PAML Final Project:
Mental Health Prediction and Support

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Abstract

Mental health challenges affect a significant portion of the population, with one in five adults in the U.S. suffering from some form of mental illness. Despite growing awareness, early diagnosis and timely intervention remain challenging due to stigma and difficulty recognizing early symptoms. This project develops a machine learning-based risk assessment tool that predicts the risk of depression and provides personalized support recommendations based on lifestyle and behavioral data. We implemented and compared three supervised machine learning methods: Logistic Regression, Linear Regression, and Support Vector Machines (SVM), evaluated using multiple metrics including accuracy, mean average error (MAE), and R². Our logistic regression model achieved the highest accuracy (83% on training data, 82% on test data) and demonstrated strong interpretability, making it our primary deployed model. Our web application, developed using Streamlit, offers users a comprehensive depression assessment with personalized recommendations based on their risk level. This project addresses a critical gap in mental health support by creating an accessible tool that not only predicts risk levels but also provides personalized, evidence-based recommendations, making mental health resources more accessible while contributing valuable insights into the relationship between lifestyle factors and mental well-being.

1. Introduction

A. Motivation

Mental health challenges affect a significant portion of our population, making it an increasingly important issue. Depression, one of the most common forms of mental health disorders, is recognized as deep sadness, loss of interest or pleasure in daily activities, and a range of other emotional and physical problems. Depression can impact how a person thinks, feels and functions daily. Despite the growing awareness of depression and its severe impact on an individual's well-being, the ability to provide early diagnosis and timely interventions is lacking.

Many individuals hesitate to seek help due to the stigma around mental health or simply not being able to recognize early signs. Researchers have begun using behavioral data as a key indicator of the early stages of mental health conditions, particularly our sleep patterns, socialization, and activity levels[3]. This data can be used to intervene early and prevent these problems from worsening.

B. Technical Focus

Our project addresses this concern by using machine learning to provide a risk assessment for depression. We implemented supervised learning algorithms, specifically Logistic Regression, Linear Regression, and Support Vector Machines, to analyze behavioral and survey data for predicting and evaluating depression risk. These algorithms are well-suited for this classification problem and offer interpretability that's crucial in healthcare applications.

C. Prior Work

Current research on mental health conditions has assessed mental health using data and the capabilities of machine learning algorithms to make predictions that have advanced mental health diagnoses. Two approaches stand out:

1. *Wearable Device Data:* Tracking heart rate, sleep patterns, and physical activity to monitor changes that may signal mental health concerns. Researchers combine real-time data from these devices with speech data to create predictive machine-learning models[1].

2. *Social Media and Digital Footprints:* Collecting data

on activity, such as posts, usage times, and language, which is employed in various machine-learning models to predict mental health conditions[8].

However, these methods have several limitations, including data misuse, lack of informed consent, and a focus on identifying conditions rather than offering individualized prevention recommendations.

D. Machine Learning Pipeline

Our solution involves:

- Data collection from user inputs on sleep patterns, academic/work metrics, and other behavioral metrics
- Feature preprocessing and selection
- Training multiple classification models (Logistic Regression, Linear Regression, and SVMs)
- Model evaluation through accuracy, MAE, and R^2 metrics
- Integration into a Streamlit application for user interaction
- Generation of personalized recommendations based on risk assessment

E. Impact

Our project has the potential to significantly impact mental health by providing early predictions of risk for depression, allowing users to recognize issues before they worsen and enabling timely interventions. The personalized recommendations enhance the effectiveness of interventions compared to general solutions. Additionally, using an accessible Streamlit interface improves access to mental health resources, particularly in areas with limited availability, while collecting anonymous data that can contribute to larger research efforts.

2. Background

Mental health disorders represent one of the most significant public health challenges of our time, affecting approximately 20% of adults in the United States [5]. These conditions, including depression, anxiety, bipolar disorder, PTSD, and schizophrenia, can severely impact quality of life, productivity, and overall well-being. Despite their prevalence, many individuals do not receive proper diagnosis or treatment due to various barriers, including stigma, lack of awareness about early symptoms, and limited access to mental health resources. Our project focuses on leveraging machine learning to create an accessible screening tool that can identify depression risk based on user-reported data, ultimately facilitating earlier intervention and support [3].

