IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 13, Issue 4, April 2024

DOI: 10.17148/IJARCCE.2024.134226

EmoAssist Counseling Chatbot

Divya[1], Kavya[2], Shama[3], Shifali Shetty[4], Shravya[5]

Assistant Professor, Information Science, AJ Institute Of Engineering and Technology, Mangalore, India[1]

Student, Information Science, AJ Institute of Engineering and Technology, Mangalore, India[2-5]

Abstract: The Student Counselling System through Artificial Intelligence (AI) is a cutting-edge platform designed to enhance student well-being, and career readiness. Leveraging advanced AI algorithms, thesystem provides personalized counselling, emotional support, and career guidance to students. A keyfeature of this system is its ability to generate comprehensive reports of counselling conversations, allowing both students and educators to track progress and identify areas of concern. The platform supports both voice and text input during counselling sessions, ensuring flexibility and accessibility for a diverse range of users. The role of Artificial Intelligence in human monitoring and recognition istaking advanced steps on every progress. This technology makes a greater impact on student's life inhelping parents and teachers understand and realize their panic situations. This project introduces a student counseling system integrating Convolutional Neural Networks (CNNs) for emotion recognition from facial expressions. Utilizing open-source Face Emotion Recognition (FER) dataset,the system classifies seven basic emotions: angry, disgusted, fearful, happy, neutral, sad, and surprised. The classifications guide personalized counseling sessions conducted through a chatbot interface integrated with the RASA framework. Interactions are securely stored in a database accessible only to teachers, offering insights into students' emotional states. The CNN model achievedan overall accuracy of 80%, with varying precision and F1-score metrics across emotion categories. The model achieved high accuracy rates of approximately 75% for happiness and 67% for surprise, while demonstrating moderate accuracy of around 53% for neutral and 48% for angry emotions. However, it showed lower accuracy rates of approximately 65% for disgust, 38% for fear, and 49% for sadness. Despite variations in accuracy across emotions, the system aims to enhance student counseling efficacy, promoting holistic well-being and academic success in educational settings.

Keywords: Chat2bot Interface; Convolutional Neural Networks; Emotion Recognition; Face Emotion Recognition (FER) ;RASA framework.

I. INTRODUCTION

M. Sharma, A. Kumari and Jyotsna, " AI-Based Deep Learning Chatbot for Career and Personal Mentorship," 2023 IEEE 3rd International Conference on Technology, Engineering, Management for Societal impact using Marketing, Entrepreneurship and Talent (TEMSMET), Mysuru, India, 2023 [2] .In today's rapidly evolving educational landscape, the well-being and academic success of students are of paramount importance. However, navigating the complexities of student life, including academic challenges, career decisions, and emotional well-being, can often be daunting. To address these multifaceted needs effectively, there is a growing recognition of the importance of comprehensive counselling support within educational institutions. In response to this need, the integration of artificial intelligence (AI) technologies offers a transformative approach to student counselling, providing personalized guidance, emotional support, and career advice. Users can access relevant information efficiently and seamlessly, with the chatbot responding instantly around the clock. The goal is to create an experience where users may find it challenging to distinguish between interacting with a chatbot and a human user. Crucially, he chatbot provides a safe and confidential space for users to express themselves openly, catering to those who may prefer anonymity. By integrating a chatbot into the counseling system, accessibility, efficiency, and support are enhanced, ensuring users receive the assistance they need when navigating mental health challenges [3]. Data collection is vital for AI projects, as the trained data influences algorithm accuracy and efficiency. Data can be gathered from various sources including employees, social media APIs, random generation, and college databases [1]. Data preprocessing follows collection, aiming to organize and clean the data by addressing null values, invalid entries, and formatting issues. This involves replacing missing data, handling garbage values, and ensuring proper organization for further processing. In the final step of training and testing, the quality of data and algorithm performance are evaluated. Approximately 80% of the data is used for training, while 20% is reserved for testing. Training enables the machine to learn and make predictions based on the provided data. Testing verifies if the model accurately predicts outcomes. If the model demonstrates high accuracy in predictions, it remains unchanged; otherwise, adjustments are made to improve its performance [1].The machine learning model utilizes TensorFlow, an open-source platform by Google, for building various AI models including deep neural networks, image recognition, and natural language processing.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2024
DOI: 10.17148/IJARCCE.2024.134226

