



An Improved Deep Learning Approach For Mental Health Check Using Face Recognition And MCQ

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Abstract— In essence, "Mental Health Check using Face Recognition and MCQ's" is a system combining advanced facial recognition techniques coupled with deep learning to class people's mental states. These employ TensorFlow and Keras to detect emotions; catch and analyze facial expressions occurring when users answer their MCQs. By combining that information with users' responses, it leads to a more holistic examination of mental health. This paper presents a tool which is designed for various uses such as education and healthcare and aims at early identification of mental disorders. Keeping accuracy, real-time analytics, and secured data storage in mind, the proposed system is the most vital leap in individualized assessment of mental well-being.

Keywords— Artificial Intelligence, Machine Learning, Deep Learning, Convolution Neural Networks, Mental Health.

I. INTRODUCTION

The human face is such an essential part of one's body and plays the most essential role in understanding the person's mood. The face is where the human gives out all of his basal emotions. An increasingly fundamental aspect of general well-being for people of this fast life is becoming mental health in today's fast-paced life. With the growing concern towards mental health issues, people are in dire need of innovative and efficient monitoring and assessment methods for mental health status. Traditional approaches, like personal consultations and self-report questionnaires, often face challenges such as access, time, and biased results. This need has led to the emergence of technology-driven solutions to mental health assessment, wherein artificial intelligence plays a critical role.

One promising way forward is to use the combination of face recognition and MCQs to examine mental health conditions. The basis for this approach includes the fact that facial recognition employs AI algorithms in detecting expressions and micro-expressions, which are usually believed to relate to emotional states, such as stress, anxiety, or

depression. AI models use such minor facial changes in revealing a certain level of information regarding the psychological status of a person. If MCQs are added designed to screen for different psychological disorders, then in some way, it facilitates overall active and dynamic monitoring regarding your mental health.

This hybrid combination of facial analysis and MCQs provides a non-intrusive, scalable, and efficient solution for mental health assessment. This can be put to use in healthcare institutes, workplaces, or remotely to bring mental health closer to people who might not be able to access it. Further AI developments will make such technology useful for early intervention and mitigation of the influence of mental health disorders.

The proposed system offers an advanced hybrid architecture of facial recognition technology and deep learning toward real-time assessment of a user's mental states. By monitoring the emotions of a human, conducting tests on him like MCQ, and all other activities lead the human's mental state into this route. Combination of the results from above facial expression recognition with the performance in MCQ has promising results toward mental health disease detection even at early stages such as neuroticism, OCD, depression, schizophrenia, mental state, and self-control. Our proposed system monitors the emotions continuously and, based on those emotions, the information for the classification of mental illness of that person is obtained, and that undergoes for the MCQ test to check the psychometric study, providing a tool for mental health check.

The rest of the paper is organized in the following manner: Section II gives review of related researches on mental health detection in the Literature Survey. Section III presents the Methodology of the proposed system. Section IV presents the Experimental Evaluations, and the Conclusion is summed up in Section V.

II. LITERATURE SURVEY

In recent years, facial recognition technology with deep learning techniques has been increasingly used for mental health assessment. The researchers are looking forward to further knowledge about how the AI can work in detecting depression, anxiety, and stress. In medical science, human expressions handle many complicated situations in fact give a better understanding than the recording or the physical actions sometimes. Facial expression recognition has been used immensely as an indication of emotions and psychological states. These proofs can be gleaned from the works of Ekman and Friesen as laid down the groundwork perceptive on how the expression on a face may or may not reflect some subconscious emotional conditions[4]. Recently, deep learning models mainly CNNs have been instituted in automating high accuracy in recognition of such facial expressions.

Yang et al. in 2018 established the application of CNNs in analyzing facial micro-expressions, which are serious needle of hidden emotions[10]. The authors implemented a deep learning-based facial expression recognition system to detect early signs of depression and anxiety. Their system attained high rank of accuracy in predicting mental health conditions by identifying patterns in facial movements that are difficult for humans to notice. Such techniques appear promising, particularly in such situations where a patient will not candidly present when they are to be treated. In the same way, MCQs are also heavily used in psychological testing as the standardized tools in assessing conditions of mental health[6]. The BDI and the GAD-7 scale are examples of commonly used mental health assessment scales. Though these tools can be beneficial in a more structured means of assessing mental health symptoms they are often characterized by limited self-report bias by Smith et al[7].

Recent studies have required to unite MCQ-based assessments with real-time facial recognition data to reduce this bias. Zhang et al. in 2020 explored the integration of deep learning models with MCQs to create a more robust system for identifying mental health disorders[11]. By analyzing facial expressions during the administration of MCQs, the system could detect inconsistencies between self-

reported data and emotional indicators, thereby improving the reliability of mental health assessments.

