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An Empirical Study of Depression,Anxiety and Stress using Machine Learning

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Abstract - This study develops a machine learning–assisted analytical system for evaluating psychological distress using the 42-item Depression Anxiety Stress Scales (DASS-42). The proposed system implements an end-to-end pipeline encompassing data preprocessing, standardized scoring, visualization, and multi-class classification of depression severity levels. A Random Forest classifier (Breiman , 2001) was employed to predict depression severity directly from raw questionnaire responses.The model was trained and evaluated using a stratified train-test split on a DASS-42 dataset. It achieved an overall accuracy of 86.67% on the held-out test set. Performance was excellent for the Normal (100%) and Extremely Severe (93.5%) categories, and acceptable for the Severe category (75.0%). However, classification of Mild and Moderate levels remained challenging, primarily due to class imbalance and limited sample representation within these intermediate categories.The findings demonstrate the feasibility of integrating machine learning with validated psychometric instruments such as the DASS-42 (Lovibond & Lovibond, 1995) to enable scalable and automated mental health screening. Feature importance analysis further revealed key questionnaire items contributing to predictions. While the system shows promise for identifying extreme severity levels, the study underscores the need for balanced datasets and advanced techniques (e.g., resampling or cost-sensitive learning) to improve performance across all severity categories.

***Key Words*:** Depression Anxiety Stress Scales (DASS-42); machine learning; Random Forest; mental health assessment; depression severity classification; class imbalance

1. INTRODUCTION

Mental health disorders, particularly depression, anxiety, and stress, constitute a significant global public health challenge. According to the World Health Organization (2023), approximately 280 million people worldwide experienced depression in 2019, with prevalence estimates indicating that about 5–5.7% of adults are affected. Early detection and accurate classification of psychological distress are critical for timely intervention and improved treatment outcomes.

Traditional mental health assessment has largely depended on standardized psychometric tools. The Depression Anxiety Stress Scales (DASS), originally developed by Lovibond and Lovibond (1995), is among the most widely used instruments. The full 42-item version (DASS-42) measures three interrelated dimensions of negative emotional states—depression, anxiety, and stress—with strong reliability and construct validity. Although effective, manual scoring and interpretation of the DASS-42 can be time-consuming and difficult to scale for large populations or screening programs.
Recent advances in data science and artificial intelligence have enabled the integration of machine learning techniques into mental health analysis. Ensemble methods such as the Random Forest algorithm (Breiman, 2001) are particularly well-suited for questionnaire-based data because they handle high- dimensional features, capture complex interactions,

and are robust to overfitting.

This study proposes a DASS-42 Analysis System that combines traditional psychometric evaluation with machine learning. The system automates the full analytical pipeline— including data preprocessing, scoring, visualization, and severity classification. The primary objective is to build and evaluate a Random Forest model capable of predicting depression severity levels directly from raw item responses, using standard performance metrics such as accuracy and confusion matrix analysis.

By bridging validated psychometric instruments with computational approaches, this research contributes to the emerging field of computational mental health and supports the development of scalable screening tools. The study also highlights persistent challenges, such as class imbalance, that affect the classification of intermediate severity levels.

2. LITERATURE REVIEW

Mental health assessment has traditionally relied on standardized psychometric instruments designed to measure emotional and psychological distress. One of the most widely used tools is the Depression Anxiety Stress Scales (DASS), developed by Lovibond and Lovibond (1995). The full 42-item version (DASS-42) offers a comprehensive framework forevaluating three related but distinct dimensions of negative emotional states: depression, anxiety, and stress. Its structured design and strong psychometric properties, including high reliability and construct validity, have made the DASS-42 a widely accepted instrument in both clinical and research settings.

Subsequent research extended the utility of the DASS through the development and validation of a short form. Henry and Crawford (2005) examined the 21-item version (DASS-21), demonstrating strong construct validity and providing normative data in a large non-clinical sample. Their findings confirmed that the three-factor structure remains robust in the abbreviated version, supporting its practical use when brevity is prioritized without significant loss of measurement quality.

With advances in computational techniques, there has been growing interest in integrating machine learning approaches into mental health analysis using psychometric data. The Random Forest algorithm, introduced by Breiman (2001), has proven especially suitable for this domain. Its ensemble learning method effectively handles high-dimensional questionnaire data, captures complex interactions among correlated features, and reduces overfitting—characteristics that align well with the structure of DASS-42 responses.

Recent studies have applied machine learning models such as Random Forest, Support Vector Machines, and Neural Networks to predict mental health conditions from survey responses and behavioral data. These approaches provide automated and scalable alternatives to traditional manual assessment. However, the literature consistently identifies challenges including class imbalance across severity levels, limited dataset sizes, and reduced predictive accuracy for intermediate (mild-to-moderate) severity categories.

Open-source libraries such as Scikit-learn (Pedregosa et al., 2011) have greatly facilitated the implementation and reproducibility of these models in psychological research by offering standardized tools for data preprocessing, model training, and evaluation. Principles of tidy data (Wickham, 2014) further enhance the structuring and cleaning of questionnaire datasets before analysis. Global reports by the World Health Organization (2023) emphasize the urgency of such innovations, highlighting the high prevalence of depressive disorders and the need for scalable, data-driven assessment systems.