Keras, a framework running on top of TensorFlow, is employed for model development. HTML and CSS are utilized for creating the graphical user interface (GUI) of the chatbot, providing structure and visual layout to interactive web pages[2]. Flask, a Python web framework, is integrated with HTML to develop a user-friendly web application for efficient mentoring tasks. Using TensorFlow API, the chatbot selects the best-suited answer from the dataset and provides it to the user either in speech or text format. The conversation continues in a loop until the user exits with a designated greeting, shutting down the API [2]. In a counseling system, Natural Language Processing (NLP) serves as the backbone, enabling the system to understand and respond to user queries effectively. Through Natural Language Understanding (NLU), the system analyzes user input to grasp the underlying intent, emotions, and topics of concern. This allows it to tailor responses that are personalized and empathetic, addressing the user's needs comprehensively. Meanwhile, Natural Language Generation (NLG) empowers the system to craft coherent and contextually appropriate responses, fostering a supportive and engaging interaction. By leveraging NLP techniques, the counseling system creates a conducive environment for users to express themselves, receive guidance, and access relevant resources, thereby enhancing the overall counseling experience[3]. Speech Emotion Recognition (SER) is employed to extract spectral and prosodic features from audio input, enabling the system to understand the emotional state of the user. This is followed by speech-to-text conversion to transform the audio signal into text data, which undergoes structuring,cleaning, and preprocessing for further analysis. An ensemble of Deep Learning Models is then utilized for emotion classification based on Mel-frequency features extracted from the audio signal and sentiment analysis of the processed text data. Finally, an interactive chatbot application is developed to generate appropriate responses based on the comprehensive analysis conducted on user input, facilitating a supportive and engaging interaction experience [9]. The chatbot utilizes predefined reply suggestions stored in a database, with each suggestion linked to a specific emotion. Upon detecting the emotion of a received message, the system stores the message linked with the corresponding emotion.

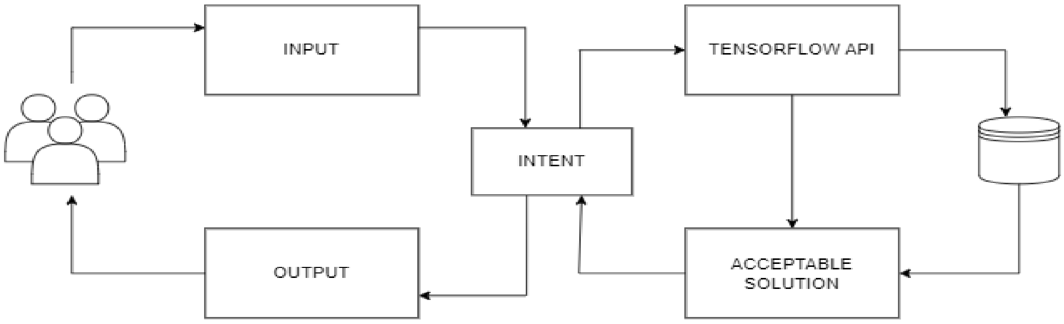


Figure: Workflow Of The Chatbot System

The Process flow involving user input, intent determination, processing through the TensorFlow API, and generating an output. The system begins with user input, identifies the intent, processes it using TensorFlow, evaluates the solution's acceptability, and finally produces an output. It's a simplified representation of natural language understanding and response systems [2].

II. LITERATURE SURVEY

[2] AI -Based Deep Learning Chatbot for Careerand Personal Mentorship:Muskan Sharma, Anita Kumari, Jyostna A proposed AI-based counseling system allows students to express themselves anonymously, seeking guidance on academic and personal matters. Utilizing NLP, it offers tailored responses but may lack nuanced emotional support. Standardized documentation is absent, hindering comprehensive progress tracking. Addressing panic attacks and decision-making struggles early can prevent tragic outcome.[11] Machine Learning based Intelligent Career Counselling Chatbot(ICCC): Dr. Reema Goyal, Navneet Chaudhary, and Mandeep Singh present ICCC, a chatbot, offers tailored career guidance for 10th, 12th, and BTech CSE/IT students. Incorporating Emotional Intelligence and a user-friendly interface, it resolves doubts, aids learning, and addresses personal and professional concerns.Positioned within the CA and AI chatbot landscape, it draws on Io and Lee's and Adam et al.'s analyses.[1] Online Career Counseling System Based on Artificial Intelligence:Yoshitaka Sakurai, Ernesto Damiani, and Andrea Kutics CRECA introduces a Virtual Counseling Agent (VCA) with human-friendly features, aiding diverse demographics, especially the elderly. Utilizing Google Cloud Speech API, it ensures effective dialogue with error processing. Evaluation with 14 subjects demonstrates enhanced engagement and positive outcomes, highlighting its potential to address mental health challenges with compassion and tailored counselling. [12] Student's Attention Monitoring System in Learning Environments based on Artificial Intelligence: Daniel F. Terraza, Mauricio Alejandro, Martinez- vargas Terraza et al. and Canedo, Trifan, and

