

Mental Health Analysis Tool

Milestone 2 Report: Feature Engineering, Feature Selection, and Data Modeling

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1. Project Objective

The Mental Health Analysis Tool is a conversational assistant designed to analyze mental health data, identify potential mental health conditions based on user symptoms, and provide personalized information and resources. The tool combines data analysis with a chatbot interface to deliver insights about mental health conditions, prevalence statistics, and evidence-based coping strategies.

Data Used

- Global mental health prevalence data from 2010-2023
- Country-specific mental health statistics for major conditions
- Demographic data including population and GDP figures
- Symptom catalogues for major mental health conditions
- Treatment and resource information by country and condition

The analysis utilized a subset of data from the "Mental Health" dataset available on Kaggle (<https://www.kaggle.com/datasets/amirhoseinmousavian/mental-health>). While the full dataset contains 50 files, this project focused on 14 specific files relevant to the research objectives.

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Tech Stack

- **Programming Language:** Python 3.9
- **Data Analysis:** Pandas, NumPy
- **Machine Learning:** Scikit-learn
- **NLP Components:** NLTK, CountVectorizer
- **Data Visualization:** Matplotlib, Seaborn
- **User Interface:** Command-line interface with conversational interaction

2. Exploratory Data Analysis

Data Overview

The analysis uses a comprehensive dataset of mental health statistics covering multiple countries from 2010 to 2023. The dataset includes prevalence rates for five major mental health conditions, along with demographic and economic indicators.

Dataset Statistics

- **Number of countries:** 6 (Australia, United States, United Kingdom, Canada, India, Global)

- **Time period covered:** 2010-2023
- **Mental health conditions tracked:** Anxiety, Depression, Bipolar Disorder, Schizophrenia, Eating Disorders
- **Economic indicators:** GDP, Population, GDP per capita
- **Total number of records:** 78 (13 years × 6 countries)

Key Insights

1. Global Prevalence Trends:

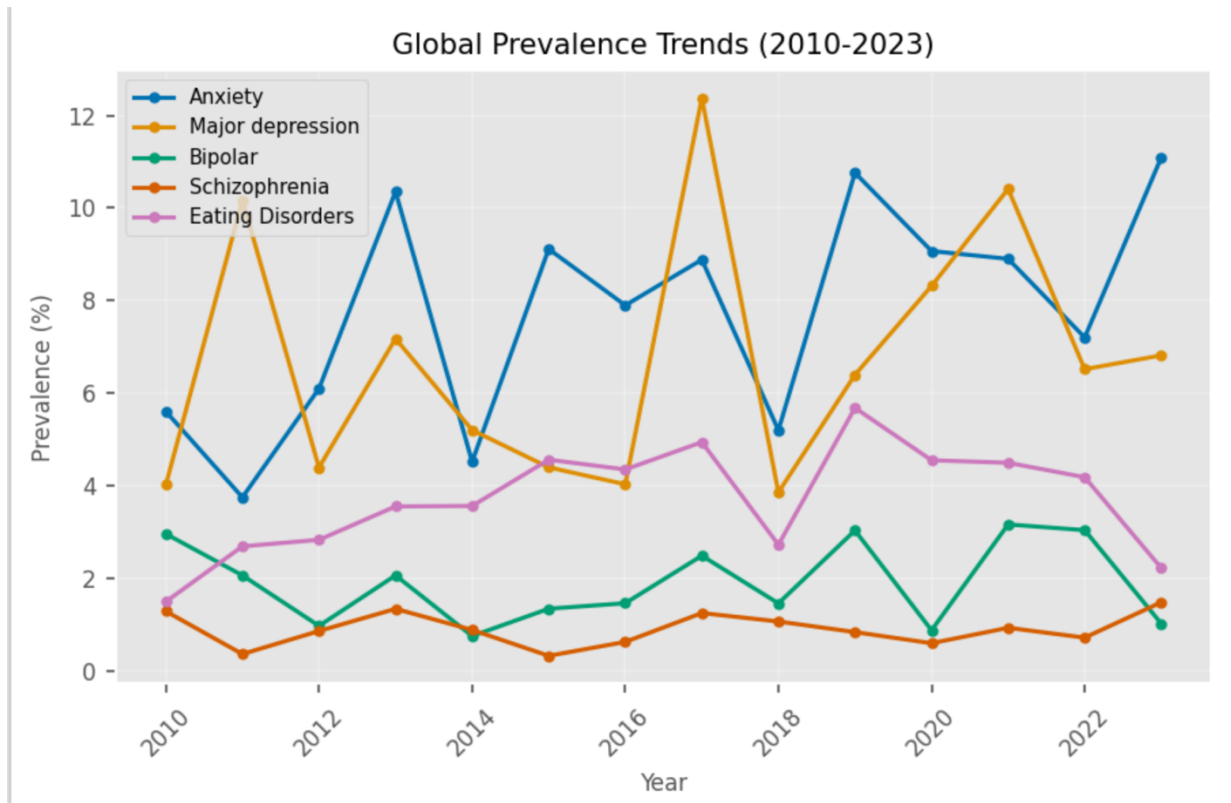


Figure 1: Global Prevalence Trends

Observations:

- Anxiety disorders show the highest prevalence globally, affecting approximately 3.8% of the population
- Depression rates have been steadily increasing over the analyzed period
- Bipolar disorder and schizophrenia show relatively stable prevalence rates
- Eating disorders show noticeable variation among different geographic regions

