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Recognizing the Stages of Depression and Optimizing through Guided Imagery

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***Abstract*—Difficult to diagnose in a timely fashion, but early detection, prevention, and intervention are critical public health interventions in the emerging epidemic of depression. To overcome these challenges, we develop EmoCare, a novel system based on guidance imagery interventions, to first detect depression stages and accordingly offer personal assistance in this study. This project is based on the awareness of the high prevalence of mental health issues and the demand for effective and accessible interventions. We explore the use of computer vision techniques in emotion detection, machine learning algorithms in depression measurement, and guided imagery techniques in the delivery of the intervention. This is an extensive system in terms of methodologies: we used facial expressions, structured questionnaires, and data analytics. With the potential to provide personalized interventions, EmoCare may lead the way for new approaches to addressing emotional health in a timely manner, thereby opening up avenues of emotional support to millions of people to get ahead of depression.**

***Index Terms*—Depression detection, Emotion Recognition, Guided Imagery, BDI test, CV, Machine learning, pre-evaluation, intervention, Emotional wellness.**

I. INTRODUCTION

Depression is one of the top global burdens, and it affects millions of people globally. Unfortunately, stigma and access barriers to traditional care undermine effective management. This is where EmoCare comes in, using technology to fill this gap. EmoCare aims to provide scalable personalized support for assessment and intervention of depression through the integration of computer vision, machine learning, and guided imagery. Conventional approaches depend on qualitative evaluations and in-person actions which might not be available to everyone.

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How is EmoCare unique? EmoCare is unique in the fact that it is able to provide accessible tools with technology. EmoCare utilises computer vision algorithms to monitor facial expressions and body language and identifies potential depressive symptoms so that early intervention can occur.

In addition, EmoCare employs machine learning to customize interventions based on individual likes and reactions. This helps improve engagement and effectiveness over time. Another essential aspect of EmoCare is guided imagery interventions, which involve visualization tools to foster emotional well-being. By means of custom audio-visual experiences, users are led through relaxation exercises and positive affirmations, assisting in decreased stress and enhanced position.

II. Literature Review

Instead, a cross-modal attention network which was additive across text and audio [1] was built upon BiLSTM for the purpose of training and selecting the best weights that accurately represent the correlations and cross-modal interactions of the proposed modalities. They further evaluated their method on the DAIC-WOZ dataset for depression diagnosis and on the EATD-Corpus to assess model performance. Their results show that this methodology can detect sadness in patients without the need for pre-programmed questions, using both textual and speech modalities. Adil o. K o. Khadidos et al [2] did a framework to identify depression accurately and portability in the few routes used. They considered the Public + Private datasets. Different brains and features are chosen which reduces to find fewer channels and features and thus increase accuracy. According to the study, depression uniquely impacts the temporal and parietal hemispheres asymmetrically. Depression also has effect on Detrended Fluctuation Analysis. The study results in a four-channel high-accuracy (91.74%) model that is cheaper, quicker, and in delicate to the state of the art methods. Hence, this model can help with diagnosing depression.

Since only the temporal channel EEG data has been employed and the same features and classifiers were likewise used on both the public and private datasets, it could be concluded that sadness affects the the brain's temporal area, which can be observed from the relatively high accuracy of MDD classification achieved from this channel. Applying only temporal channel (T8 and T9) features' delta, alpha, beta paired asymmetry and DFA gave us the good accuracy of 89.24% (Public Dataset) and 82.68% (Private Dataset) and supports the brain temporal lobe affected by depression. The four-channel, high-accuracy (91.74%) model created by the study is also low-cost, fast, and portable.

Hence, this model can complement other tools to screen for depression. This is demonstrated in a study comparing the accuracy of the Public and Private data sets when using only temporal channel EEG data and both data sets have the same feature and classifier set. The fact that temporal region features induce high accuracy of 89.24% and 82.68% when combined with features delta, alpha, beta paired asymmetry, and DFA—meaning only two out of five temporal channels (T8 and T9)—supports the fact that depression is a temporal region disease.

