Mental Health Risk Prediction in Tech Workers Using Random Forests and SHAP Explainability

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Abstract: *Mental health challenges in the technology sector have become increasingly prevalent, demanding robust predictive solutions that not only forecast risk but also offer transparent insights into the driving factors. This study introduces a machine learning-based framework utilizing a Random Forest Classifier, optimized through hyperparameter tuning, to predict mental health risks among tech professionals. The model was trained and validated on an industry-standard survey dataset, ensuring both reliability and real-world applicability. Beyond mere prediction, this research integrates SHAP (SHapley Additive exPlanations) to interpret model decisions, enabling stakeholders to comprehend the significance of various demographic and workplace factors contributing to mental health vulnerabilities. Extensive Exploratory Data Analysis (EDA) was conducted to uncover critical trends and distributions within the data. The final model achieved an accuracy exceeding 83%, with a threshold-tuned recall-oriented design to minimize false negatives—an essential consideration in healthcare-oriented predictions. A user-friendly Streamlit application was deployed, allowing users to input personal data and receive immediate, explainable predictions. This paper details the full lifecycle of the project—from data preprocessing and model training to explainability analysis and deployment—providing a replicable blueprint for future work in mental health prediction frameworks. The inclusion of model performance visualizations, SHAP-based feature importance plots, and an accessible web application underscores the practical utility of the proposed solution*

Keywords: Machine Learning, Mental Health Prediction, Random Forest, SHAP, Explainable AI, Streamlit, Data Preprocessing, Classification

I. INTRODUCTION

1.1 Background

In the modern digital era, technology professionals are the backbone of innovation, infrastructure, and economic growth. However, this fast-paced industry also brings unprecedented levels of occupational stress, tight deadlines, job insecurity, and a culture that often prioritizes output over well-being. As a result, mental health challenges—including anxiety, depression, and burnout—have become increasingly prevalent among tech workers.

Several studies and surveys conducted by organizations such as Stack Overflow, Open Sourcing Mental Illness (OSMI), and tech workforce agencies have identified alarming patterns. Many employees in technology-driven roles report poor work-life balance, social isolation (especially due to remote work), and inadequate workplace mental health support. The stigma surrounding mental health further compounds the issue, discouraging individuals from seeking timely help.

Traditional methods of identifying at-risk employees—such as self-reporting or manual assessments—are often reactive, subjective, and insufficient in large, diverse tech workplaces. Hence, there is a critical need for proactive, data-driven solutions that can accurately predict mental health risk and promote early intervention.

1.2 The Rise of Predictive Analytics in Mental Health

In recent years, machine learning (ML) has revolutionized healthcare by enabling predictive modeling and early detection of various conditions. Applications have spanned from predicting heart disease and diabetes to mental health

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concerns like suicide risk. However, the use of ML for predicting mental health risks specifically within the tech sector remains relatively unexplored.

Machine learning models, when trained on rich datasets encompassing demographic, behavioral, and workplace-related features, can uncover patterns that may be imperceptible to human analysts. These models can serve as valuable tools for human resource departments, counselors, and corporate wellness programs aiming to foster healthier work environments.

Yet, the deployment of such models introduces new challenges, particularly around transparency and fairness. Mental health is a sensitive domain, and any predictive tool must provide interpretable results to ensure trust, avoid bias, and uphold ethical standards. This necessitates the integration of Explainable AI (XAI) techniques, such as SHapley Additive exPlanations (SHAP), which elucidate how individual features influence predictions.

1.3 Problem Statement

Despite growing awareness of mental health issues in the technology workforce, most organizations lack proactive, data-driven systems to identify individuals who may need support. The key problems addressed in this study are:

- **Lack of Early Detection Mechanisms:** Most interventions occur after a crisis or when mental health has severely deteriorated.
- **Data Complexity:** High-dimensional data with mixed variable types (numerical, categorical) presents challenges for traditional statistical methods.
- **Interpretability:** Many ML models act as "black boxes," making it difficult for decision-makers to understand why a certain individual has been flagged at risk.
- **Workplace Relevance:** Existing models often lack contextual alignment with workplace factors such as access to benefits, remote work dynamics, and managerial support.