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 13, Issue 4, April 2024

DOI: 10.17148/IJARCCE.2024.134226

Neves explore computer vision techniques for monitoring students' attentiveness in online and classroom settings. Using deep learning, they analyze facial landmarks and video sequences to track attention levels, highlighting the importance of understanding students' emotional states during teaching and learning. [13]Visualizing Student Opinion Through Text Analysis:Yoshitaka Sakurai, Yukino Ikegami, Andrea Kutics,Rainer Knauf The proposed system employs text analysis techniques, notably Latent Dirichlet Allocation (LDA), to visualize student satisfaction remarks. By incorporating sentiment analysis and visualization, educators gain insights into recurring themes across semesters, facilitating pedagogical improvements. The methodology emphasizes sentiment and visualization for practical usage, aiding educators in course enhancement. [2] Using Machine Learning to explore the relation between student engagement and student performance: Fidelia Orji, Julita Vassileva.The paper explores the relationship between student engagement and performance in blended learning. Utilizing MindTap technology, it analyzes students'actions and assessments to predict performance and identify learning-related traits. The study underscores the importance of leveraging machine learning algorithms to enhance teaching and personalize interventions based on students' engagement levels.Acoustic Monitoring System for Teacher and Student Engagement Evaluation: The authors of the paper Arce-Lopera, Cardona, andGarcia

A web application was developed to facilitate and document auditory exchanges between students and teachers during classroom learning. Findings indicate that smartphone apps and in-class response systems enhance engagement and learning outcomes. The study emphasizes the potential of technology-mediated interaction monitoring to improve classroom dynamics and learning outcomes.[7] Monitoring and alerting panic situation in students using artificial intelligence:Aishwarya Gowda A G, Hui-Kai Su The proposed AI-based system monitors and alerts students in panic situations, emphasizing the importance of identifying and addressing their emotions and behaviors. Using facial expression recognition and behavioral patterns, it aims to enhance student safety and well-being, stressing the importance of privacy, accuracy, and efficiency in future research.[5] Monitoring system to ease self-regulated learning processes:Mario Manso-Vazquez, Martin Llamas-Nistal The proposed article introduces the MLO, integrating the KWL learning technique to facilitate self-regulated learning (SRL). By promoting reflection and awareness, users identify knowledge gaps and set goals. MLO employs ad hoc and learning analytics techniques to analyze user behavior, fostering critical thinking and autonomy in learners within a personal learning environment.

[9]Student performance analysis and counselling system (SPACS) using soft computing by Fuzzy rule formation and decision making: Bharati Sanjay Ainapure, Pratibha Reddy, Srika R Khope, N. B. Hulle, B. AppasaniThe paper introduces a system using fuzzy logic to analyze student performance and counseling. While exploring various fuzzy logic methods, it highlights the challenge of efficiently determining important factors and accounting for emotional stability. Despite proposing models for assessment, their effectiveness and accuracy remain uncertain, particularly with limited sample sizes.

III. EXISTING SYSTEM

In today's educational landscape, AI-driven student counselling systems have become increasingly prevalent, offering tailored and scalable assistance to students to enhance both their mental well-being and academic performance. Here's a closer look at how these systems operate.

A. Support Vector Machines (SVM)[11]: SVM is a sophisticated machine learning algorithm utilized for tasks such as emotion detection. However, the efficacy of SVM models heavily relies on factors like the choice of kernel function and model parameters. Poor selections in these aspects can compromise the model's performance and its ability to generalize well across different scenarios.

B. Random Forest[5]: Random Forest is another machine learning technique applied in emotion detection. This method constructs decision trees based on features extracted from various data modalities like text or speech. Nevertheless, Random Forest models are susceptible to overfitting, particularly when trained on noisy or highly correlated features. Such overfitting can diminish the model's ability to generalize accurately to new data.

C. Long Short-Term Memory (LSTM)[10]: LSTM, a type of recurrent neural network (RNN), is adept at capturing long-term dependencies within sequential data, making it suitable for tasks involving emotional analysis. However, LSTM models may encounter challenges such as the vanishing gradient problem, especially when processing lengthy sequences.

D. K-Nearest Neighbours (KNN)[7]: KNN is a straightforward and intuitive classification algorithm commonly employed in various domains, including emotion detection. However, KNN algorithms can be computationally intensive during inference, particularly with large datasets. This computational burden arises from the necessity to compute distances between the query instance and all training instances, potentially leading to slower response times in real-time applications.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 4, April 2024
DOI: 10.17148/IJARCCE.2024.134226

IV. METHODOLOGY

A. Facial Emotion Recognition Model Development In the development of a Facial Emotion Recognition (FER) model, an open-source dataset is utilized to gather diverse facial expression images annotated with various emotions. The dataset undergoes thorough preprocessing, augmentation, and division intotraining, validation, and test sets. Emotion labels are encoded to ensure compatibility with the training algorithm, ensuring data quality before proceeding to training.