Overall, the literature supports the integration of well-validated psychometric instruments like the DASS-42 with machine learning techniques as a promising approach to improve the efficiency, scalability, and analytical depth of mental health assessment. While existing studies demonstrate encouraging results, further research is required to address limitations related to data imbalance, model generalization across populations, and interpretability of predictions.

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METHODOLOGY

The proposed system is designed to analyze psychological distress using the DASS-42 questionnaire and classify mental health severity levels using machine learning techniques. The system operates through a structured pipeline that includes data preprocessing, scoring, visualization, and classification using an intelligent model. The methodology combines psychometric evaluation with artificial intelligence to automate mental health assessment and improve scalability and efficiency.

2.1System Overview

The system consists of five major modules: Input Module, Preprocessing Module, Scoring & Classification Module, Visualization Module, and Machine Learning Module. The Input Module loads the dataset containing DASS-42 responses. The Preprocessing Module cleans and prepares the data for analysis. The Scoring Module calculates depression, anxiety, and stress scores and assigns severity levels. The Visualization Module generates graphical insights. Finally, the Machine Learning Module predicts depression severity using a trained model..

2.2Data Collection and Feature Extraction

The dataset is collected in the form of a CSV file containing responses to 42 DASS questionnaire items. Each row represents a participant, and each column corresponds to a question. Feature extraction involves selecting all 42 questionnaire responses (Q1–Q42) as input features. These features represent psychological indicators and are used for both scoring and machine learning classification.

2.3Data Preprocessing

Data preprocessing is performed to ensure data quality and consistency. Steps include:
Renaming columns to a standardized format (Q1– Q42)
Converting all responses into numeric values (using pd.to_numeric with coercion)
Handling missing values using zero imputation (replacing NaNs with 0)
This step ensures the dataset is clean, structured, and suitable for further analysis.

2.4Scoring and Severity Classification

The system computes scores for three subscales (Depression, Anxiety, and Stress) following the DASS-42 guidelines established by Lovibond and Lovibond (1995). The procedure is:

1. **Sum** the relevant 14 items for each subscale (raw score range: 0–42)
2. **Multiply** each raw score by 2 to obtain scaled scores (range: 0–84), aligning with DASS-21 normative thresholds
3. **Assign severity levels** based on published cutoffs:

Table 3.2: DASS-42 Severity Classification Thresholds (Scaled Scores)

Severity Label	Depression	Anxiety	Stress	Encoded Label
Normal	0 – 9	0 – 7	0 – 14	0
Mild	10 – 13	8 – 9	15 – 18	1
Moderate	14 – 20	10 – 14	19 – 25	2
Severe	21 – 27	15 – 19	26 – 33	3
Extremely Severe	28+	20+	34+	4

2.5Machine Learning Model

The system uses the **Random Forest** algorithm (Breiman, 2001) to classify depression severity. The model is trained using:
Input features: All 42 raw item responses (Q1–Q42)
Target variable: Integer-encoded depression severity label (0- 4)
The dataset is split into training and testing sets using a **70:30 ratio with stratified sampling** to preserve class distribution. Model hyperparameters are configured as:
n_estimators = 200 class_weight = 'balanced'
This configuration improves handling of imbalanced data by automatically weighting minority classes. Implementation

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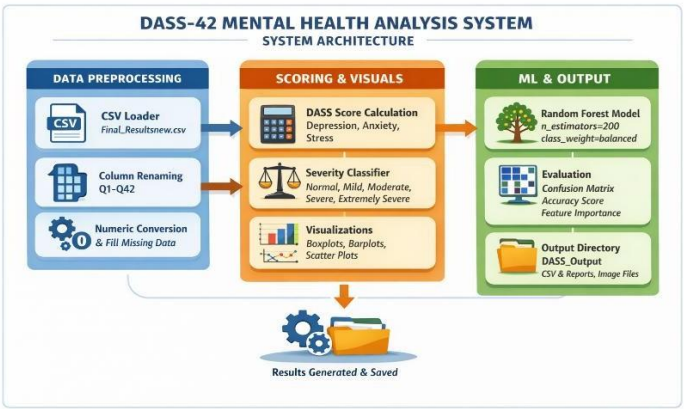
is carried out using the Scikit-learn library (Pedregosa et al., 2011).

3.5 Algorithm Algorithm:

Step1: Load the CSV dataset
Step2: Preprocess data (cleaning, type conversion,missing value imputation)
Step3: Extract features (Q1–Q42)
Step4: Compute DASS-42 subscale scores
Step5: Assign severity labels and encode themnumerically
Step6: Split dataset into training (70%) and test (30%) sets
Step7: Train Random Forest model on the training set
Step8: Predict depression severity on the test set
Step9: Evaluate model performance using accuracy and confusion matrix

3.6 System Architecture

The system follows a modular pipeline architecture:
Input Layer: Loads CSV dataset
Processing Layer: Data cleaning and transformation **Scoring Layer**: DASS-42 score computation and severity classification
Machine Learning Layer: Model training and prediction
Output Layer: Results, visualizations, and reports Python-based tools such as Pandas, NumPy, and Scikit-learn are used for implementation.



