JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Student Well-being Prediction and Support System

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***Abstract* - Depression, a multifaceted global mental health challenge, often faces delayed diagnosis reliant on self-reporting. This project aims to revolutionize depression detection and management through an advanced system that analyzes non-verbal cues, social media activity, and emotional expressions for early warning signs. Utilizing Convolutional Neural Networks (CNNs), the system processes images and video data, emphasizing facial expressions linked to depression. Real-time face detection is achieved via Haar Cascade classifiers. Notably, the project incorporates emotional expressions from Bharatanatyam, an Indian classical dance celebrated for its emotional richness, enhancing the understanding of human emotions in this context. The system also analyzes Twitter data using Natural Language Processing (NLP) techniques and machine learning algorithms to identify patterns such as negative sentiment and isolation that indicate depression. By merging non-verbal and textual data, the system improves predictive capabilities, providing a comprehensive approach to early detection. Expected outcomes include a real-time, user-friendly interface facilitating timely interventions for at-risk individuals. With a focus on privacy and accessibility, this project offers a valuable tool for healthcare providers and individuals, aiming to enhance mental health awareness and treatment outcomes.**

***Keywords*: Depression, Mental Health, Early Detection, Machine Learning, Social Media Analysis, Emotion Detection, Predictive Analytics, Public Health.**

I. INTRODUCTION

Depression is a widespread mental health disorder that affects millions globally. Despite its prevalence, accurate and timely diagnosis remains a significant challenge due to the complex and often subtle nature of its symptoms. Traditional diagnostic tools, such as the Patient Health Questionnaire (PHQ), rely heavily on subjective self-reporting, which can result in under-diagnosis and delayed treatment. Early detection is critical for effective intervention, making advancements in artificial intelligence (AI) and machine learning (ML) pivotal to improving mental health outcomes.

Recent research by Al Hanai et al. demonstrated the potential of Long-Short Term Memory (LSTM) networks for analyzing audio and text data in depression detection. Building on this foundation, our project adopts a more comprehensive AI-based approach that integrates multiple data sources, including social media behavior, non-verbal cues, and emotional analysis, to identify early signs of depression. Recognizing the emotional impact of social media, platforms like Twitter provide valuable data for analyzing user behavior and sentiment patterns, particularly for those experiencing emotional distress.

Our system employs a combination of Convolutional Neural Networks (CNNs) and Haar Cascade classifiers to analyze video, image, and real-time facial expressions, which are critical indicators of emotional states. These tools enable precise recognition of non-verbal cues, such as microexpressions and shifts in facial emotion, providing deeper insights into an individual’s mental state. Additionally, we incorporate the expressive elements of Bharatanatyam, a traditional Indian dance form, to enhance cultural sensitivity in detecting emotional nuances. This approach addresses a gap in existing Western-centric models by accounting for culturally specific expressions of emotion, thereby improving the model’s inclusivity and accuracy.

Natural Language Processing (NLP) and ML algorithms complement this non-verbal analysis by examining textual data from social media platforms. By detecting patterns of negative sentiment, emotional volatility, and linguistic markers associated with depression, our system adopts a dual analysis framework that integrates verbal and non-verbal cues. This comprehensive methodology refines depression detection, offering a nuanced understanding of mental health indicators.

A key feature of our system is its emphasis on privacy and data security, ensuring that users’ information is protected throughout the analysis process. Designed for accessibility, the platform supports real-time evaluations, enabling healthcare professionals to make informed decisions promptly. This dual benefit of user-focused design and robust security facilitates timely intervention, empowering mental health practitioners with reliable tools to support their patients effectively.

Our innovative, culturally inclusive AI model holds significant promise for transforming the diagnosis and management of depression on a global scale. By leveraging advanced technologies and diverse data sources, the system aims to raise awareness, improve diagnostic accuracy, and enable earlier interventions. Ultimately, this approach aspires to reduce the global burden of depression, fostering better mental health outcomes and enhancing the quality of life for affected individuals.