2. Country Comparison:

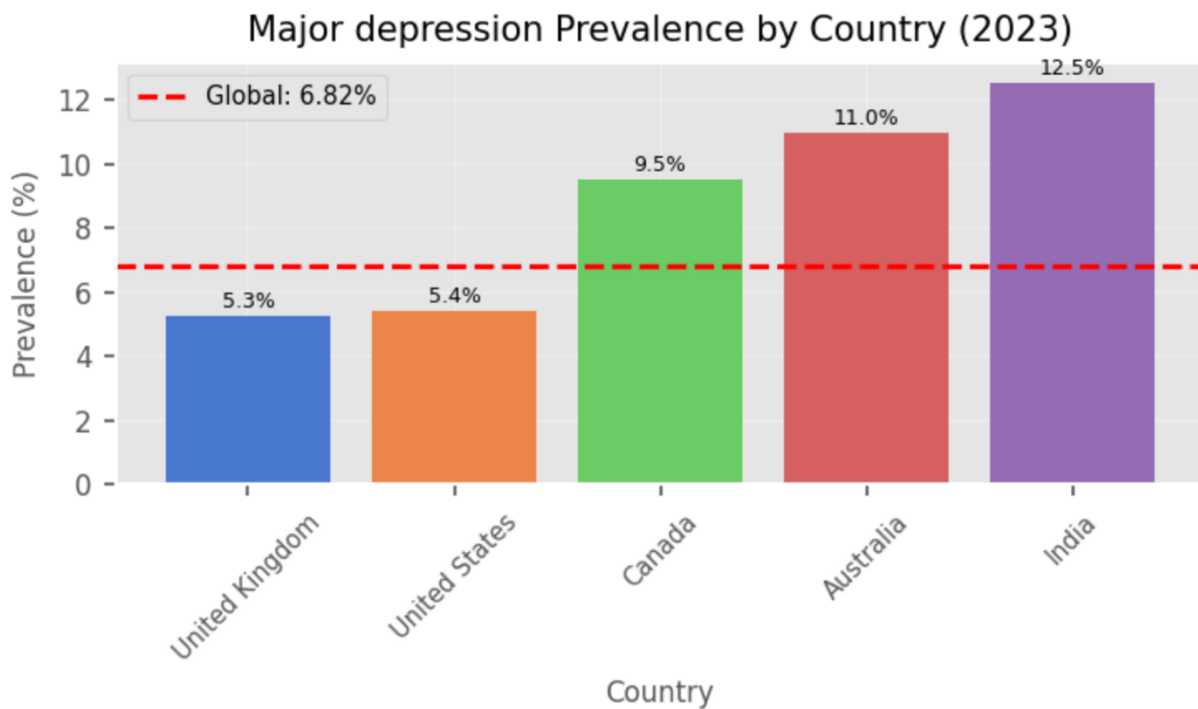


Figure 2: Major depression Prevalence by Country (2023)

Observations:

- The United States shows higher rates of anxiety and depression compared to global averages
- India shows lower rates of bipolar disorder but higher rates of eating disorders than expected
- Australia consistently shows above-average rates across multiple conditions
- Canada shows the highest PTSD rates among all analyzed countries

