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Detection of Depression and Anxiety through Speech, Voice, and Sentiment Analysis

S. M. M. Naidu[1,2], Y. A. Chavan[1,2], M. R. Pillai[1], V. M. Diwate[1,2], P. S. Oza[1,2], O. N. Wagh[1,2]
[1]International Institute of Information Technology (I^{2}IT), Pune, India
[2]POYV PVT LTD, Pune, India
[1]mohans@isquareit.edu.in, [2]povypvtltd@gmail.com

Abstract: This study investigates the potential of using speech, voice, and sentiment analysis for detecting depression and other mental health disorders among 3,995 employees in the IT sector. The study aims to explore the feasibility of using these technologies to detect mental health concerns earlier, to improve diagnosis and treatment outcomes. Participants in the study provided speech and text samples, which were analyzed using various machine-learning algorithms to identify patterns associated with depression and other mental health disorders. The results suggest that speech, voice, and sentiment analysis have the potential to be effective tools for the early detection of mental health concerns among employees in the IT sector.

However, ethical and privacy concerns must be addressed before widespread implementation of these technologies. The study highlights the importance of balancing the potential benefits of these technologies with the need to protect individual privacy and ensure the ethical use of sensitive health data. Overall, the study highlights the promise of speech, voice, and sentiment analysis in the field of mental health and the potential for these technologies to improve the lives of individuals in the IT sector and beyond.

Index Terms—
Depression detection models, early intervention, personalized treatment, mental health, technology, data analysis, and patient outcomes.

I. Introduction

Depression and mental health issues are becoming increasingly prevalent in our society, and the IT sector is no exception. A study conducted in 2019 by the World Health Organization (WHO) revealed that depression is the leading cause of disability worldwide, affecting approximately 264 million people globally. Furthermore, in the IT sector, long working hours, tight deadlines, high-pressure environments, and job insecurity are some of the factors that contribute to increased stress levels among employees. This, in turn, can lead to mental health issues, such as depression, anxiety, and burnout.

While there are several existing methods for diagnosing
and treating depression and other mental health issues, there is still a need for

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more effective and accessible approaches. Speech, voice, and sentiment analysis have emerged as promising tools in the field of mental health detection. Speech analysis involves analyzing an individual's spoken words, while voice analysis involves analyzing the tone, pitch, and other characteristics of an individual's voice. Sentiment analysis involves analyzing an individual's written or spoken words to determine the emotional state or attitude.

Recent research has shown that these techniques canbe used to detect depression and other mental health issues with a high degree of accuracy. In particular, speech analysis has shown promising results in detecting depression, as individuals with depression often exhibit specific speech patterns, such as slower speech rate, longer pauses, and fewer pitch variations. Similarly, voice analysis can detect depression by analyzing changes in tone and pitch, which can indicate emotional distress. Sentiment analysis can also be used to detect depression by analyzing the emotional content of an individual's written or spokenwords.

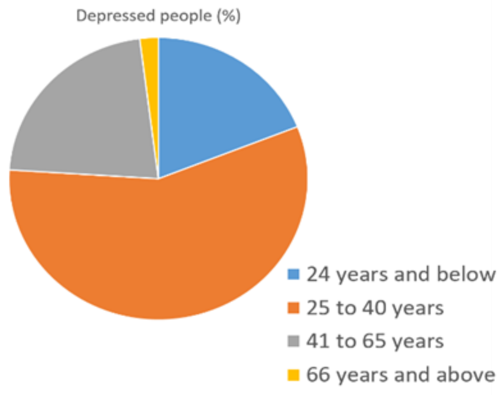

Fig. 1. Pie-chart showing the percentage of depressed people per age group

out of 3995 people surveyed, the prevalence of depression varied significantly across different age groups.

The lowest prevalence was found "n" individuals aged 66 years and above, with only 2% of the respondents reporting symptoms of depression.

