



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 6, June 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com

Mental Health AI Chatbot

Dr.A.R.Jayasudha¹, S. Balakumar²

Head of the Department, Department of Master of Computer Applications, Hindusthan College of Engineering and
Technology, Coimbatore, India¹

II MCA Students, Department of Master of Computer Applications, Hindusthan College of Engineering and
Technology, Coimbatore, India²

ABSTRACT: Due to the increasing number of mental health problems, new and creative methods of quickly and easily delivering support are required. In order to provide early psychological aid, information, and resources, this study describes the development and evaluation of an AI-driven chatbot for mental health. The chatbot may converse with users, identify emotional distress, and recommend suitable coping mechanisms or point them toward professional assistance when necessary by using natural language processing (NLP) and machine learning (ML) techniques.

To guarantee thorough comprehension and empathy in its responses, the chatbot was trained on a wide range of datasets that included different scenarios of mental health emergencies. Personalized counsel, connectivity with emergency services, and real-time mood tracking are some of the key features. Expert evaluations, simulated interactions, and user input were used to gauge the system's performance.

KEYWORDS: assistance for mental health, Processing of natural language (NLP), Artificial Intelligence (AI), psychological support, Recognizing emotional anguish

I. INTRODUCTION

Millions of individuals worldwide suffer from mental health illnesses, which impact a wide range of demographic groups. Anxiety, despair, and stress are becoming more common, which emphasizes how urgently accessible mental health services are needed. Many people lack timely help because traditional mental health care systems are frequently overburdened, have few resources, and have lengthy wait times. In this regard, technology—more specifically, artificial intelligence, or AI—offers potentially effective ways to close the gap in mental health services.

The introduction of AI-powered chatbots is a game-changer in the way that mental health services are delivered. These chatbots communicate with consumers in real-time, providing prompt help and direction, by utilizing machine learning (ML) and natural language processing (NLP). AI chatbots are always available, unlike human therapists, therefore assistance is always

II. RELATED WORK

The future of AI in mental health is still being shaped by technological developments. The use of multimodal data, such as voice and facial expressions, to improve emotion identification and response accuracy is one of the more recent innovations. Furthermore, as Liu et al. (2021) argue, continual learning from user interactions and feedback loops holds potential for enhancing the chatbot's performance and flexibility over time.

In conclusion, there has been a lot of advancement in NLP, emotion recognition, and user assessment as demonstrated by the related work in AI-driven mental health chatbots. Ongoing research is still necessary to address issues with privacy, integration with human services, and ethical considerations. By expanding on these pioneering research, our work seeks to improve AI mental health support's efficacy, empathy, and accessibility.

III. METHODOLOGY

3.1 Proposed System:

This is an AI-powered bot designed to provide emotional support and assistance to individuals struggling with mental health issues. It can help individuals access mental health resources, offer guidance and support.

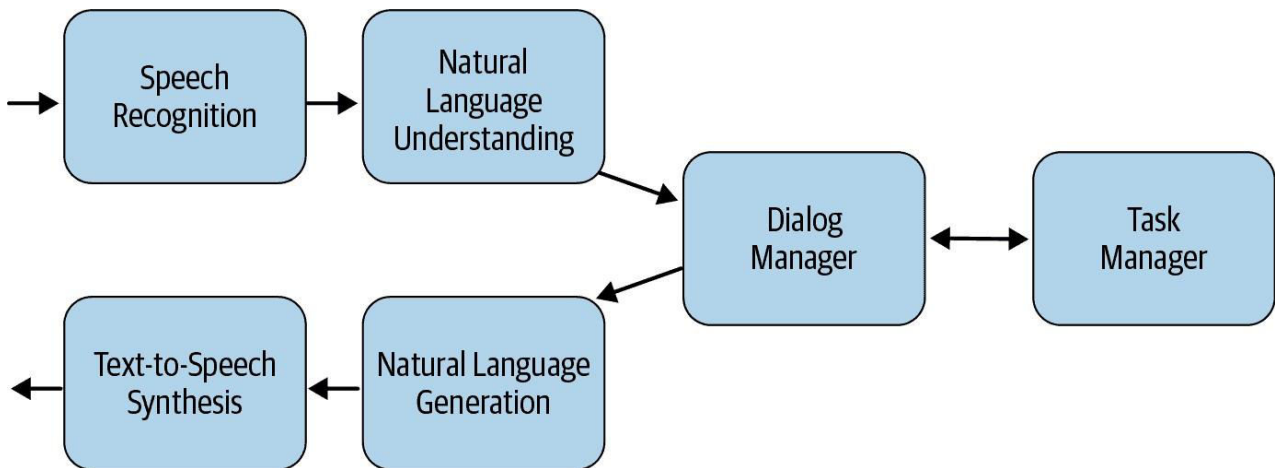


Figure 1: An illustration of the proposed method.

