Development of a CNN-Based Mental Health Consultation Application Integrating Facial Expressions and DASS-42 Questionnaire

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Article Info

Article history:
Received May 18th, 2025
Revised Jun 14th, 2025
Accepted Jul 22th, 2025

Keyword:
Convolutional Neural Network
DASS-42
Facial Expression
Mental Health

ABSTRACT

Early detection of psychological disorders such as Depression, stress, and anxiety is still limited due to a lack of awareness and inadequate access to mental health consultation services. This study aims to develop a mental health consultation application that utilizes facial expressions and the Depression, Anxiety, and Stress Scale (DASS-42) questionnaire, employing a Convolutional Neural Network (CNN) algorithm. The CNN algorithm is used to detect and classify facial expressions into emotional categories, such as anger, sadness, disgust, and fear, as early indicators of mental conditions. In addition, the DASS-42 questionnaire provides a structured psychological assessment to determine the severity of Depression, anxiety, and stress. This combination offers a more comprehensive and accurate evaluation, thus bridging the gap in early detection methods for mental health. Based on the development and testing results, a mental health consultation app utilizing facial expressions and the DASS-42 questionnaire was successfully created by using the CNN algorithm as a facial expression detector. The system can identify facial expressions such as sadness, anger, disgust, and fear with an accuracy of 81%, showing excellent performance in detecting early signs of mental disorders.

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DOI: http://dx.doi.org/10.24014/ijaidm.v8i2.37525

1. INTRODUCTION

Mental health is now an increasingly pressing global concern, especially among adolescents who are vulnerable to academic, social, and family pressures. Data from the World Health Organization states that more than 970 million people worldwide experience mental disorders, and approximately 14% of them are young people[1]. Unfortunately, the majority of them do not have access to adequate mental health services due to limited resources, social stigma, and a lack of awareness of the importance of early detection [2][3].

One approach that can be used to identify psychological disorders early is through facial expression analysis. Emotions such as sadness, anger, fear, or disgust, which are visible through facial expressions, can be important indicators of a person's emotional state [4]. Research in the field of neuropsychology shows that facial expressions reflect internal affective states and have diagnostic value in psychological contexts [5]. However, in practice, manual interpretation of facial expressions by psychologists is subjective and highly dependent on individual expertise [6].

With the development of artificial intelligence technology, the Convolutional Neural Network (CNN) has proven to be a practical approach for classifying emotions based on facial images. CNN can extract complex visual features and recognize emotional patterns with high accuracy on various datasets, including FER-2013[7][8]. Several recent studies have also shown that CNN can be used to detect early symptoms of mental disorders, including stress and depression, by exploiting subtle changes in facial expressions [9].

To be more comprehensive, this image-based approach can be strengthened by integrating psychometric instruments, such as the DASS-42. The DASS-42 is a validated and widely used measurement tool to quantitatively identify the severity of depression, anxiety, and stress symptoms [10]. The combination of CNN-based facial expression analysis and completion of the DASS-42 questionnaire provides a more accurate and objective multimodal approach for initial screening of psychological conditions.

This research aims to develop a mental health consultation application that combines CNN-based facial expression recognition technology with the DASS-42 questionnaire. This system is expected to help users independently identify their emotional states and provide relevant baseline data for professionals. This approach could enable the early detection of mental disorders to be more efficient, accurate, and accessible to the broader public.

2. RESEARCH METHOD

This research adopts a structured system development workflow, starting from dataset retrieval, followed by data preprocessing, facial expression classification using a CNN model, triggering of the DASS-42 questionnaire based on the classified emotion, and ending with result interpretation and final analysis. Each stage in this flowchart Figure 1 ensures an integrated and systematic approach in building a mental health consultation application that combines image-based emotion detection with psychometric assessment.