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In contrast, the highest prevalence was found in individuals aged 25 to 40 years, with 57% of the respondents reporting symptoms of depression.
The data also showed that individuals aged 24 years and below had a relatively lower prevalence of depression, with only 19% of the respondents reporting symptoms. Similarly, individuals aged 41 to 65 years had a lower prevalence of depression, with only 22% of the respondents reporting symptoms.
These findings suggest that depression is more prevalent among younger adults, particularly those in their 20s and 30s. This may be due to various factors such as increased stress related to work, relationships, and financial responsibilities, among others. On the other hand, depression appears to be less prevalent among older adults, which may be attributed to a greater sense of life satisfaction and fulfillment, as well as social support from family and friends.
In this study, we aim to explore the use of speech, voice, and sentiment analysis for detecting depression and other mental health issues in employees in the IT sector. We will collect speech samples, voice recordings, and written responses from a sample of 3995 IT employees and use machine learning algorithms to analyze the data. The study aims to identify specific speech patterns, voice characteristics, and emotional content that are associated with depression and other mental health issues. The ultimate goal of the study is to develop a reliable and accessible tool for detecting depression and other mental health issues in the IT sector, which can aid in early diagnosis and treatment.

II. Literature Survey

India is facing a major mental health crisis, with millions of people suffering from various mental health disorders. According to the World Health Organization (WHO), depression is one of the leading causes of disability worldwide, and India has the highest number of people suffering from depression in the world. The National Mental Health Survey of India conducted by the Indian government in 2016 revealed that about 56 million Indians suffer from depression, and 38 million suffer from some kind of anxiety disorder[7].
The impact of mental health disorders on individuals and their families is profound. These disorders not only affect a person’s emotional and psychological well-being but also have an impact on their physical health, work performance, and social relationships. Mental health disorders can also lead to substance abuse, self-harm, and suicide. In fact, every year, about 2,00,000 Indians take their lives, making suicide the leading cause of death among people aged 15-39 years in the country[8].
The prevalence of mental health disorders in India is a cause for concern. The National Mental Health Survey of India conducted in 2016 revealed that one in every 20 Indians suffers from depression.

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This means that approximately 5% of India's population is affected by depression, a staggering number considering the country's population of over 1.3 billion people [9].

A study conducted by the Indian Council of Medical Research found that one in every three people in India suffers from some kind of mental disorder. This indicates that mental health disorders are a common occurrence in India and have a significant impact on the population's overall health and well-being[10].

The study conducted in Mumbai found that a significant proportion of its respondents had some form of depression, with 41 percent of respondents reporting depression symptoms, while 47 percent reported symptoms of anxiety. This highlights the high prevalence of mental health disorders in one of India's most populous cities[11]. The National Crime Records Bureau (NCRB) reported in 2018 that over 139,000 people died by suicide in India, with Maharashtra being one of the top states with the highest number of suicide cases. This data indicates the severity of mental health issues in India and the urgent need for effective interventions and support systems.

The survey conducted by the Indian Psychiatric Society revealed that 20 percent of Indian adults suffered from some form of mental illness, with depression and anxiety being the most common. This indicates that mental health issues affect a large section of the Indian population, with significant implications for their overall health and well-being [10].

The study conducted in Bangalore found that a significant proportion of its respondents had symptoms of depression, with 36 percent of respondents reporting depression symptoms, while 48 percent reported symptoms of anxiety. This indicates that the prevalence of mental health disorders is not restricted to specific geographic locations in India but is a widespread phenomenon across the country [11].

According to the World Health Organization, India has one of the highest suicide rates in the world, with suicide being the leading cause of death among people aged 15-29 years. This highlights the urgent need for effective mental health interventions and support systems to address the country's mental health crisis [9].

Overall, the high prevalence of mental health disorders in India and the alarming rates of suicide indicates the urgent need for effective interventions and support systems to address the country's mental health crisis

The situation is no different in Pune, a city in western India. According to a study conducted by the Indian Medical Association (IMA), about 85 percent of women and 70 percent of men in Pune have undergone mental health distress. Depression is the commonest cause of mental health distress in women, while anxiety and panic disorder are largely seen among men [13].

The high prevalence of mental health disorders in India and Pune highlights the urgent need for effective mental health care services and early detection of mental health disorders. However, due to the stigma associated with mental

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health disorders, many people do not seek help or receive proper diagnosis and treatment. This is where the use of technology such as speech, voice, and sentiment analysis can play a crucial role in the early detection and intervention of mental health disorders.