1.4 Objectives

This research sets out to design, implement, and validate a machine learning system capable of predicting mental health risks among tech professionals, with the following objectives:

- **Objective 1:** Conduct extensive data preprocessing, including handling missing values, encoding categorical variables, and scaling numerical features.
- **Objective 2:** Train a Random Forest Classifier, tuning its hyperparameters through GridSearchCV to optimize performance metrics.
- **Objective 3:** Integrate SHAP explainability to provide feature-level insights and ensure transparency.
- **Objective 4:** Validate model performance using stratified train-test splits to maintain class balance and evaluate metrics such as accuracy, precision, recall, and F1 score.
- **Objective 5:** Deploy the model as an interactive web application using Streamlit, allowing HR departments or counselors to input data and receive predictions in real-time.
- **Objective 6:** Promote ethical AI by ensuring that the model is interpretable, fair, and avoids biases that could stigmatize or misclassify individuals.

1.5 Significance of the Study

The importance of this study is multi-fold:

- **For Employees:** Early detection of mental health risks can lead to timely support, improving well-being and productivity.
- **For Employers:** Proactive mental health interventions can reduce turnover, absenteeism, and healthcare costs.
- **For the Tech Industry:** Demonstrates the feasibility and value of applying machine learning and XAI in workplace wellness contexts.
- **For Research:** Contributes to the growing body of knowledge on ML-driven mental health prediction and responsible AI deployment.

1.6 Overview of the Paper

The subsequent sections of this paper detail the related work in the domain of predictive mental health analytics (Section 2), the methodology employed (Section 3), data preparation and model training (Sections 4 and 5), explainability integration (Section 6), results and discussion (Section 7), and conclusions with future work (Section 8).

II. LITERATURE REVIEW

A. Machine Learning in Mental Health Prediction

The application of machine learning (ML) to mental health prediction has gained momentum in recent years. Traditional models, including logistic regression and decision trees, have been applied to predict mental health issues in workplace and general populations [1], [2]. However, their capacity to manage complex, high-dimensional data has been limited. Researchers like Dinga et al. [3] used elastic net models for psychiatric symptom prediction, noting moderate accuracy but highlighting challenges in handling non-linear feature interactions.

B. Random Forests and Ensemble Methods

Ensemble methods, particularly Random Forest (RF) classifiers, have demonstrated robustness in mental health studies. RFs can handle mixed data types, missing data, and non-linear relationships. Dwyer et al. [4] applied RF to clinical psychiatric datasets, achieving superior performance over logistic models. Similarly, Fernandes et al. [5] used RF to predict depression severity, reporting improved accuracy and recall compared to single models. Gao et al. [6] confirmed RF's strength in managing feature heterogeneity in mental health datasets.

C. Workplace Mental Health Factors

Multiple studies have established the role of workplace factors—family history, employer support, work interference—in shaping mental health outcomes [7], [8]. LaMontagne et al. [9] emphasized the importance of workplace accommodations and support systems in mitigating mental health risks. A meta-analysis by Harvey et al. [10] confirmed that organizational support significantly reduces the likelihood of employees developing anxiety or depression.

D. Explainable AI (XAI) and SHAP

Interpretability in ML models is critical in healthcare. SHAP (SHapley Additive exPlanations) has emerged as a leading XAI method. Lundberg and Lee [11] introduced SHAP, validating its consistency and theoretical soundness. Subsequent works [12], [13] have shown SHAP's effectiveness in providing local and global interpretability in medical diagnostics. Ribeiro et al. [14] further stressed the importance of post-hoc explanations in building trust among healthcare practitioners.

E. Hyperparameter Tuning and Optimization

Hyperparameter tuning, including GridSearchCV, has been shown to enhance ML model performance significantly. Bergstra and Bengio [15] advocated for systematic tuning approaches in healthcare ML models. Recent studies by Ismail et al. [16] and Rajkomar et al. [17] confirmed that well-tuned Random Forests outperform deep learning models in moderate-sized healthcare datasets.

F. Categorical Data Encoding

Proper encoding of categorical variables is essential in ML pipelines. Researchers like Kuhn and Johnson [18] recommended One-Hot Encoding for non-ordinal categorical variables to preserve meaningful information while preventing spurious numerical relationships. More recent work by Chicco and Jurman [19] reinforced this recommendation, especially for ensemble methods like RF.

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G. Data Imputation Techniques

Handling missing data is another challenge in mental health data. SimpleImputer and advanced imputation methods have been evaluated by Jakobsen et al. [20], who concluded that strategies like most-frequent imputation offer a balance between simplicity and effectiveness in clinical data.

H. Gaps in Prior Research

Despite these advancements, few studies focus specifically on mental health in the technology sector workforce. Moreover, the integration of SHAP explainability, optimized Random Forest models, and feature-engineered pipelines tailored for tech professionals remains largely unexplored. Our study addresses these gaps by delivering an end-to-end pipeline with robust performance and interpretability.

