitepaper only provides a brief overview of MHMS instances and applications. Gao et al. analyzed studies on prediction of brain images for ML-based classification and diagnosis.
- Major depressive disorder (MDD) and bipolar disorder (BD) were studied in combination with MRI data. This research covers SVM, LDA, GPC, DT, RVM, NN, and LR algorithms. However, it does not mention depression screening methods used in other studies. Only MDD and BD related research papers are included.
- Many studies have been conducted over the years to use DL to enhance research into mental health issues.
- Major depressive disorder (MDD) and bipolar disorder (BD) have been combined with MRI data. was studied.

Literature Review (Contd.):

- To identify depression, the author of [6] used his DL approach to extract representations of depression cues in audio and video. To sort and integrate their work, this study introduced a database and specified objective markers for automatic estimation of depression (ADE).
- Additionally, they investigated deep learning (DL) approaches (DCNN, RNN, and LTMS) for automated depression detection in audio and video. Finally, they identified problems and possible means of automated depression detection using the DL method.
- The authors of [21] use a convolutional multiple kernel learning algorithm to detect emotions in movies and analyze moods. Dalili et al. We performed a large-scale meta-analysis of the relationship between existing facial emotion recognition and depression [22]
- . The author of [23] uses a temporal her LSTM-based approach to obtain contextual information from movies in a sentiment analysis task. The authors of [24] use social media platforms to diagnose depression using social media data. Categorize Twitter API data into depression and no depression categories.

DESIGN APPROACH AND DETAILS:

Psychological Grounds:

This study relied on the general tools described in the next section: Depression Anxiety Stress Scale (DASS). The DASS is a scale used by psychiatrists to rate the intensity of three emotional states: depression, anxiety, and stress. The intensity of the emotional state is determined by the scores as follows: Normal (0-9 depression score), Mild (depression score of 10- 13), moderate (depression score of 14-20), severe (depression score of 21-27), and very severe (depression score of 28+).

Data Collection:

VoxCeleb is an extensive speaker identification dataset sourced from open-source media. VoxCeleb consists of over 1 million of his utterances from over 6,000 speakers. Since the dataset was collected ”in the wild”, the speech segments were corrupted by real-world sounds such as laughter, crosstalk, channel effects, music, and other noises. The collection is also multilingual, containing voices for 145 different nationalities, accents, ages, ethnicities, and languages. Since the dataset is audio-visual, it has a wide variety of additional applications such as visual speech synthesis, speech separation, face-to-face or speech-to-speech cross-modal transmission and training facial recognition from video to complement current facial recognition. can be used for data set.

DESIGN APPROACH AND DETAILS (Contd.):

Proposed Architecture:

We present a unique non-intrusive multilayer neural network-based architecture for predicting DASS levels using facial expressions and auditory sentiment analysis. A unique non-invasive architecture on three layers designed to offer high accuracy and fast convergence.

The First Layer:

- **Importing Libraries:** Required libraries are imported at first.

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from matplotlib.colors import Normalize
from deepface import DeepFace
from mtcnn.mtcnn import MTCNN
from keras.layers import Flatten, Dense
from keras.models import Model
#from keras.preprocessing.image import ImageDataGenerator , img_to_array, load_img
from keras.applications.mobilenet import MobileNet, preprocess_input
from keras.losses import categorical_crossentropy
from transformers import AutoTokenizer, AutoModelWithLMHead
```

DESIGN APPROACH AND DETAILS (Contd.):

- **Train – test split:** Voxceleb1 dataset contains 1251 speaker's frame-by-frame images. Here we consider first 350 speaker's data (contains almost 40000 images) to create the model and train the model, rest for testing the model. This process is done manually because of huge amount of data.
- First, we read all those images by OS and Open-Cv module in python. And store them in an array.