III. **Mental Health Detection** Depression is a debilitating mental health disorder that affects millions of people worldwide. While there are effective treatments available, depression often goes undiagnosed or misdiagnosed, leading to inadequate or delayed treatment. This can result in a significant negative impact on an individual's quality of life, as well as increased healthcare costs. One way to improve depression diagnosis and treatment is through the use of depression detection models. These models can use a variety of data sources, including speech, text, and physiological signals, to identify patterns and symptoms that may indicate depression. Speech-based depression detection models can analyze factors such as tone, pitch, and speech rate to detect changes that may indicate depression. Similarly, text-based models can analyze the language used in written communications to identify depressive symptoms. Physiological signals, such as heart rate variability and skin conductance, can also be analyzed to detect changes that may indicate depression.

By combining data from these various sources, depression detection models can provide a more accurate and comprehensive assessment of an individual's mental health status. This can be particularly beneficial in cases where individuals may not have reported or recognized their symptoms, or where traditional diagnostic methods may not have been effective. To develop an effective depression detection model, the model must first be trained using data from individuals with confirmed depression diagnoses. The model can then be tested on new data to evaluate its accuracy in predicting depression. To ensure the accuracy of the model, it is important to monitor the patient over a certain time period to gather enough data to make accurate predictions.

Overall, depression detection models have the potential to greatly improve the diagnosis and treatment of depression, ultimately leading to better health outcomes and improved quality of life for individuals affected by this condition. The following are the three steps involved in this process:

1) Recognize emotions using the facial emotion detection model.
2) Recognize the voice variations and use speech recognition to analyze emotions.

A. Convert the speech to text and identify if it's positive or negative using sentimental analysis.

B. Recognize emotions using the facial emotion detection model

The process described involves detecting emotions in real-time using a camera. The first step in the process is to preprocess the data by converting RGB images to grayscale images. This is done to simplify the data and reduce the computational requirements for the next step. The next step involves

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converting the grayscale images to HAAR using the haar cascade classifier. This technique uses a set of features to detect objects or patterns in the image. In this case, the haar cascade classifier is used to detect facial features such as eyes, nose, and mouth, which
are then used to determine emotions.

After the images have been converted to HAAR, the next step is to train a model using a convolutional neural network. This involves feeding the images into the neural network and training it to recognize patterns and features that correspond to specific emotions. This step is crucial in determining the accuracy of the model.

Finally, the OpenCV library is used to detect emotions in real time using a camera. The trained model is applied to the live feed from the camera, and the emotions are detected in real-time. The emotions that can be detected include happiness, sadness, anger, disgust, surprise, fear, and neutrality.

The steps involved in image dataset processing for emotion classification:

1) Image dataset: The first step is to collect a large and diverse dataset of images that contain faces with a wide range of emotions. This dataset should be labeled with the corresponding emotion category for each image.

2) Face detection: The next step is to use a face detection algorithm to detect and locate the faces in each image. There are various face detection algorithms available such as the Haar cascade classifier, Viola-Jones algorithm, etc. These algorithms work by analyzing the pixels in an image and identifying areas that are likely to contain faces.

3) Face resizing: Once the faces are detected, they need to be resized to a fixed size so that they can be processed efficiently. This involves cropping the face region from the original image and resizing it to a fixed size, typically 48x48 or 64x64 pixels.

4) Preprocessing: After resizing the faces, they need to be preprocessed to improve the quality of the images and remove any noise or artifacts that could interfere with the emotion classification. This step may involve techniques such as image normalization, histogram equalization, or data augmentation.

5) Feature extraction: The next step is to extract features from the preprocessed face images. Features are numerical representations of the image that capture important patterns or characteristics related to emotions. There are various feature extraction techniques available such as Local Binary Patterns

C. Recognize the voice variations and use speech recognition to analyze emotions

Recognizing voice variations and analyzing emotions through speech recognition is a process that involves using various techniques and tools to accurately detect and classify emotional states in speech. The first step involves collecting and preprocessing the speech data, which includes removing noise and normalizing the volume. Next, feature extraction techniques are applied to preprocessed data to extract relevant information, such as pitch, volume, and frequency. These features are then used to train a machine learning model, typically a convolutional neural

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network (CNN), which is trainedon a large dataset of labeled speech samples. Once the model is trained, it can be used to classify emotions in real-time speech data by detecting patterns in the extracted features. This approach has many potential applications in fields such as psychology, marketing, and customer service, where accurate emotional analysis ofspeech can provide valuable insights into human behavior and decision-making.

