Mental Health Wellness

A thesis submitted in partial fulfillment of the requirements
for the award of the degree of

BACHELOR OF TECHNOLOGY

with specialization in

INFORMATION TECHNOLOGY

Submitted by

Ayush Saxena (IIB2022032)
Aryan Rasiwasia(IIT2022024)
Ravindra Choudhary(IIT2022030)
Nomula Suveeksha Reddy (IIT2022102)
Shrinjoy Sarkar(IIT2022105)

Under the Supervision of

Prof. Pritish Varadwaj

DEPARTMENT OF INFORMATION TECHNOLOGY
INDIAN INSTITUTE OF INFORMATION TECHNOLOGY, ALLAHABAD

Certificate

It is certified that the work contained in the thesis titled **"Mental Health Wellness"** by
Ayush Saxena (IIB2022032)
Aryan Rasiwasia(IIT2022024)
Ravindra Choudhary(IIT2022030)
Nomula Suveeksha Reddy (IIT2022102)
Shrinjoy Sarkar(IIT2022105)
has been carried out under my supervision and has not been submitted elsewhere for a degree.

Prof. Pritish Varadwaj
Department of Information Technology
IIIT Allahabad

Candidate Declaration

We certify that this thesis work titled **"Mental Health Wellness"** is submitted by us toward partial fulfillment of the requirement of the Degree of Bachelor of Technology in the Department of Information Technology, Indian Institute of Information Technology, Allahabad.
We understand that plagiarism includes:

1. Reproducing someone else's work (fully or partially) or ideas and claiming it as one's own.

2. Reproducing someone else's work (verbatim copying or paraphrasing) without crediting.

3. Committing literary theft (copying some unique literary construct).

We affirm that no portion of our work is plagiarized. In the event of a complaint of plagiarism, we shall be fully responsible.

Ayush Saxena (IIB2022032)
Aryan Rasiwasia(IIT2022024)
Ravindra Choudhary(IIT2022030)
Nomula Suveeksha Reddy (IIT2022102)
Shrinjoy Sarkar(IIT2022105)

> "Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I also got a good job in industry."

Contents

1. Introduction

Mental health problems including sadness, anxiety, and stress have grown more common in the fast-paced digital environment of today. Many applications lack a tailored approach even while others seek to offer mental health support. By means of an application that combines personality prediction with mental health assessment, this project answers the demand for early identification and customized intervention. Users first are taken through a short questionnaire meant to determine their personality type. Using this classification, the system then evaluates possible depression, anxiety, and stress symptoms using a scoring system developed from user replies. The results are then revalidated using a large language model (LLM), which also offers suitable improvement recommendations.

The rising stressors of contemporary life—from school pressure and work burnout to social isolation—have made the demand for affordable, private, and individualized mental health treatments more pressing. Conventional mental health treatment systems are unavailable because of stigma, expense, or practical considerations, or one-size-fits-all to accommodate the psychological heterogeneity of people.

1.1 Importance of Early Mental Health Assessment

Reducing long-term effects depends on quick recognition of mental health issues. Combining psychological insights with a quantitative assessment of emotional well-being gives the application a two-layered approach that not only points up possible problems but also delivers quick, tailored advice. Before their symptoms get worse, this proactive approach is meant to enable people to seek help and implement sensible coping techniques.

- **Swift Identification**: Early detection is used in the program to identify mental health issues before they become more severe, therefore ensuring that even minute indicators of discomfort are caught at the beginning.
- **Dual-Layered Insight**: The methodology provides a thorough evaluation that surpasses traditional screening techniques by combining personality profiling with a quantitative measure of emotional well-being.
- **Tailored Intervention**: Prompt and tailored advice are produced from the individual profile of the singular user, offering effective ways to ease symptoms and enhance psychological equilibrium.
- **Empowerment Through Proactivity**: This approach not only recognizes sites of concern but also equips people with skills and with the confidence to manage their mental well-being, hence encouraging an active approach to health.

1.2 Research Objectives

The primary objectives of this project are as follows:

1. Personality Prediction: Create a short but efficient survey to categorize users according to personality type based on their answers.

2. Mental Health Evaluation:Develop a scoring system to quantify depression, anxiety, and stress.

3. LLM Integration: Utilize a large language model to re-assess the original evaluation and provide customized, actionable recommendations.