During data preprocessing, collected facial expression images are standardized to 48x48 pixels using OpenCV and converted into NumPy arrays. Pixel values are normalized to [0, 1] to facilitate efficient training and maintain data consistency. Emotion labels, including anger, disgust, fear, happiness, neutrality, sadness, and surprise, are encoded and converted into categorical format using Label Encoder and Keras to_categorical function, enhancing compatibility with the emotion recognition model.

B. CNN Model Architecture
A Convolutional Neural Network (CNN) model is crafted employing Keras to analyze facial expressions. The CNN architecture encompasses multiple convolutional and pooling layers, facilitating the extraction of significant features from facial images.

These layers are succeeded by fully connected layers, aiding in the classification of emotions discerned during counselling sessions.

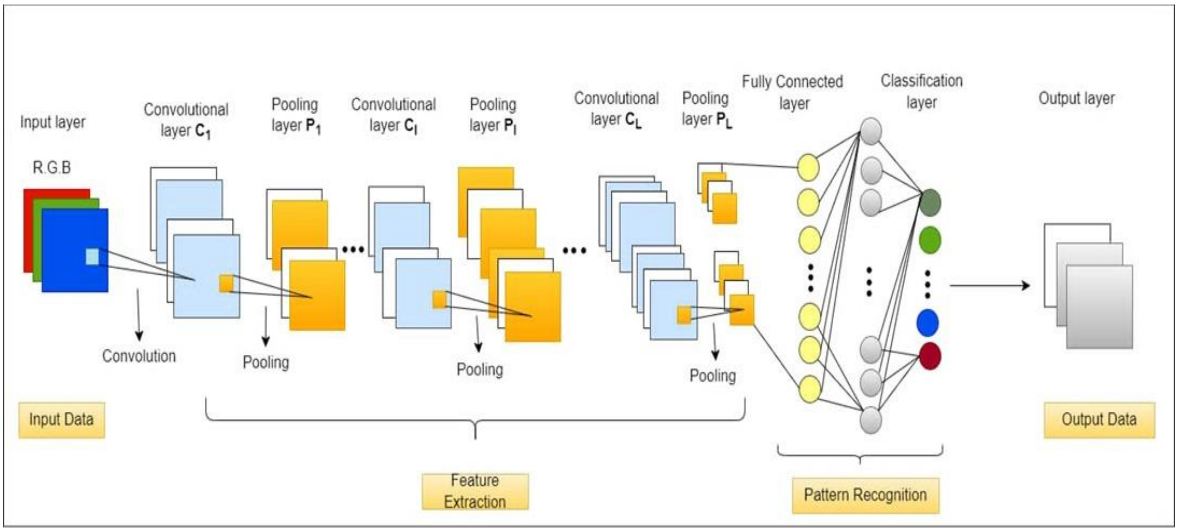


Figure 2: CNN Model Architecture in Counseling

B. Train Test Split Data classification is pivotal for organizing data into groups or classes based on specific characteristics, facilitating comparisons among observation categories. The training and testing data split involves visualizing the prepared data to ensure correct labeling of the target attribute. The dataset is divided into 90 samples for training and 10 for testing. Training the machine learning (ML) model entails providing the learning algorithm with training data containing the correct answers, known as the target attribute.

The algorithm identifies patterns in the training data, mapping input attributes to the target, and outputs an ML model that captures these patterns, enabling accurate predictions. Testing the data refers to the process of evaluating the performance and accuracy of a machine learning model using a separate dataset that was not used during the training phase. This involves feeding the unseen data (test data) into the trained model and comparing the model's predictions with the actual known outcomes.