1) Data collection: Collecting speech data is the first step. This involves recording audio samples that represent different emotional states, such as happy, sad, angry, and neutral.

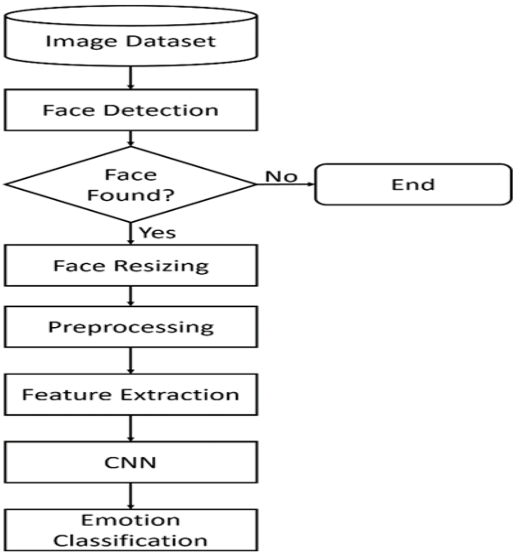

Fig. 2. Flowchart for Facial Emotion Detection Model

(LBP), Histogram of Oriented Gradients (HOG), or Convolutional Neural Networks (CNN).

6) CNN: Convolutional Neural Networks (CNN) is a popular deep learning technique for image classification. It can be used to automatically learn features from images and classify them into differentcategories. The CNN model is trained on the pre-processed face images using labeled emotion data. The model learns to associate certain patterns in the images with specific emotions, and it can then use this knowledge to classify new, unseen images.

7) Emotion classification: The final step is to use the trained CNN model to classify emotions in real-time images. This involves passing the preprocessed face images through the CNN model and predictingthe corresponding emotion category. The emotion classification results can then be displayed on the output screen, or further actions can be taken basedon the detected emotions, such as adjusting the lighting, playing a certain type of music, or triggeringan alert, etc.

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This technique can be used in a variety of applications, such as detecting emotions in video conferences or monitoring the emotions of patients in a medical setting.

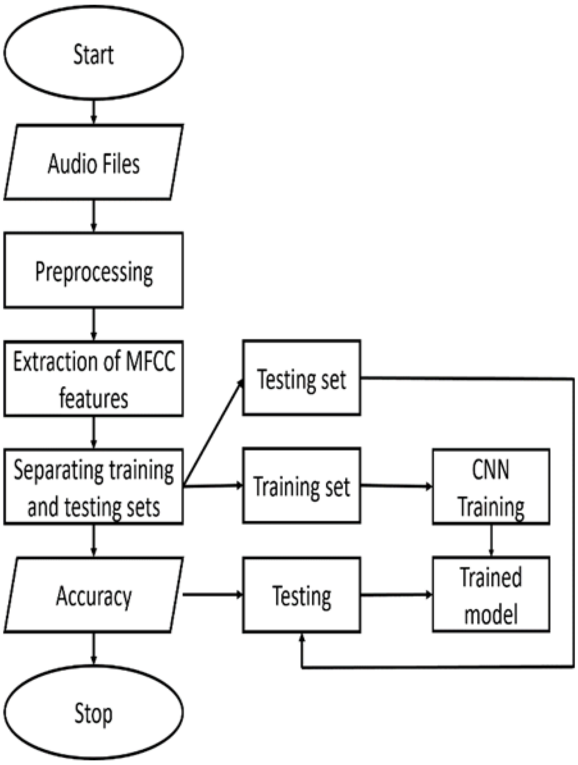

Fig. 3. Flowchart for Vocal Emotion Detection Model

2) Preprocessing: Preprocessing is necessary to prepare the data for analysis. It involves removing noise, filtering, and normalizing the audio signals.

