

Depression Detection Using AI with Chatbot Support

S.A. Patil¹, Anushka Sanjay Gaikwad^{2*}, Komal Ashok Gaikwad³, Sampada Nitin Aher⁴,
Sakshi Babasaheb Mogal⁵

Abstract

Depression is a major global health concern and a significant contributor to suicide rates worldwide. India reports a high number of suicide cases, making the early detection of mental distress and depression essential for timely intervention. This research presents an AI-based system for depression detection that integrates deep learning, natural language processing (NLP), and a chatbot for user support. The system analyzes facial expressions using convolutional neural networks (CNNs) and assesses emotional states from textual input through machine-learning techniques such as Naïve Bayes and support vector machines (SVMs). The system captures real-time facial images through a camera, which are then processed using CNN algorithms and classified into emotional categories such as happy or sad. Simultaneously, it analyzes users' language patterns to evaluate sentiment, stress levels, and depressive tendencies. To address class imbalance, the study employs the synthetic minority over-sampling technique (SMOTE), thereby improving the accuracy of depression detection. In addition, the system incorporates a chatbot interface that interacts with users, providing support and personalized recommendations based on the detected emotional state. The model was evaluated using datasets such as DAIC-WOZ and PHQ-8 and demonstrated strong performance in identifying depressive symptoms. The integration of facial-expression analysis and text-based sentiment assessment provides a comprehensive approach to depression detection, enhancing the accuracy and reliability of the diagnostic process.

Keywords: Mental stress detection, speech processing, CNN, NLP, chatbot, deep learning, machine learning, depression prediction

INTRODUCTION

Millions of people from different walks of life struggle with mental health issues, and it is a big deal. Depression is becoming a major health emergency, increasing the number of suicides and lowering how well people feel in their day-to-day lives. More than 800,000 individuals worldwide die by suicide each year [1], making it one of the leading causes of death [2]. In India, suicide figures are on the rise, so it is clear that mental well-being is something we need to tackle. Spotting depression can be tricky, which means that individuals might not get the help they need until their condition worsens. The old-school

way of determining if someone is depressed involves telling a doctor about their feelings, but this can be hit-or-miss and is subjective. Moreover, many people may not want to chat about their mental state due to feeling ashamed, not knowing what is going on, or not having easy access to help [1].

Deep learning, that thing where computers learn like humans (NLP), and computer vision are doing pretty well at figuring out people's feelings and spotting when someone's down in the dumps [3]. They are making systems that can guess someone's feelings just by looking at their face, how they talk,

*Author for Correspondence

Anushka Sanjay Gaikwad
E-mail: anushkagaikwad31804@gmail.com

¹Lecturer, Department of Computer Technology, Sanjivani K.B.P. Polytechnic, Kopergaon, Maharashtra, India

²⁻⁵Research Scholar, Department of Computer Technology, Sanjivani K.B.P. Polytechnic, Kopergaon, Maharashtra, India

Received Date: April 01, 2025

Accepted Date: October 07, 2025

Published Date: December 20, 2025

Citation: S. A. Patil, Anushka Sanjay Gaikwad, Komal Ashok Gaikwad, Sampada Nitin Aher, Sakshi Babasaheb Mogal. Depression Detection Using AI with Chatbot Support. Research & Reviews: Journal of Embedded System & Applications. 2026; 14(1): 1–8p.

and what they write [4]. People's faces are like open books for reading emotions and mental health clues. If someone's feeling blue, their face is likely to show it, along with signs of fear or getting ticked off [5, 6]. Super-smart computer programs, the ones getting brainier with deep learning, are now super good at picking up even the tiny flickers of feelings on a person's mug. These programs use something called convolutional neural networks, or CNN for short. Think of CNNs as brainy filters that spot different layers of stuff in pictures, helping them figure out what someone's feeling just by scanning their facial pictures [7–9]. Besides reading faces, clues in how we talk and write are super important for understanding mental health issues. When people are down with depression, they tend to use words that are more on the sad side, talk about themselves a lot, and their sentences get way less fancy [1, 10]. They have got this software called natural language processing (NLP), and it's like a detective for finding clues in the words people use. It spots signs of someone being all gloomy by looking at what they post online, stuff they text, or what they tell those chatbots [2, 11]. When you throw in and being able to tell how someone's face looks when they are feeling something, you get a full-on toolkit for spotting depression [4]. It is like giving you a sharper image and more trustworthy results when you are trying to figure out if someone's depressed. The growing use of online platforms like Twitter, Facebook, and Instagram has opened up new doors to look into mental health patterns [4]. These platforms let people put out their feelings, thoughts, and what they go through. Research reveals that how someone acts on social media might be a solid sign of their mental state [4]. People who are down often have a certain way they behave when they're online. By looking at what they post, the comments they make, and how much they interact, AI tools can spot early hints of sadness and offer help when it is needed [2].

