Mental Health Detection Using Custom CNN through, Facial Expressions

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***Abstract*—This project is designed to efficiently and precisely detect faces in images, analyze variations in facial features that correspond to different emotional states, and categorize these emotions. It considers a broad spectrum of emotions, ranging from basic to complex expressions. The system is composed of three essential modules: facial detection, feature extraction, and emotion classification.**

***Index Terms*—Facial Expression Recognition, Face Detection, Facial Feature Extraction, Expression Classification**

I. INTRODUCTION

The human face is a vital medium of non-verbal communication and plays a significant role in daily life interactions. Recognizing and interpreting facial expressions typically involve identifying a different emotions including happiness, sadness, anger, fear, surprise, and disgust.

Machine Learning techniques have been increasingly daily and used to predict mental health conditions among individuals. The growing prevalence of mental health challenges in individuals have raised serious concerns among educators, healthcare providers, and policymakers. Since mental health significantly influences emotions, decision-making, and social interactions, there is a strong need for proactive prevention strategies. Early identification plays a vital role, and advancements in medical predictive analytics have the potential to transform healthcare, especially in addressing the critical effects of mental health on individuals. The rapid advancement of technology has significantly influenced mental health, both positively and negatively. Social media and digital dependency contribute to anxiety, depression, and decreased attention spans. The pressure to maintain an online presence and the spread of misinformation further intensify stress. Additionally, factors such as academic pressure, workplace stress, financial instability, and social isolation also play a crucial role in deteriorating mental well-being.

This project focuses on identifying facial expression and it aims to develop a system capable of automatically detecting and categorizing diverse emotional states by analysing facial expressions.

II. RELATED WORK

Already developed facial Emotion recognition system include identifying a persons mental health using a questionnarie or a survey which lacks the efficiency of the project and it can't see the emotion state of the person who is using.

Jyoti Kumari.,et al,[1] discuused the detection of mental disorders and synthetic human expressions was discussed, with the author highlighting that two primary methods widely utilized in the literature for Facial Emotion Recognition systems are based on geometry and appearance.

Khan, R. et.al,[2] emotion recognition was identified as a crucial field for enhancing human-machine interaction. Due to the complexity of emotions, acquiring accurate data for recognition becomes a challenging task. However, the application of deep learning and neural networks has significantly improved the success rate of machines in recognizing emotions.

Elzbieta kukla, et al[3] a method was introduced that utilizes a series of neural networks to identify facial expressions. The algorithm takes a natural image of the face as input and outputs the emotion being expressed. To identify the most effective classifiers for recognizing particular emotions, both single-layer and multi-layered networks were tested.

Proposed System

A Convolutional Neural Network architecture is designed with pooling layers to identify patterns and minimize spatial dimensions. By optimizing trainable parameters, the network becomes proficient in detecting distinct patterns linked to various emotional expressions. The model assigns significance to different features within a image using adjustable weights and biases, enabling it to differentiate between multiple emotional states effectively.

We have developed a website which consists of three parts: Detection, Live Video Facial and Emotion Detection Performance.

Detection includes various questions related to mental health, While User answering the questions it automatically captures user's image.

Emotions that detects: Happy, Sad, Neutral, Angry and Disgust. Using Live video Detection we can easily find the present facial expression.

Using the CNN Model we are getting an accuracy of 98% Confusion Matrix: It gives the information regarding the Real Emotion and Detected Emotion.

III. METHODOLOGY

We made a project which develops an intelligent system for analyzing an individual emotional state and assessing their mental well-being using face expression recognition. The system begins by displaying a nine to ten questions on the screen, which the user answers sequentially. During this process, the system automatically captures an image of the user's face for each response, ensuring real-time emotional analysis. Once the questionnaire is completed, the system processes the collected images to generate an insightful output.

The output consists of three key components. First, it displays all the captured images, allowing users to review their facial expressions throughout the assessment. Second, it generates a bar graph representing the probability distribution of various emotions, such as happiness, sadness, anger, disgust, fear, and surprise, across the collected images. This visualization helps in identifying emotional patterns and fluctuations. Third, the system evaluates the overall behavioural state of the individual and determines their mental health risk level, categorizing it as low, medium, or high based on predefined parameters.