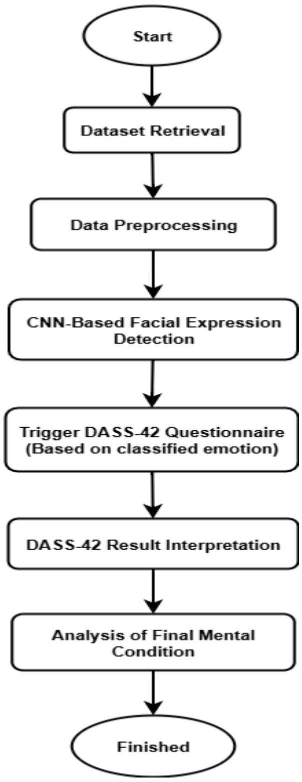

Figure 1. Methodology

2.1. Dataset Retrieval

The collection of facial information from the study employed a publicly available facial expression dataset titled “9 Facial Expressions for YOLO” by Aklima Akter Rimi, which is accessible via Kaggle [11]. The original dataset comprises nine labeled facial emotion categories: angry, disgust, fear, happy, sad, surprise, neutral, contempt, and unknown. However, for this research, only four emotional expressions were selected: angry, sad, disgust, and fear, due to their psychological relevance in the early detection of mental health conditions[12].

Each selected expression corresponds to a specific mental health indicator: anger is commonly associated with stress, sadness with depression, and fear and disgust with anxiety[13] [14]. This targeted selection allows the model to focus on classifying emotions that serve as early non-verbal cues for psychological distress. These images, which include emotion annotations, were used to train and evaluate a CNN-based facial expression recognition model.

Importantly, the dataset is anonymized and adheres to ethical standards in research. No personally identifiable information (PII) is included, and the data are publicly shared solely for academic and non-commercial purposes. The subset used in this study ensures privacy compliance while enabling the development of a reliable and focused mental health screening tool [15].

2.2. Data Preprocessing

To optimize the model's ability to recognize facial expressions, a structured data preprocessing workflow was implemented. Although the available dataset comprises more than 70,000 annotated facial images sourced from public repositories such as FER-2013 and Kaggle, this study utilized a selected subset of approximately 11,000 images. This selection was based on relevance to the targeted emotional categories sadness, anger, fear, and disgust and data quality considerations to ensure the practicality of model training. The chosen subset was then divided into 70% for training and 30% for validation and testing, following standard machine learning practices to support both learning and model generalization. Facial expression recognition using CNN has been widely validated for real-time applications, as demonstrated by FER-2013, including in recent hybrid model studies that combine deep learning and traditional methods to enhance classification accuracy [16].

To ensure suitability for CNN-based learning, several preprocessing steps were conducted. First, all images were resized to 128×128 pixels, ensuring consistent input for the model's convolutional layers. Normalizing pixel scaling values to the [0, 1] range stabilized the learning process and improved convergence. Additionally, data augmentation techniques such as random rotations, horizontal flipping, and zoom transformations were applied to the training data to simulate real-world variations and mitigate overfitting, consistent with current FER research approaches [17][18].

The dataset was partitioned into a 70:30 ratio and trained with a batch size of 32 over 20 epochs using the Adam optimizer (learning rate = 0.001), implemented via the TensorFlow and Keras frameworks. In recent studies similar to this, optimized preprocessing has significantly enhanced the performance of CNNs on FER datasets.

This preprocessing stage directly supports the pipeline integration with the DASS 42 questionnaire. The CNN classifier's output one of four facial expressions is mapped to the corresponding psychological domain: sadness → depression, anger → stress, and fear or disgust → anxiety. This mapping triggers the appropriate 14-item DASS-42 subscale [19]. The CNN output thus functions as a trigger for initiating the questionnaire, rather than a parallel assessment module.

This multimodal approach transforms raw facial images into structured diagnostic input, combining image-based emotional inference with validated psychometric measurement. Model evaluation was conducted using confusion matrices and classification metrics (accuracy, precision, recall, F1-score). At the same time, DASS-42 outcomes were quantified via a Likert scale and classified into five severity levels (normal to very severe), ensuring continuity between CNN detection and psychometric scoring in a clinically relevant mental health screening pipeline.

2.3. CNN-Based Facial Expression Detection

Following preprocessing, the facial expression classification is conducted using a CNN architecture. CNNs are well-suited for image-based tasks due to their ability to automatically extract spatial features and patterns relevant to specific classes. In this research, CNN is employed to detect four key facial expressions sadness, anger, fear, and disgust each of which is mapped to an associated mental health condition: depression, stress, and anxiety.

The CNN model architecture consists of multiple convolutional layers for feature extraction, interleaved with max-pooling layers for dimensionality reduction. Dropout layers are added for regularization to prevent overfitting. Finally, a dense fully connected layer with a softmax activation function is used to output the probabilities of each classified emotion class.