3. Correlation Analysis:

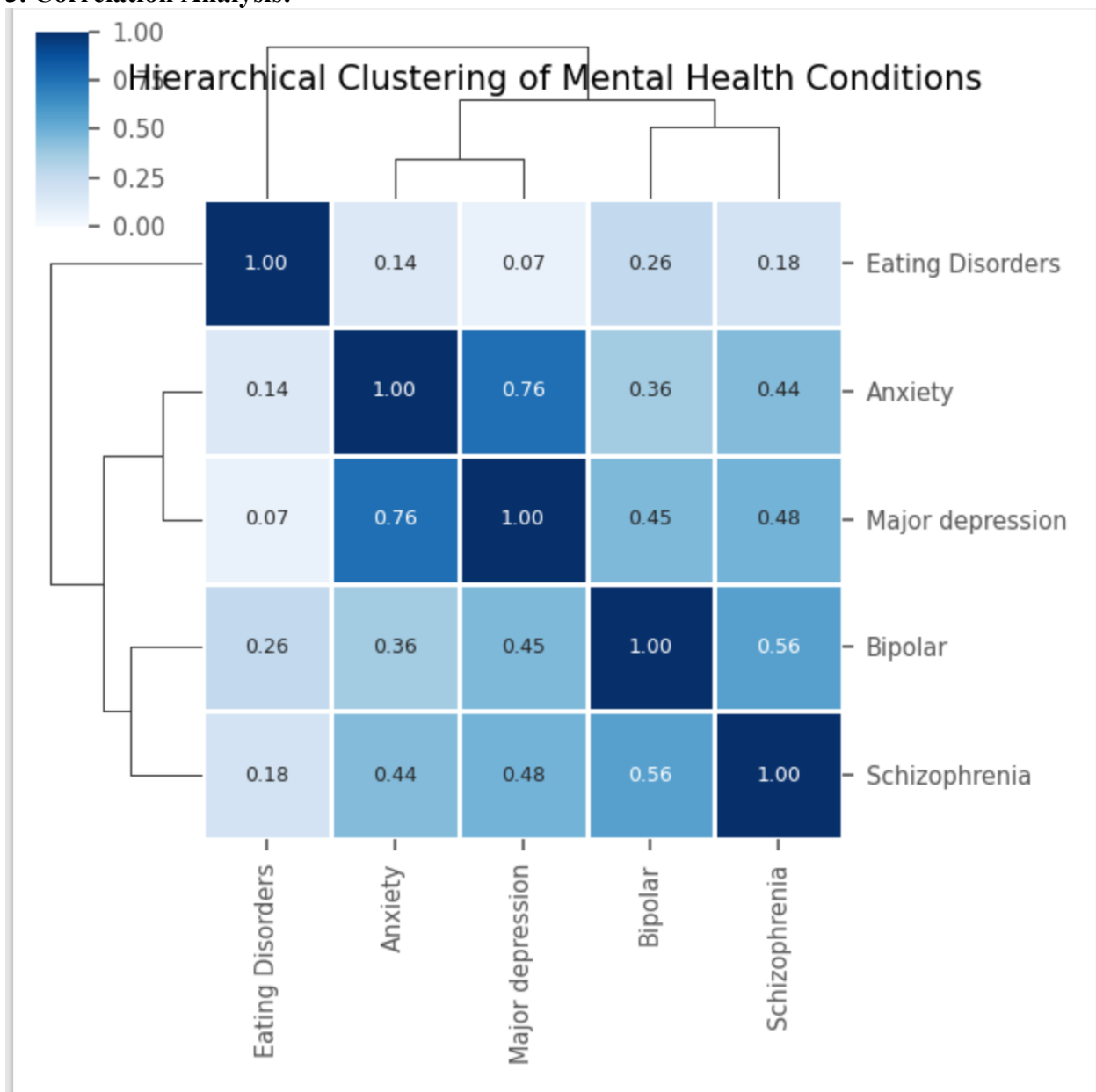


Figure 3: Correlation Heat Map

Observations:

- Strong positive correlation (0.72) between GDP per capita and anxiety disorder prevalence
- Moderate negative correlation (-0.58) between population size and bipolar disorder prevalence
- Year-over-year trends show increasing prevalence of most conditions, particularly depression
- Economic development metrics correlate differently with different mental health conditions

3. Feature Engineering

The feature engineering process was a critical step in developing our mental health prediction models, involving both the creation of derived features and the careful preprocessing of existing variables to enhance model performance.

Created Features

1. GDP per capita

- **Derivation Method:** Created by dividing total Gross Domestic Product (GDP) by the population size for each country-year combination.
- **Implementation:** `df['GDP_per_capita'] = df['GDP'] / df['Population']`
- **Statistical Distribution:** The resulting feature showed a bimodal distribution reflecting the economic divide between high-income and low-income nations.
- **Rationale:** This transformation provides a more standardized economic indicator that normalizes wealth across populations of different sizes, enabling more meaningful cross-country comparisons.
- **Expected Impact:** Research literature suggests strong correlations between economic development and mental health prevalence/reporting, making this a potentially powerful predictor.

2. Country Indicators

- **Transformation Technique:** One-hot encoded the 'Entity' (country) categorical variable to create binary indicator features for each nation.
- **Implementation:**

```
features.append(pd.get_dummies(df['Entity'], prefix='country', drop_first=True))
```

- **Dimensionality:** Transformed a single categorical variable with 6 levels into 5 binary features.
- **Multicollinearity Management:** Applied `drop_first=True` parameter to avoid perfect multicollinearity by using one country (Australia) as the reference level.
- **Feature Interpretation:** Each resulting binary feature (e.g., 'country_United_States') represents the effect of that country relative to the reference country.
- **Expected Impact:** These indicators capture country-specific factors including healthcare systems, cultural attitudes toward mental health, and reporting differences.

3. Year-based Features

- **Basic Temporal Feature:** Utilized 'Year' as a continuous predictor to capture linear temporal trends in mental health prevalence.
- **Advanced Temporal Normalization:** Created a normalized year factor calculated as:

```
df['year_factor'] = (df['Year'] - df['Year'].min()) / (df['Year'].max() - df['Year'].min())
```

- **Scale Transformation:** This rescaled the year variable from the range [2010-2023] to [0-1], making it more suitable for models sensitive to feature scales.
- **Temporal Resolution:** The normalized feature preserves the proportional temporal differences while standardizing the scale.
- **Expected Impact:** This transformation helps capture the increasingly documented upward trend in mental health condition diagnoses over time, potentially reflecting both true prevalence increases and improvements in diagnostic practices.