To provide further assistance, the system recommends two personalized YouTube videos tailored to the user's emotional state and risk level. These videos may include mindfulness exercises, stress management techniques, or motivational content aimed at improving mental well-being. By integrating facial expression recognition, predictive analytics, and AI-based recommendations, the system offers a non-intrusive, automated approach to mental health assessment.

This project holds significant potential for applications in education, workplaces, and healthcare, where early detection of emotional distress can lead to timely intervention. By leveraging technology to analyze emotions, the system promotes mental health awareness and provides users with resources to manage their well-being effectively.

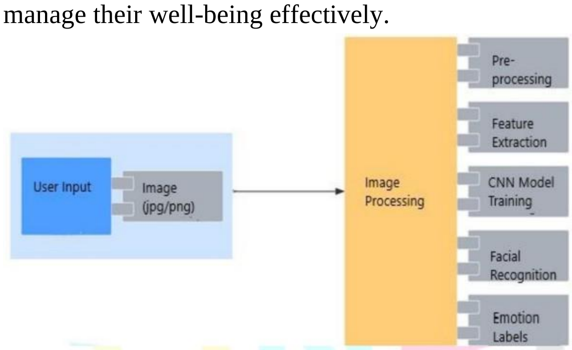

Fig. 1. Architecture Diagram

Preprocessing is essential in image classification as it enhances image quality and optimizes data for accurate model training. It involves resizing images to maintain consistency, normalizing pixel values for faster convergence, and converting images to grayscale if color information is unnecessary, reducing complexity. Noise reduction techniques, such as filtering and contrast adjustments, remove distortions, ensuring better feature extraction. Data augmentation, like rotation, flipping, and scaling, increases dataset variability, improving model generalization. These steps help the model focus on critical patterns, reduce overfitting, and improve classification accuracy, making preprocessing a vital component of any image-based deep learning system.

CNN Helps to Extract and Analyze Facial Expressions

[4]CNNs play an important role in facial expression recognition by automatically extracting and analyzing facial features from images. CNNs are effective in processing image data due to their ability to detect complex patterns, which makes them ideal for identifying emotions based on facial expressions.

1. Image pre-processing and input layer: The process begins with the capture of images of the user's face. These images are preprocessed by resizing, normalizing pixel values, and sometimes converting to grayscale to reduce computational complexity. The preprocessed image is then fed into the CNN model as input.
2. Feature Extraction: [5]The CNN model consists of multi- ple convolutional layers that apply filters (kernels) to the input image. These filters scan the image in small sections, detect- ing essential facial features such as eyes, eyebrows, mouth, and nose. As the layers go deeper, the model learns more complex features, subtle muscle movements that correspond to emotions like happiness, sadness, anger, or surprise.
3. Pooling Layers for Dimensional Reduction: Pooling lay- ers follow convolutional layers to decrease the spatial dimensions of feature maps while preserving essential information. Max pooling, a common technique, selects the most prominent features, ensuring that only the most important expressions are retained.

4. Fully Connected Layers for Classification:

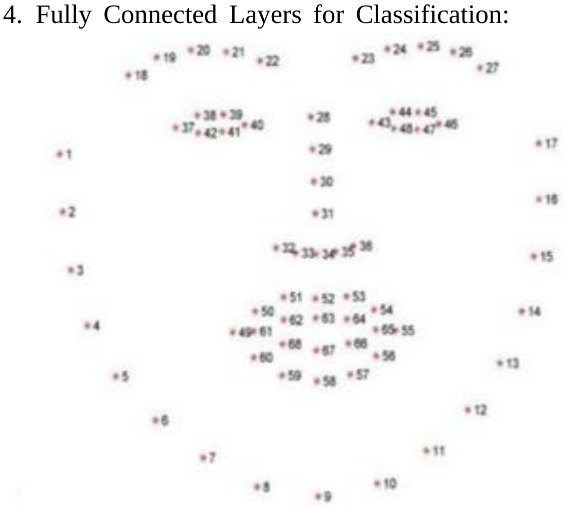

Fig. 2. Critical Points Representation

The output is flattened and passed through fully connected layers. These layers analyze the extracted patterns and classify the emotion associated with the facial expression. The final layer typically uses a Softmax activation function to assign probabilities to different emotion categories (e.g., happy, sad, angry, etc.).