The model is trained using the augmented training dataset and evaluated based on standard classification metrics, including accuracy, precision, recall, and F1-score. The output emotion class from the CNN model is not treated as a final diagnosis. Still, it serves as a trigger to present the user with a tailored section of the DASS-42 questionnaire, depending on whether the detected emotion aligns with depression, stress, or anxiety.

This sequential approach ensures that the CNN acts as the initial screening tool, seamlessly integrated with the psychometric assessment to provide a more comprehensive and early evaluation of a user's mental health condition. The mapping of facial expressions to psychological conditions (sadness → depression) follows clinical insights as commonly referenced in psychological research.

In addition to the evaluation using the FER-2013 dataset, the system has also been implemented directly with real users through an application interface. In this test, users are asked to activate the camera to take facial images, which a CNN model then processes. The system will display the results of the facial expression classification in the form of a predicted mental state: depression, anxiety, or stress. After the prediction results are displayed to the user, the system will automatically proceed to fill out the corresponding DASS-42 questionnaire section for that category. This implementation has been carried out directly by users and reflects the actual flow of the developed mental detection and assessment system.

2.4. Trigger DASS-42 Questionnaire

The DASS-42 questionnaire is a standardized psychometric instrument used to assess the emotional states of depression, anxiety, and stress[20]. After the CNN-based facial expression recognition process classifies a user's emotional state into one of the three categories (depression, anxiety, or stress), the system proceeds by presenting the user with the relevant section of the DASS-42 questionnaire. Indications of depression, anxiety, or stress can be seen in Table 3,4, and 5.

Each subscale in the DASS-42 consists of 14 items, totaling 42 questions across the three domains. Responses are recorded on a four-point Likert scale ranging from 0 to 3, where 0 = Never, 1 = Sometimes, 2 = Often, and 3 = At all times (Table 1). Participants are instructed to reflect on their emotional state over the past week when answering [21].

Once the responses are collected, the scores for each subscale are summed to produce a total score for depression, anxiety, and stress. Based on these scores, users are categorized into five severity levels: Normal, Mild, Moderate, Severe, and Very Severe. Each category has a defined score range (Table 2), which serves as the interpretation metric for the final mental health condition[20].

This classification enables the system to conduct an early-stage mental health assessment by combining facial expression analysis with validated psychological self-reporting. The integration of the DASS-42 as a follow-up step ensures that the emotional classification obtained through image-based detection is complemented with a structured, quantitative measurement tool, thereby reinforcing the accuracy and reliability of the system [21].

Table 1. Likert Scale Measurement

Score	Category
0	Never
1	Sometimes
2	Often
3	At all times

Table 2. Score Interpretation Range

Level	Depression	Anxiety	Stress
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Very Severe	>28	>20	>33

Table 3. Indications of Depression

No	Indications of Depression
1	Feeling a loss of interest in previously enjoyable activities.
2	Feeling hopeless or devoid of hope about the future.
3	Having trouble sleeping or staying awake longer than usual.
4	Feeling very tired even though you haven't done much activity.
5	Having difficulty coping with everyday tasks or challenges.
6	Feeling excessively anxious or unable to control feelings.
7	Unable to feel satisfied or enjoy the achievements that have been achieved.
8	Feeling irritable or impatient with yourself and others.
9	Feeling excessively anxious or worried about things that don't usually cause anxiety.
10	Having difficulty concentrating on the activity or work being done.
11	Having difficulty concentrating on the activity or work being done.
12	Feeling very worthless or having low self-esteem.
13	Feeling unable to handle or cope with difficult situations or feelings.
14	Experiencing drastic changes in eating patterns or appetite.

Table 4. Indications of Anxiety

No	Indications of Anxiety
1	Feeling anxious, worried, or fearful about many things.

No	Indications of Anxiety
2	Experiencing constant tension or fear, even for no apparent reason.
3	Feeling nervous, tense, or unable to relax.
4	Having difficulty sleeping due to anxiety or worry.
5	Feeling irritable or easily affected by stress.
6	Experiencing physical symptoms such as shaking, heart palpitations, or shortness of breath due to anxiety.
7	Feeling anxious or fearful about things happening in your life or the future.
8	Experiencing feelings of inability to cope with existing worries.
9	Feeling tense, even in situations that should not cause anxiety.
10	Feeling confused or having difficulty focusing due to anxiety.
11	Feeling trapped in excessive feelings of anxiety or worry.
12	Avoiding certain situations or activities due to excessive anxiety.
13	Feeling anxious or worried about your health or well-being or that of others.
14	Feeling unable to control or cope with feelings of anxiety.