```
path=r'E:\VIT\SET Project Work\unzippedIntervalFaces\data'
images=os.listdir(path)
```

```
img_data=[]


for root, dirs, files in os.walk(path):
    g=0
    for g,f in enumerate(files):
        i=os.path.join(root, f)
        g=g+1
        if g==2:
            img_arr=cv2.imread(i)
            img_data.append(img_arr)
            g=0
```

```
img_copy=img_data
```

```
len(img_data)
```

```
41833
```

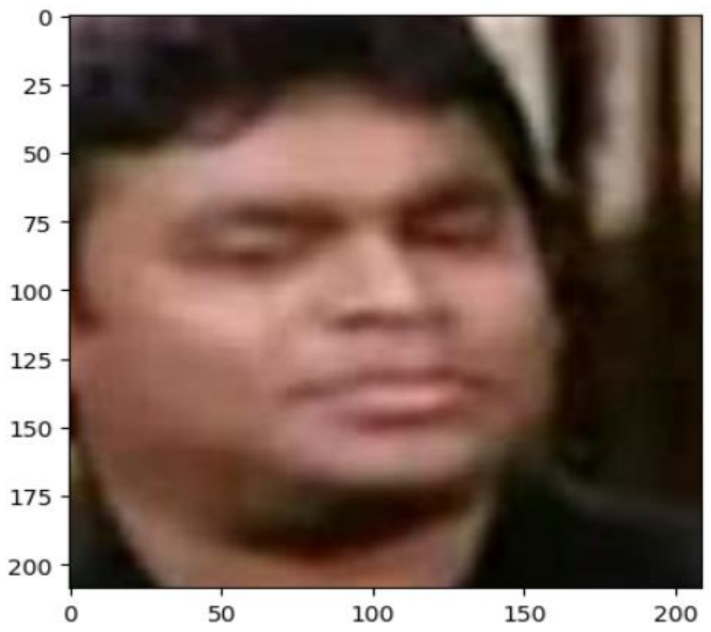
DESIGN APPROACH AND DETAILS (Contd.):

The array:

```
array([[[123, 117, 134],
        [122, 116, 133],
        [120, 114, 131],
        ...,
        [114, 134, 159],
        [116, 136, 161],
        [117, 134, 160]],

       [[119, 113, 130],
        [118, 112, 129],
        [115, 109, 126],
        ...,
        [115, 135, 160],
        [117, 137, 162],
        [118, 135, 161]],

       [[113, 107, 124],
        [111, 105, 122],
        [108, 102, 119],
        ...,
        [117, 137, 162],
        [119, 139, 164],
        [120, 137, 163]],

       ...,
```

The image:

<matplotlib.image.AxesImage at 0x1e292950ee0>



DESIGN APPROACH AND DETAILS (Contd.):

- **Pre-processing:** Then, we have done face detection process by using MTCNN to check bad quality photos and the photos where the face is not clearly visible. In this process we consider the accuracy of the model greater than equal to 70%. If the accuracy is less than 70%, we remove those.

```
detector = MTCNN()
o=[]
for p,h in enumerate (img_data):
    results = detector.detect_faces(h)
    if (results[0]['confidence']>=70):
        continue
    else:
        o.append(p)
```

```
1/1 [==============================] - 1s 694ms/step
1/1 [==============================] - 0s 112ms/step
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 43ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 131ms/step
1/1 [==============================] - 0s 148ms/step
1/1 [==============================] - 0s 85ms/step
```

```
for ele in sorted(o, reverse = True):
    del img_copy[ele]
```

```
len(img_copy)
```

```
41785
```

DESIGN APPROACH AND DETAILS (Contd.):

- After that, we detect the emotions from the facial expression as they are 'angry', 'sad', 'surprise', 'happy', 'fear' or 'neutral' etc. by **DeepFace** module. And store the emotions in an array.

```python
arr=[]
u=[]
for k,i in enumerate(img_copy):
    try:
        obj = DeepFace.analyze(i, actions = ['emotion'])
        emotion=max(obj['emotion'], key=obj['emotion'].get)
        arr.append(emotion)
    except Exception as e:
        u.append(k)
```

```
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 12ms/step
1/1 [==============================] - 0s 27ms/step
1/1 [==============================] - 0s 32ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 38ms/step
```

DESIGN APPROACH AND DETAILS (Contd.):

The array containing the emotions of corresponding images:

```
arr
```

```
['sad',
 'fear',
 'fear',
 'angry',
 'sad',
 'sad',
 'neutral',
 'neutral',
 'angry',
 'sad',
 'angry',
 'sad',
 'angry',
```

- And also store the images from which the emotion detection was not possible in an different array. Then delete those images from the main array.

```
for ele in sorted(u, reverse = True):
    del img_copy[ele]
```

```
len(img_copy)
```

```
37628
```

DESIGN APPROACH AND DETAILS (Contd.):

- Then we separate those images based on the predicted emotions i.e, if the image is classified as "angry", then it will go to the "Angry" folder of the system.. So on.