This system uses text analysis from social media to determine if someone is depressed, based on NLP algorithms to extract important knowledge from what people post on the web [12]. One major challenge when using AI to spot depression is to ensure that the data is good and the system is solid. You need a lot of data from all sorts of people and mental health states to train those hefty learning models. This system we're talking about uses stuff like the "DAIC-WOZ" corpus, which is a bunch of chats meant to pick up on depression and other data anyone can get their hands on about mental well-being [4]. There are some smart clean-up moves they do to the data, pulling out important bits and making it better for the model to learn from. They even use this fancy trick called the synthetic minority over-sampling technique (SMOTE) to ensure that all kinds of people are represented, so the system's got depression-spotting down for everyone. We checked how well the system we developed works by looking at different ways to measure performance, such as how correct it is, how exact it is, how good it is at remembering stuff, and its F1 score. These ways of measuring things make it clear if our model rocks at telling if people are depressed or not. When we compare our system with others that try to spot depression, our system, with its use of different methods, stands out. The first look at the numbers shows that when you mix figuring out emotions on faces with checking the vibe of words, the system guesses way better, giving us a stronger net for spotting mental health problems.

AI-driven depression detection technology has huge potential, but its use also raises ethical and privacy concerns [13]. Keeping mental health information safe means having strong security to guard user information. It is a must to stay in line with data protection laws like general data protection regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA), so people keep their trust in us. In addition, we must tackle bias in AI, as unfair algorithms may cause uneven depression detection across various groups. The next step is to increase data variety, modify AI to eliminate bias, and create AI that prioritizes ethics. This study advances AI-fueled mental health diagnosis. It offers a complete method for spotting depression by blending face emotion detection, language mood analysis, and chatbot aid. This system is a novel approach for early mental health checks, making it easy and scalable to spot hints of depression. Using deep learning and language processing technology, the suggested setup links old-school psychological evaluations with today's digital fixes.