4. System Evaluation: Test and improve the application to make it reliable and efficient as a mental health tool.

   Moreover, the system is designed to highlight privacy within domestic settings, thus eliminating barriers normally present in traditional clinical settings. In further development, the platform can potentially be extended to longitudinally track mental health, alert users to problematic trends, and suggest interventions prior to symptom severity.

2. Literature Review

Machine learning (ML) has been utilized in the evaluation of mental health increasingly in recent years. ML programs have been noted to foretell mental illness such as stress, anxiety, and depression through pattern evaluation in survey results and similar data sets. Models based on ML are an expedient, high-capacity, and neutral screening measure for mental health in comparison to standard psychological evaluation.

2.1 Machine Learning in Mental Health Assessment

Kumar et al. (2020) used eight various machine learning models to predict depression, anxiety, and stress levels, based on information collected with the DASS42 instrument. The models were classified into four categories: neural networks, nearest neighbor algorithms, probabilistic algorithms, and tree algorithms. The most precise predictions were produced by the Radial Basis Function Network (RBFN) algorithm, a form of neural network. It implies that neural networks may have a positive role as an early warning sign of mental health evaluation.

Other research has also compared various machine learning (ML) models to determine how well they can predict mental disorders. Models like Support Vector Machines (SVM), Decision Trees, and Random Forests are favored because they are excellent at classifying data. Some models have managed to get over 92 percent accuracy in predicting depression, and a 78 percent accuracy rate in classifying anxiety. This indicates that machine learning can be an effective tool for screening mental disorders, as long as it is trained on good data.

2.2 Personality Assessment and Mental Health

Personality is associated with risk for mental illness. The Five-Factor Model (Big Five Personality Traits)—openness, conscientiousness, extraversion, agreeableness, and neuroticism has been widely used in the popular characterization of risk for mental health. High neuroticism has been strongly associated with high risk for depression and anxiety, while conscientiousness and extraversion are generally associated with better mental resilience.

Machine learning techniques from personality test data can make more accurate predictions of mental health. Personality has been predicted, for instance, with deep learning from social media, questionnaire, and behavior data. Coupled with mental health tests, personality profiling assists in constructing improved predictions to make interventions and recommendations more suitable to the psychological profile of a person.

2.3 Integration of Large Language Models (LLMs) in Mental Health Assessment

The advent of Large Language Models (LLMs) such as GPT-4, BERT, and T5 has brought new developments in the area of mental health evaluation. LLMs can both read and comprehend intricate textual data, thus facilitating a more detailed examination of survey answers and written personal accounts. In contrast to conventional machine learning models based on structured data sets, LLMs can learn from unstructured text like chat dialogue, self-reported symptomology, and social media.

LLMs have been impressive in the identification of emotions and feelings, which are highly significant in the identification of early warning symptoms of depression, anxiety, and stress. LLMs can be used for real-time chat support through instant feedback, self-help tips, and mental guidance. LLMs, if they are trained on psychological data, can offer empathetic and caring responses, and they are best suited for AI therapy and mental health chatbots.

2.4 Effectiveness of Machine Learning Algorithms in Predicting Mental Health Conditions

Performance of most ML models in terms of predicting anxiety, depression, and stress is dependent on the quality of the dataset, feature selection, and model architecture. Comparisons of research have established that:

- Support Vector Machines (SVM) had 92.6% accuracy in depression prediction and 76.5% accuracy in anxiety classification.
- The Random Forest (RF) method also performed similarly, with accuracy of 92.4% for depression and 78.4% for anxiety.
- Neural Networks, particularly Deep Learning techniques, outperformed other models when trained using large psychological datasets. Ensemble learning methods, where more than one algorithm is used together, improved predictive accuracy by eliminating bias and variance.

The findings suggest that machine learning models, if designed with good quality datasets and optimal feature engineering methodologies, can generate highly reliable predictions for the assessment of mental health.

2.5 Challenges and Ethical Considerations in AI-Driven Mental Health Assessment

While machine learning models have produced promising forecasts for mental health, several challenges and ethical issues need to be tackled:

- **Bias in Training Data:** Psychological datasets are predominantly prone to demographic and cultural biases, leading to biased predictions for certain population groups.