II. LITERATURE REVIEW

AI and machine learning advancements have revolutionized depression detection, moving beyond self-reported methods. This review explores key techniques, models, and challenges shaping these systems' development. *Ashraf(2021)* reviewed visual depression datasets, emphasizing the use of Recurrent Neural Networks (RNNs) and pre-trained models like VGGNet for emotion recognition from facial expressions. However, they noted limitations in data variability, model performance, and ethical concerns regarding privacy[1]. *Zhang (2021)* employed Natural Language Processing (NLP) and Support Vector Machines (SVM) to detect depression in Twitter data. While this improved real-time detection, challenges with data quality, context, and privacy remained[2]. *Li and Ding (2020)* applied predictive models and clustering to personalize cognitive therapies. However, data quality, generalizability, and model interpretability limited the study[3]. *Tiryaki, Sonawane, et al.(2020)* focused on using Convolutional Neural Networks (CNNs) to analyse single-lead ECG data for detecting depression-related episodes. The system improved accuracy and speed but struggled with real-time processing challenges and data variability, which affected the robustness of the model[4]. *Lee and Park (2022)* the authors utilized Fast R-CNN to analyse facial expressions for diagnosing depressive disorders. Although the system showed potential in diagnosing emotional states, limitations included challenges with model generalization across diverse populations and cultural differences in emotional expression[5]. Kuhaneswaran, Govindasamy, and Palanichamy (2021) explored depression detection using machine learning techniques on Twitter data. The study focused on employing natural language processing and machine learning models to analyze user tweets for identifying signs of depression. While their methods showed promise in detecting patterns linked to depressive behavior, the researchers highlighted challenges such as the complexity of sentiment analysis, the need for large, diverse datasets, and ethical considerations related to user privacy[6]. Al Asad, Mahmud, Pranto, Afreen, and Islam (2019) investigated depression detection by analyzing social media posts. Their research leveraged machine learning and natural language processing techniques to extract insights from user-generated content. The study demonstrated the potential of social media as a data source for identifying depressive behavior. However, the authors pointed out challenges, including the need for more comprehensive datasets, the complexity of accurately interpreting user intent, and ethical concerns regarding user data privacy and consent[7]. Wang, Chen, Wang, and Diao (2020) proposed a CNN-GAN model for audio-based depression recognition. The study highlighted promising results but noted limitations in dataset diversity, real-world applicability, and audio privacy concerns[8]. Solieman and Pustozerov (2021) investigated depression detection using multimodal models combining text and voice quality features. Their approach demonstrated improved accuracy by integrating linguistic and vocal cues. However, the study highlighted challenges such as limited dataset diversity, complexity in feature fusion, and privacy concerns related to sensitive data[9]. Ding, Chen, Fu, and Zhong (2020) proposed a depression recognition method for college students using a deep integrated support vector algorithm. The approach showed effectiveness in identifying depressive patterns but faced challenges with dataset diversity, scalability, and privacy concerns in sensitive data handling[10].

III. PROPOSED METHODOLOGY

The system architecture combines visual and textual analysis to detect depression through non-verbal cues and social media behavior. It includes Convolutional Neural Networks (CNNs) for real-time facial expression detection, Haar Cascade Classifiers for face detection and non-verbal cue analysis, and Natural Language Processing (NLP) models to analyze Twitter data for emotional patterns linked to depression. This architecture ensures seamless integration and real-time processing of both visual and textual data for accurate depression detection.