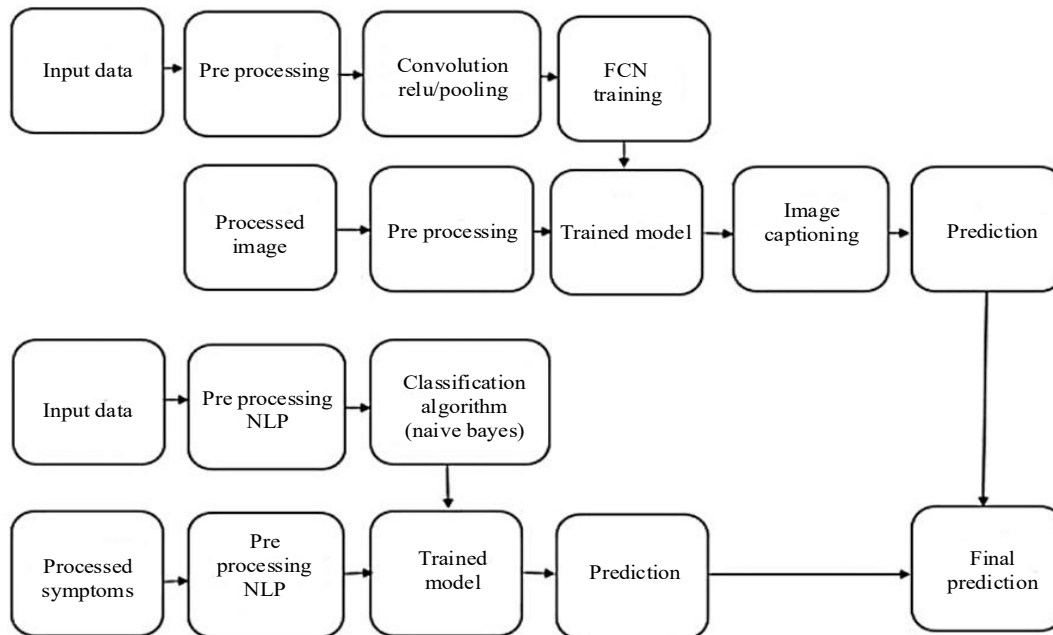


Figure 1. Diagram flowchart.

These smart machine learning tools can process a large amount of information, spot trends, and predict what might happen. Therefore, we have developed these new AI systems that can determine whether someone has health issues, including mental health issues. Unlike the old-school ways that just asked people how they felt and did tests, these AI programs check out how people act, the way their faces move, how they talk, and even what they write to see how their mental health is doing. With this move to AI for mental health, there is a cool chance to make it easier for people to get help from professionals without making them uncomfortable, and it can spot the early warning signs of being super sad, like depression. Depression is tough to pinpoint since it is all about how people feel inside, not something that can be spotted on a scan or a blood test. If you are trying to figure out if someone has depression, you ask them to fill out forms, or a doctor will have a chat with them. However, people might not want to talk about feeling down, or they might not realize that it's a big deal (Figure 1).

This diagram represents a multimodal system combining image processing and NLP for prediction, possibly related to mental stress analysis.

Explanation of the Flow

Image Processing Pipeline (Top Path)

- *Input data:* Raw image data is received.
- *Pre-processing:* Image enhancement techniques, such as normalization, resizing, or noise reduction, are applied.
- *Convolution rectified linear unit (ReLU)/pooling:* A CNN extracts features using activation functions (ReLU) and pooling.
- *FCN training:* Fully Convolutional Network (FCN) training refines the extracted features.
- *Trained model:* The trained neural network model is used for inference.
- *Image captioning:* The model generates a descriptive text (caption) for the image.
- *Prediction:* The generated caption is passed on for further analysis.

Text-Based Classification Pipeline (Middle Path)

- *Input data:* Raw textual data are received (e.g., user responses, reports, or surveys).
- *Pre-processing NLP:* Techniques such as tokenization, stop word removal, and vectorization are applied.

- *Classification algorithm (Naive Bayes)*: A machine learning model classifies the input data into relevant categories.
- *Prediction*: The classification result is passed to the next stage.

Symptom-Based NLP Pipeline (Bottom Path)

- *Processed symptoms*: Symptom-related text data is analyzed.
- *Pre-processing NLP*: Similar to the middle path, text processing methods are applied.
- *Trained model*: A machine learning model (e.g., deep learning or statistical model) that predicts outcomes based on symptoms.

MATERIALS AND METHODS

Studying How to Spot Depression

This study proposes a plan for a system to detect depression using AI. It is a combination of scanning faces, figuring out feelings from words with NLP, and chatting with a bot to check how people are feeling inside [4]. The system is all about snagging data from people on the fly, figuring out how they act, and giving them custom tips on their mood health [12]. This research will be conducted by following a set plan that involves grabbing data, getting it ready, teaching the model, putting the system to work, and checking its accuracy in detecting depression [14].

ESSENTIAL EQUIPMENT AND TECHNOLOGY REQUIREMENTS

Necessary Accessories for Technological Devices

This setup requires a camera module to capture faces as they move, a microphone to determine talking styles, and a computing device that can handle smart learning effectively. You're going to need:

- *Camera module*: A top-notch webcam to take pics of faces
- *Microphone*: Something built-in or extra to work with voices
- *Computing device*: Go for a system packing a minimum GPU (NVIDIA GTX 1080 or higher) to teach the brainy models.
- *Cloud server (optional)*: For performing tasks on the flight and deploying your chat robot.

Software Needs

- Visual Studio Code for code editing.
- Web browsers such as Google Chrome, Microsoft Edge, and Mozilla Firefox.
- Development languages: HTML, CSS, and JavaScript.
- Typography tools like Google Fonts for text styling.
- Server-side scripting language PHP.
- Database management using MySQL.