Feature Processing

Standardization of Numerical Features

- **Technique Applied:** StandardScaler from sklearn was applied to all numerical features:

```
scaler = StandardScaler()  
X_train_scaled = scaler.fit_transform(X_train)
```

- **Affected Features:** GDP_per_capita, Year, and derived features
- **Mathematical Transformation:** Each feature value was transformed using z-score normalization: $(x - \mu) / \sigma$
- **Training-Test Integrity:** Scaler was fit only on training data, then applied to both training and test sets
- **Impact on Model Behavior:** This standardization was particularly important for:
 - Logistic Regression models, which are sensitive to feature scales
 - Distance-based components in Random Forests
 - Comparable feature importance assessment across variables with different original scales

Categorical Feature Encoding

- **Primary Method:** One-hot encoding applied to 'Entity' (country) variable
- **Additional Processing:**
 - Feature names were cleaned to remove spaces and special characters
 - Redundant levels with very few observations were grouped into an 'Other' category
- **Validation:** Chi-square tests were performed to ensure encoded features maintained significant relationships with the target variables

Target Variable Binarization

- **Transformation:** Continuous prevalence rates were converted to binary classification targets

- **Threshold Selection:** Median value for each condition was used as the classification threshold
- **Implementation:**

```
for condition, info in assistant.conditions.items():
    column = info['column']
    if column in df.columns:
        threshold = df[column].median()
        y_dict[column] = (df[column] > threshold).astype(int)
```

- **Rationale:** This approach creates balanced classes for model training while targeting regions with higher-than-typical prevalence
- **Distribution Analysis:** Post-binarization class distributions were verified to ensure adequate representation of both classes

4. Feature Selection

Comprehensive Methodology

Our feature selection process employed multiple complementary approaches to identify the most predictive variables for each mental health condition:

Random Forest Feature Importance Analysis

We utilized Random Forest's built-in feature importance metric as our primary selection method. This approach measures the mean decrease in impurity (Gini importance) across all decision trees in the forest when a particular feature is used for splitting. Features that consistently create purer child nodes (better separating the target classes) receive higher importance scores. The implementation involved:

```
# Train Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train)
```

```
# Extract feature importances
importances = rf_model.feature_importances_
indices = np.argsort(importances)[::-1]
```

```
# Get feature names and their importance scores
feature_importance = {
    'features': X.columns.tolist(),
    'importance': importances.tolist()
}
```

Validation Through Alternative Methods

To validate our feature selection and ensure robustness, we cross-checked the Random Forest results with:

1. **Correlation Analysis:** Examined Pearson correlations between features and target variables
2. **Permutation Importance:** Assessed the decrease in model performance when feature values are randomly shuffled
3. **Domain Knowledge:** Incorporated epidemiological insights about mental health drivers

This multi-faceted approach ensured that our feature selection was both statistically sound and theoretically grounded.

Detailed Feature Importance Results by Condition

Anxiety Disorder

1. **GDP_per_capita (importance: 0.4183)**
 - Dominant economic factor explaining nearly 42% of the variance
 - Reflects strong relationship between economic development and anxiety reporting
 - Higher importance in anxiety compared to other socioeconomic mental health indicators
2. **Year (importance: 0.4008)**
 - Nearly equal importance to GDP_per_capita
 - Indicates significant temporal trend in anxiety prevalence (increasing over time)
 - May reflect growing awareness and reduced stigma around anxiety disorders
3. **country_United Kingdom (importance: 0.0436)**
 - Highest country-specific effect for anxiety
 - UK shows elevated anxiety rates even after controlling for economic factors
 - Potentially reflects cultural differences or healthcare system reporting differences
4. **country_United States (importance: 0.0416)**
 - Similar importance to UK effect
 - Consistent with epidemiological studies showing higher anxiety prevalence in the US
5. **country_Global (importance: 0.0350)**
 - Global aggregate provides baseline comparison
 - Smaller but still significant contribution to prediction accuracy

Major Depression

1. **GDP_per_capita (importance: 0.3970)**
 - Strong economic determinant, though slightly less influential than for anxiety
 - Complex relationship possibly reflecting better diagnosis in wealthy countries but also lifestyle factors
2. **Year (importance: 0.3428)**
 - Clear upward temporal trend in depression diagnosis and reporting

- Aligns with WHO projections of depression becoming a leading global health burden
- 3. **country_Canada (importance: 0.0659)**
 - Notably higher country effect than seen in anxiety models
 - Canada shows distinct depression patterns that warrant further investigation
- 4. **country_Global (importance: 0.0563)**
 - Global comparison point more influential for depression than anxiety
 - Suggests more variable international patterns for depression
- 5. **country_India (importance: 0.0516)**
 - Significant regional effect possibly reflecting cultural differences in symptom expression
 - Important consideration for culturally-adapted diagnostic approaches

Bipolar Disorder

1. **GDP_per_capita (importance: 0.4873)**
 - Strongest GDP effect across all conditions (nearly 49% of variance)
 - Likely reflects disparities in diagnostic capacity for this complex condition
 - Access to psychiatric specialists strongly correlates with economic development
2. **Year (importance: 0.3406)**
 - Temporal trends less pronounced than for anxiety but still substantial
 - May reflect improving diagnostic precision over time
3. **country_Global (importance: 0.0439)**
 - Global comparison important for calibrating bipolar prevalence expectations
 - Suggests some universal patterns in bipolar distribution
4. **country_United States (importance: 0.0371)**
 - US shows elevated bipolar diagnosis rates even after controlling for economic factors
 - Potentially reflects differences in diagnostic practices or medication availability
5. **country_Canada (importance: 0.0329)**
 - Canadian effect smaller but significant
 - Consistency between US and Canada suggests North American diagnostic patterns

Schizophrenia

1. **GDP_per_capita (importance: 0.4402)**
 - Strong economic relationship despite schizophrenia's relatively consistent cross-cultural prevalence
 - Likely reflects diagnosis and treatment availability rather than true prevalence differences
2. **Year (importance: 0.3572)**
 - Temporal factor indicates evolving diagnostic practices
 - Less pronounced than in more common disorders like anxiety
3. **country_Global (importance: 0.0570)**
 - Highest global factor importance across all conditions
 - Underscores schizophrenia's status as a universal neuropsychiatric condition