3.2 Dataset:

This dataset includes a single text including conversational questions and answers about mental health. The dataset was assembled from internet FAQs, WebMD, Mayo Clinic, and HealthLine, among other well-known healthcare blogs. Every question and response has been pre-processed to eliminate any unnecessary characters and anonymized to remove any PII data.

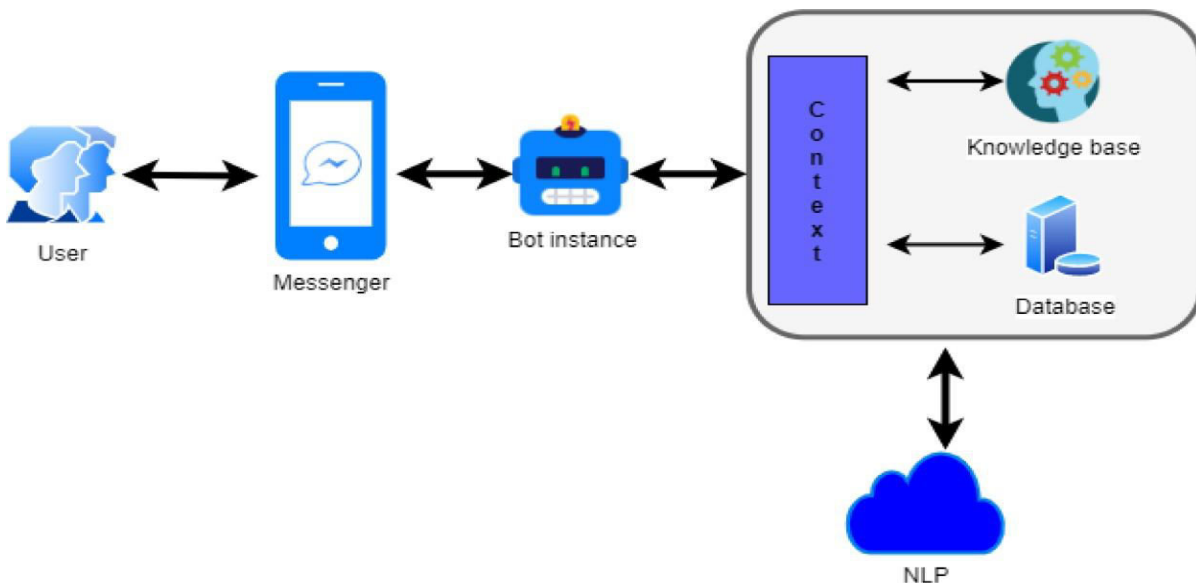


Figure 2: A sample view of the dataset

3.3 Convolution Neural Network:

I built an educational mental health chatbot that uses NLP and a Deep Neural Network. My chatbot's name is **Serenity** (I chose the name serenity as it means peaceful), and through my program you can chat with Serenity and build your knowledge on mental health disorders as well as supporting your peers with mental illness.

3.4 Transfer model:

Transfer learning is one of the most important steps in CNN. In our study, transfer learning and fine-tuning were applied to GoogleNet, ResNet-50, and AlexNet networks pretrained to the ImageNet dataset. Transfer learning is based on training a dataset to solve a specific problem and then transferring that learning to solving another related dataset problem. Transfer learning works by choosing the pretrained model and the size of the problem and using what has been learned to transfer the generalisation to another task. Transfer learning also avoids overfitting. In this work, transfer learning was applied to GoogleNet, ResNet-50, and AlexNet, where the weights were fine-tuned. The GoogleNet, ResNet-50, and AlexNet models were trained on the ImageNet dataset, and the learning was then transferred to the gastrointestinal dataset. The last three layers of the patterns were deleted and replaced with a fully connected layer. The first connected layer received 9,216 neurons and outputted 4,096 neurons, while the second connected layer received 4,096 neurons and outputted those. The softmax layer produced the five classes: dye-lifted polyps, normal cecum, normal pylorus, polyps, and ulcerative colitis.

