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Gamification Model and Behavior Analysis Using NLP

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Abstract Gamification is a trending topic in study and practice, drawing the attention of academics, practitioners and business professionals in domains as diverse as education, information studies, human-computer interaction, and health. In this paper, we present a systematic survey on the use of gamification in published theoretical reviews and research papers involving interactive systems and human participants. We outline current theoretical understandings of gamification and draw comparisons to related approaches, including alternate reality games (ARGs), games with a purpose (GWAPs), and gameful design. We present a multidisciplinary review of gamification in action, focusing on empirical findings related to purpose and context, design of systems, approaches and techniques, and user impact. This project introduces an innovative web-based platform that combines interactive gaming with mental and emotional health analysis. Leveraging the power of Natural Language Processing (NLP) and Large Language Models (LLMs), the platform aims to create a supportive and engaging environment for users to explore their emotions and mental well-being. By integrating gamified elements, the system provides a more approachable and interactive way to engage with personal mental health assessments, making it appealing and accessible to a wide range of users. Overall, this platform provides a comprehensive and user-friendly approach to mental health assessment. By utilizing interactive games and intelligent NLP-driven analysis, the system helps users gain insights into their emotional health in an engaging and approachable way. This unique blend of entertainment and mental health evaluation promotes self-awareness and proactive mental well-being, empowering users to take control of their emotional health with personalized insights and actionable advice.

Keywords: Gamification, Natural Language Processing (NLP), Large Language Models (LLMs), mental Health, Emotional Health.

I. INTRODUCTION

The last fifteen years has seen the rise of the digital game medium in entertainment, popular culture, and as an academic field of study. The success of digital games in the commercial entertainment industry—seen in record-breaking console sales and massively occupied online multiplayer environments—has spurred research into their effects and relevance in the digital age. The gains made by digital games has motivated their adoption for pursuits beyond entertainment. In general, the term is used to describe those features of an interactive system that aim to motivate and engage end-users through the use of game elements and mechanics. As yet, there is no agreed upon standard definition; likewise, there is little cohesion with respect to theoretical underpinnings and what gamification encompasses. Even so, numerous efforts have sought to take advantage of the alleged motivational benefits of gamification approaches despite a lack of empirical research and standards of practice for design and implementation.

The project introduces a web-based platform designed to integrate interactive gaming with mental and emotional health analysis. By combining engaging game mechanics with mental health evaluation, the platform provides users with a unique way to explore their emotional well-being and identify sources of stress or imbalance. With the use of Natural Language Processing (NLP) and Large Language Models (LLMs), users' inputs are carefully analyzed to assess mental and emotional states, offering a personalized approach to mental health insights. This project is particularly relevant in today's world, where mental health challenges are increasingly prevalent, and there is a need for innovative, accessible tools that empower users to understand and manage their emotional health.

II. LITERATURE SURVEY

A. Related Work

In the paper by **Akriti Jaiswal, A. Krishnama Raju, Suman Deb (2020) The Use of NLP for Facial Emotion Recognition** Human Emotion detection from image is one of the most powerful and challenging research task in social communication. This paper presents the design of an artificial intelligence (AI) system capable of emotion detection

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through facial expressions. It discusses about the procedure of emotion detection, which includes basically three main steps: face detection, features extraction, and emotion classification. Explores emotion recognition using CNNs for facial expression analysis, paired with text-based analysis using NLP techniques. Combines visual and textual data inputs. The performance of the proposed method is evaluated using two datasets Facial emotion recognition challenge (FERC- 2013) and Japaness female facial emotion (JAFFE). The accuracies achieved with proposed model are 70.14 and 98.65 percentage for FERC2013 and JAFFE datasets respectively **[1].**

The study by **Wafa Mellouka, Wahida Handouzia (2020) review paper of Facial Emotion Recognition** several areas such as safety, health and in human machine interfaces. The purpose of this paper is to make a study on recent works on automatic facial emotion recognition FER via deep learning. We underline on these contributions treated, the architecture and the databases used and we present the progress made by comparing the proposed methods and the results obtained. The interest of this paper is to serve and guide researchers by review recent works and providing insights to make improvements to this field **[2]**.