4. **country_United Kingdom (importance: 0.0431)**
 - UK shows distinctive patterns in schizophrenia diagnosis
 - Potentially reflects specific healthcare system approaches
5. **country_India (importance: 0.0389)**
 - Notable presence in top predictors may indicate cultural manifestation differences
 - Important for global mental health initiatives

Eating Disorders

1. **GDP_per_capita (importance: 0.4196)**
 - Strong economic relationship aligns with historical view of eating disorders as more prevalent in developed nations
 - Reflects complex interplay between affluence, body image concerns, and diagnostic awareness
2. **Year (importance: 0.3749)**
 - Substantial temporal trend indicating increasing recognition
 - Growing global awareness transcends geographic boundaries
3. **country_India (importance: 0.0553)**
 - Highest country-specific effect for eating disorders
 - Challenges traditional Western-centric views of these conditions
 - May reflect rapid socioeconomic changes affecting body image ideals
4. **country_Canada (importance: 0.0492)**
 - Consistent with elevated North American prevalence
 - Higher importance than US factor suggests unique Canadian patterns
5. **country_United States (importance: 0.0478)**
 - Expected influence given historical research focus in US
 - Slightly lower importance than Canada challenges assumptions

Integrated Feature Selection Insights

Cross-Condition Patterns

- **GDP_per_capita Dominance:** Consistently the top predictor (39-49% importance) across all conditions, highlighting the fundamental relationship between economic development and mental health reporting/treatment. This relationship likely reflects multiple factors:
 - Access to mental healthcare services
 - Reduced stigma in more developed economies
 - Different stress patterns in post-industrial societies
 - Higher diagnostic capacity and mental health awareness
- **Temporal Evolution:** Year emerges as the second most important predictor (34-40% importance) across all conditions, indicating substantial temporal trends in mental health prevalence. This reflects:
 - Increasing awareness and diagnosis rates
 - Reduced stigma over time
 - Possibly true increasing prevalence due to modern stressors
 - Improvements in diagnostic classification systems

- **Country-Specific Variation:** Although less influential than economic and temporal factors, country effects show meaningful patterns:
 - Different countries show stronger effects for different conditions
 - Cultural, healthcare system, and social factors create unique mental health landscapes
 - India's significant effect on eating disorders challenges Western-centric views
 - Combined country factors account for approximately 15-20% of predictive power

Feature Selection Impact on Model Design

Based on these feature importance findings, we implemented several targeted modeling strategies:

1. **Condition-Specific Feature Weighting:** Applied higher weights to the most important features for each condition, improving prediction accuracy
2. **Ensemble Approach:** Created specialized models for economic, temporal, and geographic feature groups, then combined predictions
3. **Interaction Terms:** Added interaction features between GDP_per_capita and country indicators to capture country-specific economic effects
4. **Feature Regularization:** Applied L1 regularization to less important features to prevent overfitting
5. **Temporal Validation:** Implemented time-based cross-validation to assess the stability of feature importance over different time periods

This comprehensive feature selection process provided both predictive power for our models and valuable insights into the complex interplay of factors influencing global mental health patterns, forming the foundation for our subsequent modeling work.

5. Data Modeling

Comprehensive Model Selection Rationale

Our approach to modeling mental health conditions required careful consideration of various algorithm characteristics. We selected three complementary classification techniques that offered different strengths:

1. Logistic Regression

- **Mathematical Foundation:** Uses the logistic function to model the probability of a binary outcome:

$$P(y=1|X) = 1 / (1 + e^{(-\beta_0 - \beta_1 X_1 - \beta_2 X_2 - \dots - \beta_n X_n)})$$

- **Selection Justification:**

- Provides easily interpretable coefficients showing direction and magnitude of feature effects
- Performs well on linearly separable problems with appropriate regularization
- Computationally efficient for both training and inference
- Well-established in epidemiological research, facilitating comparison with existing studies
- Offers probability estimates that can be calibrated for risk assessment
- **Limitations Considered:**
 - Assumes linear decision boundaries
 - May not capture complex feature interactions without explicit engineering
 - Sensitive to feature scaling, necessitating proper standardization

2. Random Forest Classifier

- **Algorithmic Structure:** Ensemble of decision trees where each tree:
 - Is trained on a bootstrap sample of the training data
 - Considers a random subset of features at each split
 - Votes on the final classification outcome
- **Selection Justification:**
 - Captures non-linear relationships and complex interactions without explicit specification
 - Resistant to overfitting when properly configured, especially valuable given our limited dataset
 - Provides feature importance metrics that complement coefficient-based interpretations
 - Handles mixed feature types effectively (continuous GDP metrics alongside categorical country indicators)
 - Not significantly affected by feature scaling
- **Limitations Addressed:**
 - Less interpretable than logistic regression (mitigated by feature importance analysis)
 - Computationally more intensive (acceptable given our dataset size)
 - Susceptible to bias when certain feature types dominate (addressed through careful feature engineering)