3.5 VGG-19

In image categorization, deep neural networks have played a key role in several innovations. These sophisticated models have also proven beneficial for numerous other visual recognition tasks. As a result, we usually become more proficient with time, taking on increasingly difficult jobs and increasing our accuracy. However, as we go farther into neural networks, accuracy suffers and training becomes more difficult. The implementation of VGG-19 is addressing these problems. Rather than having a large number of hyperparameters, the CNN-based VGG-19 model uses 3×3 filters with a single stride and always uses the same padding and maxpooling layers of 2×2 filters with a stride of 2. The maxpooling and convolution layers are arranged similarly in the architecture. In the model, there are two FC layers. This VGG-19 network is a huge network with about 138 million trainable parameters. The architecture of the VGG-19 network is shown in Figure 4. A sequence of convolutional layers (conv1, conv2, conv3, conv4, and conv5) were applied following the classification layer, which comprised a dropout layer and a densely connected classifier. Every neuron in a dense layer is linked to every other neuron in the layer that came before it. Densely linked layers, as opposed to convolutional layers, use the features of the preceding layer to learn new information. It is necessary to specify how the densely connected layer is activated.

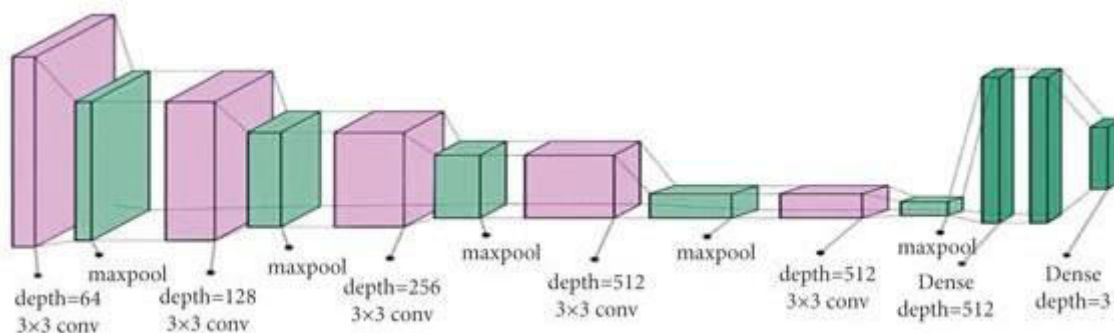


Figure 3: VGG-19 architecture

IV. RESULTS AND ANALYSIS

4.1 Overview Of Outcomes:

We determined the solution to the class imbalance issue by capturing an equal number of pictures. In the ODIR dataset, there was a significant difference between the classes. When the quantity of photos is somewhat smaller, we may greatly increase our accuracy by using this strategy. We next looked at and displayed graphically the relative metrics, accuracy loss graphs, and other comparable indicators of the performance evaluation approaches. We showed that our model could correctly forecast a certain circumstance using the VGG-19 architecture. The test's confusion

matrix was utilized to demonstrate the predictive accuracy of this model.

The CNN-based architecture VGG-19 was employed in our experiment to evaluate the performance of the model. First, a picture is extracted from the dataset and the data are transformed into train labels and target labels in the data sequencing and splitting phase. The training-test split technique from the scikit-learn package was applied. Thirty percent of the data were used for testing and seventy percent of the data were used for training. This section presents the prediction capabilities of both models together with their performance measures. These are a few outcomes for every class.