Research in machine learning applications for mental health has evolved significantly in recent years. Early approaches primarily focused on analyzing clinical data from mental health professionals or medical records. In 2018, researchers began exploring wearable device data to track physiological signals that might correlate with mental health states [4]. By 2020-2022, social media analysis emerged as another promising approach, with researchers developing models to identify linguistic patterns associated with various mental health conditions [8]. Most recently, as described by Diaz-Ramos et al [1], combining multimodal data from wearables and speech has shown improved prediction accuracy. However, these approaches have predominantly focused on detection rather than providing personalized support recommendations, and many have raised concerns about privacy and consent.

The relationship between lifestyle factors and mental health is well-established in the scientific literature. Sleep disruption is recognized as both a symptom and potential cause of various mental health conditions [7]. Work-life balance also contributes significantly to overall mental well-being as well as stress factors like financial stress. These established connections provide a strong foundation for our machine learning approach, which aims to identify patterns across these variables that may indicate mental health risks.

While existing research has made significant progress in using machine learning for mental health detection, several important gaps remain. Most current approaches are either highly invasive (requiring continuous physiological monitoring) or passive (analyzing social media without direct user engagement) [2]. Few studies have combined user-provided lifestyle data with machine learning to create actionable, personalized recommendations. Additionally, existing models often lack transparency, making it difficult for users to understand how predictions are made. Our approach differs by implementing interpretable models (logistic regression, linear regression, and SVM) that allow us to identify which lifestyle factors most strongly contribute to depression risk, while also providing users with concrete, evidence-based recommendations tailored to their specific situation. This combination of prediction and personalized support represents a novel contribution to the field.

3. End-to-End ML Pipeline

3.1. Data Collection, Exploration & Processing

For this project, we used the 'Student Depression Dataset' [6] from Kaggle. This dataset contained information on various factors that can contribute to depression among college students. It was 2.81 MB in size and contained 140699 unique IDs. It included information from both numerical characteristics such as age and work/study hours, and categorical features such as gender, duration of sleep, dietary habits, family history of mental health issues, and various pressure and satisfaction metrics. Ground truth labels are provided in the form of depression indicators, making this suitable for our supervised learning approach.

Examples of Dataset Columns:

- ID
- Age
- Gender
- City
- CGPA
- Sleep Duration
- Profession
- Work Pressure
- Academic Pressure
- Study Satisfaction
- Job Satisfaction
- Dietary Habits
- ...more

The data set was used to train machine learning models that predict the risk of depression based on lifestyle indicators and personal factors. Our specific task was framed as a binary classification problem to predict whether an individual is at risk of depression based on the provided characteristics.

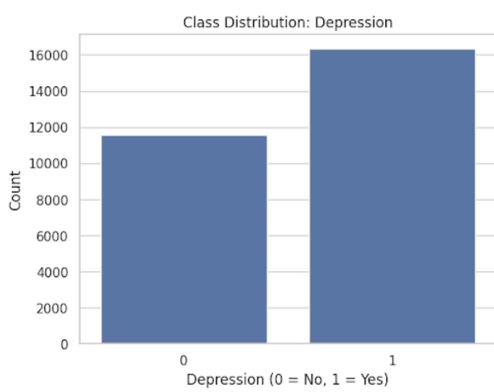

Figure 1: This bar chart illustrates the distribution of the depression variable within the dataset. The x-axis represents the two classes: 0 (No Depression) and 1 (Depression), while the y-axis shows the count of individuals in each class.

Taking an initial look at the data, we observed that a slight majority of the participants reported experiencing symptoms of depression. This indicates that depression was relatively common within the surveyed population.

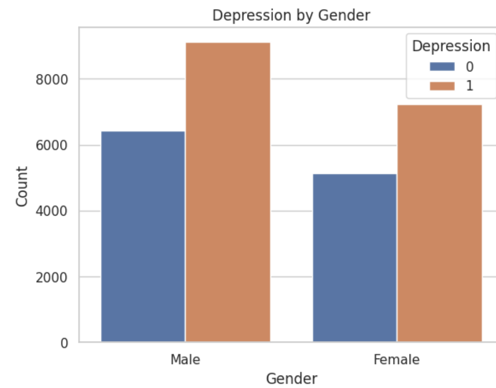

Figure 2: This grouped bar chart examines the relationship between gender and depression. Within each gender category, there are two bars representing the presence (1) or absence (0) of depression.