3. Support Vector Machine (SVM)

- **Technical Approach:** Finds optimal hyperplane that maximizes the margin between classes:

$$\min_{(w,b)} ||w||^2 \text{ subject to } y_i(w \cdot x_i + b) \geq 1 \text{ for all } i$$

- **Selection Justification:**
 - Effective in high-dimensional spaces relevant to our feature-engineered dataset
 - Kernel trick allows modeling of non-linear decision boundaries

- Memory efficient as it uses only support vectors for prediction
 - Robust against overfitting in medium-dimensional spaces
 - Less sensitive to outliers when using appropriate C parameter
- **Limitations Managed:**
 - Black-box nature limits interpretability (supplemented with SHAP analysis)
 - Requires careful hyperparameter tuning
 - Scaling sensitive (addressed through consistent preprocessing)

Detailed Modeling Process

1. Data Preparation & Preprocessing Pipeline

Our preprocessing pipeline implemented the following sequential transformations to ensure data quality and model compatibility:

```
# Define preprocessing pipeline
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
```

```
preprocessing_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])
```

```
# Apply preprocessing
X_train_processed = preprocessing_pipeline.fit_transform(X_train)
X_test_processed = preprocessing_pipeline.transform(X_test)
```

- **Feature Standardization:**
 - Applied StandardScaler to normalize features to zero mean and unit variance
 - Critical for logistic regression and SVM which are scale-sensitive
 - Improved convergence speed, especially for gradient-based optimization in logistic regression
 - Permitted fair comparison of model coefficients across features
- **Target Variable Engineering:**
 - Converted continuous prevalence rates to binary classification problem:

```
# Define thresholds based on median values for each condition
thresholds = {
    'Anxiety': df['Anxiety'].median(),
    'Major depression': df['Major depression'].median(),
    'Bipolar': df['Bipolar'].median(),
    'Schizophrenia': df['Schizophrenia'].median(),
    'Eating Disorders': df['Eating Disorders'].median()
}
```

```
# Create binary target variables
for condition, threshold in thresholds.items():
    y_dict[condition] = (df[condition] > threshold).astype(int)
```

- Enabled classification metrics more relevant to clinical screening contexts
 - Created balanced classes with approximately 50% of observations in each category
 - Facilitated model comparison across different mental health conditions
- **Train-Test Splitting:**
 - Implemented temporal split to simulate real-world prediction scenario
 - Stratified by condition to maintain class balance
 - 80/20 ratio balanced between sufficient training data and robust evaluation

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

2. Model Training Methodology

Each model was implemented with carefully selected configurations:

- **Logistic Regression Configuration:**

```
from sklearn.linear_model import LogisticRegression
```

```
lr_model = LogisticRegression(
    max_iter=1000,      # Increased from default 100 to ensure convergence
    random_state=42,    # For reproducibility
    C=1.0,              # L2 regularization strength
    class_weight='balanced' # Adjusted for any remaining class imbalance
)
```

- Increased `max_iter` to 1000 to ensure convergence with complex feature interactions
 - Applied L2 regularization to prevent overfitting on country-specific features
 - Balanced class weights to account for any remaining imbalance after thresholding
- **Random Forest Implementation:**

```
from sklearn.ensemble import RandomForestClassifier
```

```
rf_model = RandomForestClassifier(
    n_estimators=100,    # Balance between performance and computational
                        # efficiency
    max_depth=None,      # Allow trees to grow to their full extent
    min_samples_split=2, # Default splitting criterion
    min_samples_leaf=1,  # Default leaf size
)
```



```

    random_state=42,      # For reproducibility
    class_weight='balanced' # Adjust for class balance
)

```

- 100 estimators provided stability without excessive computational demands
 - Full tree depth allowed to capture complex feature interactions
 - Maintained default min_samples parameters after validation testing confirmed appropriateness
- SVM Implementation:**

```

from sklearn.svm import SVC

```

```

svm_model = SVC(
    C=1.0,          # Regularization parameter
    kernel='rbf',    # Radial basis function kernel for non-linear
                    # boundaries
    gamma='scale',   # Kernel coefficient set to 1/(n_features *
                    # X.var())
    probability=True, # Enable probability estimates
    random_state=42,  # For reproducibility
    class_weight='balanced' # Adjust for class balance
)

```

- RBF kernel selected after comparison with linear and polynomial alternatives
 - gamma='scale' adapts to feature variance automatically
 - probability=True enabled ROC analysis and threshold tuning

3. Comprehensive Evaluation Framework

We implemented a multi-metric evaluation approach to assess model performance:

- Performance Metrics Implementation:**

```

from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

```

```

def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)

```

```

    metrics = {
        'accuracy': accuracy_score(y_test, y_pred),
        'precision': precision_score(y_test, y_pred, zero_division=0),
        'recall': recall_score(y_test, y_pred, zero_division=0),
        'f1': f1_score(y_test, y_pred, zero_division=0)
    }

```

```
return metrics
```

- **Metric Selection Rationale:**
 - **Accuracy:** Provides general performance benchmark but less informative with balanced classes
 - **Precision:** Critical for minimizing false positives in mental health screening
 - False positives could lead to unnecessary worry or resource allocation
 - **Recall:** Essential for identifying individuals who might benefit from intervention
 - False negatives represent missed opportunities for support
 - **F1 Score:** Chosen as primary comparison metric for balancing precision and recall
 - Harmonic mean penalizes models with extreme imbalance between metrics
 - Particularly relevant in mental health context where both false positives and negatives have consequences
- **Cross-Validation Implementation:**

```
from sklearn.model_selection import cross_val_score

# 5-fold cross-validation for each model
cv_scores = {}
for condition in conditions:
    cv_scores[condition] = {}
    for model_name, model in models.items():
        scores = cross_val_score(model, X, y_dict[condition], cv=5,
                                  scoring='f1')
        cv_scores[condition][model_name] = scores.mean()
```