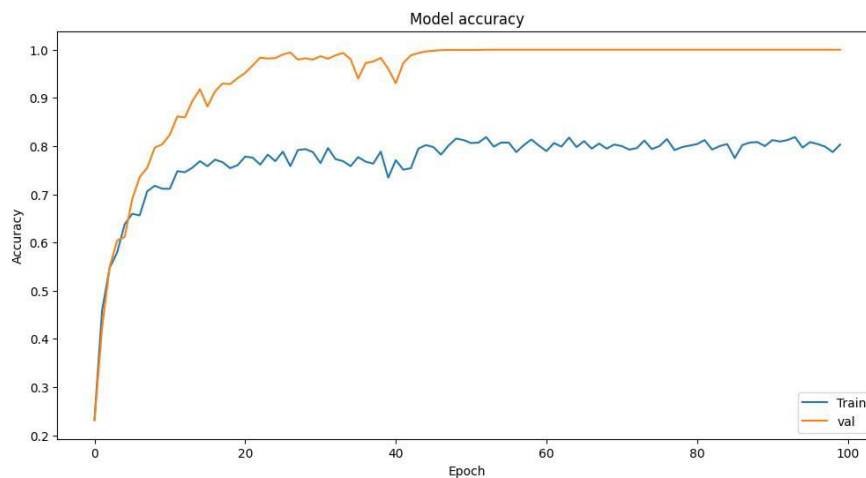


Figure 4: Model Accuracy in graph format

4.2 Training and Testing Accuracy:

We shall ascertain the extent to which our model is learning from the training dataset as we train our models with it. Finding the hyperparameters and determining if our models are overfitting or underfitting are the primary goals of training accuracy.

Accuracy

$$= \frac{\text{True Positive (TP) + True Negative (TN)}}{\text{True Positive (TP) + True Negative (TN) + False Positive (FP) + False Negative (FN)}}$$

We can only go on to test accuracy, or the ultimate accuracy of our models, if we have finished training them using our training dataset and have cross-checked that they are doing well in the validation dataset. We refer to test accuracy when we discuss accuracy in our report.

4.3 Precisions:

Accuracy alone is insufficient sometimes. We simply cannot conclude that our model is very accurate based just on accuracy because we must accurately categorize both illnesses and non-diseases for this endeavour. In the context of deep learning, those who are ill are referred to as "positive," while people who are well are referred to as "negative." A clear picture of precision is provided by the number of positive illness patients—that is, patients who are accurately identified—across the whole dataset.

4.4 Detection of Each Classification:

We tested the VGG-19 model's ability to quickly classify photos as normal or ill after it had been trained, images are detected. It's evident that our algorithm works incredibly well and can correctly forecast both the diseased and non-diseased images.

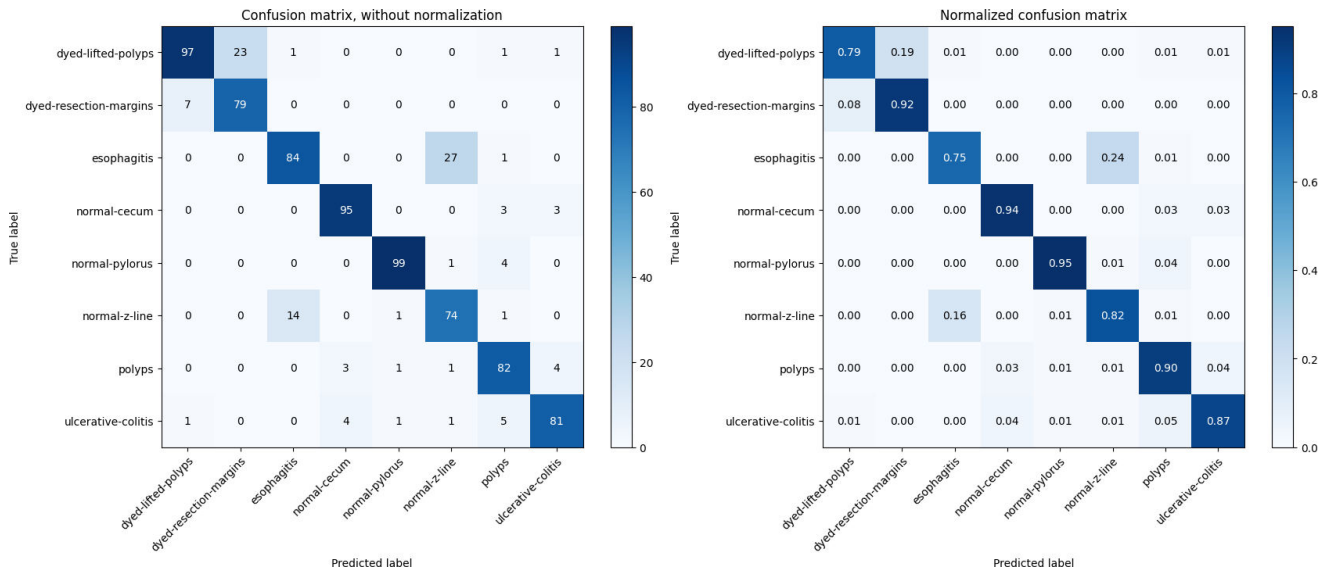


Figure 5: Predicted

We used random photos from the test set in Figures 6 to evaluate if our algorithm could accurately identify normal or diseased conditions. Every image demonstrated how VGG-19 accurately classified which dermoscopic image was normal or sick. Given the large number of factors, our model predicts with the predicted level of accuracy, which makes sense, and so VGG-19 functioned adequately in recognizing ocular pictures.