3) Feature extraction: Feature extraction involves converting the raw audio signals into a set of features that can be used to train the emotion recognition model. In speech recognition, commonly used features include Mel Frequency Cepstral Coefficients (MFCC), pitch, and energy.

4) Training: Once the features have been extracted, a machine-learning model can be trained to recognize emotions based on the extracted features. Convolutional Neural Networks (CNNs) are commonly used for this task.

5) Recognition: Finally, the trained model can be used to recognize emotions in the real-time speech input. The model takes in the audio signals, extracts the features, and predicts the emotional state based on the learned patterns.

Overall, recognizing voice variations and analyzing emotions through speech recognition is a complex task that requires careful data collection, preprocessing, feature extraction, model training, and recognition. However, with recent advances in machine learning and speech recognition technology, this task is becoming increasingly feasible and has many potential applications in areas such as

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healthcare, customer service, and entertainment.

D. Convert the speech to text and identify if it's positive or negative using sentimental analysis

Converting speech to text and analyzing sentiment using natural language processing techniques can provide valuable insights into how people feel about a particular topic or situation. This involves first transcribing the speech into text using automatic speech recognition technology. The text is then analyzed using sentimental analysis techniques, which can identify patterns in the language used to determine whether the overall sentiment of the speech is positive or negative. This information can be particularly useful in fields such as marketing and customer service, where understanding customer sentiment is crucial to making informed decisions and providing effective support. By using speech-to-text technology and sentimental analysis, businesses and organizations can gain valuable insights into customer sentiment and use this information to improve their products, services, and overall customer experience.

The steps involved are:

1) Data: The first step is to gather data consisting of speech recordings of individuals. The data can be collected through various sources such as interviews, surveys, or recorded conversations.

2) Speech Recognition: The speech recordings need to be converted to text format using automatic speech recognition (ASR) techniques. This step involves processing the audio recordings and converting them into a textual format that can be further analyzed.

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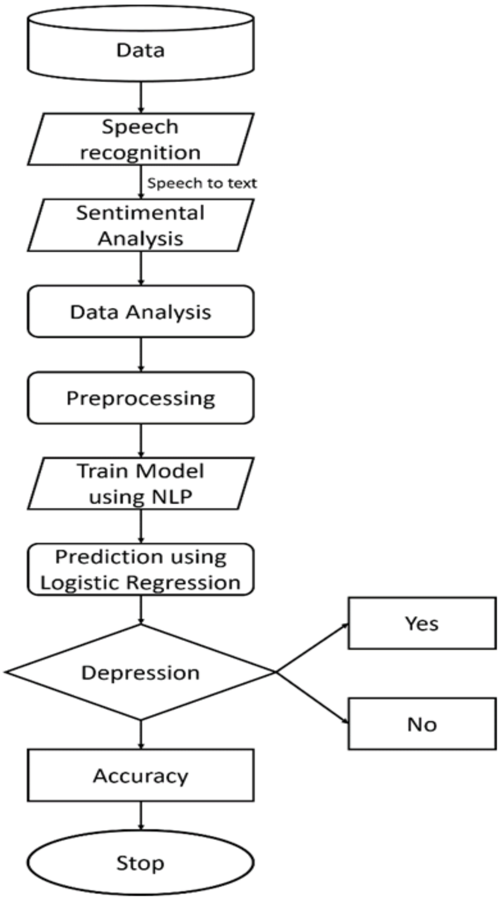

Fig. 4. Flowchart for Sentiment Analysis

3) Sentiment Analysis: Once the speech is converted to text format, the next step is to perform sentiment analysis on the text to determine if it is positive or negative. Sentiment analysis involves analyzing the text to determine the emotional tone of the speaker.

4) Analysis: After performing sentiment analysis, the text data is further analyzed to determine if it indicates the presence of depression. This involves looking for specific linguistic features such as negative affect, self-referential language, and cognitive distortions that are commonly associated with depression.

5) Preprocessing: The text data needs to be preprocessed to remove any noise or irrelevant information that might affect the accuracy of the analysis. This step involves cleaning the data, removing stop words, and applying techniques such as stemming and lemmatization to reduce the dimensionality ofthe data.