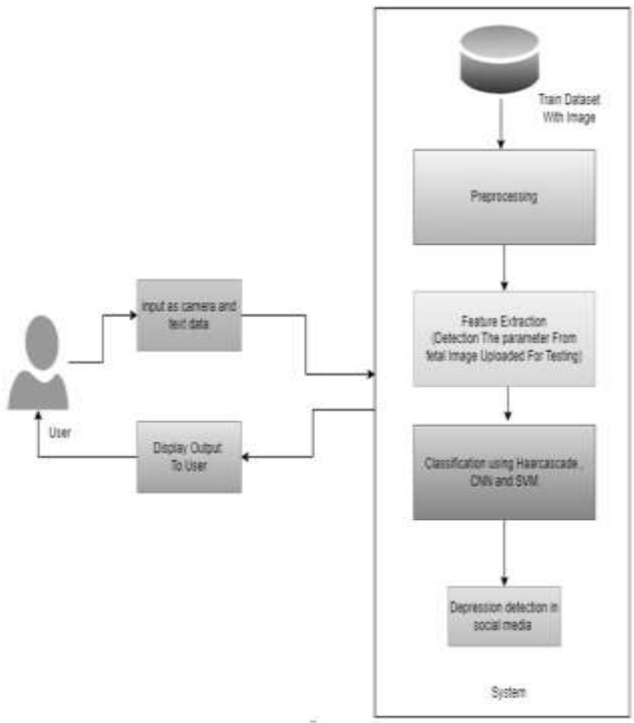

Figure 3.1: System Architecture

Facial and emotional data will be sourced from images, videos, and Bharatanatyam performances to train CNNs on emotional cues. Public Twitter datasets focused on mental health will be analyzed using NLP models to detect depression through sentiment and language patterns.

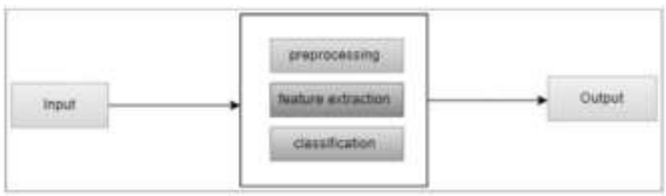

Figure 3.2: Data Flow Diagram

Visual data will be normalized and resized, while Twitter data will undergo tokenization, cleaning, and sentiment analysis for depression detection.

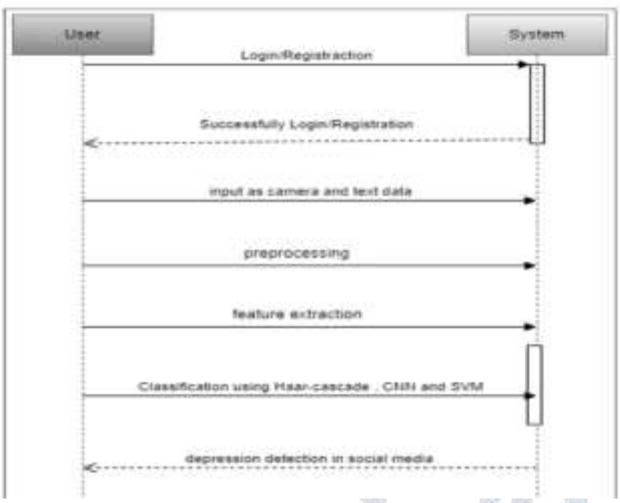

Figure 3.3: Sequence Diagram

The sequence diagram shows how different components interact when a counselor views emotional data. First, the camera captures a student's image, which is processed by the facial detection module to locate faces. The emotion detection model then classifies the emotional state. This data is securely stored in the database. If an alert is triggered, the system sends a notification to the counselor, who can access the dashboard to view emotional trends for individual students.

1.Convolutional Neural Networks (CNNs): CNNs will process visual data (images, video) to identify emotional states, especially depression-related facial expressions. Key elements include:

a) Convolution Layers: Extract image features.
b) Pooling Layers: Reduce dimensionality while preserving key details.
c) Fully-Connected Layers: Classify emotional states.

2.Haar Cascade Classifier: Utilized for real-time face detection, it:

a) Recognizes facial features (eyes, nose, mouth).
b)2Constructs an integral image for efficient feature extraction.
c) Uses a cascade of classifiers to filter non-facial regions, ensuring precision

3.Natural Language Processing (NLP): NLP models analyse tweets for depression markers, applying sentiment analysis, keyword extraction, and topic modelling to detect emotional distress.

CNNs will extract emotional cues from facial expressions, while NLP models identify depressive language and sentiment from Twitter data.