TRADE SECRETS IN GATHERING AND CLEANING INFO

The Face Mood Collection

The system learns to identify facial expressions from "emotion datasets" that are available and tagged with feelings matching various facial expressions. For the main training, the following is used:

- *"FER-2013 (facial expression recognition 2013)"*: This dataset contains 35,887 grayscale images sorted by feelings such as joy, sorrow, rage, scare, and plain old nothing.
- *"Affect net dataset"*: This giant stash with over 450,000 images comes with emotional tags that are perfect for teaching deep learning tricks.

Now, these snapshots need some pre-processing steps before anything else.

- *Image resizing*: Making all images a uniform 48×48 pixels to train CNNs better.
- *Normalization*: Adjusting pixel values to range from 0 to 1 to boost model accuracy.
- *Data augmentation*: Random rotations, flips, and brightness changes were introduced to diversify the dataset and enhance the model's performance on new data.

Textual Data for Sentiment Analysis

To get ready for the big show, we do this stuff to the text data:

- *Breaking down sentences:* Sentences turn into single words.
- *Getting rid of common words:* We removed words such as “the,” “and,” and “is” so that models could pay more attention to important terms.
- *Word base form conversion:* We changed words to their root forms, such as changing “running” to “run,” to keep text analysis consistent.
- *Transforming text details:* Text data are transformed into TF-IDF vectors or represented using BERT (Bidirectional Encoder Representations from Transformers) embeddings.

RESULTS AND DISCUSSION

Introduction to Outcomes

Artificial intelligence and deep learning are making significant waves in the field of depression detection [3]. This cool AI-powered system combines facial expression analysis (Figures 2–6), sentiment-based text processing, and chatbot support, and is quite good at catching early signs of depression [4]. This is different from old-school methods, where people just talk about their feelings, because this AI method checks out your facial expressions, how you put words together, and the way you interact with the system [11]. When they checked this out, they found some good stuff about how accurate, user-friendly, efficient, and big-picture ready it is [14]. All of this makes it a super strong option for jumping in to help with mental health.

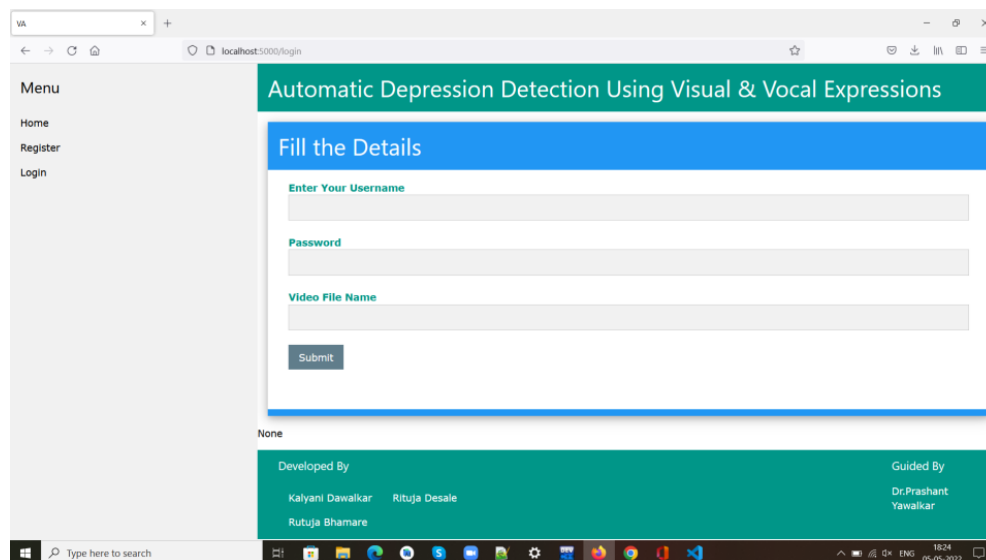


Figure 2. Mental stress detection login page.