When comparing across genders, the data showed that both male and female participants had more individuals categorized as depressed than non-depressed. While there were slightly more male participants than female, the difference in representation was not substantial.

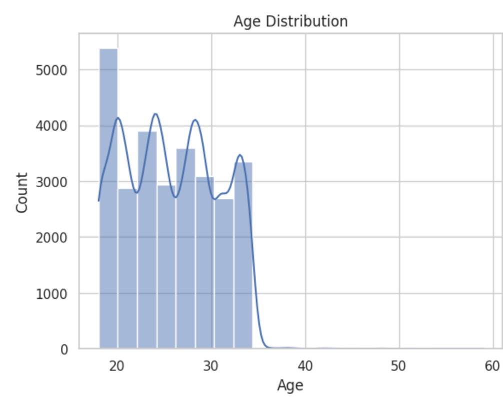

Figure 3: This histogram shows the distribution of ages among the students in the dataset. The bars represent the frequency of each age group, while the overlaid curve provides a smoothed estimate of the age distribution. The chart reveals the age range of the student population and any potential peaks or skews in the distribution.

The ages of the participants ranged from 18 to the mid-thirties, capturing a wide spectrum of young adults, including college students and early-career professionals. This age group is particularly relevant when studying mental health trends.

Regarding sleep habits, most participants reported similar depression:non-depression ratios. However, a trend emerged: participants who reported sleeping fewer than 5

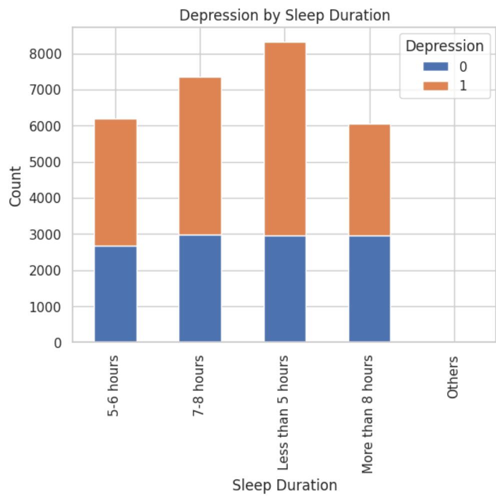

Figure 4: This stacked bar chart explores the relationship between students' sleep duration and depression.

hours per night had a significantly higher proportion of depression. This suggests a possible link between insufficient sleep and increased depressive symptoms.

Before model training, we applied several preprocessing steps: First, column names were cleaned and standardized by removing spaces and renaming fields for consistency and code-friendliness. Irrelevant or high-cardinality features such as `id`, `City`, `Degree`, `Profession`, and `CGPA` were dropped to reduce noise and dimensionality. The dataset was then split into training and testing sets using an 80-20 ratio. Features were categorized into numerical (`Age`, `WSHours`) and categorical (`Gender`, `SleepDuration`, `WorkPressure`, etc.) types. Numerical features were manually imputed using the median and standardized via z-score normalization based on training set statistics. Categorical features were one-hot encoded using scikit-learn's `OneHotEncoder` with `handle_unknown='ignore'` to ensure compatibility with test data.

1. We excluded unnecessary columns like 'id', 'City', 'Degree', 'Profession', and 'CGPA' that were not relevant to our prediction task.

2. We separated features into qualitative (categorical) and quantitative (numerical) variables for appropriate processing.

3. For categorical variables, we applied one-hot encoding to convert them into a format suitable for our models.

4. For numerical variables, we standardized them by subtracting the mean and dividing by the standard deviation to ensure all features were on a similar scale.

5. We imputed missing values with the median to maintain data integrity.

These preprocessing steps ensured our data was clean, properly formatted, and optimized for model training.

3.2. Methods and Model Training

Our task was framed as a binary classification problem, where the input consists of various features related to an individual's well-being and lifestyle, and the output is a prediction of depression risk (depressed vs. not depressed). To address this task, we explored three supervised learning approaches: logistic regression, linear regression, and support vector machines (SVMs).