Di Wang, Zhichao Xu (2020) Human-computer interaction for game design carried out a study on Human-computer interaction (HCI) attracts more and more attention in automation, multimedia retrieval, computer system, universal computing. Meanwhile, it also poses new challenges to interaction design based on HCI in user experience, aesthetics, game design, and education. This study aimed to analyze and assess literature published in the field of interaction design of HCI **[3].**

In their recent paper, **Adil Majeed, Hasan Mujtaba, Mirza Omer Beg (2020) The Use of NLP using Roman Urdu,** Emotion detection is playing a very important role in our life. People express their emotions in different ways i.e face expression, gestures, speech, and text. This research focuses on detecting emotions from the Roman Urdu text. Previously, A lot of work has been done on different languages for emotion detection but there is limited work done in Roman Urdu. One major issue for the Roman Urdu is the absence of benchmark corpora for emotion detection from text because language assets are essential for different natural language processing (NLP) tasks. There are many useful applications of the emotional analysis of a text such as improving the quality of products, dialog systems, investment trends, mental health. In this research, to focus on the emotional polarity of the Roman Urdu sentence we develop a comprehensive corpus of 18k sentences that are gathered from different domains and annotate it with six different classes **[4]**.

Mohammad Fathian, Hossein Sharifi, Elnaz Nasirzadeh (2020) Employee engagement as one of the significant achievements of gamification is a major factor for increasing organizational productivity. In this paper we try to theorize the role of gamification in the enterprises from the employee perspective. The main objective of this research is to identify the major role of gamification as a new facilitating technology and organizational capability through examining the nomological network of influences. We highlight the strong interactions among three organizational capabilities in the form of mechanic options, dynamics, and positive emotions and their mediating role between gamification competence and enterprise's performance **[5].**

Saurav Joshi, Tanuj Jain, Nidhi Nair (2021) The use of NLP using LSTM-CNN Architecture using Emotion based music, Music has greatly influenced the human brain and helps dispense an exhilarating and frivolous state of mind because it helps us work more effectively. Recommending songs based on emotions will comfort the listener by suggesting music in keeping with the listeners' pervading mental and physical state. Hence, Natural Language Processing and Deep Learning technologies made it possible for machines to read and interpret emotions through texts by recognizing patterns and finding correlations. In this paper, various deep learning models such as Long Short-Term Memory (LSTM), Convolution Neural network (CNN), CNN-LSTM, and LSTM-CNN Architectures were collated for detecting emotions such as angry, happy, love, and sad, the best model was integrated into the application **[6].**

Jeanine Krath, Linda Schürmann, Harald F.O. von Korflesch (2021) Literature Review gamification, serious games and game-based learning, Despite increasing scientific interest in explaining how gamification supports positive affect and motivation, behavior change and learning, there is still a lack of an overview of the current theoretical understanding of the psychological mechanisms of gamification. Previous research has adopted several different angles and remains fragmented. Taking both an observational and explanatory perspective, we examined the theoretical foundations used in research on gamification, serious games and game-based learning through a systematic literature review and then discussed the commonalities of their core assumptions. The overview shows that scientists have used a variety of 118 different theories. Most of them share explicitly formulated or conceptual connections **[7].**

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Aziliz Le Glaz et.al. (2021) Natural Language Processing in Mental Health, The primary aim of this systematic review was to summarize and characterize, in methodological and technical terms, studies that used machine learning and NLP techniques for mental health. The secondary aim was to consider the potential use of these methods in mental health clinical practice. Machine learning and NLP models have been highly topical issues in medicine in recent years and may be considered a new paradigm in medical research. However, these processes tend to confirm clinical hypotheses rather than developing entirely new information, and only one major category of the population is an imprecise cohort **[8].**

Fadhlan Hafizh Permana; Putu Wuri Handayani; Ave Adriana Pinem (2021), Gamification on Brand Engagement and Brand Awareness in Online Marketplaces, This study was conducted to examine the effect of gamification on brand engagement and awareness in online marketplaces. It investigated the impact of three gamification categories, namely, immersion, achievement, and social interaction, on-brand engagement's cognitive, social, emotional, and behavioral dimensions. The study involved 484 survey participants. The data were analyzed using partial least squares structural equation modeling (PLS-SEM). Finally, the cognitive and social dimensions were not found to influence brand awareness. The findings are expected to assist online marketplace developers in evaluating the future implementation of gamification. Finally, this research provides insights into gamification features that can influence brand engagement **[9]**.