```
g=0
for g,i in enumerate (img_copy):
        obj = DeepFace.analyze(i, actions = ['emotion'])
        emotion=max(obj['emotion'], key=obj['emotion'].get)
        bb=g;
        g=g+1
        if g==2:
            if emotion=='happy':
                c = cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
                cv2.imwrite(r'E:\VIT\SET Project Work\Training Data\Happy\hap{}.png'.format(bb), c)
            elif emotion=='sad':
                c = cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
                cv2.imwrite(r'E:\VIT\SET Project Work\Training Data\Sad\sad{}.png'.format(bb), c)
            elif emotion=='fear':
                c = cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
                cv2.imwrite(r'E:\VIT\SET Project Work\Training Data\Fear\fear{}.png'.format(bb), c)
            elif emotion=='angry':
                c = cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
                cv2.imwrite(r'E:\VIT\SET Project Work\Training Data\Angry\ang{}.png'.format(bb), c)
            elif emotion=='neutral':
                c = cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
                cv2.imwrite(r'E:\VIT\SET Project Work\Training Data\Neutral\neu{}.png'.format(bb), c)
            elif emotion=='surprise':
                c = cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
                cv2.imwrite(r'E:\VIT\SET Project Work\Training Data\Surprise\ang{}.png'.format(bb), c)
            elif emotion=='disgust':
                c = cv2.cvtColor(i, cv2.COLOR_BGR2RGB)
                cv2.imwrite(r'E:\VIT\SET Project Work\Training Data\Disgust\dis{}.png'.format(bb), c)
            g=0
```

DESIGN APPROACH AND DETAILS (Contd.):

- **Build a model:** Here **MobileNet** was used to build a model for image classification. MobileNet is chosen after doing several research work that concludes that for emotion prediction of human MobileNet gives the higher accuracy rate.

```
# Working with pre trained model

base_model = MobileNet( input_shape=(224,224,3), include_top= False )

for layer in base_model.layers:
  layer.trainable = False


x = Flatten()(base_model.output)
x = Dense(units=7 , activation='softmax' )(x)

# creating our model.
model = Model(base_model.input, x)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet/mobilenet_1_0_224_tf_no_top.h5
17225924/17225924 [==============================] - 34s 2us/step
```

DESIGN APPROACH AND DETAILS (Contd.):

- Using Data Generator to prepare our dataset:

```
train_datagen = ImageDataGenerator(
     zoom_range = 0.2,
     shear_range = 0.2,
     horizontal_flip=True,
     rescale = 1./255
)

train_data = train_datagen.flow_from_directory(directory= r"E:\VIT\SET Project Work\Training Data",
                                               target_size=(224,224),
                                               batch_size=32,
                                  )


train_data.class_indices
```

```
val_datagen = ImageDataGenerator(rescale = 1./255 )

val_data = val_datagen.flow_from_directory(directory= r"E:\VIT\SET Project Work\Training Data",
                                           target_size=(224,224),
                                           batch_size=32,
                                  )
```

- Output:

```
Found 37628 images belonging to 7 classes.

{'angry': 0,
 'disgust': 1,
 'fear': 2,
 'happy': 3,
 'neutral': 4,
 'sad': 5,
 'surprise': 6}
```

DESIGN APPROACH AND DETAILS (Contd.):

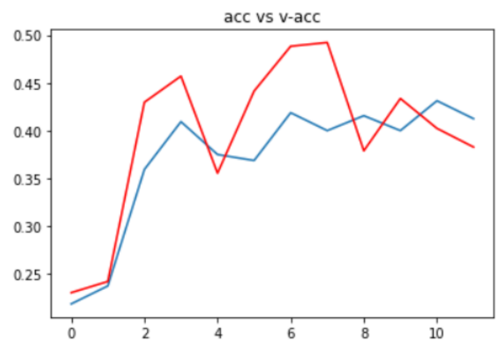
- Using fit_generator:

```
hist = model.fit_generator(train_data,
                           steps_per_epoch= 10,
                           epochs= 30,
                           validation_data= val_data,
                           validation_steps= 8,
                           callbacks=[es,mc])
```

our **.fit_generator()** function first accepts a batch of the dataset, then performs backpropagation on it, and then updates the weights in our model.

- Accuracy check:

```
plt.plot(h['accuracy'])
plt.plot(h['val_accuracy'] , c = "red")
plt.title("acc vs v-acc")
plt.show()
```



DESIGN APPROACH AND DETAILS (Contd.):

❖ The Second Layer (proposed):

- ➢ After importing all audio dataset we used T5 module to extract the emotion from that audio dataset.