3.2.1 Logistic Regression

Logistic Regression is a statistical method that models the probability of a binary outcome based on one or more predictor variables. For our depression prediction task, the model estimates the probability of depression using the logistic function:

$$P(y=1|x) = \frac{1}{1+e^{-(\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_nx_n)}} \tag{1}$$

Where y is the depression status, x_i are the input features (like age, sleep duration, etc.), and β_i are the model parameters learned during training. The model makes a prediction by comparing this probability to a threshold (typically 0.5).

3.2.2 Linear Regression

While traditionally used for regression tasks, we adapted Linear Regression for our classification problem. The model predicts a continuous value that we then threshold to obtain a binary prediction:

$$\hat{y} = \beta_0 + \beta_1x_1 + \beta_2x_2 + \ldots + \beta_nx_n \tag{2}$$

Where $\hat{y}$ is the predicted value, and we classify as depressed if $\hat{y} \geq 0.5$.

3.2.3 Support Vector Machine (SVM)

SVM finds the hyperplane that best separates the two classes (depressed and not depressed) with the maximum margin. The objective function for SVM is:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\max(0, 1-y_i(\mathbf{w}\cdot\mathbf{x}_i - b)) \tag{3}$$

Where $\mathbf{w}$ is the normal vector to the hyperplane, b is the bias term, C is the regularization parameter, and the second term is the hinge loss.

These algorithms are particularly well-suited for our mental health prediction task for several key reasons:

1. **Interpretability**: Especially for Logistic Regression, the coefficients directly indicate the influence of each feature on depression risk, which is crucial for healthcare applications where understanding the "why" behind predictions is important.

2. **Performance with Limited Data**: These models perform well even with moderate-sized datasets like ours, without requiring the large amounts of data needed for more complex models.

3. **Efficiency**: All three models are computationally efficient, making them suitable for deployment in a web application where quick predictions are necessary.

4. **Binary Classification Strength**: Logistic Regression and SVM excel at binary classification tasks like our depression prediction problem.

The models take as input the processed features (standardized numerical variables and one-hot encoded categorical variables) and output either a probability (Logistic Regression), a continuous value (Linear Regression), or a class assignment (SVM) that indicates depression risk.

3.3. Model Evaluation

To evaluate our models, we used three primary metrics, including Accuracy, Mean Absolute Error (MAE), and R-squared (R^2). Accuracy is the measure of the proportion of correct predictions among the total number of cases examined.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \tag{4}$$

MAE is the average of the absolute differences between predictions and actual observations.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

Finally, R^2 is a statistical measure that represents the proportion of variance in the dependent variable that can be explained by the independent variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

These metrics were chosen because they provide complementary perspectives on model performance. Accuracy gives us a straightforward measure of how often the model is correct, MAE provides insight into the magnitude of errors, and R^2 helps us understand how well our model explains the variance in depression status compared to simply using the mean.

For our training and validation procedure, we split the dataset into 80% training and 20% testing sets using a random state of 42 to ensure reproducibility. This allowed us to evaluate how well our models generalize to unseen data.

We conducted several experiments to fine-tune our models:

1. **Feature Selection**: We experimented with different subsets of features to identify those most predictive of depression. This led us to drop some features.

2. **Hyperparameter Tuning**: For SVM, we experimented with different learning rates (0.01 - 0.001), regularization parameters (0.1 - 0.9), and maximum iterations (500 - 1000) to find the optimal configuration.

3. **Model Comparison**: We compared the performance of all three models (Logistic Regression, Linear Regression, and SVM) to determine which was most suitable for our application.

To prevent overfitting and underfitting, we implemented several techniques:

1. **Train/Test Split**: By evaluating our models on a separate test set, we could detect if they were overfitting to the training data.

2. **Regularization**: We applied regularization in both SVM and Logistic Regression models to penalize complex models and prevent overfitting.

3. **Feature Engineering**: Proper handling of categorical variables through one-hot encoding and standardization of numerical features helped the models learn meaningful patterns.

4. **Loss Monitoring**: We tracked loss during training to monitor convergence and potential overfitting.

5. **Multiple Model Comparison**: By implementing three different algorithm types, we could compare model complexity and performance trade-offs.