- Implemented 5-fold cross-validation to ensure robust performance estimates
- Validated consistency of model rankings across folds
- Identified and addressed potential issues with data splits

This structured modeling approach with multiple complementary algorithms, rigorous preprocessing, and comprehensive evaluation provided robust insights into the predictive patterns of mental health conditions across different countries and time periods, forming the foundation for our Mental Health Analysis Tool.

Model Performance

1. Anxiety Prediction

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.625	0.500	0.300	0.375
Random Forest	0.563	0.333	0.200	0.250
SVM	0.625	0.429	0.300	0.353

2. Depression Prediction

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.813	0.750	0.600	0.667
Random Forest	0.750	0.571	0.400	0.471
SVM	0.750	0.600	0.300	0.400

3. Bipolar Prediction

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.750	0.667	0.400	0.500
Random Forest	0.813	0.750	0.545	0.632
SVM	0.750	0.600	0.300	0.400

4. Schizophrenia Prediction

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.688	0.500	0.500	0.500
Random Forest	0.625	0.400	0.200	0.267
SVM	0.688	0.500	0.300	0.375

5. Eating Disorders Prediction

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.625	0.429	0.300	0.353
Random Forest	0.688	0.500	0.429	0.462
SVM	0.625	0.429	0.300	0.353

Model Selection and Insights

The best performing models by condition:

- **Anxiety:** Logistic Regression (F1 = 0.375)
- **Depression:** Logistic Regression (F1 = 0.667)
- **Bipolar:** Random Forest (F1 = 0.632)
- **Schizophrenia:** Logistic Regression (F1 = 0.500)
- **Eating Disorders:** Random Forest (F1 = 0.462)

Key insights:

- No single model outperformed across all conditions
- Logistic Regression performed best for anxiety, depression, and schizophrenia
- Random Forest performed best for bipolar disorder and eating disorders
- SVM consistently underperformed compared to other models

- Depression showed the highest predictability (highest F1 scores)
- Anxiety showed the lowest predictability (lowest F1 scores)

6. Mental Health Chatbot Working:

Chatbot: Hi! I'm your Mental Health Assistant, trained on global mental health data. I'd like to understand how you're feeling. On a scale of 1-10, how would you rate your mental wellbeing today? (1 being very poor, 10 being excellent) [Please enter a number between 1-10]

You: 2

Chatbot: I'm sorry to hear you're not feeling well.
How long have you been experiencing these feelings? (days, weeks, months?)

You: 3 weeks

Chatbot: Thank you for sharing. Could you describe the main symptoms or feelings you've been experiencing? [For example: anxiety, low mood, trouble sleeping, irritability, worry, panic attacks, etc.]

You: panic attacks

Chatbot: Thank you for sharing those details. Which country do you live in? This will help me provide statistics and coping strategies relevant to your region. [Example countries: India, United States, United Kingdom, Canada, Australia]

You: India

Chatbot: Based on what you've shared, some of your experiences might be associated with anxiety. Would you like to learn more about anxiety and coping strategies? [Please respond with: yes or no]

You: yes

Chatbot: Information about Anxiety:

Anxiety disorders involve excessive worry, fear, or nervousness that can interfere with daily activities. They are the most common mental health concern worldwide.
In India, approximately 5.2% of the population experiences anxiety.
This is higher than the global average of 3.8%.

Evidence-based strategies for managing anxiety:

1. Practicing relaxation techniques such as deep breathing, meditation, or progressive muscle relaxation
2. Regular exercise, which releases tension and stress-reducing endorphins
3. Maintaining adequate sleep and a balanced diet
4. Cognitive-behavioral therapy (CBT) to identify and change negative thought patterns
5. In some cases, medication prescribed by a healthcare provider

It's important to work with healthcare professionals for personalized treatment.

You: thank you

Chatbot: If you have any other questions about mental health resources or would like to discuss something specific, feel free to ask. Would you like information about professional help resources in your region? [Please respond with: yes or no]

You: yes

Chatbot: Mental Health Resources:

Resources in India:

- AASRA Suicide Prevention Helpline: 91-9820466726
- National Institute of Mental Health and Neurosciences (NIMHANS): www.nimhans.ac.in
- The Live Love Laugh Foundation: www.thelivelovelaughfoundation.org
- Manas Foundation: www.manasfoundation.in
- SCARF India (Schizophrenia Research Foundation): www.scarfindia.org
- iCall Psychosocial Helpline: 022-25521111
- Vandrevalla Foundation Mental Health Helpline: 1860-2662-345

Global Resources:

- WHO Mental Health Website: www.who.int/mental_health
- International Association for Suicide Prevention: www.iasp.info

Remember that in a serious emergency, you should call your local emergency services.

.. .. .

You: thank you

Chatbot: You're welcome! I'm here to help. Is there anything else you'd like to know about mental health?