Table 5. Indications of Stress

No	Indications of Stress
1	Feeling anxious or tense about many things.
2	Having difficulty sleeping or sleep disturbances due to stress.
3	Feeling irritable or depressed in certain situations.
4	Feeling anxious or worried about things you can't control.
5	Experiencing physical tension, such as stiff muscles or stress headaches.
6	Feeling stressed or overwhelmed by too many demands or work.
7	Experiencing excessive fatigue even though you haven't done much activity.
8	Having difficulty relaxing or releasing tension after hard work.
9	Having difficulty concentrating due to pressure or stress.
10	Feeling stressed or anxious about situations that should be easy to deal with.
11	Feeling helpless or overwhelmed by the situation at hand.
12	Experiencing an increase or decrease in appetite due to stress.
13	Feeling anxious or worried about the future or things that haven't happened yet.
14	Feeling tension in the body or feeling under pressure for a long time.

2.5. DASS-42 Result Interpretation

The DASS-42 is a standardized psychometric tool consisting of 42 items equally divided into three subscales: depression, anxiety, and stress. Each item is rated using a 4-point Likert scale, ranging from 0 (never) to 3 (almost always), allowing users to reflect on their experiences over the past week. After completing the questionnaire, the total score for each subscale is calculated by summing the values assigned to the relevant 14 items. These cumulative scores are then interpreted into five levels of severity: normal, mild, moderate, severe, and very severe, based on threshold ranges established in the DASS manual. For instance, a depression score above 28 is categorized as very severe, while a score between 0 and 9 is considered normal. This scoring system enables the system to provide an objective and clinically relevant interpretation of the user's mental state. When integrated with the CNN-based emotion recognition system, this interpretation offers a more comprehensive assessment of psychological well-being, facilitating early detection and potential intervention. This interpretation stage builds upon the CNN classification output and reinforces the final evaluation by combining objective and subjective indicators.

After the facial expression classification process using the CNN model and the user's completion of the DASS-42 questionnaire, the system conducts a final analysis to determine the user's mental condition. The CNN output, which identifies one of four emotions sadness, anger, fear, or disgust is first mapped to an associated psychological state: sadness indicates potential depression, anger correlates with stress, and fear or disgust suggest anxiety. Based on this initial classification, the system dynamically triggers the corresponding subscale of the DASS-42 questionnaire. Once the user responds, the system calculates a total score for that subscale. It categorizes it into one of five severity levels: normal, mild, moderate, severe, or very severe, in accordance with the DASS-42 guidelines. This sequential integration of emotion detection and psychometric assessment ensures a more accurate and holistic evaluation of the user's mental health condition. It combines objective facial analysis with subjective self-assessment, allowing for a nuanced understanding and early identification of potential psychological disorders.

3. RESULTS AND ANALYSIS

This chapter outlines the outcomes of the system development and experimental evaluation. It includes a detailed description of the dataset used, the evaluation results of the CNN model, the flow of the application interface, and the findings from functional testing using the black box method to ensure each module operates as intended.

3.1. Dataset Description and Preparation

Model performance evaluation was conducted using the FER-2013 dataset, which was divided into two subsets: 70% training data and 30% testing data, as shown in Tables 6 and 7. This dataset was classified into three categories of facial expressions related to mental states: depression, anxiety, and stress. The test data consisted of 616 samples for depression, 293 for anxiety, and 1,081 for stress. The CNN model was evaluated using standard classification metrics: precision, recall, F1-score, and overall accuracy. The results are presented in Table 8.

Tabel 6. FER-2013 Training Dataset

Face Classification	Number of Training Datasets
Depression	2870
Anxiety	1361
Stress	5038

Tabel 7. FER-2013 Testing Dataset

Face Classification	Number of Testing Datasets
Depression	616
Anxiety	293
Stress	1081

3.2. Model Evaluation Results: Admin and Patient Perspectives

Table 8 presents the confusion matrix and classification report used to evaluate the performance of the emotion detection model, which classifies facial expressions into three categories: depression, anxiety, and stress. Out of 1,990 test samples, the model achieved an overall accuracy of 81%.
According to the confusion matrix, the stress category achieved the highest classification performance with 969 correct predictions, followed by depression with 410, and anxiety with 220. Misclassifications were also observed, such as 126 depression samples being misclassified as stress and 62 stress samples being incorrectly predicted as anxiety.