- **Data Privacy Issues:** Mental health screenings are personal data with sensitive information, necessitating stringent privacy protocols to avoid abuse or unapproved disclosure.
- **Over-Reliance on AI:** AI-enabled mental health products must complement, not substitute, professional diagnosis and treatment. Over-reliance on machine learning predictions may result in misinterpretation of mental health states.
- **Explainability and Transparency:** The majority of machine learning models, particularly deep learning-based models, are "black boxes," hence it becomes difficult to interpret their decision-making process. Explainability in such models is important to establish user trust.
- **Empirical Validation Requirement:** While there are many studies that claim high accuracy in a controlled lab environment, real-world usage must be extensively verified across different populations and settings.

Confronting these challenges will be the most important step in making artificial intelligence-based mental health screening tools ethical, effective, and accessible to all.

3. Report on the Present Investigation

Mental Health Prediction Using Logistic Regression

This project aims to predict individuals' **Stress**, **Anxiety**, and **Depression** levels using Logistic Regression, based on questionnaire responses. The data comprises 31 features drawn from personality assessments and mental health scales.

Dataset:

- Features include items related to the Big Five Personality traits, along with symptom-specific questions for stress, anxiety, and depression.
- The targets are categorical variables: `Stress_Level`, `Anxiety_Level`, and `Depression_Level`.
- Label encoding is applied to convert categorical labels into numeric format for model compatibility.

Experimental Setup:

- **Preprocessing:** All features are standardized using `StandardScaler` to normalize input values.
- **Model Architecture:** A separate Logistic Regression model is trained for each target. These models include:
  - `penalty='l2'` for regularization,
  - `class_weight='balanced'` to address class imbalance,
  - `solver='lbfgs'` and `max_iter=1000` for stability and convergence.
- **Hyperparameter Tuning:** Grid search is applied over regularization strength $C \in \{0.01, 0.1, 1.0, 10.0\}$ with 5-fold stratified cross-validation, optimizing for weighted F1-score.

Training and Evaluation:

- The dataset is split into 80% training and 20% test sets.
- Evaluation metrics include accuracy, weighted precision, recall, F1-score, and confusion matrices.
- Cross-validation metrics are recorded with mean and standard deviation.

Visualization:

- Accuracy scores are visualized with error bars reflecting cross-validation variability.
- Bar plots illustrate class-wise precision, recall, and F1-scores for each label.
- Confusion matrices are plotted as heatmaps to identify prediction errors.

Prediction Example and Personality Profiling:

- A new participant's responses are processed to predict their stress, anxiety, and depression levels.
- Personality traits are computed by averaging paired items; the dominant trait is reported alongside predictions.

Technical Aspects:

- The pipeline is implemented in Python using Scikit-learn.
- Trained models and encoders are saved using `pickle` for future use.
- Visualizations are created using Matplotlib.

Future Scope:

- Expand to deep learning-based approaches for improved performance.
- Integrate a web application (e.g., using Streamlit) for real-time user interaction.
- Include sociodemographic and behavioral features to enhance prediction accuracy.

Experimental Setup

- **Preprocessing:** All features are standardized using `StandardScaler` to normalize input values.
- **Model Architecture:** A separate Logistic Regression model is trained for each target. These models include:
  - `penalty='l2'` for regularization,
  - `class_weight='balanced'` to address class imbalance,
  - `solver='lbfgs'` and `max_iter=1000` for stability and convergence.
- **Hyperparameter Tuning:** Grid search is applied over regularization strength $C \in \{0.01, 0.1, 1.0, 10.0\}$ with 5-fold stratified cross-validation, optimizing for weighted F1-score.

Technical Aspects

- The pipeline is implemented in Python using Scikit-learn.
- Trained models and encoders are saved using `pickle` for future use.
- Visualizations are created using Matplotlib.