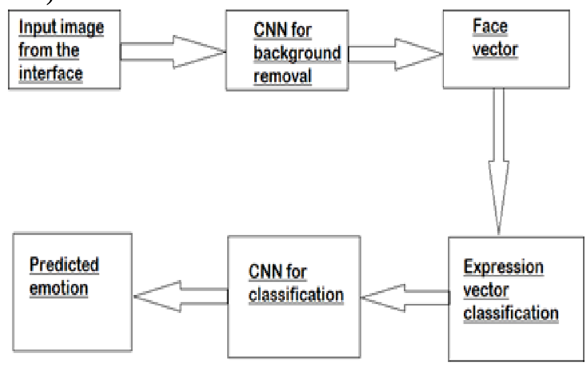

Fig. 3. Convolutional Layers

5. Emotion Prediction and Analysis Once classification is complete, the system determines the probability of each emotion based on the user's facial expressions. This information is then visualized in a bar graph, showing the likelihood of various emotional states. The CNN's ability to learn intricate facial features ensures accurate emotion recognition.

By leveraging CNNs, our system provides a robust and automated approach to facial expression analysis, enabling real-time emotion assessment for mental health applications.

IV. IMPLEMENTATION AND TESTING

Software testing is a process of identifying the correctness of software by considering its all attributes (Reliability, Scalability, Portability, Re-usability, Usability) and evaluating the execution of software components to find the software bugs or errors or defects.

User Interaction Testing: Users can engage with the software in real-time as it processes input data, allowing them to view visual outputs while also receiving textual feedback.

Error notifications in the terminal: It delivers informative messages in the command prompt or terminal, notifying users of any errors, warnings, or issues that arise during processing.

Types of Testing:
Manual Testing Automation Testing
Manual Testing: Testing any software or an application according to the client's needs without using any automation tool is known as manual testing. In other words, we can say that it is a procedure of verification and validation. Manual testing is used to verify the behavior of an application or software in contradiction of requirements specification.
We do not require any precise knowledge of any testing tool to execute the manual test cases. We can easily prepare the test document while performing manual testing on any application.

Automation Testing: The most significant part of Software testing is Automation testing. It uses specific tools to automate manual design test cases without any human interference.
Automation testing is the best way to enhance the efficiency, productivity, and coverage of Software testing.
It is used to re-run the test scenarios, which were executed manually, quickly, and repeatedly.

Machine Learning Model Testing:
Machine Learning Model Testing refers to the process of evaluating a trained machine learning model to assess its performance, generalizability, and reliability when applied to unseen data. The goal of model testing is to ensure that the model is not only accurate on the data it was trained on but also performs well on new, unseen data in real-world scenarios. This testing is crucial for determining how well the model will behave in production.

Functional testing
In functional testing, all the components are tested by giving the value, defining the output, and validating the actual output with the expected value.
Functional testing is a part of black-box testing as its emphases on application requirement rather than actual code. The test engineer has to test only the program instead of the system.

V. RESULTS AND DISCUSSION

The suggested model demonstrates by capturing the complexities of mental health recognition, utilizing diverse training data and incorporating a system for providing actionable recommendations.
The suggested model demonstrates a high level of proficiency by capturing the complexities of mental health recognition, utilizing diverse training data, offering real-time prediction capabilities, and incorporating a system for providing actionable recommendations.
Using the CNN Model, we get an accuracy of 98.7%.
Precision(98%): Measures how many of the predicted positive cases are actually correct.
Recall(98.7%): Measures how well the model identifies actual positive cases.
F1-Measure (98.7%): A balance between Precision and Recall, useful when data is imbalanced. It is the HM of Precision and Recall.

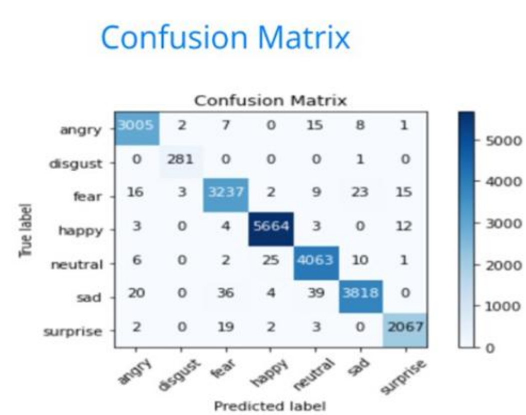

Fig. 4. Confusion Matrix

Confusion matrix is a powerful evaluation tool for calculating the performance of our facial expression recognition model. It provides a detailed breakdown of the model's predictions by comparing the actual and predicted emotion categories, helping us assess accuracy and identify areas for improvement.