The classification metrics provide deeper insights into the model's effectiveness. For the depression class, the model achieved a precision of 0.83, a recall of 0.66, and an F1-score of 0.74. The anxiety class yielded an accuracy of 0.60, recall of 0.75, and F1-score of 0.67, indicating that while most anxiety cases were detected, the predictions lacked precision. The stress class had the strongest performance across all metrics, achieving an accuracy of 0.85, a recall of 0.89, and an F1-score of 0.87.

Overall, the model shows reliable performance, especially in recognizing stress-related expressions. The lower scores in distinguishing between depression and anxiety may be due to overlapping facial cues, which pose challenges to the classifier. For balanced performance evaluation across all classes, the macro average F1-score of 0.76 is more appropriate than the weighted average, as it equally considers each class regardless of its size. This macro average score reinforces the model's capability to handle multi-class emotion classification tasks in a balanced and consistent manner, making it suitable for real-world deployment.

Table 8. Confusion Matrix

Label	Precision	Recall	F1-Score	Support
Depression	0.83	0.66	0.74	616
Anxiety	0.60	0.75	0.67	293
Stress	0.85	0.89	0.87	1081
Accuracy			0.81	1990
Macro Avg	0.76	0.77	0.76	1990
Weighted Avg	0.79	0.81	0.81	1990

3.3. Application Flow View: Admin and Patient Perspectives

To provide a comprehensive understanding of the system's functionality, this section describes the application flow from both the patient's and admin's perspectives in Figure 2. Each user role interacts with the system through distinct features designed to support mental health screening and data management.

From the admin's perspective, the system offers comprehensive access to manage and monitor all user interactions. Admins can view the history of all patient sessions, including facial expression snapshots, questionnaire results, session timestamps, and predictive outputs. This enables administrators to track patient conditions over time and manage data records effectively, including the ability to update or delete session logs as needed. The pages accessible to these admins are shown in Figures 3 and 4. This role is crucial for ensuring data quality, supporting evaluation, and facilitating early intervention when signs of mental health issues are detected.