3.4. Results

Our experimental results showed varying performance across the three models we implemented:

Logistic Regression:

- Training Accuracy: 0.83
- Testing Accuracy: 0.82
- Training MAE: 0.17
- Testing MAE: 0.18
- Training R^2: 0.31

- Testing R^2: 0.25

SVM:

- Training Accuracy: 0.59
- Testing Accuracy: 0.58
- Training MAE: 0.41
- Testing MAE: 0.42
- Training R^2: -0.70
- Testing R^2: -0.72

Linear Regression:

- Training Accuracy: 0.85
- Testing Accuracy: 0.84
- Training MAE: 0.26
- Testing MAE: 0.27
- Training R^2: 0.52
- Testing R^2: 0.50

Based on these results, both Logistic Regression and Linear Regression performed significantly better than SVM across all metrics. Linear Regression showed the highest accuracy and R^2 values, while Logistic Regression had the lowest MAE, indicating smaller prediction errors on average.

The poor performance of our SVM implementation (with negative R^2 values) suggests that it failed to capture the underlying patterns in the data effectively, possibly due to the complexity of the optimization problem or the need for more sophisticated kernel functions.

For our deployment, we selected Logistic Regression as our primary model due to its strong balance of accuracy, interpretability, and natural production of probability scores that can be easily communicated to users as confidence percentages.

3.5. Model Deployment & Front-End Application Using Streamlit

We developed a user-friendly web application using the Streamlit library to make our mental health assessment tool widely accessible. Streamlit was selected for its rapid development capabilities, intuitive interface design, and straightforward deployment options. The application allows users to complete a comprehensive mental health assessment through an interactive form, receive immediate risk assessment results, and obtain personalized recommendations based on their responses. The app has been fully deployed and can be accessed at https://paml-mental-health-project.streamlit.app/.

Metric	Logistic Regression	SVM	Linear Regression
Training Accuracy	High	High	Moderate
Test Accuracy	Good	Moderate	Moderate
MAE	Low	Moderate	Moderate
R^2	Good	Moderate	Moderate
Interpretability	High	Moderate	High
Classification Task Fit	Excellent	Good	Limited

Table 1: Comparison of model performance and characteristics

After experimenting with multiple machine learning algorithms (Linear Regression, Support Vector Machine, and Logistic Regression), our team made a deliberate decision to primarily rely on the Logistic Regression model for our deployed application. This selection was based on careful consideration of various performance metrics and practical requirements:

Logistic Regression was selected as our primary model for several key reasons:

1. **Task Appropriateness:** Depression prediction is fundamentally a binary classification problem (depressed vs. not depressed), which aligns perfectly with Logistic Regression's strengths.

2. **Interpretability:** In healthcare applications, model interpretability is crucial for building user trust and providing explainable predictions. Logistic Regression offers straightforward coefficient interpretation that can be traced back to specific input features.

3. **Performance Balance:** The Logistic Regression model demonstrated a good balance between accuracy and generalization on unseen data compared to the other models.

4. **Confidence Scores:** Logistic Regression naturally produces probability scores between 0 and 1, which we convert to confidence percentages in our application. This allows us to communicate prediction certainty to users.

Our application targets several key populations:

1. **College/University Students:** Young adults facing academic pressures, potentially living away from support networks, and experiencing significant life transitions. The dataset used for training specifically focuses on student depression indicators.

2. **Working Professionals:** Individuals dealing with work-related stress, time management challenges, and potential financial pressures.

3. **Underserved Communities:** People with limited access to mental health resources, whether due to geographic, financial, or social barriers.

4. **Mental Health Self-Monitors:** Individuals who want to proactively track their mental health status over time.

The application provides several distinct benefits to these populations:

- **Accessibility:** Users can access mental health screening from anywhere with internet access, removing geographical barriers.
- **Privacy:** The assessment can be completed privately, reducing stigma concerns that might prevent seeking professional help.
- **Early Detection:** Identifies potential depression risk before symptoms become severe.
- **Personalized Guidance:** Provides tailored recommendations based on individual risk factors.
- **Crisis Resources:** For high-risk users, immediate access to crisis support information.
- **Empowerment:** Puts mental health monitoring tools directly in users' hands, fostering a sense of control and awareness.