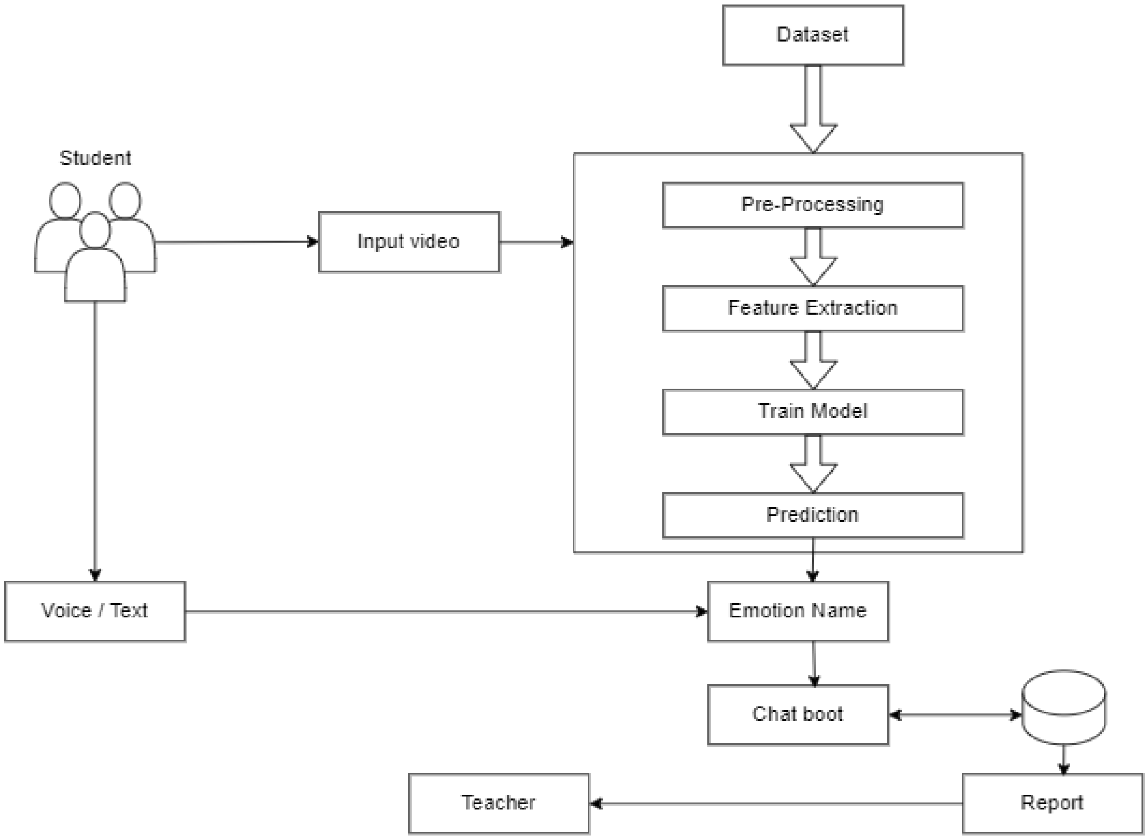
IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⸎ Peer-reviewed & Refereed journal ⸎ Vol. 13, Issue 4, April 2024

DOI: 10.17148/IJARCCE.2024.134226

V. SYSTEM ARCHITECTURE



Dataset: The FER 2013 dataset would serve as the foundational source for training a machine learning model dedicated to emotion detection. Initially, the dataset undergoes preprocessing steps to standardize image dimensions and pixel values. Following this, the dataset is partitioned into training, validation, and testing sets to facilitate model development and evaluation. Leveraging a convolutional neural network (CNN) architecture, the model learns to extract relevant features from facial expressions, discerning nuances in emotion expressions like anger, disgust, fear, happiness, sadness, surprise, and neutrality.

Pre-processing: In a student counseling system, data preprocessing is integral to refining raw data into a format conducive to effective machine learning model utilization. Initially, data is collected from diverse sources like surveys, academic records, and counseling sessions, undergoing rigorous cleaning to rectify inconsistencies and handle missing values. Feature selection and engineering are then conducted to distill relevant attributes and potentially create new features to enhance predictive capabilities.

Input Video: In processing video input for a student counseling system, frames are extracted sequentially, employing specialized libraries or frameworks, and undergo preprocessing to standardize dimensions, convert to appropriate color spaces, and normalize pixel values.

Feature Extraction: In feature extraction for emotion detection in a student counseling system, raw video data undergoes analysis to extract relevant information for understanding the student's emotional state. Initially, facial landmarks are detected using facial landmark detection, enabling the identification of key points on the face such as eyes, nose, and mouth.

Train Model: The model training process begins by preparing the dataset for training, which involves loading the images, resizing them to a consistent size, and normalizing the pixel values. In this code snippet, images from different emotion categories are loaded and prepared using OpenCV and NumPy. After preprocessing the images, they are split into training and validation sets using the train_test_split function from Scikit-learn.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2024
DOI: 10.17148/IJARCCE.2024.134226

Prediction: In predicting emotions using a Convolutional Neural Network (CNN) algorithm, the process involves leveraging the CNN's hierarchical architecture to automatically extract relevant features from input images or video frames, discerning patterns indicative of different emotions. During prediction, the CNN passes the input through convolutional and pooling layers, which detect spatial patterns and features, followed by fully connected layers that learn to map these features to specific emotion categories. Through a softmax activation function, the model outputs a probability distribution over possible emotions, with the highest probability indicating the predicted emotion. This approach enables the CNN to analyze visual cues, such as facial expressions and gestures, and infer the underlying emotional states expressed in the input data, facilitating nuanced and accurate emotion prediction.