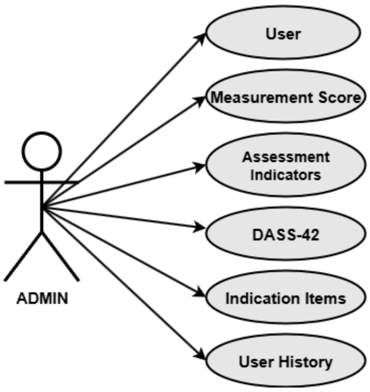

Figure 2. Use Case Diagram of Admin Operating System

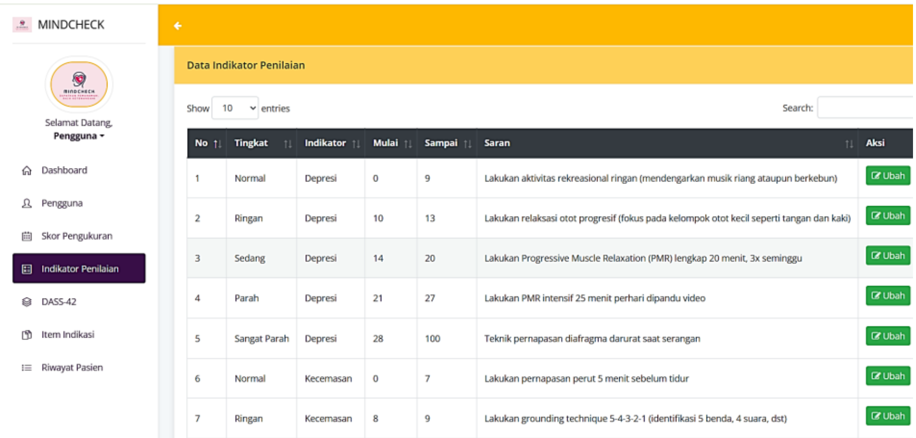

Figure 3. Measurement Indicator in admin

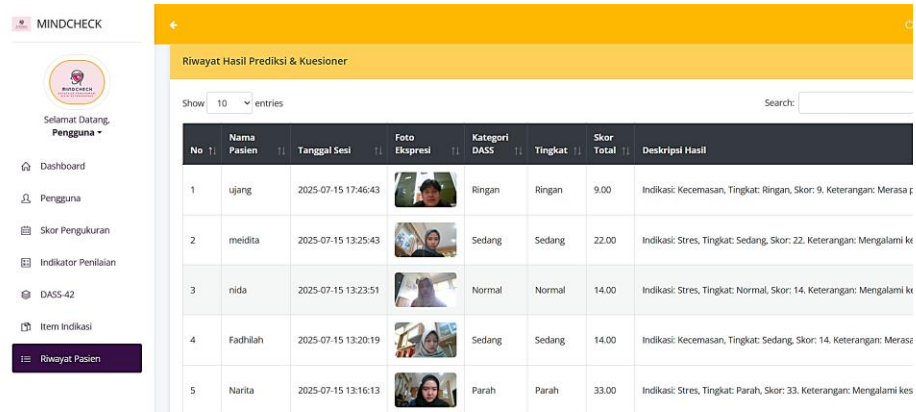

Figure 4. User History is accessed by admin

From the patient's perspective, the application provides a structured process for conducting self-assessments related to mental health. The journey starts with live facial expression analysis via the device's camera, where the system identifies emotional states such as depression, anxiety, or stress. Afterward, patients are guided to complete the DASS-42 questionnaire (see Figure 7). The application then integrates the results from both inputs facial recognition and questionnaire to produce an instant emotional health summary displayed on the screen (see Figure 8).

The patient use case highlights the core interaction with the system, enabling users to perform facial emotion detection, fill out the DASS-42 form, and receive immediate feedback on their mental condition. To demonstrate the system's real-time detection capability, Figure 6 showcases the live facial expression interface. The use case diagram of patient operating system can see Figure 5.

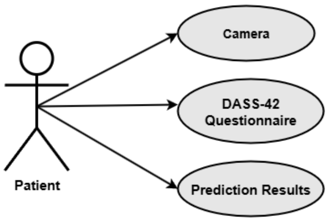

Figure 5. Use Case Diagram of Patient Operating System

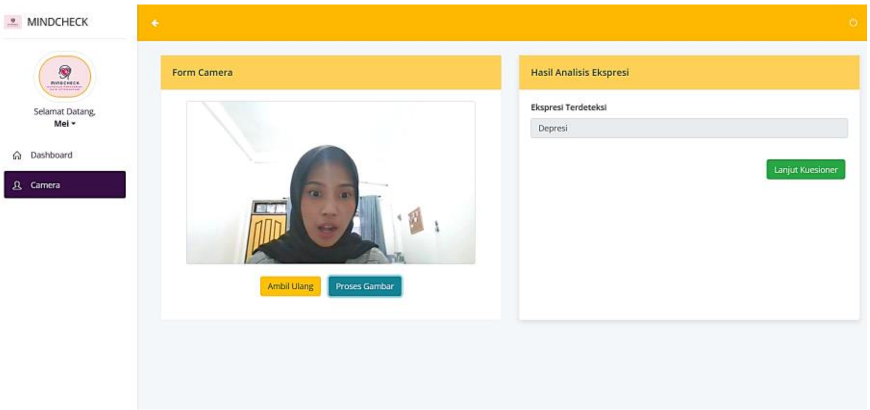

Figure 6. Real-time facial expression detection using a camera input.