The application features a carefully designed user interface that guides users through the assessment process:

1. **Introduction Section:** Explains the purpose of the assessment and ensures users understand its non-diagnostic nature.
2. **Form-Based Assessment:** Structured into logical sections:
   - Personal Information (gender, age)
   - Academics & Work (study/work hours, satisfaction metrics, pressure ratings)
   - Lifestyle & Health (sleep duration, dietary habits)
   - Mental Health History (family history, suicidal thoughts)
   - Financial Stress assessment
3. **Interactive Input Components:**
   - Selection boxes for categorical variables
   - Sliders for rating scales (1-5)
   - Numeric inputs for age and hours
   - Form validation to ensure complete responses
   - Submit button to process the assessment
4. **Results Display:**
   - Clear risk level indication (Low, Moderate, High) with appropriate color coding
   - Confidence percentage from the model
   - Personalized recommendations section based on risk level
   - Additional action buttons for relaxation exercises and finding local help
   - Crisis resources section (displayed for high-risk assessments)
   - Medical disclaimer

The application maintains a clean separation between frontend presentation and backend processing while ensuring seamless integration:

1. **frontend Components (Assessment.py):**
   - Handles all UI rendering using Streamlit components
   - Manages form validation and user interactions
   - Provides CSS styling for visual presentation
   - Displays results and recommendations
2. **Backend Components (Recommendation.py):**
   - Contains the trained machine learning models
   - Processes user assessment data
   - Standardizes and transforms input features
   - Generates predictions and confidence scores
3. **Data Flow:**
   - User inputs are collected through the Streamlit form interface
   - Upon submission, validation occurs in the frontend
   - Valid form data is passed to the `process_user_assessment()` function
   - Backend processes the data through:
     - Feature standardization (matching training data distribution)
     - One-hot encoding of categorical variables
     - Model prediction generation
     - Confidence score calculation
   - Results are returned to the frontend as a structured dictionary
   - Frontend displays results and generates appropriate recommendations

This architecture ensures that the machine learning models remain separate from the presentation layer, allowing for independent updates to either component, clear separation of concerns, simplified testing and maintenance, and potential future API-based deployments.

3.5.1 Final User Interface and Evolution

The final user interface (UI) of our Streamlit application provides a seamless experience for users, guiding them from an initial overview of the tool, through the assessment process, to receiving personalized results and recommendations. Screenshots of the key UI components are presented in Figures 5 (the homepage), 6 (the assessment form), and 7 (the assessment results section).

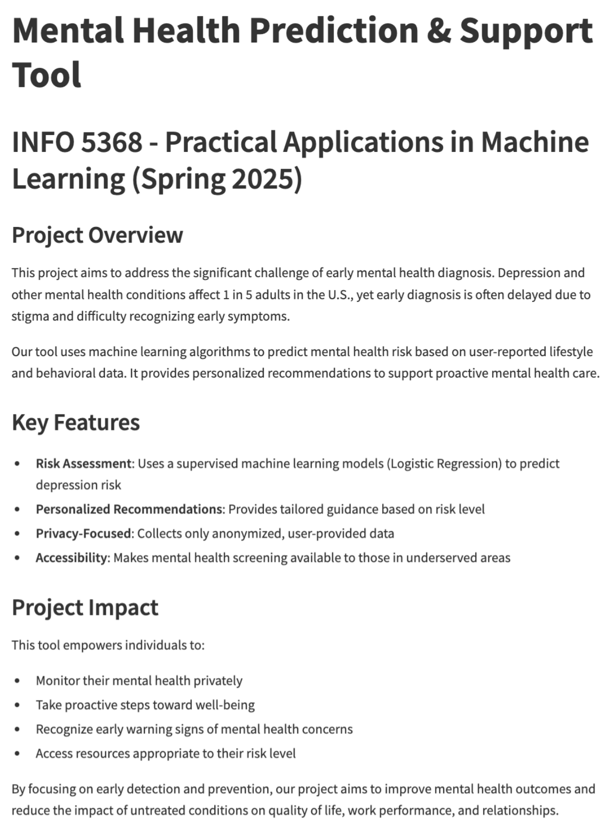

Figure 5: The homepage of our Mental Health Prediction & Support Tool, outlining the project overview, key features, and intended impact.

The homepage introduces the "Mental Health Prediction & Support Tool," detailing its purpose as a project for INFO 5368, its key features such as risk assessment and personalized recommendations, and its overall impact on empowering individuals to monitor their mental well-being.

The assessment form is a single, well-structured page where users provide data across several categories: Background Information (i.e., assigned sex at birth, age), Academics & Work (i.e., academic/work pressure, study/job satisfaction, work/study hours), Lifestyle & Health (i.e., sleep duration, dietary habits), Mental Health History (i.e., suicidal thoughts, family history of mental illness), and Financial Stress. This consolidated form uses a variety of input fields like drop-down menus, sliders, and numerical inputs to facilitate easy data entry.