In 2022, Shangguan et al. [3] presented a novel multiple instance learning framework for depression recognition from dynamic facial expression videos. Their work is the first instance of weakly supervised learning on raw video data, considering the dynamic aspect of emotions in faces and focusing on critical states.The method surpasses state-of-theart MIL methods while matching the performance of the previous state-of-the-art methods. By analyzing attention weights between video frames, we found significant differences in how healthy individuals and depressed patients responded to negative video stimuli.

In 2024, Yuchen Pan et al. [6] proposed a new approach to identify depression through a sequence of facial video frames using the STA mechanism - STA-DRN. They first did this by introducing a spatial and temporal attention module to facilitate the capture of both global and local information and then learn adaptive weights in the process of feature extraction. Second, they proposed applying the STA module as the spatial and temporal feature representations are integrated through an integration method.

This is a second-hand step to utilize these approaches by pixel-by-pixel STA mechanisms for the detection of depression through 3D video analysis. Moreover, they suggested an attention vector-wise integration method to combine the temporal and spatial data in the STA module. Then the STA modules were stacked in a ResNet fashion to form the STA-DRN. A study of illustrations indicates that the STA-DRN is very active in particular regions associated with depression. Depression can be treated and the same holds true for the majority of disorders, but one of the keys to treatment is early detection [8, 8, 8]. This study searched for early warning signs of suicidal thoughts and behaviours, and ways to identify and screen individuals who may be on a mental illness trajectory, Ribeiro adds. This study introduces novel reliable classifier which can adjust any potential bias that may arise during the data acquisition process to enable objective model construction.

III. PROPOSED METHODOLOGY

The glaucoma project worked on real-time depression detection system using computer vision techniques. It started off by detecting faces using Haar cascade classifiers. Complex emotion and depression detection models were then implemented using CNNs that were trained on heterogeneous datasets. These models evaluated emotional upsurge to assess the severity of depression through structured interviews and questionnaires. All ethical considerations such as informed consent and data privacy were prioritized.

A. Data Collection

- Google Survey for Depression Assessment: The participants filled out a Google survey, based on the Beck Depression Inventory (BDI), assessing their depression symptoms. Responses are assessed to ascertain levels and stages of depression.
- Emotion Detection: Data collection can be performed using expected FER 2013 dataset from Kaggle, which is a collection of labeled images of faces. These images correspond to seven emotions: anger, disgust, fear, happiness, neutrality, sadness, and surprise. Before training any model, we need to preprocess the images to ensure quality and standardization.

B. Feature Extraction

- Google-survey data preprocessing: Data collected through google surveys on the Beck Depression Inventory (BDI) are processed to compute depression scores and determine the level of depression.
- Survey Responses Feature Selection: Clinical relevant depressive symptoms features are collected including features with high discriminative potential.
- Model Development for Emotion Detection: In order to develop a CNN-based model for emotion recognition, the data is partitioned into the training, validation and test subset. Privacy and consent are addressed according to ethical inquiries. In order to assist in the robust development of the model, the FER 2013 dataset provides a wide variety of labeled data.

C. Depression Assessment

- CNN Based Classification: An individual needs to connect Google surveys along with emotion detection methods to extract features and use a three-layer Convolutional Neural Network (CNN) as a classifier on the extracted features to classify him or her in different stages of depressions.
- Emotion detection for depression recognition: When identifying emotions due to BDI response facial expressions and vocal cues are analyzed. These are associated with major depressive disorder scores for initial evaluations. Facial expression analysis uses Haar cascade classifiers to detect faces and extracts features such as facial landmarks and expressions. These include pitch, intensity, tempo, and spectral features obtained from the audio recordings. Combining this approach with EmoCare's depression assessment enables a more comprehensive evaluation that can lead to prompt interventions and support.