Output: The output of the student counseling system, based on the emotion detected, aims to facilitate personalized and supportive conversations tailored to the individual's emotional state. Upon detecting emotions such as happiness, sadness, anger, or others, the system dynamically adjusts its responses to suit the detected emotional context. For example, if the detected emotion is sadness, the system may offer empathetic support, suggest coping strategies, or encourage the individual to share their feelings. Conversely, if the detected emotion is happiness, the system may provide positive reinforcement, acknowledge achievements, or encourage continued engagement.

Chatbot/Teacher: The output can then be directed to a chatbot or a teacher. A chatbot is a computer program that simulates conversation with human users, while a teacher, in the context of machine learning, could be a human instructor who evaluates the model's performance and refines the training process as needed.

Report: Finally, a report is generated. This report likely summarizes the performance of the machine learning model.

VI. RESULT ANALYSIS

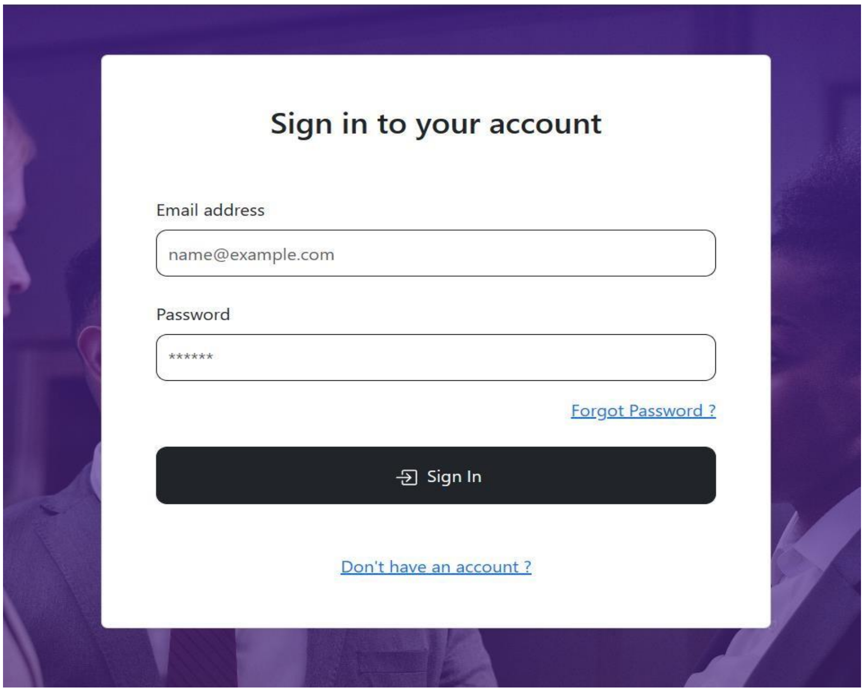


Figure 3: Snapshot of login page

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2024

DOI: 10.17148/IJARCCE.2024.134226

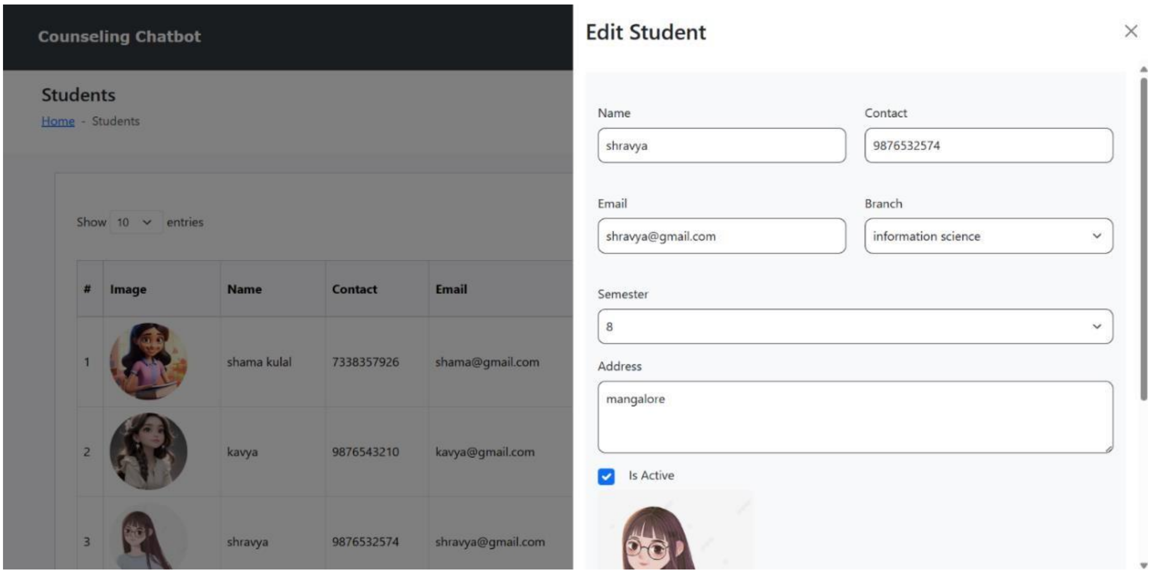