Upon submission, the results page clearly presents the predicted risk level (e.g., "High"), the machine learning model's confidence in this prediction (e.g., "76.5% confidence"), a list of personalized recommendations, actionable buttons like "Start Relaxation Exercise" and "Find Local Help," and a crucial section for Crisis Resources. A disclaimer appropriately notes that the tool is not a substitute for professional medical advice.

The final user interface represents an evolution from our initial plans outlined during the proposal and midpoint check-in. At the midpoint, we described a UI with a main descriptive page and "a series of pages" for inputting lifestyle information, along with considerations for using React alongside Streamlit for a more customized interface. The final version refines this by:

- **Consolidating Input:** We opted for a single, comprehensive form page instead of multiple sequential pages for data entry. This streamlines the user experience, making the assessment process quicker and more straightforward.
- **Streamlit Implementation:** The entire front-end was successfully developed using Streamlit, leveraging its capabilities for rapid development and integration with our Python-based machine learning backend. This decision was made after initial considerations of incorporating React, ultimately finding Streamlit sufficient for our needs and simplifying the development workflow, a focus noted in our midpoint check-in due to the "closely integrated" nature of front-end and back-end code.
- **Enhanced Clarity and Functionality:** The final UI exhibits a more polished design with clear sectioning in the assessment form and a dedicated, actionable results page that includes direct links to crisis resources and tailored recommendations. The visual presentation and user flow are more refined than the basic layouts conceptualized earlier.

This iterative development process allowed us to arrive at a user-friendly and effective interface for our mental health assessment tool.

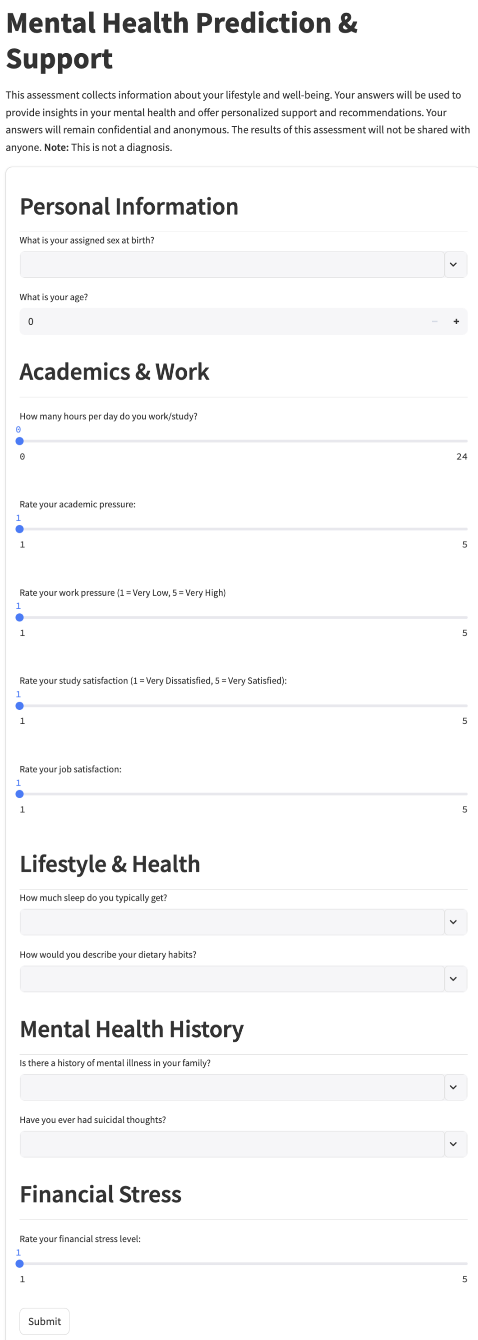

Figure 6: The comprehensive assessment form where users input their information across various categories.