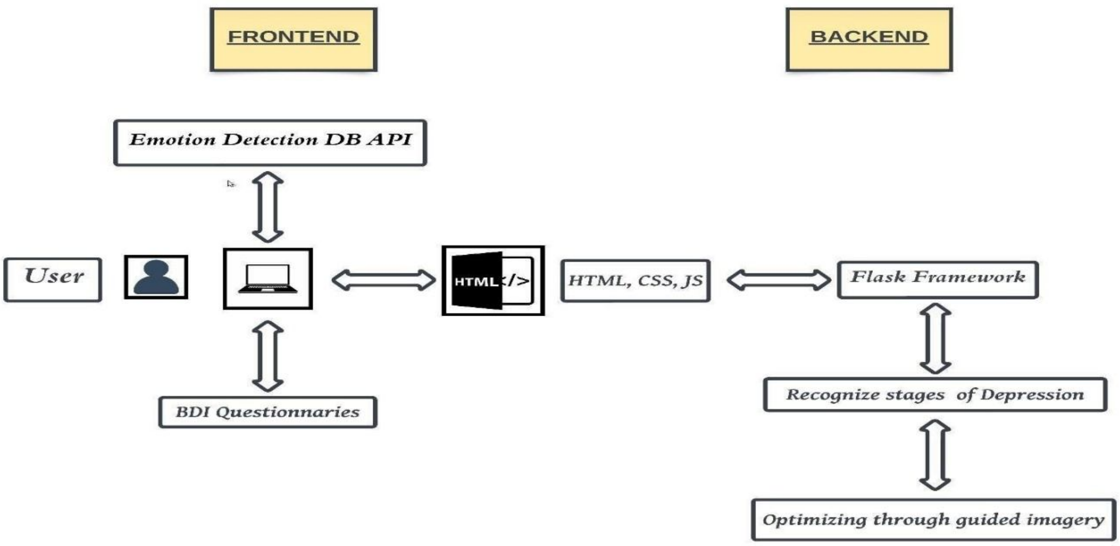

Fig 1: Proposed workflow

Bock's Depression Inventory

1
0 I do not feel sad.
1 I feel sad.
2 I am sad all the time and I can't snap out of it.
3 I am so sad and unhappy that I can't stand it.

2
0 I am not particularly discouraged about the future.
1 I feel discouraged about the future.
2 I feel I have nothing to look forward to.
3 I feel the future is hopeless and that things cannot improve.

3
0 I do not feel like a failure.
1 I feel I have failed more than the average person.
2 As I look back on my life, all I can see is a lot of failures.
3 I feel I am a complete failure as a person.

4
0 I get as much satisfaction out of things as I used to.
1 I don't enjoy things the way I used to.
2 I don't get real satisfaction out of anything anymore.
3 I am dissatisfied or bored with everything.

5
0 I don't feel particularly guilty.
1 I feel guilty a good part of the time.
2 I feel quite guilty most of the time.
3 I feel guilty all of the time.

6
0 I don't feel I am being punished.
1 I feel I may be punished.
2 I expect to be punished.
3 I feel I am being punished.

7
0 I don't feel disappointed in myself.
1 I am disappointed in myself.
2 I am disgusted with myself.
3 I hate myself

. 8
0 I don't feel I am any worse than anybody else.
1 I am critical of myself for my weaknesses or mistakes.
2 I blame myself all the time for my faults.
3 I blame myself for everything bad that happens.

9
0 I don't have any thoughts of killing myself.
1 I have thoughts of killing myself, but I would not carry them out.
2 I would like to kill myself.
3 I would kill myself if I had the chance.

10
0 I don't cry any more than usual.
1 I cry more now than I used to.
2 I cry all the time now.
3 I used to be able to cry, but now I can't cry even though I want to.

11
0 I am no more irritated by things than I ever was.
1 I am slightly more irritated now than usual.
2 I am quite annoyed or irritated a good deal of the time.
3 I feel irritated all the time.

12
0 I have not lost interest in other people.
1 I am less interested in other people than I used to be.
2 I have lost most of my interest in other people.
3 I have lost all of my interest in other people.