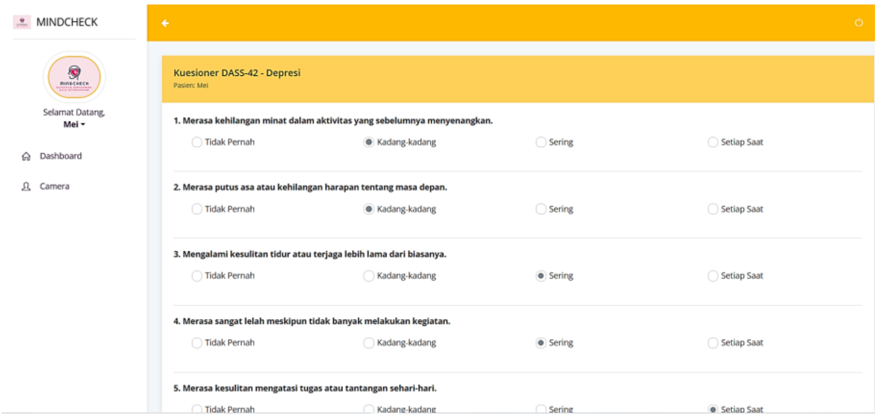

Figure 7. View On DASS-42 Questionnaire

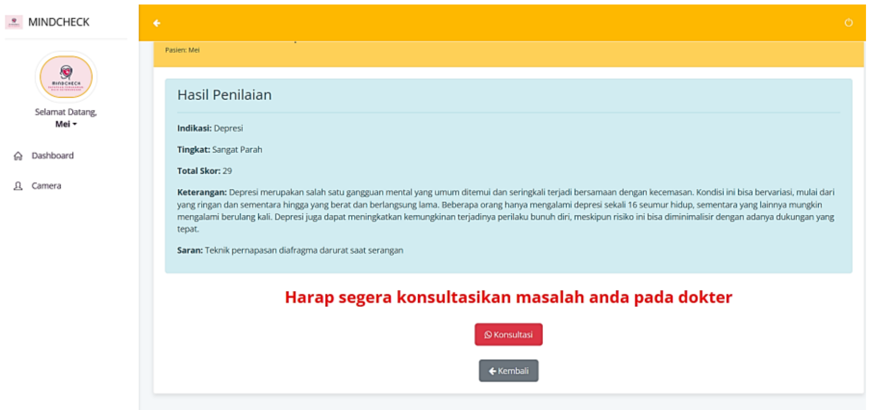

Figure 8. Assessment Results

3.4. Functional Testing (Black Box Testing)

To evaluate the functional reliability of the developed application, black box testing was conducted on all main features. Table 9 summarizes the test scenarios, actions, results, and statuses for each tested module.

Table 9. Black Box Testing

No	Tested Features	Testing Steps	Test Results	Status
1	Account List Menu	Account List Menu Users fill in the registration form with valid data and press the register button.	The account is successfully created, and the user is redirected to the login page.	Succeed
2	Login	The user enters a valid username and password.	The system successfully redirects the user to the main page.	Succeed
3	User View	Admin can access the user list and add other users.	The addition of saved and new users appears according to the access rights granted.	Succeed
4	Measurement Score	Admin can add, change, and delete score data.	Score data is successfully displayed, added, changed, and deleted according to admin actions.	Succeed
5	Measurement Indicator	Admin can set the range and description of the indicator.	The system stores and displays indicators according to the given configuration.	Succeed
6	DASS-42 Questionnaire Indication Items	The Admin can add details of questions and indicators related to the DASS-42 Questionnaire.	Question item data was successfully displayed and modified according to admin input.	Succeed
7	Facial Expression Detection Using Camera	The user activates the camera, and the system automatically captures and detects facial expressions using the CNN Algorithm.	The camera is active, and the system successfully recognizes and classifies facial expressions (sad, angry, scared, and disgusted).	Succeed
8	DASS-42 Questionnaire	After the expression detection process, the user is directed to fill out 42 DASS-42 questionnaire questions based on the results of the facial expression classification.	Users can fill in questions according to facial expression classification without error, and data is stored correctly.	Succeed
9	Assessment Results	The system calculates a score from the questionnaire results.	It displays the level of impairment (normal, mild, moderate, severe) The system successfully displays the assessment results based on the appropriate scores and indicators.	Succeed

4. CONCLUSION

This study has successfully designed and developed a mental health consultation application that integrates facial expression recognition using a CNN with the DASS-42 questionnaire. The system aims to support early detection of mental health conditions by analyzing facial expressions such as sadness, anger, fear, and disgust, each corresponding to indicators of depression, stress, and anxiety.

The CNN model, trained on the FER-2013 dataset, achieved an accuracy of 81% on the test set, with the stress category showing the highest classification performance. Based on evaluation metrics, including precision, recall, and F1-score, the model demonstrated strong reliability in detecting stress-related expressions, while its performance in distinguishing between depression and anxiety still requires improvement. The macro average F1-score of 0.76 indicates balanced classification performance across the three emotional categories. Functional validation through black box testing confirmed that all major system modules—such as account registration, facial expression detection, questionnaire processing, and result presentation—operated correctly as intended. The integration of visual-based emotion detection with psychometric scoring provides a comprehensive and responsive assessment flow. In conclusion, the proposed application presents a promising tool for preliminary mental health screening. It has the potential to assist practitioners and institutions by offering an efficient, data-driven approach to early psychological evaluation and condition monitoring.

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