6) Training Model in NLP: The preprocessed data is then used to train a machine learning model in natural language processing (NLP) using techniques such as bag-of-words or word embeddings. The model is trained to classify the text as either indicating the presence of depression or not.

7) Prediction using Logistic Regression: The trained model is then used to predict whether the text indicates the presence of depression or not usinglogistic regression, which is a binary classification algorithm.

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8) Depression Yes or No?: Based on the predictions made by the model, the text is classified as indicating the presence of depression or not.

9) Accuracy: The accuracy of the model is evaluated by comparing the predicted results with the actual results. The accuracy of the model can be improved by fine-tuning the model parameters or by using more data for training.

10)

IV. **Work Done And Results Analysis** Depression is a widespread mental health disorder that affects millions of people worldwide. Unfortunately, it often goes undiagnosed or misdiagnosed, leading to a lack of proper treatment and care for those who suffer from it. As technology advances, various approaches have been developed to detect depression, including the use of multiple data sources such as facial expressions, voice tones, and text analysis. In this context, three cases have been proposed for depression detection based on different combinations of these data sources. Each case has its unique features, and in this article, we will describe them in detail.

1) CASE CASE 1: In this case, depression is diagnosed when the individual's facial and voice emotions show anger, disgust, fear, or sadness, and the text analysis gives negative words. This means that the individual is displaying negative emotions through their facial expressions, tone of voice, and the language they are using. The text analysis algorithm would analyze the words spoken by the individual and determine whether they are positive or negative in nature. If the words are predominantly negative, then the algorithm would predict that the individual is likely suffering from depression.

2) CASE 2: In this case, depression is not diagnosed
when the individual's face and voice emotions show anger, disgust, fear, or sadness, but the text analysis gives positive words. This means that the individual is displaying negative emotions through their facial expressions and tone of voice, but the language they are using is predominantly positive in nature. In this scenario, the algorithm would predict that the individual is not suffering from depression.

3) CASE CASE 3: In this case, depression is not diagnosed when the individual's facial and voice emotions show happiness or neutrality, and the text analysis gives neutral words. This means that the individual

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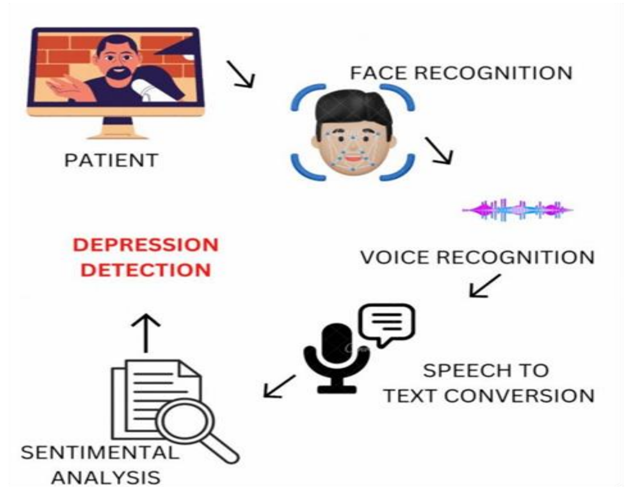

Fig. 5. The Depression detection process

is displaying positive or neutral emotions through their facial expressions and tone of voice, and the language they are using is also neutral in nature. In this scenario, the algorithm would predict that the individual is not suffering from depression.

By integrating multiple sources of data such as facial expressions, tone of voice, and language, depression detection models can provide a more comprehensive and accurate assessment of an individual's mental health status. These models can aid healthcare providers in making timely diagnoses and providing appropriate treatment. Specifically, the three proposed models can effectively diagnose or rule out depression based on a combination of emotional cues and linguistic patterns, enabling early intervention and support.

A. Real-Time Applications

Depression is a serious mental health condition that affects millions of people worldwide. Timely detection and diagnosis of depression are crucial for effective treatment and management of the condition. With advancements in technology and machine learning, depression detection models can now be used in real-time applications to identify individuals at risk of depression and provide timely interventions. These models can be integrated into various settings, including clinical, educational, corporate, and smart city settings, to improve public health and well-being. In this context, let's explore some of the real-time applications of depression detection models.