13
0 I make decisions about as well as I ever could.
1 I put off making decisions more than I used to.
2 I have greater difficulty in making decisions more than I used to.
3 I can't make decisions at all anymore.

14
0 I don't feel that I look any worse than I used to.
1 I am worried that I am looking old or unattractive.
2 I feel there are permanent changes in my appearance that make me look unattractive.
3 I believe that I look ugly.

15
0 I can work about as well as before.
1 It takes an extra effort to get started at doing something.
2 I have to push myself very hard to do anything.
3 I can't do any work at all.

16
0 I can sleep as well as usual.
1 I don't sleep as well as I used to.
2 I wake up 1-2 hours earlier than usual and find it hard to get back to sleep.
3 I wake up several hours earlier than I used to and cannot get back to sleep.

17
0 I don't get more tired than usual.
1 I get tired more easily than I used to.
2 I get tired from doing almost anything.
3 I am too tired to do anything.

18
0 My appetite is no worse than usual.
1 My appetite is not as good as it used to be.
2 My appetite is much worse now.
3 I have no appetite at all anymore.

19
0 I haven't lost much weight, if any, lately.
1 I have lost more than five pounds.
2 I have lost more than ten pounds.
3 I have lost more than fifteen pounds.

20
0 I am worried about physical problems like aches, pains, upset stomach, or constipation.
1 I am very worried about physical problems and it's hard to think of much else.
2 I am so worried about my physical problems
3 I have not noticed any recent change in my interest in sex.

21
0 I am less interested in sex than I used to be.
1 I have almost no interest in sex.
2 I have lost interest in sex completely.
3 I am worried about physical problems like aches, pains, upset stomach, or constipation.

Fig 2: BDI Questionnaires

- Content Creation: Customized guided imagery scripts and audiovisual aids facilitate relaxation, positive visualization, and emotional regulation. These relate to particular symptoms identified in a depression assessment
- Delivery Mechanism: EmoCare delivers its base of interventions via interactive multimedia presentations on its platform, and the same interventions are made available in bibliotherapy format (personalized and on-demand) through the website or mobile app.
- User Engagement: Users are encouraged to engage actively, with cues and prompts during sessions. Interactive elements such as progress tracking and feedback mechanisms increase engagement and motivation.
- Outcome Monitoring: Ongoing tracking of user feedback, mood ratings, and symptom fluctuations provides an indication of progress over time. This allows for refinement and adaptation of the strategies for interventions.

E. Evaluation

- Quantitative Performance Metrics: For assessing accuracy of depression recognition and intervention effectiveness
- User Feedback: Focus groups with users provide qualitative data informing user-system interaction and intervention utility (Feasibility).
- Longitudinal Studies: This involves assessing the long-term effects of the intervention on depressive symptoms and overall well-being. EmoCare is also tested to show how well it can treat depression and offer millions of interventions successfully in the field of mental well being.

IV. RESULT & DISCUSSION

The project creates a mental health care system using a depression-focus. That provides users with depression scores along with personalized recommendations, allowing them to take control over their mental health. Through the user-centered design and scalability, the system seeks to lower barriers to mental health care and promote proactive self-care in a movement to destigmatize mental health itself.