```
from transformers import AutoTokenizer, AutoModelWithLMHead

tokenizer = AutoTokenizer.from_pretrained("mrm8488/t5-base-finetuned-emotion")

model = AutoModelWithLMHead.from_pretrained("mrm8488/t5-base-finetuned-emotion")

def get_emotion(text):
  input_ids = tokenizer.encode(text + '</s>', return_tensors='pt')

  output = model.generate(input_ids=input_ids,
               max_length=2)

  dec = [tokenizer.decode(ids) for ids in output]
  label = dec[0]
  return label
```

- ➢ Output: `get_emotion("i have a feeling i kinda lost my best friend") # Output: 'sadness'`

DESIGN APPROACH AND DETAILS (Contd.):

- Exploring the limits of transfer learning with an integrated text-to-text transformer, the T5 model was proposed. Transfer learning, which pre-trains models for data-rich jobs before turning them for downstream tasks, has emerged as a powerful approach in natural language processing. The effectiveness of transfer learning has spawned a variety of techniques, methods and practices.

The Third Layer (Proposed):

- In this layer we will use FFNN to classify that the person is depressed or not.
- The two input of FFNN will be coming from 1st layer and 2nd layer respectively. The 1st layer will give the emotion from their facial expression and from the 2nd layer will give emotion from their voice.
- Then he output of FFNN will be compared with the Anxiety Stress Scale (DASS). And prediction will be done, if the person is depressed or not.
- We use backpropagation of regressor loss to train the learned weights at each layer of the network to ensure end-to-end training.

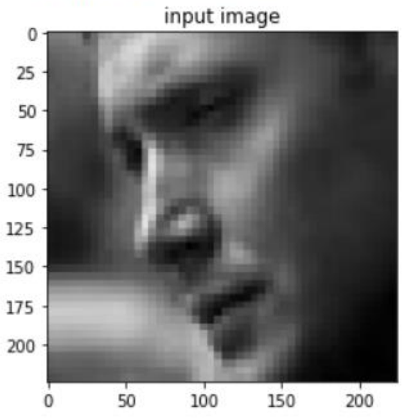
RESULTS AND DISCUSSION:

- The obtained accuracy was pretty good or average from the 1st layer. The calculated prediction time was averaged around 64 s.

```
path = "/content/test/angry/PrivateTest_1054527.jpg"
img = load_img(path, target_size=(224,224) )

i = img_to_array(img)/255
input_arr = np.array([i])
input_arr.shape

pred = np.argmax(model.predict(input_arr))

print(f" the image is of {op[pred]}")
```

- Output:

```
the image is of neutral
```



- We are still working to get high accuracy from the 2^{nd} layer and 3^{rd} layer.

FUTURE SCOPE AND CONCLUSION:

- Since this architecture is designed to evaluate only frontal face video recordings, various strategies (e.g., head pose changes using facial markings) can be used to improve the proposed architecture. or partial occlusion of the face) can be considered.
- Electronic Health data (like, MRI report, Diabetes report, CT scan report) could be attached to the model to enhance the quality of prediction.
- At the end we can conclude that our model can be used in real-time allowing health practitioners to evaluate the evolution of DASS levels over time. Further evaluation of the model is possible with better model that will generate the result with good accuracy.

References:

- [1] Vitriol, V., Cancino, A., Weil, K., Salgado, C., Asenjo, M. A., & Potthoff, S. (2014). Depression and psychological trauma: an overview integrating current research and specific evidence of studies in the treatment of depression in public mental health services in Chile. Depression research and treatment, 2014.
- [2] World Health Organization. (2020). World Mental Health Day: an opportunity to kick-start a massive scale-up in investment in mental health. News release.
- [3] James, S. L., Abate, D., Abate, K. H., Abay, S. M., Abbafati, C., Abbasi, N., ... & Briggs, A. M. (2018). Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. The Lancet, 392(10159), 1789-1858.
- [4] Aleem, S., Huda, N. U., Amin, R., Khalid, S., Alshamrani, S. S., & Alshehri, A. (2022). Machine Learning Algorithms for Depression: Diagnosis, Insights, and Research Directions. Electronics, 11(7), 1111.
- [5] World Health Organization. (2017). Depression and other common mental disorders: global health estimates (No. WHO/MSD/MER/2017.2). World Health Organization.
- [6] Tharwat, A., Gaber, T., Ibrahim, A., & Hassanien, A. E. (2017). Linear discriminant analysis: A detailed tutorial. AI communications, 30(2), 169-190.
- [7] Patel, M. J., Khalaf, A., & Aizenstein, H. J. (2016). Studying depression using imaging and machine learning methods. NeuroImage: Clinical, 10, 115-123.
- [8] Garcia-Ceja, E., Riegler, M., Nordgreen, T., Jakobsen, P., Oedegaard, K. J., & Tørresen, J. (2018). Mental health monitoring with multimodal sensing and machine learning: A survey. Pervasive and Mobile Computing, 51, 1-26.

References (Contd):

- [9] Cho, G.; Yim, J.; Choi, Y.; Ko, J.; Lee, S.-H. Review of Machine Learning Algorithms for Diagnosing Mental Illness. Psychiatry Investig. 2019, 16, 262–269.
- [10] Liu, G. D., Li, Y. C., Zhang, W., & Zhang, L. (2020). A brief review of artificial intelligence applications and algorithms for psychiatric disorders. Engineering, 6(4), 462-467.
- [11] He, L., Niu, M., Tiwari, P., Marttinen, P., Su, R., Jiang, J., ... & Dang, W. (2022). Deep learning for depression recognition with audiovisual cues: A review. Information Fusion, 80, 56-86.
- [12] Gavrilescu, M., & Vizireanu, N. (2019). Predicting depression, anxiety, and stress levels from videos using the facial action coding system. Sensors, 19(17), 3693.
- [13] Aleem, S., Huda, N. U., Amin, R., Khalid, S., Alshamrani, S. S., & Alshehri, A. (2022). Machine Learning Algorithms for Depression: Diagnosis, Insights, and Research Directions. Electronics, 11(7), 1111.
- [14] Learning, S. M. (2007). A review of classification techniques, sb kotsiantis. Informatica, 31, 249-268.
- [15] Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussain, A., & Aljaaf, A. J. (2020). A systematic review on supervised and unsupervised machine learning algorithms for data science. Supervised and unsupervised learning for data science, 3-21.
- [16] Van Engelen, J. E., & Hoos, H. H. (2020). A survey on semi-supervised learning. Machine Learning, 109(2), 373-440.
- [17] Sutton, R. S.,& Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.
- [18] Dwyer, D. B., Falkai, P., & Koutsouleris, N. (2018). Machine learning approaches for clinical psychology and psychiatry. Annual review of clinical psychology, 14, 91-118

References (Contd):

- [19] Sidey-Gibbons, J. A., & Sidey-Gibbons, C. J. (2019). Machine learning in medicine: a practical introduction. BMC medical research methodology, 19(1), 1-18.
- [20] Thieme, A., Belgrave, D., & Doherty, G. (2020). Machine learning in mental health: A systematic review of the HCI literature to support the development of effective and implementable ML systems. ACM Transactions on Computer-Human Interaction (TOCHI), 27(5), 1-53.
- [21] Poria, S., Chaturvedi, I., Cambria, E., & Hussain, A. (2016, December). Convolutional MKL based multimodal emotion recognition and sentiment analysis. In 2016 IEEE 16th international conference on data mining (ICDM) (pp. 439-448). IEEE.
- [22] Dalili, M. N., Penton-Voak, I. S., Harmer, C. J., & Munafo, M. R. (2015). ` Meta-analysis of emotion recognition deficits in major depressive disorder. Psychological medicine, 45(6), 1135-1144.
- [23] Poria, S., Cambria, E., Hazarika, D., Majumder, N., Zadeh, A., & Morency, L. P. (2017, July). Context-dependent sentiment analysis in user-generated videos. In Proceedings of the 55th annual meeting of the association for computational linguistics (volume 1: Long papers) (pp. 873-883).
- [24] Shen, G., Jia, J., Nie, L., Feng, F., Zhang, C., Hu, T., ... & Zhu, W. (2017, August). Depression detection via harvesting social media: A multimodal dictionary learning solution. In IJCAI (pp. 3838-3844).