The system integrates CNN-based visual emotion detection with NLP text analysis for accurate depression diagnosis. Haar Cascade classifiers enable real-time face detection, CNNs analyze facial expressions, and NLP models assess depression-related language patterns from Twitter data, ensuring timely intervention and efficient real-time processing of both visual and textual information.

The system which relies on both visual data & text to build its models, uses advanced mathematical functions & computing algorithms for early depression detection.

1.*Convolutional Neural Networks (CNNs)* have layers that will process the image where there are convolutional layer to extract features. The expressed as $y = \sigma(Wx + b)$.

2.Haar Cascade Classifier uses Haar features based on pixel intensity difference for object detection, and calculates these values efficiently with integral images and represented as $A(x,y) = \sum_{i=0}^{x}\sum_{j=0}^{y} I(i,j)$.

3.Natural Language Processing (NLP) utilizes Term Frequency-Inverse Document Frequency (TF-IDF) to assess word relevance and sentiment analysis to calculate sentiment scores.

4.Support Vector Machines (SVM) classify textual data using a decision function defined as $f(x) = \text{sign}(w^T \phi(x) + b)$.

5.Evaluation Metrics include accuracy, precision, recall, and F1 score to assess system performance.

IV. RESULT & DISCUSSIONS

The development of the depression detection system aims to achieve several significant outcomes that will enhance mental health support:

1.Accurate Depression Detection: A robust system capable of accurately detecting early signs of depression through non-verbal cues and social media behaviour using machine learning techniques like CNNs and NLP.

2. Real-Time Analysis: Real-time face detection and emotion recognition, enabling immediate assessment of emotional states from video streams or images for timely intervention.

4. Some Snapshots:

Figure 4.1: Registration Form

Figure 4.1 shows the home page of the Student Well-Being Prediction & Support System, which allows new users to register and existing users to log in. The registration form collects essential details like name, email, phone number, and password to create a secure account. The login form requires a username and password for profile access.

The layout is user-friendly, with clear sections for registration and login, and easy-to-spot buttons. It is responsive, working smoothly on desktops, tablets, and smartphones. Both forms prioritize security through data validation and encryption.

Figure 4.2: CNN Evaluation

Figure 4.2 shows the CNN Analysis Page for users selecting the CNN model. This page lets users analyze their emotions using visual data and either proceed with predictions or exit the session.

The self-evaluation section allows users to upload an image or use a live camera feed for real-time emotion analysis, helping them reflect on their emotional state. A "Predict" button runs the CNN-based analysis, providing a detailed report on emotions and stress levels. An "Exit" button lets users leave the process and return to the home page or dashboard.

The page includes brief instructions, like how to upload an image or use the live feed, ensuring a smooth process. Its responsive design guarantees usability across all devices.

Figure 4.3: Evaluation Outcome

Figure 4.3 shows the Stress Evaluation Results Page, which presents the outcomes of the stress analysis clearly and provides insights into the process.

The page displays the identified emotion, such as "Stress Level: High" or "Emotion: Anxious," along with recommendations or next steps. It also shows the evaluation's execution time, e.g., "Execution Time: 2.34 seconds," ensuring transparency and highlighting system efficiency.

Users can retake the evaluation or exit to the home page using actionable buttons. The design is user-friendly, with a clear layout, icons, and color coding to indicate stress levels (e.g., green for normal, red for high). The responsive layout ensures accessibility on all devices.

5. Increased Awareness of Mental Health:
Raising awareness about early detection and intervention contributing to greater understanding and discussions around mental health issues.
6. Support for Mental Health Professionals:
A valuable tool for healthcare providers, offering insights into patients' emotional states to enhance identification and tailor interventions.
7.Sample Output:
The system will provide output such as:

a. Emotional State Classification: "Depressed" or "Neutral".

b. Facial Expression Analysis: Visual representation of detected

emotions.

Figure 4.4: Different Emotions

8. Impact on Treatment Outcomes:
Improved mental health treatment outcomes through earlier interventions, fostering a supportive environment for individuals struggling with depression.