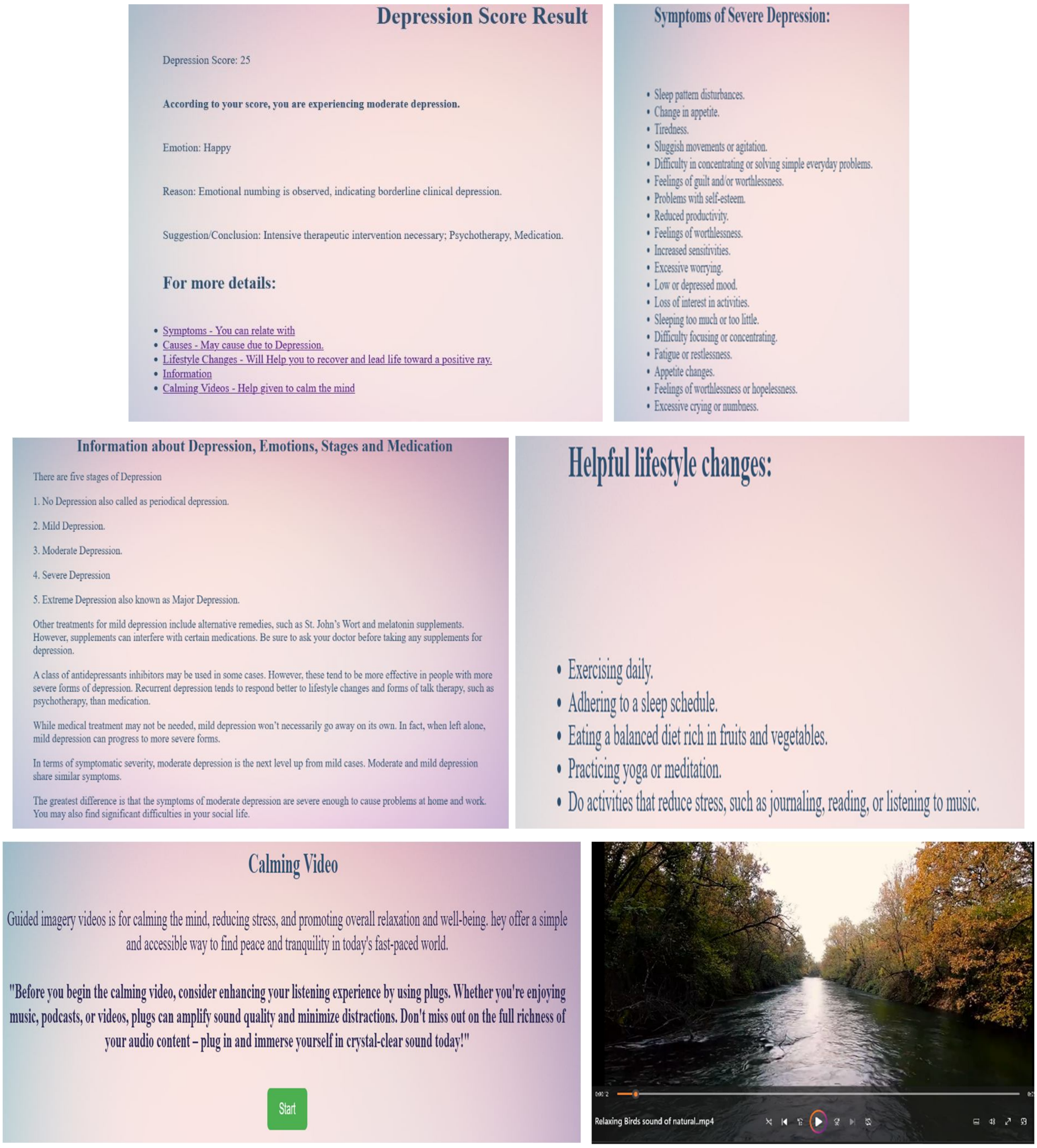

Fig3: Result

V. DISCUSSION

This is a major step forward in creating a personalized mental health support system for those suffering from depression. Users will provide assessments, and they will need a personalized approach to this. User centered design and accessible technology design promote engagement and scalability, yet work needs to be done to mitigate differential access. It is a novel approach to destigmatise mental health as well as a way to encourage self-care.

VI. Conclusion

They present an approach that aims to put to work existing screening instruments for the diagnosis and assessment of depression for improving accurate diagnosis and classification through machine learning techniques like the CNN model. This nuanced understanding of the levels of depression allows for fine-tuned strategies for intervention on the part of individual users the style, whether or not a user wants to receive a reminder such that lifestyle recommendations or some emotional insights are now tailored to users' needs.

The incorporation of therapeutic techniques, such as guided imagery, indicates that the project acknowledges complementary interventions to maintain emotional balance. Them being all bundled together indicates the commitment of this project to holistic mental health support.

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