3.7 Working Mechanism

The system operates in a sequential workflow. Data is loaded and preprocessed first. DASS scores are then calculated, and severity levels are assigned. Visualizations such as boxplots, bar plots, and scatter plots are generated to provide exploratory insights. The machine learning model then predicts depression severity, and results are evaluated using accuracy and confusion matrix. The system thereby provides automated, accurate, and scalable mental health analysis..

3.9 Ethical Considerations

The anonymized dataset was collected under appropriate ethical approvals, including informed consent and institutional review board oversight. This system is intended as a research and decision-support tool only; it does not replace clinical judgment. All outputs should be interpreted by qualified mental health professionals.

3. RESULTS AND DISCUSSION

The proposed system was evaluated to analyse its effectiveness in classifying psychological distress levels using the DASS-42 dataset. The system successfully processed questionnaire responses, computed scores, and predicted depression severity using a machine learning model.

The data preprocessing module accurately handled missing values, converted responses into numerical format, and ensured a clean dataset for further analysis. This improved the reliability of the scoring and classification process.

The scoring mechanism based on the DASS-42 guidelines developed by Lovibond and Lovibond correctly calculated depression, anxiety, and stress levels and assigned appropriate severity categories. The classification output was

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consistent with standard psychological assessment methods.

The machine learning model using the Random Forest algorithm introduced by Leo Breiman demonstrated strong performance in predicting depression severity. The model achieved an overall accuracy of **86.67%**, indicating that the majority of the test samples were correctly classified.

The model showed excellent performance in identifying Normal cases, achieving 100% accuracy, and very good performance in detecting Extremely Severe cases with an accuracy of 93.5%. This indicates that the system is highly effective in recognizing extreme levels of psychological distress.

However, the model showed limited performance for Mild and Moderate categories, where no samples were correctly classified. This is mainly due to the very small number of samples available for these categories in the test dataset. The Severe category showed moderate performance with 75% accuracy.

The confusion matrix analysis revealed that most misclassifications occurred between adjacent severity levels, especially between Severe and Extremely Severe. In some cases, misclassification occurred between distant categories due to data imbalance and limited representation.

Overall, the results indicate that the proposed system is effective in classifying psychological distress, particularly for extreme severity levels. The integration of machine learning with psychometric analysis provides an automated and efficient approach for mental health assessment.

An experimental evaluation was conducted on the dataset to assess model performance. The results show that the system performs well for majority classes and provides reliable predictions. However, improving dataset balance and increasing sample size for underrepresented categories can further enhance the model's accuracy and generalization capability.

```
C:\Users\rayav>python finalcombnew.py
 Data Loaded Successfully

 TRAINING MODEL...

 Accuracy: 86.67 %

 Confusion Matrix:

Predicted         Normal  Mild  Moderate  Severe  Extremely Severe
Actual
Normal                 7     0         0       0                 0
Mild                   0     0         0       0                 1
Moderate               1     0         0       1                 0
Severe                 1     0         0       3                 0
Extremely Severe       0     0         0       2                29

 Per-Class Summary:

Class                Correct    Total   Accuracy
-----------------------------------------------------
Normal                     7        7     100.0%
Mild                       0        1       0.0%
Moderate                   0        2       0.0%
Severe                     3        4      75.0%
Extremely Severe          29       31      93.5%

 PROJECT COMPLETED SUCCESSFULLY!
```

4. CONCLUSIONS

The proposed DASS-42 Analysis System successfully demonstrates the integration of psychometric assessment with machine learning techniques for automated mental health classification. The system effectively processes raw questionnaire data, performs standardized scoring based on the guidelines developed by Lovibond and Lovibond, and classifies psychological distress levels using a supervised learning approach.

The implementation of the Random Forest classifier introduced by Leo Breiman proved to be effective in handling high-dimensional questionnaire data and predicting depression severity levels. The model achieved an overall accuracy of **86.67%**, indicating strong performance in classifying the majority of instances correctly.

The results show that the system performs exceptionally well in identifying extreme severity levels, particularly Normal and Extremely Severe categories, while maintaining moderate performance for the Severe class. However, the model demonstrated limited accuracy for Mild and Moderate categories due to the imbalance and limited representation of these classes in the dataset.

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The system provides a scalable and automated solution for mental health assessment, reducing the need for manual scoring and enabling efficient analysis of large datasets. Additionally, the use of feature-based learning offers insights into important psychological indicators contributing to severity classification. In conclusion, the study confirms that integrating machine learning with standardized psychological tools such as DASS-
42 is a promising approach for improving mental health screening systems. Future improvements can focus on addressing class imbalance, increasing dataset size, and exploring advanced models to enhance classification performance across all severity levels.

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