V.CONCLUSION

This work provides a robust framework for classifying the gastrointestinal tract diseases in the Kvasir dataset. Deep learning techniques can reduce the probability of developing malignant diseases by aiding in early detection, while also reducing the unnecessary removal of benign tumors. Video endoscopy is the most widely used diagnostic method for diagnosing gastrointestinal polyps, but many human factors lead to improper diagnosis of gastrointestinal diseases. This paper presents three deep learning models, GoogleNet, ResNet-50, and AlexNet, that can direct the doctor’s focus to the most important regions that may have been missed. The dataset was divided into 70% for training and 30% for testing and validation. The images were optimised to remove noise and artifacts. The data augmentation technology works by multiplying the images during the training phase for high accuracy. Convolutional layers extract features of shape, colour, and texture. Overall, 9216 features were extracted and passed into the fully connected layers that produced 1000 neurons. The softmax layer produces five classes, classifying each image into one of the five types of gastrointestinal diseases. All three models achieved equally promising results. Advanced deep learning algorithm will be applied in future.

REFERENCES

1. Team Capacity. The Complete Guide to AI Chatbots: The Future of AI and Automation. 2023. Available online: <https://capacity.com/learn/ai-chatbots/> (accessed on 19 August 2023).
2. Caldarini, G.; Jaf, S.; McGarry, K. A Literature Survey of Recent Advances in Chatbots. Information **2022**, *13*, 41. [Google Scholar] [CrossRef]
3. Bryant, A. AI Chatbots: Threat or Opportunity? Informatics **2023**, *10*, 49. [Google Scholar][CrossRef]
4. The Center for Humane Technology. Align Technology with Humanity’s Best Interests. 2023. Available online: <https://www.humanetech.com/> (accessed on 19 August 2023).
5. World Health Organization. Mental Health. 2023. Available online: https://www.who.int/health-topics/mental-health#tab=tab_1 (accessed on 19 August 2023).
6. Australian Bureau of Statistics. National Study of Mental Health and Wellbeing. 2021. Available online: <https://www.abs.gov.au/statistics/health/mental-health/national-study-mental-health-and-wellbeing/latest->