Deep learning techniques have transformed diverse fields, such as diagnostics in medicine and evaluation for mental health[5].

Mental health assessment using face recognition: Promising models for this kind of assessment are LSTM networks, CNNs, and RNNs. As noted in a 2021 study by Lu et al., deep learning models trained on large datasets of facial expressions may be used to predict emotional states with considerable accuracy[1].

Deep learning algorithms have transformed many industries, including medical diagnosis and mental health evaluation[5]. Long short-term memory (LSTM) networks, CNNs, and recurrent neural networks (RNNs) have all demonstrated significant potential in the area of mental health evaluation using facial recognition. According to a study conducted by Lu et al. in 2021, deep learning algorithms trained on massive datasets of facial expressions might predict emotional states with high accuracy[1]. Their research focuses on employing RNNs and CNNs to analyze facial dynamics over time, which can be very effective in detecting mental health problems like depression or chronic anxiety.

Moreover, the work by Ahmed et al. in the year 2022 proved that hybrid models can be developed and integrated with deep learning technology and traditional psychological evaluation processes, such as MCQs[8]. Thus, their research was carried out to develop a system that uses facial recognition information to enhance the diagnostic value of psychological questionnaires, and by integrating these methods, their system outscored the traditional diagnostic tests in identifying early signs of mental health disorders. The most important point is that facial expressions may be misinterpreted because people express affects differently. According to Patel and Walker, well-defined facial expressions can be influenced much by cultural differences and personal characteristics thus causing potential errors in AI-based mental health evaluations[2]. The solution form to escape from the challenge raised in Patel et al [9] is studied well and Lee et al. in 2023 suggest further refining deep learning models by including more diverse datasets and developing more interpretability of AI-generated insights[2],[3].

III. METHODOLOGY

This section discusses the innovative proposed approach that begins with the loading of a dataset followed by the multistep procedure.

1. Data Collection: Gather a diverse dataset of facial images with various expressions (happy, sad, angry, etc.), and label them accordingly.

2. Feature Extraction: Use CNN to extract facial features from the images and encode them into a feature space where distances reflect emotional similarity.

3. Data Pre-processing: Use OpenCV to pre-process images for face detection and alignment. Normalize and resize images to the same size and split the dataset into training, validation, and test sets.

4. Model Selection and Training: Design a deep learning model using TensorFlow and Keras either from scratch or fine-tune a pre-trained model, such as VGGFace or ResNet, for emotion classification.

5. Model Evaluation: This is done to assess the performance of the model on accuracy, precision, and recall on the validation and test datasets for proper emotion prediction.

6. Prediction Phase: Capture real-time facial images during the MCQ session, process them with the trained model to predict emotional states, and combine these predictions with MCQ responses to assess the user's mental state.

Below is the formal algorithm with all the steps for the execution of the methodology:

Algorithm for Emotion Detection System

ALGO:

1. Start: User accesses the quiz page with a webcam feed.

2. MCQs Submission & Image Capturing:

- User answers quiz questions.
- For each question submission, the webcam captures and stores an image temporarily.

3. Image Processing & Prediction:

- Captured images are passed to a deep learning (DL) model for emotion detection.

4. MCQs & Emotion Prediction Combination:

- DL model outputs predicted emotion from images.
- Quiz answers and emotion predictions are combined.

5. Final Output Generation:

- User's mental state is assessed based on quiz responses and emotions.

6. Display Final Output:

- Final result is shown to the user, along with a graph showing the confidence level of each emotion.

7. Stop: User reviews the result, and the process ends.

IV. EXPERIMENTAL EVALUATIONS

This section illustrates the experimental analysis and results of the proposed modal. The experiment is implemented in TensorFlow and Keras APIs. These implementations have been done with the FER-2013 dataset. The data consists of 48x48 pixel grayscale images of faces. The task is to categorize each face based on the emotion shown in the facial expression into one of seven categories (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral). The training set consists of 28,709 examples and the public test set consists of 3,589 examples.

The "Mental Health Check Using Face Recognition and MCQs" system is comprised of several integrated modules designed to assess users' mental states. The Data Collection module gathers diverse facial images with various emotions, while the Feature Extraction module utilizes a CNN-based model to encode these images into a feature space for emotion recognition. The Data Pre-processing module ensures that images are standardized through detection, alignment, normalization, and resizing. The Model Selection and Training module involves developing and fine-tuning a deep learning model using TensorFlow and Keras for accurate emotion classification. The Model Evaluation module assesses the model's performance using metrics like accuracy and recall to ensure reliability. Finally, the Prediction Phase module captures real-time facial images during an MCQ session, processes them to predict emotional states, and integrates these predictions with user responses to provide a comprehensive mental health assessment. The screen of sample dataset for implementation can be seen in the following Figures.