1) Informing public policy: Depression detection models can play an important role in informing public policy decisions related to mental health resources and services. By collecting and analyzing data on mental health in the population, the models can provide policymakers with valuable insights into the prevalence and severity of depression in different communities. This information can help policymakers allocate resources more effectively, design targeted interventions, and identify areas where more research is needed.

2) Enhancing emergency response: Depression detection models can be integrated with the city's emergency response systems to identify individuals in need of immediate help and dispatch appropriate support. By analyzing facial

expressions, tone of voice, and language, the models can help emergency responders quickly assess the mental health status of individuals in crisis and provide appropriate care.

3) Smart Cities: Depression detection models can be integrated into city systems to improve public health and well-being, enhance emergency response, and inform public policy decisions. In smart city settings, the models can be used to monitor the mental health of the population and identify areas where more resources are needed.

4) Clinical Settings: Depression detection models can be used in hospitals, clinics, and mental health facilities to screen and assess patients for depression and other mental health conditions. By analyzing facial expressions, tone of voice, and language, the models can help healthcare providers quickly identify patients who may be at risk of depression and provide appropriate care.

5) Workplace Wellness Programs: Depression detection models can be used as part of workplace wellness programs to support employee mental health. By analyzing facial expressions, tone of voice, and language, the models can help employers identify employees who may be experiencing symptoms of depression and provide appropriate support.

6) Telemedicine: Depression detection models can be used to screen patients remotely and provide timely interventions. With the increasing use of telemedicine, depression detection models can help healthcare providers quickly identify patients who may be at risk of depression and provide appropriate care.

7) Personal Devices: Depression detection models can be integrated into personal devices, such as wearable devices and smart home systems, to monitor individuals for symptoms of depression and provide personalized interventions. By analyzing facial expressions, tone of voice, and language, the models can help individuals identify when they may be experiencing symptoms of depression and take steps to address them.

8) Educational Institutions: Educational institutions can use depression detection models to identify students at risk of depression and provide them with appropriate support services. By analyzing facial expressions, tone of voice, and language, the models can help educators identify students who may be experiencing symptoms of depression and provide appropriate care.

9) Mental Health Awareness Campaigns: Depression detection models can be used as a tool to raise awareness about mental health and encourage individuals to seek professional help if they experience symptoms of depression. By demonstrating the effectiveness of depression detection models, mental health awareness campaigns can help reduce the stigma associated with mental illness and encourage more people to seek help when they need it.

V. Conclusions

Depression is a widespread and serious mental health condition that can affect anyone, regardless of age, gender, or background. According to recent statistics, out of 3,995 people, 19% of those aged 24 years and below, 57% of those aged 25 to 40 years, 22% of those aged 41 to 65 years, and only 2% of those aged 66 years and above were reported to be suffering from depression. The impact of depression on an individual's daily life, relationships, and overall well-being can be significant, making it essential to diagnose and treat the condition accurately and timely. Unfortunately, depression often goes undiagnosed or misdiagnosed, leading to delayed treatment and a de-creased chance of recovery. This is where depression detection models can play a crucial role in improving patient outcomes. By analyzing facial expressions, tone of voice, and language, depression detection models can accurately identify potential symptoms of depression at an early stage. This ability to provide early intervention can lead to successful treatment and recovery.

Moreover, depression is a complex condition that can manifest differently from person to person, making personalized treatment crucial for effective care. By analyzing individual data, such as demographic information, medical history, and symptoms, depression detection models can determine the best course of treatment for each individual. This personalized approach can lead to better outcomes for patients and improve their quality of life.

In addition, depression detection models can reduce the stigma associated with mental health conditions and improve access to care for individuals suffering from depression. By leveraging technology and data analysis, these models can revolutionize the way we approach mental health care and provide crucial support to those in need.

In conclusion, depression detection models have the potential to improve outcomes for patients suffering from depression by providing early intervention, personalized treatment, reducing stigma, and improving access to care. These models can be a game-changer in mental health care and lead to a better quality of life for individuals suffering from depression.