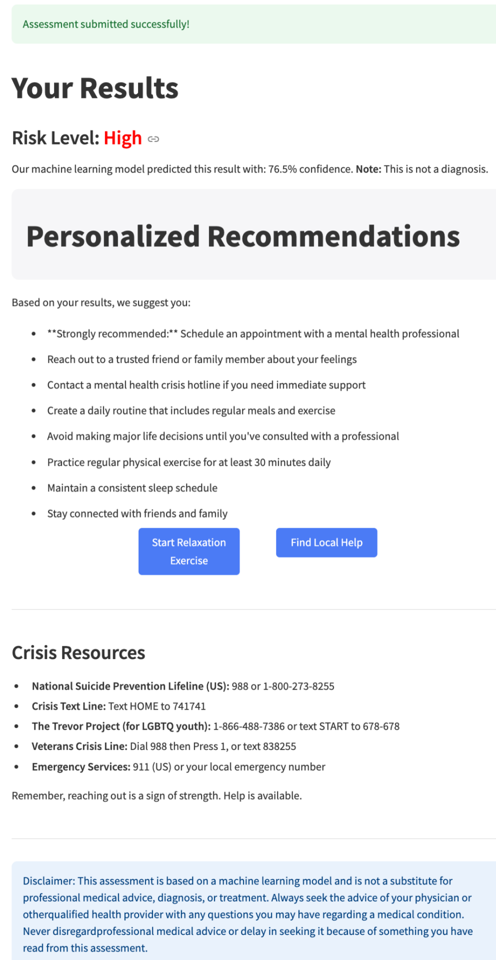

Figure 7: An example of the results page, displaying the user's risk level, model confidence, personalized recommendations, and crisis resources.

4. Conclusion

Our project successfully developed a machine learning-based mental health risk assessment tool that predicts depression risk and provides personalized, actionable recommendations. We implemented and compared three machine learning algorithms: Logistic Regression, Linear Regression, and Support Vector Machine, evaluating them using accuracy, MAE, and R^2 metrics.

The Logistic Regression model emerged as the most robust choice for deployment, achieving an 82% accuracy on test data while offering a crucial balance of predictive power, interpretability, and the generation of user-friendly probability scores. While Linear Regression also demonstrated strong predictive capabilities with 84% test accuracy, the comparatively poorer performance of our SVM implementation showed the importance of careful algorithm selection and hyperparameter tuning for this domain.

We integrated our model into a user-friendly Streamlit web application that guides users through a comprehensive assessment process, provides immediate risk evaluation, and offers personalized recommendations based on individual risk factors. The application features a clean interface with form-based assessment, interactive input components, and clear results display with appropriate resources.

Our tool addresses a critical gap in mental health support by making early screening accessible to various populations, including college students, working professionals, and underserved communities. By facilitating private, early detection, this work contributes to reducing the pervasive stigma surrounding mental health and empowers individuals to take informed steps toward enhanced well-being.

Building directly on the lessons from our model training and evaluation, particularly the variance in algorithmic performance and the recognized need for broader data representation, our future efforts will concentrate on several key areas. We plan to strategically expand our dataset to encompass greater demographic diversity, which we anticipate will improve model generalizability. Further, we will explore and integrate additional sophisticated machine learning algorithms to potentially enhance predictive accuracy and offer deeper insights. The recommendation engine will also undergo refinement for greater personalization. Crucially, iterative user studies will remain central to our process, ensuring the application's continued evolution in usability and real-world effectiveness, thereby maximizing its positive impact.

5. Team Member Contribution

5.1. Technical Component

The technical work was divided into frontend and backend development. For backend development, Aika and Konrad implemented the machine learning algorithms (Logistic Regression, Linear Regression, and SVM), conducted data preprocessing and feature engineering, as well as evaluated model performance.

For the frontend development, Alaysia and Aima designed and implemented the Streamlit user interface and created interactive form components and visualization elements, as well as the frontend and backend connection. Ony selected the best-performing model and deployed it for public access.

5.2. Writing Component

The writing work was divided into parts. Alaysia made sure to update the Abstract, Introduction, and Background from our prior midpoint check-in. Aima wrote the Model Deployment and Frontend Application Using Streamlit. Konrad wrote the Data Collection, Exploration and Preprocessing section, as well as the Methods and Model Training. Aika wrote the Model Evaluation as well as the Results section; she and Aima also wrote the Team Contribution section, given teaching staff feedback. Ony wrote the Conclusion.

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6. Appendix

6.0.1 Streamlit App

6.0.2 GitHub Repository

6.0.3 Jupyter Notebook