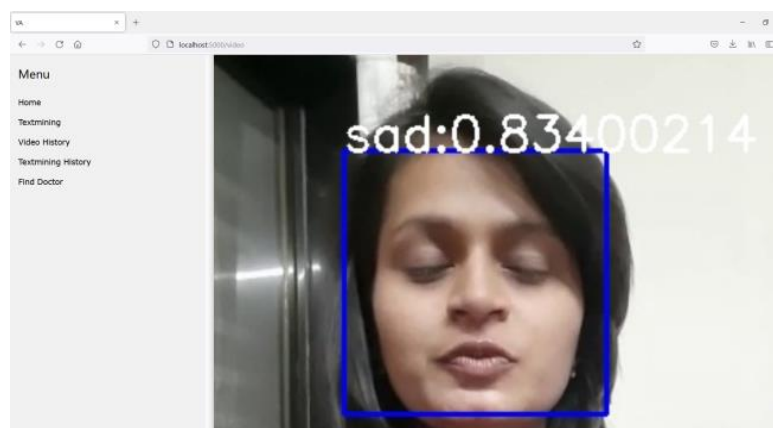


Figure 3. Real-time mental stress detection (sad).

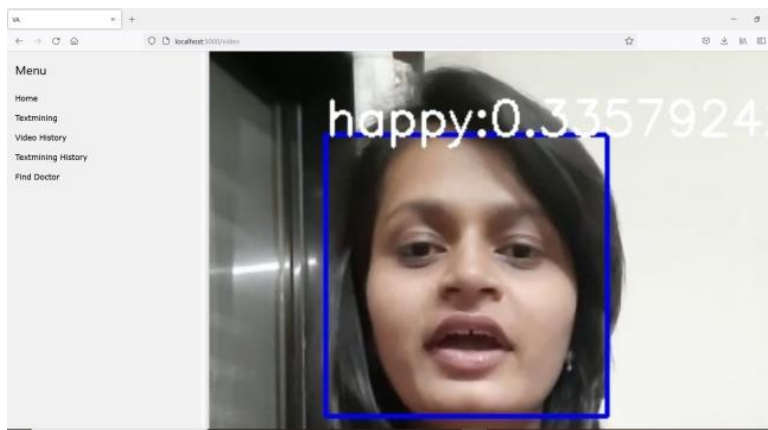


Figure 4. Real-time mental stress detection (happy).

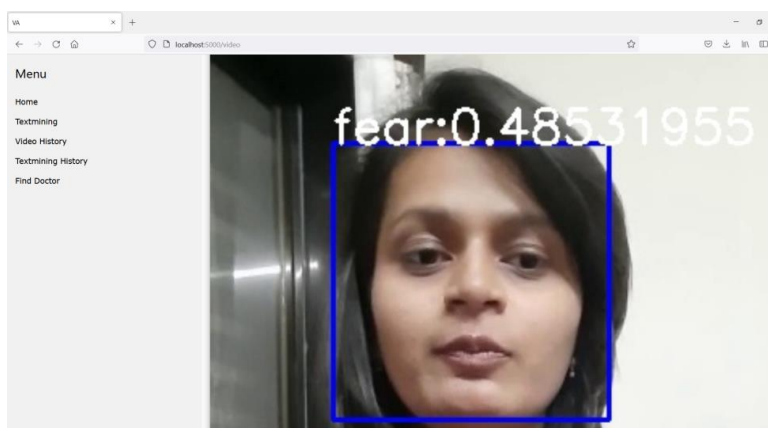


Figure 5. Real-time mental stress detection (happy).