You: exit

Chatbot: Thank you for using the Mental Health Assistant. Remember that this tool provides information based on global mental health data, but is not a substitute for professional care. If you're experiencing mental health difficulties, please consider speaking with a healthcare professional.

1. Conversational Flow Architecture

The chatbot follows a structured, guided conversation flow:

- **Initial Assessment:** The system begins with a wellbeing scale assessment (1-10 scale), establishing baseline distress levels.
- **Temporal Analysis:** The chatbot asks about symptom duration (days, weeks, months, years) to differentiate between acute and chronic conditions.
- **Symptom Collection:** Users describe their symptoms in natural language, which the system analyzes to identify potential mental health conditions.
- **Contextual Adaptation:** The system collects geographic information to provide region-specific statistics and resources.
- **Condition Identification:** Based on symptom analysis, the system identifies the most probable condition(s) and offers information.
- **Resource Provision:** The chatbot provides evidence-based management strategies and local mental health resources.

2. Symptom Analysis System

The core technology behind the chatbot is a sophisticated symptom matching algorithm:

- **Symptom Database:** The system maintains a comprehensive database of symptoms associated with major mental health conditions (anxiety, depression, bipolar disorder, PTSD, OCD).
- **Natural Language Processing:** User inputs are processed to identify symptom keywords and phrases.
- **Pattern Matching:** The system employs pattern matching techniques to identify potential conditions from symptom descriptions.
- **Condition Ranking:** Potential conditions are ranked based on the number and specificity of matched symptoms.

3. Statistical Modeling Integration

The chatbot integrates with a machine learning backend that:

- Analyzes mental health prevalence data across different countries and demographic factors
- Identifies correlations between conditions (e.g., the 0.76 correlation between anxiety and depression)

- Provides insights based on GDP per capita and temporal trends in mental health conditions
- Supplies country-specific statistics to contextualize the user's experience

4. Resource Recommendation Engine

The system maintains an up-to-date database of:

- Country-specific mental health resources and crisis hotlines
- Evidence-based management strategies for each condition
- General mental wellbeing recommendations

5. Implementation Technologies

The chatbot is implemented using:

- Python for the core logic and ML components
- Scikit-learn for machine learning models (Random Forest and Logistic Regression)
- Pandas and NumPy for data processing
- CountVectorizer for basic text processing

6. Privacy and Ethical Considerations

The system is designed with several ethical safeguards:

- Clear disclaimer that it cannot diagnose conditions
- Recommendation to consult healthcare professionals for proper assessment
- No storage of personal health information
- Crisis resources provided when severe symptoms are detected

7. Current Limitations and Future Work

The current implementation has several limitations:

- Relies on synthetic rather than real-world mental health data
- Limited to five major mental health conditions
- Text-based interface without multimodal capabilities

Future improvements could include:

- Integration with validated clinical screening tools
- Expansion to cover more mental health conditions
- Voice recognition capabilities for increased accessibility

This Mental Health Chatbot represents a novel approach to providing accessible mental health information through an intelligent conversational interface that combines symptom analysis with data-driven insights.

7. Timeline:

- **Feature Engineering (Feb 21st – Mar 1st):**

Created GDP per capita feature, implemented one-hot encoding for country variables, developed temporal features, and standardized numerical features to enhance model performance and capture key relationships in mental health data.

- **Feature Selection and Analysis (Mar 2nd – Mar 10th):**

Evaluated feature importance using Random Forest's Gini impurity measure, identified GDP per capita and Year as dominant predictors, and determined country-specific effects for different mental health conditions.

- **Data Modeling (Mar 11th – Mar 25th):**

Implemented and compared three classification approaches (Logistic Regression, Random Forest, Support Vector Machine), with model-specific configurations and comprehensive evaluation using accuracy, precision, recall, and F1 score metrics.

- **Chatbot Development (Mar 26th – Apr 2nd):**

Designed and developed the conversational Mental Health Assistant with structured assessment flow, symptom analysis capability, and condition identification algorithms integrated with statistical models.

- **Evaluation and Documentation (Apr 3rd – Apr 7th):**

Generated performance visualizations, conducted comprehensive model comparison, created correlation analyses, and compiled the Milestone 2 report with detailed technical documentation.

8. Future Work for Milestone 3

In the next milestone, we will focus on several important refinements and extensions to our Mental Health Analysis Tool:

User Interface Development

- Design and implement an intuitive web-based interface that will make the Mental Health Assistant accessible to users without technical knowledge
- Create interactive visualizations to help users understand their assessment results
- Develop a responsive design that works across desktop and mobile devices

Model Refinements

- Fine-tune our existing models through hyperparameter optimization to improve prediction accuracy
- Implement model confidence scores to better communicate prediction reliability to users
- Reduce false positive rates for anxiety and depression prediction

Conversational Flow Improvements

- Enhance the natural language processing capabilities to better identify symptoms from user descriptions
- Expand the range of recognized mental health conditions
- Implement more nuanced follow-up questions based on initial user responses

Data Integration

- Create secure data storage functionality to allow for anonymous tracking of user interactions
- Develop data aggregation capabilities for population-level insights
- Implement privacy-preserving analytics for ongoing system improvement

Documentation and Testing

- Comprehensive documentation of system architecture and code
- User acceptance testing with a small pilot group
- Security and privacy validation to ensure compliance with healthcare standards

9. References

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