Alicia Ruvinsky et.al. (2021) Gamifying Impact on Military Strategy of Nation States, Complex Systems in which humans play a role, namely Human-Integrated Complex Systems (HICS), can be difficult to model or simulate due to the uncertainty introduced by the human component. The game play thereby becomes a means of providing situation awareness and management of the HICS by using human action during game play as a heuristic for pruning the intractable possibility space of the problem at large into a likely probability subspace based on the actions players actually take when playing an HICS game simulation. This paper explores the approach of gamification of real-world HICS problem spaces for situation awareness and management. A gamification methodology is introduced and investigated through the use case of military acquisitions **[10].**

Krishna Somandepalli et.al. (2021) Human-Centered Machine Analysis of Media, Modern deep learning models combined with audiovisual signal processing can analyze entertainment media, such as Film & TV content to quantify gender, age, and race representations. This creates awareness in an objective way that was hitherto impossible. On the other hand, text mining and natural language processing allow nuanced understanding of language use and spoken interactions in media, such as News to track patterns and trends across different contexts. Moreover, advances in human sensing have enabled us to directly measure the influence of media on an individual's physiology (and brain), while social media analysis enables tracking the societal impact of media content on different cross sections of the society **[11].**

Jia-Hao Hsu, Chung-Hsien Wu, Tsung-Hsien Yang (2021) BERT-based Sentiment Analysis from Multiple Essences of the Text, Text sentiment analysis has always been an important topic in the research of human-computer interactions and is generally applied to help businesses monitor product satisfaction and understand customer needs. The BERT - based model is employed to integrate the outputs from sentence, key terms and events of the input text for task-aware sentiment analysis. The pre-trained sentence-based BERT model is fine-tuned using the Ren-CECps, a large-size Chinese weblog emotion corpus. Then we transfer the encoder weights to a new model and initialize a new linear layer, and finally fine- tune this model to fit the specific task **[12].**

Pradnya Kedari; Mihir Kapile; Divya Kadole; Sagar Jaikar (2021) Face Emotion Detection Using Deep Learning, Human facial expressions convey abundant information visually instead of vocally. Face expression recognition plays an important role within the world of human-machine interaction. Recognition of facial expression by computer with high recognition accuracy remains a challenging task. This article gives the summary of current Facial Emotion Recognition (FER) stages, techniques, and datasets. FER is usually carried out in three stages involving face detection, feature extraction, and expression classification **[13].**

Alwin Poulose, Jung Hwan Kim, Dong Seog Han (2021) Facial Emotion Recognition Using Facial Landmarks, The facial emotion recognition (FER) system classifies the driver's emotions and these results are crucial in the autonomous driving system (ADS). we propose a feature vector extraction technique that combines the facial image pixel values with the facial landmarks and the deep learning model uses these combined features as its input. Our experiments and results show that the proposed feature vector extraction-based FER approach reduces the classification error for emotion recognition and enhances the performance of the system. The proposed FER approach achieved a classification accuracy of 99.96% and a 0.095 model loss from the ResNet architecture **[14].**

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Cristina Luna-Jiménez et.al. (2021) Multimodal Emotion Recognition Using Aural Transformers, Emotion recognition is attracting the attention of the research community due to its multiple applications in different fields, such as medicine or autonomous driving. In this paper, we proposed an automatic emotion recognizer system that consisted of a speech emotion recognizer (SER) and a facial emotion recognizer (FER). Results showed that sequential models beat static models by a narrow difference. Finally, combining these two modalities with a late fusion strategy, we achieved 86.70% accuracy on the RAVDESS dataset on a subject-wise 5-CV evaluation, classifying eight emotions. Results demonstrated that these modalities carried relevant information to detect users' emotional state and their combination allowed to improve the final system performance **[15].**

K.R. Prabha, B. Nataraj, R. Ajaydevan, S. Kabilan, V. Muthuselvam (2022) Facial Emotion Recognition Methods using Different Machine Learning Techniques, Artificial intelligence has faced a rapid growth and it has made a huge change in this world. In real time the traditional algorithm has go phut to reach the human demands. The thoughts, behavior and feeling of a human can be determined by his/her emotions. By utilizing the characteristics of deep learning/machine learning and different methods such as input analysis, face unlocking, etc. A facial emotions recognition system can be built and can be implemented with good accuracy. The project mainly focuses on comparison of different available deep and machine learning algorithm and find different metrices like matrix, accuracy, estimated time, validation time, etc **[16].**