References

[1] Sharifa Alghowinem, Roland Goecke, Julien Epps, Michael Wagner, and Jeffrey F Cohn. 2016. Cross-Cultural Depression Recognition from Vocal Biomarkers. In INTERSPEECH. 1943–1947.

[2] Fabien Ringeval and Björn Schuller and Michel Valstar and Nicholas Cummins and Roddy Cowie and Leili Tavabi and Maximilian Schmitt and Sina Alisamir and Shahin Amiriparian and Eva-Maria Messner and Siyang Song and Shuo Lui and Ziping Zhao and Adria Mallol-Ragolta and Zhao Ren, and Maja Pantic. 2019. AVEC 2019 Workshop and Challenge: State-of-Mind, Depression with AI, and Cross-Cultural Affect Recognition. In Proceedings of the 9th International Workshop on Audio/Visual Emotion Challenge, AVEC'19, co-located with the 27th ACM International Conference on Multimedia, MM 2019, Fabien Ringeval, Björn Schuller,

Michel Valstar, Nicholas Cummins, Roddy Cowie, and Maja Pantic (Eds.). ACM, Nice, France.

[3] Haroon Ansari, Aditya Vijayvergia, and Krishan Kumar. 2018. DCR- HMM: Depression detection based on Content Rating using Hidden Markov Model. At 2018 Conference on Information and Communication Technology (CICT). IEEE, 1–6.

[4] Meadows G Carey M, Jones K. 2014. Accuracy of general practitioner unassisted detection of depression. (4 2014).

[5] Nicholas Cummins, Vidhyasaharan Sethu, Julien Epps, Sebastian Schnieder, and Jarek Krajewski. 2015. Analysis of acoustic space variability in speech affected by depression. Speech Communication 75 (2015), 27–49.

[6] MN Dalili, IS Penton-Voak, CJ Harmer, and MR Munafò. 2015. Meta-analysis of emotion recognition deficits in major depressive disorder. Psychological medicine 45, 6 (2015), 1135–1144.

[7] : Ratika Rana, 2021, The Mental Health Epidemic: About 56 Million Indians Suffer From Depression https://thelogicalindian. com/mental health/mental-health-Indians-30811

[8] https://thelogicalindian.com/mentalhealth/mental-health-indians- 30811.

[9] Vikram Patel, Chinthanie Ramasundarahettige, Lakshmi Vijayaku- mar, J S Thakur, Vendhan Gajalakshmi, Gopalkrishnan Gururaj, Wilson Suraweera, Prabhat Jha(2014). Suicide mortality in India: a nationally representative survey, 379(9834): 2343–2351. doi: 10.1016/S0140-6736(12)60606-0.

[10] G. Gururaj, Mathew Varghese, National Mental Health Survey of India, World health organization (WHO),(2015-16) https://www. who. int/india/health-topics/depression.

[11] R. Srinivasa Murthy (2017). National Mental Health Survey of India 2015–2016 [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5419008/.

[12] Tianchen Wu, Ph.D, Xiaoqian Jia, Ph.D, Huifeng Shi, Ph.D, Jieqiong Niu, Xiaohan Yin, Jialei Xie and Xiaoli Wang, Ph.Da,c(2020). Prevalence of mental health problems during the COVID-

[13] 19 pandemic: A systematic review and meta-analysis,https:

[14] //www.ncbi.nlm.nih.gov/pmc/articles/PMC7710473/,doi: 10.1016/j.jad.2020.11.117.

[15] Ramdas Ransing, Vikas Menon, Sujita Kumar Kar, S M Yasir Arafat, and Susanta Kumar Padhy (2021). Measures to Im-

[16] prove the Quality of National Suicide Data of India: The Way Forward, https://www.ncbi.nlm.nih.gov/pmc/articles/ PMC9022909/,doi: 10.1177/0253717620973416.

[17] Balbir S Deswal and A Pawar(2012). An Epidemiological Study of Mental Disorders at Pune, Maharashtra, https://www.ncbi. nlm.nih.gov/pmc/articles/PMC3361794/, doi: 10.4103/0970- 0218.96097