Figure 4: Student details edit page for admin

Figure 5: admin dashboard

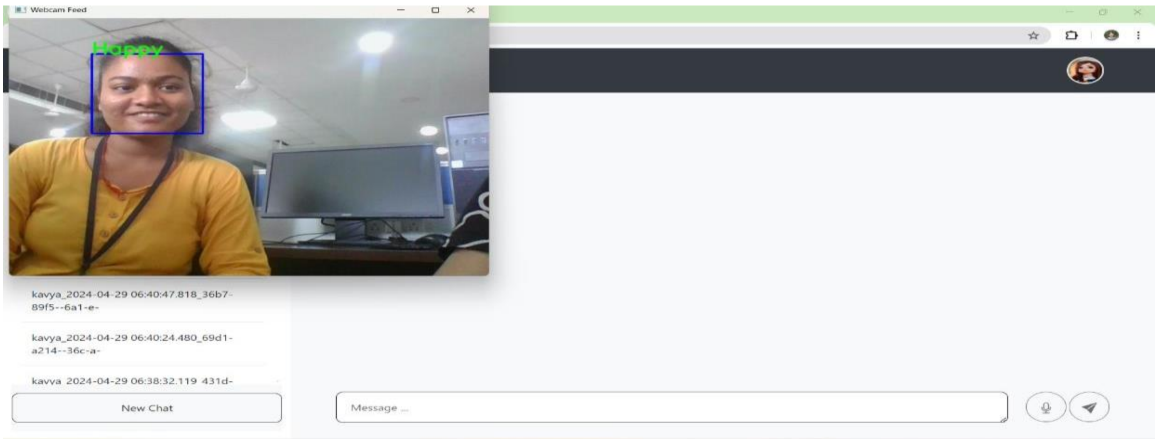


Figure 6: Web Cam Activation for Emotion Detection

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 4, April 2024
DOI: 10.17148/IJARCCE.2024.134226

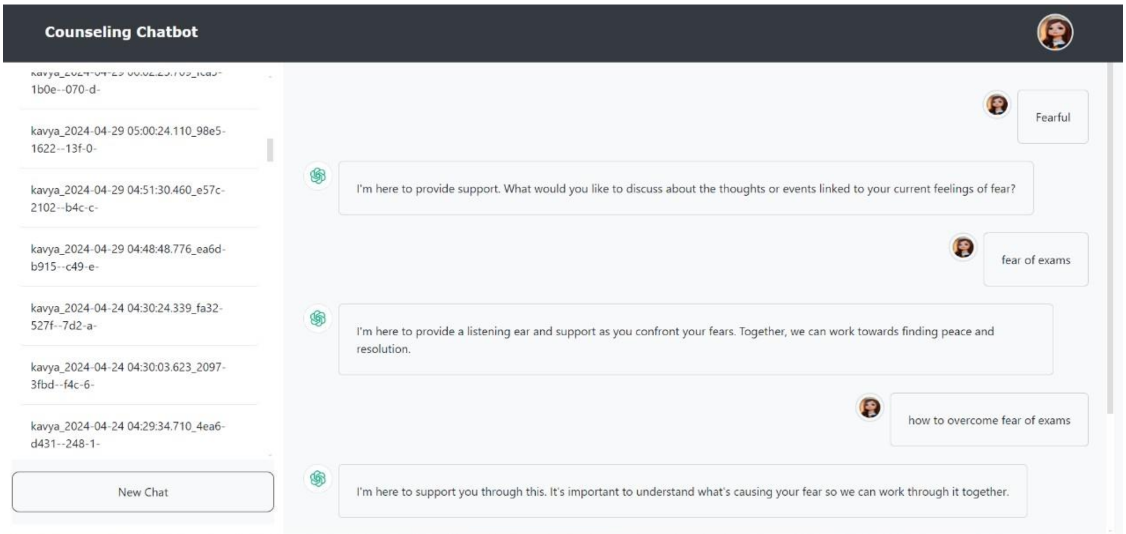


Figure 7: Conversation between student and system in chatbot

VII. CONCLUSION

The implementation of an AI-powered student counseling system heralds a paradigm shift in the landscape of educational support services. By harnessing the capabilities of natural language processing (NLP) and emotion detection, the system transcends traditional boundaries, offering students a dynamic platform to express their concerns and seek guidance in a manner that closely mimics human interaction. This simulated conversation, whether through text or speech, cultivates an environment of trust and openness, encouraging students to freely articulate their emotions and challenges without fear of judgment. Moreover, the incorporation of webcam-based emotion detection adds a new dimension to the counseling experience, enabling the system to discern and respond to individual emotional states in real-time. This personalized approach fosters a sense of empathy and understanding, essential components in nurturing students' holistic well-being.