Ashley Dowd, Navid Hashemi Tonekaboni (2022) Facial Emotion Detection Through the Use of Machine Learning and On-Edge Computing, In this research study, we implemented a customized deep learning model for sentiment analysis through facial emotion detection to be used in real-time. This study aims to maximize the model's accuracy and create a lightweight model for real-time Facial Expression Recognition (FER) on edge devices. The primary advantage of the proposed model is the simplified architecture which makes it lightweight and suitable to be deployed on various edge devices for real-time applications. We show how a lightweight but fine-tuned model can achieve higher accuracy than more complicated models proposed in recent studies **[17].**

Tejashwini S Konappanavar; Jagadish S Loni; Shrinivas Adhyapak; Shashidhar B Patil (2023) Facial Emotion Detection Using Machine Learning, In recent years, the advancements in Machine Learning (ML) and Computer Vision (CV) techniques have facilitated the development of "Real-time Facial Emotion Detection" systems. These platforms find utility in a range of domains, encompassing human-computer Engagement, psychology, and human emotion analysis and provides a novel approach for "Real-time Facial Emotion Detection Using Machine Learning" (RFEDUML) algorithms. The proposed system utilizes ML functionalities, particularly "Convolutional Neural Networks" (CNNs), to analyze and classify facial emotions from live pictures **[18].**

Sridhar K V; Sitaram Thripurala (2023) Facial Emotion Detection System Using Multimodal Fusion Deep Learning Architecture, One of the crucial applications in the area of computer vision is face emotion detection. Systems for detecting facial emotions are frequently utilized in fields of study such as the detection of human social and physiological interactions and the diagnosis of mental diseases. To improve accuracy, the facial landmarks of the images are extracted and incorporated into the deep learning network through the Multimodal Fusion approach. By incorporating the facial landmarks through multimodal fusion, the validation accuracies of the deep learning networks are improved, and the highest accuracy of 83.458% is obtained with the CoAtN et model **[19].**

Saif Ansari; Praveen Kulkarni; Tm Rajesh; V R Gurudas (2023) Emotion Detection Using Deep Learning: A Survey, The long history of facial expression analysis has influenced current research and public interest. In this analytical study, the creation of an artificial intelligence (AI) system that can recognize emotions from facial expressions is presented. It discusses the various techniques for doing so, which generally involve three steps: face uncovering, feature extraction, and sentiment categorization. This study describes the various existing solutions and methodologies used by the researchers to build facial landmark interpretation **[20].**

Akshita Sharma; Vriddhi Bajaj; Jatin Arora (2023) Real-Time Emotion Detection from Facial Expressions, Facial expressions recognition by emotion is a crucial component in many applications. This paper covers the recent trends in human emotion detection. An overview of various facial emotion recognition and its applications are presented. In the literature review, major machine-learning techniques used for facial emotion identification have been explored. Machine learning approaches are compared on the basis of their advantages, disadvantages, and their accuracy **[21].**

Hala J. Alshahrani et.al. (2023) Optimizer-Based Ensemble Learning Strategy in Natural Language Processing, Natural Language Processing (NLP) is the most vital technology in currently utilized, specifically caused by the huge and growing count of online texts that requires that understood for its massive value that completely asserted. NLP is

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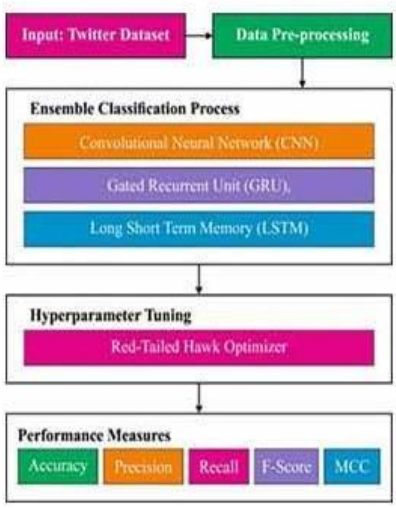
creating a sense of unstructured data, which are created by social networks and other social data sources, and is supported to organize them into an additional structured model that assists several kinds of tasks and applications. Sentiment analysis (SA), a subfield of NLP contains determining the sentiment expressed or emotional tone from a piece of text. Deep learning (DL) approaches are significantly advanced the field of SA, permitting for more accurate and nuanced classification of sentiments from the text data **[22].**