9.*Tested Dataset:*

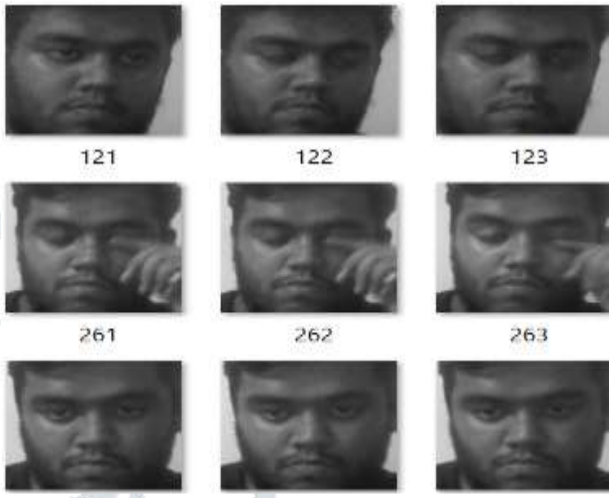

Figure 4.5 Sad Emotion Sample Tested Dataset

Figure 4.6 Happy Emotion Sample Tested Dataset

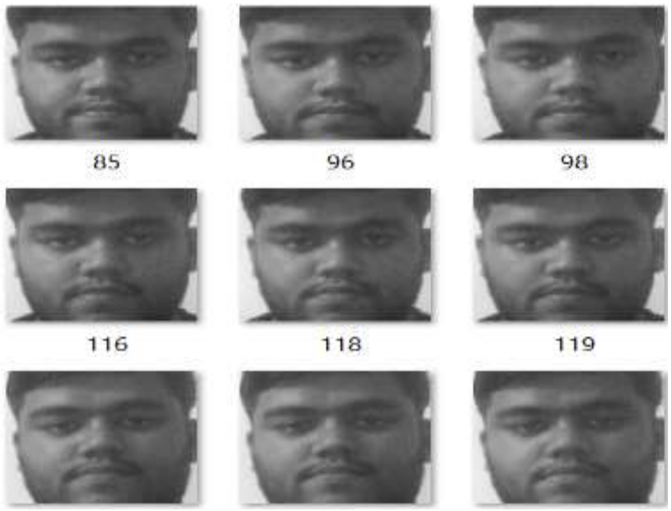

Figure 4.7 Neutral Emotion Sample Tested Dataset

IV. POTENTIAL IMPACT & APPLICATION

1. *Early Intervention*: Facilitates timely detection and support for individuals at risk of depression, potentially reducing severity and improving outcomes.

2. *Mental Health Support*: Enhances existing mental health platforms by integrating objective data analysis, aiding healthcare providers in identifying and monitoring patients' emotional states.

3. *Public Awareness*: Promotes awareness of mental health issues, encouraging open discussions and reducing stigma

associated with seeking help.

4. *Cultural Insights*: Integrates emotional expressions from Bharatanatyam, providing a culturally nuanced understanding of mental health, which can inform future research and applications.
5. *Educational Tools*: Serves as a resource for educational institutions to support students' mental well-being, fostering a healthier learning environment.
6. *Stress Evaluation*:

Stress Evaluation Table :

ID	Risk Description	Probability	Schedule	Quality	Overall
1	Correctness	Low	Low	High	Low
2	Availability	High	Low	High	Low

Stress Evaluation Probability :

Probability	Value	Description
High	Probability of Occurrence is	>75%
Medium	Probability of Occurrence is	26-75%
Low	Probability of Occurrence is	<25%

V. CONCLUSION

In conclusion, the proposed depression detection system marks a significant advancement in mental health support. By integrating sophisticated machine learning techniques, including Convolutional Neural Networks and Natural Language Processing, the system adeptly analyses visual and textual data to detect early signs of depression. Incorporating cultural elements, such as emotional expressions from Bharatanatyam, enhances the nuanced understanding of emotional states.

Expected outcomes include precise, real-time detection, heightened mental health awareness, and robust support for healthcare professionals. The user-friendly interface ensures accessibility for individuals seeking assistance. By promoting early intervention and fostering openness around mental health, this project aspires to positively impact depression treatment and understanding, ultimately improving mental health outcomes

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