In tandem with its counseling capabilities, the system integrates on-demand career assistance, recognizing the interconnectedness of academic success and professional aspirations. By providing students with timely guidance and resources tailored to their career interests and goals, it empowers them to make informed decisions about their educational pathways and future endeavors. This forward-thinking dimension not only equips students with practical skills and knowledge but also instills a sense of agency and purpose in their academic journey.

Furthermore, the system's flexibility in accommodating both speech and text inputs ensures inclusivity, catering to diverse learning preferences and needs. Whether students prefer to engage verbally or through written communication, the system adapts seamlessly, ensuring accessibility for all. Additionally, the incorporation of attendance tracking functionalities serves as a valuable tool for educators and counselors, offering insights into student engagement and participation patterns. By monitoring login counts and identifying trends, the system enables proactive intervention strategies to enhance overall student engagement and academic outcomes. In sum, the AI-powered student counseling system represents a holistic approach to student support, leveraging technology to address the multifaceted needs of learners. Its fusion of NLP, emotion detection, career assistance, and attendance tracking creates a comprehensive support ecosystem designed to nurture student well-being and academic success. As educational institutions continue to embrace innovation in student services, this system stands as a beacon of progress, symbolizing the transformative potential of technology in advancing the educational experience

REFERENCES

[1]. B. McMahan et al., "Communication-Efficient Learning of Deep Networks From Decentralized Data", *Artificial Intelligence and Statistics Proc. PMLR*, vol. 10, no. 1, pp. 1273-82, 2017.
[2]. C. En Guo, S.-C. Zhu and Y. N. Wu, "Primal Sketch: Integrating Structure and Texture", *Computer Vision and Image Understanding*, vol. 106, no. 1, pp. 5-19, 2007.

DOI: 10.17148/IJARCCE.2024.134226

[3]. S. Zhang, C. Zhu, J. K. O. Sin, and P. K. T. Mok, "A novel ultrathin elevated channel low-temperature poly-Si TFT," *IEEE Electron Device Lett*., vol. 20, no. 2, pp. 569–571,1999.
[4]. Hogade, N., Pasricha, S. and Siegel, H.J, "Energy and Network Aware Workload Management for Geographically Distributed Data Centers". *IEEE Transactions on Sustainable Computing*, vol.7, no. 2, pp.400–413. 2021
[5]. A. Wierman, Z. Liu, I. Liu and H. Mohsenian-Rad, "Opportunities and challenges for data center demand response", *Proc. Int. Green Comput. Conf.*, vol.7, no. 6, pp.1-10, 2014.
[6]. J. D. Jenkins et al., "The benefits of nuclear flexibility in power system operations with renewable energy", *Appl. Energy,* vol. 22 no. 2, pp. 872-884, 2018.
[7]. Haoying Dai, Yanne Kouomou Chembo, "RF Fingerprinting Based on Reservoir Computing Using Narrowband Optoelectronic Oscillators", *Journal of Lightwave Technology*, vol.40, no.21, pp.7060-7071, 2022.
[8]. Floris Van den Abeele, Jeroen Hoebeke, Girum Ketema Teklemariam, Ingrid Moerman, Piet Demeester, "Sensor Function Virtualization to Support Distributed Intelligence in the Internet of Things", *Wireless Personal Communications*, vol.81, no.4, pp.14-18, 2015.
[9]. J. Hwang, J. Kim and H. Choi, "A review of magnetic actuation systems and magnetically actuated guidewire-and B. Accou, J. Vanthornhout, H. V. Hamme and catheter-based microrobots for vascular interventions", *Intell. Serv. Robot*., vol. 13, no. 1, pp. 1-14, 2020.
[10]. D.G. Feitelson, D. Tsafrir and D. Krakov, "Experience with using the parallel workloads archive", J. Parallel Distrib. Comput., vol. 74, no.3, pp. 2967-2982, 2014.
[11]. T. Francart, "Decoding of the speech envelope from eeg using the vlaai deep neural network", *Scientific Reports*, vol. 13, no. 1, pp. 812, 2023.
[12]. .Serim Lee, Nahyun Kim, Junhyoung Kwon, Gunhee Jang, "Identification of the Position of a Tethered Delivery Catheter to Retrieve an Untethered Magnetic Robot in a Vascular Environment", Micromachines, vol.14, no.4, pp.724, 2023.