Overall procedure of ASA-RTHEL algorithm

Diana L. Hernández-Romero et.al. (2023) Natural Language Processing for Educational Videogame Modeling, The main objective is to motivate students to obtain new knowledge or study what they have already learned in the classroom while playing video games, and for teachers to obtain relevant data on the learning level of each student. As a result of the proposed architecture, a platform video game for mobile devices has been developed, which performs quizzes on specific topics of biology to high school level education. Users give answers through voice commands, which are processed with the VOSK library, and then compared with other options using the cosine similarity method. Finally, an algorithm leverages the scores acquired from video game actions on scenes and questionnaires to synergistically derive a comprehensive metric that assesses the user's proficiency in learning. This methodology was validated according to several experiments, and in future work, it will be applied to control and test groups of students to validate the level of learning obtained using the proposed platform **[23].**

Divyanshu Katyan; Gaurav Gulati; Gaurav Upreti (2024) NLP for Enhanced Clinical Text Mining, In this research project, key focus is delving into the dynamic landscape of NLP for Clinical Text Mining, highlighting its profound impact on the healthcare industry. Multiple papers have already been written on this topic. These papers focus on a lot of different topics like cancer terminologies, EHR analysis for job extraction, drug attributes etc. These papers include different databases and mention the precision of all the results as well. NLP empowers healthcare providers in several ways. It discusses how NLP streamlines healthcare workflows, leading to more precise and timely diagnosis, personalized treatment plans, and cost-effective healthcare services **[24].**

Yalla Dhinakar; A Reyana (2024) Analysis of Cancer Category using Bidirectional LSTM from Medical Records, Analyzing medical data effectively is critical for making educated decisions and providing patient care in this age of quickly improving healthcare technology. Natural language processing methods, particularly text classification and sentiment analysis in cancer patients' medical records is the primary objective of the proposed work. The goal is to help healthcare professionals diagnose and treat patients more effectively by extracting meaningful insights from textual data **[25].**

Snigdha Luthra et.al. (2024) Sentiment Analysis Using Community Guided Link Prediction for Connecting People with Similar Interest, this approach helps create a network structure that fosters positive interactions and reduces the occurrence of intolerable comments. The experimental comparison of community detection algorithms underscores the effectiveness of our approach, particularly the superior performance of the Cluster Edge Betweenness algorithm. It achieves high accuracy in identifying user interests and forming cohesive clusters, essential for enhancing

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user engagement and community cohesion within social media networks. The qualitative analysis of comments leads to the formation of communities within the network, uniting users with similar interests into cohesive clusters **[26].**

Chaitanya Singla, Sukhdev Singh, Preeti Sharma, Nitin Mittal & Fikreselam Gared (2024) Emotion recognition for human-computer interaction using high-level description, Recent research has focused extensively on employing Deep Learning (DL) techniques, particularly Convolutional Neural Networks (CNN), for Speech Emotion Recognition (SER). This study addresses the burgeoning interest in leveraging DL for SER, specifically focusing on Punjabi language speakers. The paper presents a novel approach to constructing and preprocessing a labeled speech corpus using diverse social media sources. By utilizing spectrograms as the primary feature representation, the proposed algorithm effectively learns discriminative patterns for emotion recognition. The method is evaluated on a custom dataset derived from various Punjabi media sources, including films and web series. Results demonstrate that the proposed approach achieves an accuracy of 69%, surpassing traditional methods like decision trees, Naïve Bayes, and random forests, which achieved accuracies of 49%, 52%, and 61% respectively. Thus, the proposed method improves accuracy in recognizing emotions from Punjabi speech signals **[27].**

Table 1. Overview of various datasets.