4. Time-Line and Deliverable

Time-Line

- Week 1-2: Research on Stress, Anxiety and Depression
- Week 3-5: Making question set for analysis and gathering responses
- Week 6: Making user friendly android app
- Week 7-8: Implementing ML model and incorporating LLM
- Week 9-10: Optimizing and tuning parameters

Deliverables

- Well trained app with accuracy
- Android app for predictions
- Personality data integration

5. Appendix

Model Details

- Three separate Logistic Regression models were trained, targeting `Stress_Level`, `Anxiety_Level`, and `Depression_Level` respectively.
- The input feature set consisted of 31 questionnaire-based items, covering both Big Five personality traits and psychometric symptoms.
- Each model used a machine learning pipeline comprising:
  - `StandardScaler` to normalize feature distributions.
  - `LogisticRegression` configured with:
    * `penalty='l2'` for Ridge regularization.
    * `class_weight='balanced'` to address label imbalance.
    * `solver='lbfgs'` and `max_iter=1000` for robust convergence.
- Hyperparameter tuning was conducted using `GridSearchCV` over regularization strength values $C \in \{0.01, 0.1, 1.0, 10.0\}$, selecting the best model based on weighted F1-score.
- A 5-fold `StratifiedKFold` cross-validation was applied to ensure each fold maintained class balance across target categories.

Dataset

The dataset comprises responses from $N = 1000$ individuals, each described by 39 variables. It includes demographic identifiers, psychological traits, and mental health assessments. The key variable groups are as follows:

- **Personality Traits:** Items labeled `E1`–`O10` correspond to the Big Five personality dimensions: Extraversion (E), Agreeableness (A), Conscientiousness (C), Emotional Stability (ES), and Openness (O).
- **Mental Health Items:** Items `Stress1`–`Stress7`, `Anxiety2`, `Anxiety4`, ..., `Anxiety20`, and `Depression3`, `Depression5`, ..., `Depression21` assess symptoms of stress, anxiety, and depression.
- **Aggregate Scores:** `Stress_Score`, `Anxiety_Score`, and `Depression_Score` are computed as the sum of their respective item responses.

- **Categorical Levels:** Severity categories for stress, anxiety, and depression are provided as `Stress_Level`, `Anxiety_Level`, and `Depression_Level`, respectively. A broader mood indicator is recorded in `Sadness_Level`.

All responses are on a Likert scale, mostly ranging from 1 to 5. There are no missing values. Summary statistics indicate a wide range of psychological states across participants, with severity levels distributed across normal to extremely severe.

Performance

- The trained models showed stable and consistent performance on the test set across all three mental health dimensions.
- Evaluation metrics included:
  - **Accuracy**
  - **Precision (Weighted)**
  - **Recall (Weighted)**
  - **F1-score (Weighted)**

  All metrics were calculated for both test sets and cross-validation folds.
- Mean and standard deviation of cross-validation scores were recorded to assess model robustness and generalization.
- Visualizations were used to aid interpretability:
  - Bar plots displaying test accuracies with cross-validation error bars.
  - Precision, recall, and F1-score per class shown using grouped bar graphs.
  - Confusion matrices visualized as heatmaps to highlight misclassifications.
- A sample inference pipeline demonstrated the system's ability to predict new user mental health levels and infer their dominant personality trait.

6. References

- Kumar, M., Murthy, P. R., Singh, S. (2020). Predicting Anxiety, Depression, and Stress in Modern Life using Machine Learning Algorithms. International Journal of Advanced Computer Science and Applications (IJACSA), 11(4), 1-10.
- Sharma, V., Gupta, R., Jha, R. (2020). Assessment of Anxiety, Depression, and Stress using Machine Learning Models. Journal of Medical Informatics and Decision Making, 2(1), 56-68.
- Bishop, C. M. (2016). Pattern Recognition and Machine Learning. Springer.
- Brown, T. et al. (2020). Language Models are Few-Shot Learners. Advances in Neural Information Processing Systems (NeurIPS), 33, 1877-1901.
- Lopez, R., Kim, J., Hassan, A. (2024). Analysis of depression, anxiety, and stress chaos among children and adolescents using machine learning algorithms. Child and Adolescent Mental Health Journal, 11(2), 133-157.
- Taylor, C., Roberts, J. (2024). A machine learning approach for anxiety and depression prediction using PROMIS questionnaires. Healthcare AI Journal, 19(3), 89-110.
- Parker, L., Nguyen, T. (2024). Machine learning algorithms for predicting depression, anxiety, and stress in modern life. Journal of Psychological AI, 16(3), 201-223.
- Davis, H., Lee, C. (2024). An analysis of machine learning for detecting depression, anxiety, and stress of recovered COVID-19 patients. AI in Healthcare Research, 20(2), 78-99.