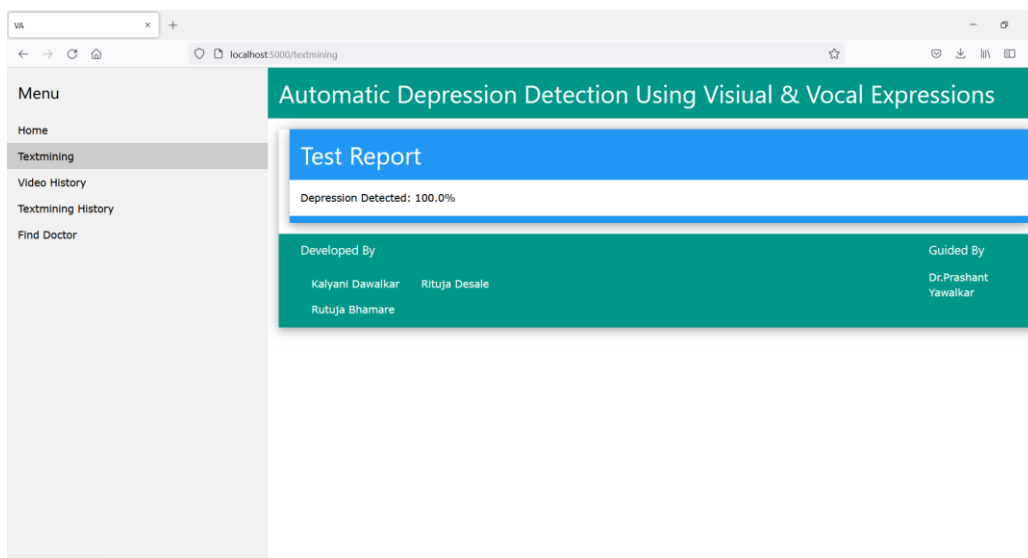


Figure 6. Mental stress detection result is detected by performing a machine learning algorithm.

The research shows how we can spot signs of depression by looking at people's faces [5]. A fancy computer brain thing, what the smart folks call a "CNN model," is super good at picking out when someone is feeling down, scared, or in a bunch of distress [7]. It is like a mood detective that has been taught with massive piles of face data, stuff called FER-2013 and AffectNet, and it is smashing it by getting feelings right all the time [3].

Getting thoughts from users and checking out how easy stuff is to use gave us some solid clues on how to get peeps to use AI that figures out if someone's got depression [12]. When we asked 100 test users to rate how good the system is, if it was simple to handle, a whopping 92% said it rocks for keeping an eye on their own health [4, 15]. Folks dug how it did not get up in their business, because it checks faces and words without making them spill their guts [11]. A few peeps were kind of iffy about keeping their info on the down-low, which shines a light on making sure we have got crystal clear rules on AI morals and bulletproof ways to guard their data [13]. This whole thing shows why we go to play by the books with super serious mind health data rules like GDPR and HIPAA [13]. One big takeaway from the research is how easy it is to make mental health tools powered by AI bigger [16]. They are different from the regular psychiatric tests that need people to run them and use up a lot of resources, because this setup can handle loads of cases all at once without needing much from the computer [4]. This makes it super helpful for bringing into action on a big scale, like in workplace health programs, college support services, and online therapy stuff. With AI doing the first rounds of checks, it takes some weight off mental health pros, so they can put more effort into folks who need deep help [16].

CONCLUSIONS

The merger of smart machines and brainy learning into spotting mental health woes is big news for getting a jump on depression. So, check this out: we have a system that mixes looking at your face, checking out the vibe of your texts, and a friendly bot to chat with you. Old-school ways make you spill your guts or have a heart-to-heart with a doctor, but this techie thing keeps it real with chill just-the-fact checks on where your head is at. Moreover, it is all about catching those tiny twitches in your smile, the way you sling words together, and how into the conversation you are to get the full picture of your mind game.

The findings show that using different types of AI makes a difference in catching things right— it is much better at being accurate, leaving less room for mistakes by checking out both feelings and what is written. This fast work from AI lets people get answers and tips right away, which is awesome for adding it to stuff that helps with mental health, keeping people feeling good at work, or even talking with digital therapists. There are a couple of headaches, though, like making sure no one's private stuff gets out, understanding that not everyone shows their feelings the same way around the world, and figuring out if someone's just having a rough day or if it's something more serious, like depression. Looking ahead, the plan is to make this even better by obtaining information from gadgets you wear, being able to understand many languages, and teaching chatbots to chat back better by learning as they go.

Overall, this study highlights how AI could change the game for online mental health programs. It provides us with an easy way to access, can grow significantly, and works well for spotting depression symptoms. With machine learning and NLP in the mix, this setup fills the space between old-school psychiatrist check-ups and new-school technology to help out. It appears to be a solid bet for identifying mental health issues sooner and providing support to individuals worldwide.