The confusion matrix is a table where:
Rows represent actual emotions (for example, happy, sad, angry, disgust, etc.).

Columns represent predicted emotions by the model. Diagonal values indicate correct classifications, while off- diagonal values show misclassifications. By analyzing these values, we can determine which emotions the model detects accurately and which ones it struggles with.

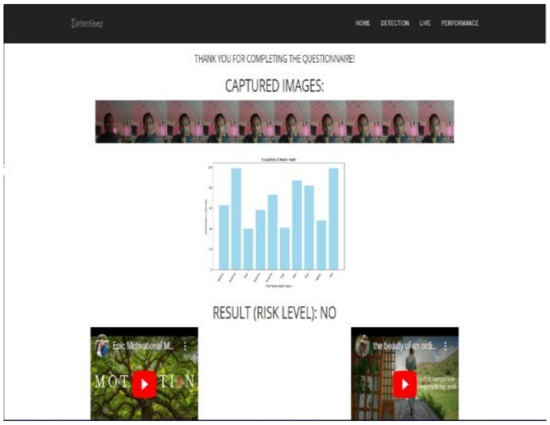

Fig. 5. User Interface

VI. CONCLUSION

Mental health issues, if left unaddressed, can significantly impact an individual's well-being, work efficiency, and overall productivity. To increase the effectiveness of this model, it is trained using images captured under diverse conditions, including different angles, lighting variations, and color intensities. This improves its ability to accurately recognize facial expressions, ensuring higher performance. In the future, the system will be extended to process video clips, enabling real-time emotion detection. The goal is to develop an integrated system where the model's predictions are displayed on a screen along with personalized recommendations. Additionally, by continuously capturing employees' facial expressions over a set period, the system can assess emotional patterns. If signs of critical mental health conditions are detected, it can provide targeted interventions or exposure to relevant support resources.

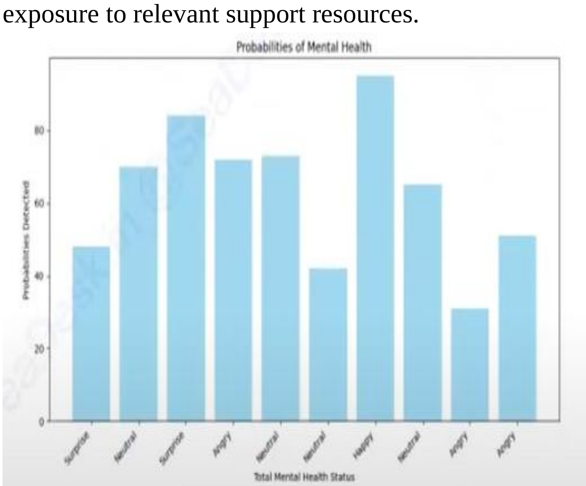

Fig. 6. Probabilities of Emotions Detected

VII.FUTURE ENHANCEMENTS

Face and Voice Integration:
Incorporating live video face emotion recognition with voice commands would be helpful integration which also increases the efficiency of the system.

User Interface Accessibility:
User interface can be made more attractive which would be helpful for the illiterate people

Improving continuous Model Training:
We should implement a mechanism to train the model continuously to keep the software updated with the changing facial expressions.

REFERENCE

[1] Jyoti Kumari, R., Rajesh, K. M. Pooja," Facial Expression Recognition: A Survey, Procedia Computer Science", Volume 58,2015, Pages 486–491, ISSN 1877 – 0509.

[2] Ravichandra Ginne, K., Jariwala, "FACIAL EXPRESSION RECOGNITION USING CNN: A SURVEY", Mar 2018, International Journal of Advances in Electronics and Computer Science, Vol 5, No. 3, 2018.

[3] Kukla, E. (2015). Facial Emotion Recognition Based on Cascade of Neural Networks. In A. Zgrzywa, K. Choros, in Multimedia and Internet Systems. (Vol.314) Cham:Springer

[4] Kalaivani, G., Anitha, S. Sathyapriya,DrD. (2016). A Literature review on Emotion Recognition for Various Facial Emotional Extraction. IOSR Journal of Computer Engineering

[5] Shaul Hammed, A., Sabanayagam, E. Ramakalaivani, A REVIEW ON FACIAL EXPRESSION RECOGNITION (2020). SYSTEMS", Journal of Critical Reviews