- release** (accessed on 19 August 2023).
7. Australian Productivity Commission. Mental Health. 2020. Available online: <https://www.pc.gov.au/inquiries/completed/mental-health#report> (accessed on 19 August 2023).
 8. Queensland Brain Institute. Life Expectancy Mapped for People with Mental Disorders. 2019. Available online: <https://qbi.uq.edu.au/article/2019/10/life-expectancy-mapped-people-mental-disorders> (accessed on 19 August 2023).
 9. Clement, S.; Schauman, O.; Graham, T.; Maggioni, F.; Evans-Lacko, S.; Bezborodovs, N.; Morgan, C.; Rüsch, N.; Brown, J.S.L.; Thornicroft, G. What is the impact of mental health-related stigma on help-seeking? A systematic review of quantitative and qualitative studies. *Psychol. Med.* **2015**, *45*, 11–27. [[Google Scholar](#)] [[CrossRef](#)]
 10. Oexle, N.; Müller, M.; Kawohl, W.; Xu, Z.; Viering, S.; Wyss, C.; Vetter, S.; Rüsch, N. Self-stigma as a barrier to recovery: A longitudinal study. *Eur. Arch. Psychiatry Clin. Neurosci.* **2017**, *268*, 209–212. [[Google Scholar](#)] [[CrossRef](#)]
 12. Australian Institute of Health and Welfare. Mental Health: Prevalence and Impact. 2022. Available online: <https://www.aihw.gov.au/reports/mental-health-services/mental-health> (accessed on 19 August 2023).
 13. U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration. Key Substance Use and Mental Health Indicators in the United States: Results from the 2018 National Survey on Drug Use and Health. 2018. Available online: <https://www.samhsa.gov/data/sites/default/files/cbhsq-reports/NSDUHDetailedTabs2018R2/NSDUHDetTabsSect8pe2018.htm#tab8-28a> (accessed on 19 August 2023).
 14. Wies, B.; Landers, C.; Ienca, M. Digital Mental Health for Young People: A Scoping Review of Ethical Promises and Challenges. *Front. Digit. Health* **2021**, *3*, 697072. [[Google Scholar](#)] [[CrossRef](#)]
 15. Iyortsuun, N.K.; Kim, S.-H.; Jhon, M.; Yang, H.-J.; Pant, S. A Review of Machine Learning and Deep Learning Approaches on Mental Health Diagnosis. *Healthcare* **2023**, *11*, 285. [[Google Scholar](#)] [[CrossRef](#)]
 16. Andreou, A. Generative AI Could Help Solve the U.S. Mental Health Crisis. *Psychology Today*. Available online: <https://www.psychologytoday.com/au/blog/the-doctor-of-the-future/202303/generative-ai-could-help-solve-the-us-mental-health-crisis> (accessed on 19 August 2023).
 17. Demiris, G.; Oliver, D.P.; Washington, K.T. The Foundations of Behavioral Intervention Research in Hospice and Palliative Care. In *Behavioral Intervention Research in Hospice and Palliative Care*; Academic Press: Cambridge, MA, USA, 2019; pp. 17–25. [[Google Scholar](#)] [[CrossRef](#)]
 18. Adamopoulou, E.; Moussiades, L. Chatbots: History, technology, and applications. *Mach. Learn. Appl.* **2020**, *2*, 100006. [[Google Scholar](#)] [[CrossRef](#)]
 19. Haque, M.D.R.; Rubya, S. An Overview of Chatbot-Based Mobile Mental Health Apps: Insights from App Description and User Reviews. *JMIR mHealth uHealth* **2023**, *11*, e44838. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
 20. Denecke, K.; Abd-Alrazaq, A.; Househ, M. Artificial Intelligence for Chatbots in Mental Health: Opportunities and Challenges. In *Multiple Perspectives on Artificial Intelligence in Healthcare: Opportunities and Challenges*; Lecture Notes in Bioengineering; Springer: Berlin/Heidelberg, Germany, 2021; pp. 115–128. [[Google Scholar](#)] [[CrossRef](#)]
 21. Rizvi, M. AI Chatbots Revolutionize Depression Management and Mental Health Support— DATAVERSITY. 2023. Available online: <https://www.dataversity.net/ai-chatbots-revolutionize-depression-management-and-mental-health-support/> (accessed on 21 August 2023).
 22. Vaidyam, A.N.; Wisniewski, H.; Halamka, J.D.; Kashavan, M.S.; Torous, J.B. Chatbots and Conversational Agents in Mental Health: A Review of the Psychiatric Landscape. *Can. J. Psychiatry* **2019**, *64*, 456–464. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
 23. Daley, K.; Hungerbuehler, I.; Cavanagh, K.; Claro, H.G.; Swinton, P.A.; Kapps, M. Preliminary Evaluation of the Engagement and Effectiveness of a Mental Health Chatbot. *Front. Digit. Health* **2020**, *2*, 576361. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
 24. Inkster, B.; Sarda, S.; Subramanian, V. An Empathy-Driven, Conversational Artificial Intelligence Agent (Wysa) for Digital Mental Well-Being: Real-World Data Evaluation Mixed-Methods Study. *JMIR mHealth uHealth* **2018**, *6*, e12106. [[Google Scholar](#)] [[CrossRef](#)]
 25. Lim, S.M.; Shiau, C.W.C.; Cheng, L.J.; Lau, Y. Chatbot-Delivered Psychotherapy for Adults with Depressive and Anxiety Symptoms: A Systematic Review and Meta-Regression. *Behav. Ther.* **2022**, *53*, 334–347. [[Google Scholar](#)] [[CrossRef](#)]