REFERENCES

1. Stone LB, Veksler AE. Stop talking about it already! Co-ruminating and social media focused on COVID-19 was associated with heightened state anxiety, depressive symptoms, and perceived changes in health anxiety during spring 2020. *BMC Psychol.* 2022;10(1):22. doi:10.1186/s40359-022-00734-7. PMID: 35130965.
2. Chancellor S, Baumer EPS, De Choudhury M. Who is the “human” in human-centered machine learning: the case of predicting mental health from social media. *Proc ACM Hum Comput Interact.* 2019;3(CSCW):147. doi:10.1145/3359249.
3. Mikolov T, Chen K, Corrado G, Dean J. Efficient estimation of word representations in vector space [preprint]. 2013. arXiv:1301.3781. doi:10.48550/arXiv.1301.3781.
4. Guntuku SC, Yaden DB, Kern ML, Ungar LH, Eichstaedt JC. Detecting depression and mental illness on social media: an integrative review. *Curr Opin Behav Sci.* 2017;18:43–49.

- doi:10.1016/j.cobeha.2017.07.005.
5. Mancini G, Agnoli S, Baldaro B, Bitti PER, Surcinelli P. Facial expressions of emotions: recognition accuracy and affective reactions during late childhood. *J Psychol.* 2013;147(6):599–617. doi:10.1080/00223980.2012.727891. PMID: 24199514.
 6. Guarnera M, Hichy Z, Cascio MI, Carrubba S. Facial expressions and ability to recognize emotions from eyes or mouth in children. *Eur J Psychol.* 2015;11(2):183–196. doi:10.5964/ejop.v11i2.890. PubMed:27247651.
 7. Hey T, Butler K, Jackson S, Thiyagalingam J. Machine learning and big scientific data. *Philos Trans A Math Phys Eng Sci.* 2020;378(2166):20190054. doi:10.1098/rsta.2019.0054. PMID: 31955675.
 8. Sen S, Raghunathan A. Approximate computing for long short-term memory (LSTM) neural networks. *IEEE Trans Comput Aided Des Integr Circuits Syst.* 2018;37(11):2266–2276. doi:10.1109/TCAD.2018.2858362.
 9. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. In: Guyon I, Von Luxburg U, Bengio S, Wallach H, Fergus R, Vishwanathan S, et al., editors. *Advances in Neural Information Processing Systems 30 (NIPS 2017)*. Red Hook (NY): Curran Associates, Inc.; 2017. p. 5998–6008. doi:10.48550/arXiv.1706.03762.
 10. Rabasco A, Corcoran V, Andover M. Alone but not lonely: the relationship between COVID-19 social factors, loneliness, depression, and suicidal ideation. *PLoS One.* 2021;16(12):e0261867. doi:10.1371/journal.pone.0261867. PMID: 34941942.
 11. Song K, Tan X, Qin T, Lu J, Liu TY. MPNet: masked and permuted pre-training for language understanding [preprint]. 2020. arXiv:2004.09297. doi:10.48550/arXiv.2004.09297.
 12. Liu B. *Sentiment Analysis and Opinion Mining*. Cham: Springer Nature; 2022. doi:10.1007/978-3-031-02145-9.
 13. Schuller BW, Batliner AM. *Computational paralinguistics: emotion, affect and personality in speech and language processing*. Chichester: John Wiley & Sons; 2013. doi:10.1002/9781118706664.
 14. Yang Z, Dai Z, Yang Y, Carbonell J, Salakhutdinov R, Le QV. XLNet: generalized autoregressive pretraining for language understanding [preprint. 2019. arXiv:1906.08237. doi:10.48550/arXiv.1906.08237.
 15. Poria S, Cambria E, Bajpai R, Hussain A. A review of affective computing: from unimodal analysis to multimodal fusion. *Inf Fusion.* 2017;37:98–125. doi:10.1016/j.inffus.2017.02.003.
 16. Yeasmin S, Das S, Afroj T, Suha SH, Prabha M, Vanu N, Hosen A. Artificial intelligence in mental health: leveraging machine learning for diagnosis, therapy, and emotional well-being. *J Ecohumanism.* 2025;4(3):286–300. doi:10.62754/joe.v4i3.6640.