Dataset	Language	Size	Emotions	Type	Modalities	Access Type
Berlin Emotional Database (EmoDB) 12	German	7 Emotions × 10 speakers (5male, 5female) × 10 utter- ances	Anger, boredom, disgust, fear, happiness, sadness, neutral	Acted	Audio	Freely Available
Chinese Emotional Speech Corpus (CASIA) 13	Mandarin	6 Emotions × 4 Speakers (2male, 2female) × 500utter- ances (300parallel, 200 non- parallel texts)	Surprise, happiness, sadness, anger, fear, neutral	Spontaneous	Audio	Commercially Available
The Interactive Emotional Dyadic Motion Capture Data- base (IEMOCAP) 7	English	10 speakers (5male, 5 female)1150 utterances	Happiness, anger, sadness, frustration, neutral	Acted	Audio, Visual	Free to research use
Toronto Emotional Speech Database (TESS) 14	English	2 speakers(female), 2800 utterances	Anger, disgust, neutral fear, happiness, sadness, pleasant, surprise	Acted	Audio	Freely Available
Chinese Annotated Spontane- ous Speech Corpus (CASS) 15	Mandarin	7 speakers (2male, 5 female), 6 h of speech	Anger, fear, happiness, sadness, surprise, neutral	Spontaneous	Audio	Commercially Available
Chinese Natural Emotional Audio–Visual Database (CHEAVD) 16	Mandarin	238 speakers 140-min emo- tional segments from movies, and TV-shows	Anger, anxiety, disgust, happi- ness, neutral, sadness, surprise, and worried	Spontaneous	Audio, Visual	Free to research use
Danish Emotional Speech Database (DES) 17	Danish	4 speakers (2male, 2 female)10 min of speech	Neutral, surprise, anger, happi- ness, sadness	Acted	Audio	Freely Available
eNTERFACE'0 5 Audio-Visual Emotion Database 18	English	42 speakers (34male, 8 female) from 14 nationalities, 1116 videos sequences	Anger, disgust, fear, happiness, sadness, surprise	Elicited	Audio, Visual	Freely Available
SUSTBangla Emotional Speech	Bangla	20 Professional actors (10 males, 10 females)	Anger, Disgust, Fear, Hap- piness, Neutral, Sadness	Acted	Audio	Freely Available

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Corpus (SUBESCO) 9		participated in the recording of 10 sentences that consists of 7000 utterances	and Surprise			
Urdu-Sindhi speech emotion corpus 10	Urdu, Sindhi	1435 utterances	Happiness, anger, sadness, disgust, surprise, sarcasm, neutral	Acted	Audio	For Research use available on Request
Indian Institute of Technology Kharagpur Simulated Emotion Hindi Speech Corpus (IITKGP-SEHSC) 8	Hindi	12,000 utterances by 10 actors	Happy, anger, fear, disgust, surprise, sad, sarcastic, neutral	Acted	Audio	For Research use available on Request

Table 2. Overview of literature review based on classifiers.

References	Dataset	Emotions	Classifier	Result Analysis
Yoon et al. 28	IEMOCAP	Happy, Sad, Angry, Neutral	RNN	A multimodal dataset was used taking speech and text modality. The accuracy achieved by combining both modalities was 68.8%
Kumbhar et al.29	RAVDEES	Happy, Sad, Angry, Surprise, Disgust, Fear	LSTM	80.81% accuracy was achieved by extracting the MFCC features after applying the LSTM model to the dataset
Mustaqueen et al. 30	IEMOCAP	Happy, Sad, Angry, and Neutral	CNN	72.2% accuracy was achieved on the IEMOCAP dataset. A novel SER architecture for the SER was also created
Shixin et al. 31	IEMPCAP, MELD	Happy, Sad, Angry, and Neutral	LSTM	63.64% accuracy was achieved on the MELD database. Spectrograms are generated from the audio data and word embedding is generated from the Text data using Word2Vec and the autoen- coder fusion method is used for the fusion of both modalities
Makiuchi et al.32	IEMOCAP	Happy, Sad, Angry, and Neutral	CNN, Word2Vec	73% accuracy was achieved using score-based fusion on the IEMOCAP dataset. 70% accuracy was achieved on the speech modality by extracting the spectrograms from the signals
Padi et al. 33	IEMOCAP	Happy, Sad, Angry, and Neutral	ResNet, BERT	Score Based fusion method was used for the recognition of emotions from multimodalities i.e., speech and text. After fusing the overall accuracy of the system was 75.76%
Yenigalla et al. 34	IEMOCAP	Happy, Sad, Angry, and Neutral	CNN	68.5% accuracy achieved. The spectrograms are extracted from the speech signals and fed

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				into the model for the recognition of emotions
Khan 35	Cross-Corpus Datasets	Happy, Sad, Angry, and Neutral	Machine Learning Algorithms	The system uses cross-corpus to train the machine learning models. MFCC features are extracted from the speech signals. The model gives 91.25% accuracy based on the XGBoost classifier on the URDU dataset