Figure 1 shows the Home Page of a Mental Health Monitoring System.

Figure 1 shows the sample questions given to the user in the MCQ test.



Feel Insight: Mental Health Check

1. How do you feel when you wake up in the morning?

- A. Excited and motivated
- B. Anxious or stressed
- C. Frustrated or irritated
- D. Indifferent or neutral

2. How do you typically react to an unexpected problem or challenge?

- A. I feel overwhelmed and shut down
- B. I feel frustrated and lose my temper
- C. I stay calm and look for a solution
- D. I feel excited by the challenge

3. How often do you feel sad or down?

- A. Almost every day
- B. A few times a week
- C. Rarely
- D. Never

4. Do you find it easy to express your emotions?

- A. Yes, always
- B. Sometimes
- C. Rarely
- D. No, never

5. How do you handle stress?

- A. I manage it well
- B. I sometimes struggle
- C. I often feel overwhelmed
- D. I ignore it

6. How often do you feel anxious?

- A. Very often
- B. Occasionally
- C. Rarely
- D. Never

7. Do you enjoy social interactions?

- A. Yes, I love it
- B. Sometimes
- C. Not really
- D. No, I avoid them

8. How often do you feel bored or unfulfilled?

- A. Often
- B. Sometimes
- C. Rarely
- D. Never

9. How do you feel about your daily activities?

- A. Very positive
- B. Somewhat positive
- C. Neutral
- D. Negative

10. How would you rate your overall mood today?

- A. Excellent
- B. Good
- C. Fair
- D. Poor

Submit

Figure 1:MCQ

Figure 2 and Figure 3 shows the training summary here. It provides insight about the complete neural network such as the layer types, count, output shape, parameters, etc.

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 48, 48, 32)	1,792
max_pooling2d (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_1 (Conv2D)	(None, 24, 24, 16)	10,544
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 16)	0
conv2d_2 (Conv2D)	(None, 12, 12, 8)	10,400
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 8)	0
flatten (Flatten)	(None, 384)	0
dense (Dense)	(None, 128)	51,040
dense_1 (Dense)	(None, 2)	256

Total params: 2,103,000 (8.24 MB)
Trainable params: 1,000,512 (4.12 MB)
Non-trainable params: 0 (0.00 0)

Optimizer params: 1,000,512 (4.12 MB)
PS: D:\Python\health\AI\training>

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Figure 2:Training Summary

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Figure 3:Training Summary

Figure 6 shows the performance measures in the confusion matrix. The confusion matrix will also represent the other performance measures Precision, Recall, and F1 Score.



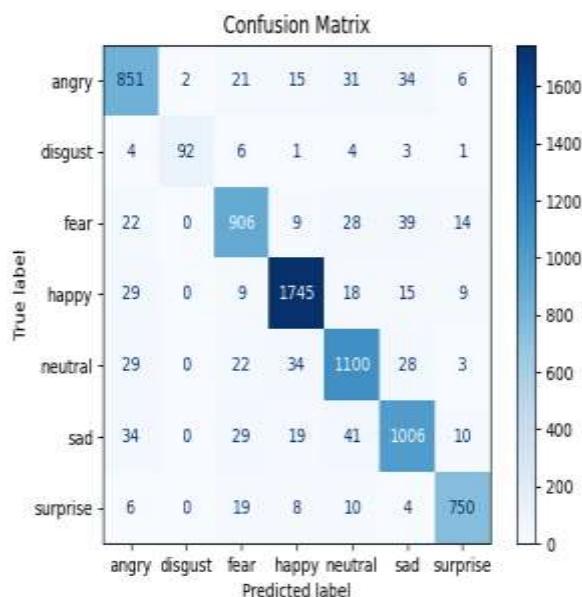


Figure 4: Confusion Matrix

V. CONCLUSIONS

This system, "Mental Health Check Using Face Recognition and MCQs," is the most significant advancement in this area for assessment purposes as it includes advanced facial recognition technology and psychometric evaluation. The proposed system utilizes CNN-based deep learning models to accurately detect and analyze emotional states from facial expressions. This holistic approach not only enhances the accuracy of mental health assessments but also gives real-time insights that make for better and timely interventions. It is scalable and accessible with cloud deployment, while robust measures to protect user data with sensitivity are taken.

Overall, this system offers a comprehensive and innovative tool for assessing mental health, blending cutting-edge technology with practical application to improve mental well-being. The hybridization of facial expression with the MCQ solver is a novel idea to get the unbiased results.

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