26. Fitzpatrick, K.K.; Darcy, A.; Vierhile, M. Delivering Cognitive Behavior Therapy to Young Adults with Symptoms of Depression and Anxiety Using a Fully Automated Conversational Agent (Woebot): A Randomized Controlled Trial. *JMIR Ment. Health* **2017**, *4*, e19. [[Google Scholar](#)] [[CrossRef](#)]
27. Klos, M.C.; Escoredo, M.; Joerin, A.; Lemos, V.N.; Rauws, M.; Bunge, E.L. Artificial Intelligence–Based Chatbot for Anxiety and Depression in University Students: Pilot Randomized Controlled Trial. *JMIR Form. Res.* **2021**, *5*, e20678. [[Google Scholar](#)] [[CrossRef](#)]
28. Jang, S.; Kim, J.-J.; Kim, S.-J.; Hong, J.; Kim, S.; Kim, E. Mobile app-based chatbot to deliver cognitive behavioral therapy and psychoeducation for adults with attention deficit: A development and feasibility/usability study. *Int. J. Med. Inform.* **2021**, *150*, 104440. [[Google Scholar](#)] [[CrossRef](#)]
29. Viduani, A.; Cosenza, V.; Araújo, R.M.; Kieling, C. Chatbots in the Field of Mental Health: Challenges and Opportunities. In *Digital Mental Health*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 133–148. [[Google Scholar](#)] [[CrossRef](#)]
30. Helmy, B.S.; Helmy, A.S. Role of Artificial Intelligence in Mental Wellbeing: Opportunities and Challenges. *J. Artif. Intell.* **2022**, *15*, 1–8. [[Google Scholar](#)] [[CrossRef](#)]
31. Singh, O. Artificial intelligence in the era of ChatGPT—Opportunities and challenges in mental healthcare. *Indian J. Psychiatry* **2023**, *65*, 297–298. [[Google Scholar](#)] [[CrossRef](#)]
32. Boucher, E.M.; Harake, N.R.; Ward, H.E.; Stoeckl, S.E.; Vargas, J.; Minkel, J.; Parks, A.C.; Zilca, R. Artificially intelligent chatbots in digital mental health interventions: A review. *Expert Rev. Med. Devices* **2021**, *18*, 37–49. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
33. Balcombe, L.; De Leo, D. Human-Computer Interaction in Digital Mental Health. *Informatics* **2022**, *9*, 14. [[Google Scholar](#)] [[CrossRef](#)]
34. Balcombe, L.; De Leo, D. Evaluation of the Use of Digital Platforms and Digital Mental Health Interventions: Scoping Review. *Int. J. Environ. Res. Public Health* **2022**, *20*, 362. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
35. Balcombe, L.; De Leo, D. Digital Mental Health Challenges and the Horizon Ahead for Solutions. *JMIR Ment. Health* **2021**, *8*, e26811. [[Google Scholar](#)] [[CrossRef](#)]
36. He, Y.; Yang, L.; Qian, C.; Li, T.; Su, Z.; Zhang, Q.; Hou, X. Conversational Agent Interventions for Mental Health Problems: Systematic Review and Meta-analysis of Randomized Controlled Trials. *J. Med. Internet Res.* **2023**, *25*, e43862. [[Google Scholar](#)] [[CrossRef](#)]
37. Darcy, A.; Daniels, J.; Salinger, D.; Wicks, P.; Robinson, A. Evidence of Human-Level Bonds Established with a Digital Conversational Agent: Cross-sectional, Retrospective Observational Study. *JMIR Form. Res.* **2021**, *5*, e27868. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
38. Beatty, C.; Malik, T.; Meheli, S.; Sinha, C. Evaluating the Therapeutic Alliance with a Free-Text CBT Conversational Agent (Wysa): A Mixed-Methods Study. *Front. Digit. Health* **2022**, *4*, 847991. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
39. Dosovitsky, G.; Bunge, E.L. Bonding with Bot: User Feedback on a Chatbot for Social Isolation. *Front. Digit. Health* **2021**, *3*, 735053. [[Google Scholar](#)] [[CrossRef](#)] [[PubMed](#)]
40. Sinha, C.; Cheng, A.L.; Kadaba, M. Adherence and Engagement with a Cognitive Behavioral Therapy–Based Conversational Agent (Wysa for Chronic Pain) among Adults with Chronic Pain: Survival Analysis. *JMIR Form. Res.* **2022**, *6*, e37302. [[Google Scholar](#)] [[CrossRef](#)]
41. Prochaska, J.J.; Vogel, E.A.; Chieng, A.; Kendra, M.; Baiocchi, M.; Pajarito, S.; Robinson, A. A Therapeutic Relational Agent for Reducing Problematic Substance Use (Woebot): Development and Usability Study. *J. Med. Internet Res.* **2021**, *23*, e24850. [[Google Scholar](#)] [[CrossRef](#)]



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details