B. Problem Statement

This project addresses the need for an innovative, web-based platform that combines interactive gaming with mental and emotional health analysis. By leveraging Natural Language Processing (NLP) and Large Language Models (LLMs), the platform offers a unique way for users to explore their emotions and mental health in an approachable, engaging manner. This solution bridges the gap between passive self-assessment and dynamic, user-centered mental health support, enabling users to track, understand, and manage their emotional states proactively. The goal is to create a more user-friendly, interactive experience that encourages self-awareness, reduces stigma, and ultimately supports mental well-being.

III. PROPOSED SYSTEM

7. System Features

1. User Management Module

- Description: This module handles all aspects of user registration, login, and profile management.
- Functionality: It enables new users to sign up, authenticates returning users, and stores profile information for personalizing the experience.
- Interactions: This module communicates with the Presentation Layer for user interaction and with the Data Layer to securely store user credentials and preferences.

2. Game Module

- Description: The Game Module is the interactive core of the platform, providing various games that guide users through emotional self-assessment exercises.
- Functional Components:
  - Card-Selection Game: Allows users to select topic-specific cards, write reflections, and submit inputs for analysis.
  - Emotional Balance Game: Uses a seesaw metaphor to visualize emotional stability based on user input, providing a real-time representation of emotional balance.
- Interactions: It interacts with the Presentation Layer to display game elements, with the Business Logic Layer for processing user inputs, and with the Data Layer for storing game outcomes and user progress.

3. NLP and Sentiment Analysis Module

- Description: This module performs the sentiment analysis of text inputs provided by users, detecting emotions and stress indicators using NLP and LLM models.
- Functional Components:
  - Sentiment Detection: Identifies positive, negative, or neutral sentiments in user inputs.
  - Emotion Recognition: Recognizes specific emotions (e.g., stress, calmness, happiness) using advanced NLP algorithms. o Interactions: The module communicates with the Game Module to receive user input, processes the text with NLP models in the Business Logic Layer, and sends analysed results to the Feedback Module. Bharati Vidyapeeth's College of Engineering for Women Pune 2024-2025

4. Feedback Module

- Description: This module is responsible for providing personalized feedback to users based on the analysis conducted by the NLP and sentiment analysis module.
- Functionality: It generates actionable recommendations and real-time feedback to encourage self-awareness and mental well-being.

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• Interactions: It receives processed sentiment data from the NLP module, communicates with the Presentation Layer to display feedback, and stores historical feedback in the Data Layer.

5. Progress Tracking and Historical Data Module
• Description: This module tracks user progress over time, recording each game session's results and providing insights into changes in emotional health.
• Functionality: It enables users to view historical emotional assessments and track long-term emotional patterns.
• Interactions: It communicates with the Data Layer to retrieve historical data and with the Presentation Layer to display progress reports to users.

IV. CONCLUSION

In conclusion, this project has been undertaken to explain the integration of interactive gaming with mental and emotional health analysis, leveraging Natural Language Processing (NLP) and Large Language Models (LLMs) to provide users with a unique platform for self-exploration and emotional assessment. The development of two engaging games—the card-selection game and the emotional balance game—serves to enhance users' self-awareness and emotional intelligence by providing them with real-time feedback based on their inputs. This study has found that interactive approaches not only increase user engagement but also facilitate a deeper understanding of personal mental health states. Throughout the project, we have emphasized the significance of personalization in mental health applications, utilizing sentiment analysis to tailor feedback and guidance to individual users. By combining gamification with evidence- based mental health strategies, we have created a platform that encourages users to reflect on their emotions and improve their mental well-being in a supportive, game-like environment. The positive response to our initial designs and functionalities highlights the potential of this innovative approach in the mental health sector.

Ultimately, this project demonstrates that technology, particularly through the lens of gamification and AI, can play a vital role in promoting mental health awareness and support. As we move forward, we are excited about the prospects of expanding the platform's features and capabilities, ensuring that it continues to meet the evolving needs of users and contributes to the broader conversation surrounding mental health and emotional well-being. The findings and insights gained from this project pave the way for future research and development in digital mental health interventions, with the aim of making such resources more accessible and effective for users worldwide.

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