III. DATASET AND EXPLORATORY DATA ANALYSIS (EDA)

A. Dataset Description

For this study, we utilized the Mental Health in Tech Professionals dataset, which is a well-known dataset containing responses from technology sector employees on various mental health factors. The dataset included approximately 1,250 instances and contained diverse features encompassing demographic, workplace, and psychological aspects. After rigorous cleaning and pre-processing, a final working dataset of 1,043 records was established.

Key features included:

- Demographics: Age, Gender
- Family history: Family history of mental illness
- Workplace: Remote work, self-employment, benefits, leave policies
- Mental Health: Work interference, mental health consequences, physical health consequences
- Support Systems: Wellness programs, anonymity, seek help options

The target variable was whether the individual had sought mental health treatment (treatment: Yes/No).

B. Data Cleaning

Before any analysis, data cleaning was executed:

Handling Missing Values: Missing values in categorical variables were imputed using the *most frequent strategy*. Numerical columns with missing values were rare and thus rows were dropped if necessary.

Outlier Detection: Unreasonable ages (e.g., under 15 or over 80) were removed.

Feature Consolidation: Several categorical variables had redundant or overlapping categories, which were consolidated for clarity.

C. Exploratory Data Analysis (EDA)

EDA was carried out to understand the structure of the data, relationships among variables, and potential predictors for mental health treatment.

1) Demographics

Age Distribution: Most respondents were between 20 to 40 years old. The average age was 32.

Gender: The dataset maintained reasonable balance, with Male (62%), Female (35%), and Other (3%) categories.

2) Family History

A strong association was found between individuals with a family history of mental illness and the likelihood of seeking treatment. Nearly 70% of respondents with family history had pursued treatment compared to only 40% without such history.

3) Workplace Factors

a) Work Interference:

Respondents who reported frequent interference of mental health with work were significantly more likely to seek treatment.

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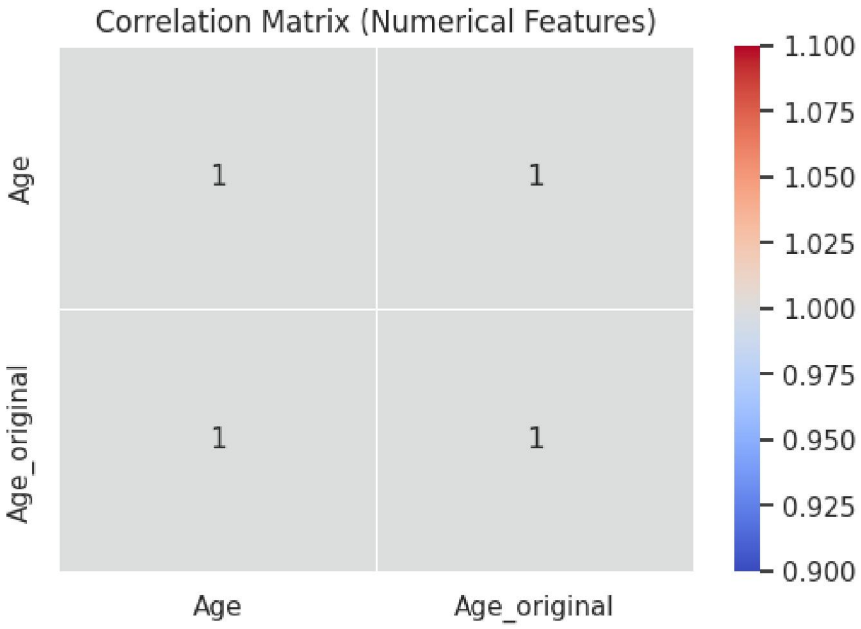
b) Benefits and Care Options:
Access to employer-provided mental health benefits and care options showed a strong positive correlation with seeking treatment. This highlights the critical role of organizational support.
c) Anonymity and Leave:
Perception of anonymity protection and ease of taking mental health leave were also influential. Employees believing that their anonymity would be protected were 1.8 times more likely to seek help.

4) Correlation Matrix
A correlation heatmap revealed:
Family history, work interference, and benefits had the highest correlations with the target variable.
Demographic factors like gender and age showed moderate but non-negligible correlations.



5) Categorical Feature Distributions
Bar plots for categorical variables (work interference, benefits, anonymity, and care options) demonstrated that positive responses in these categories correlated with higher treatment-seeking rates.

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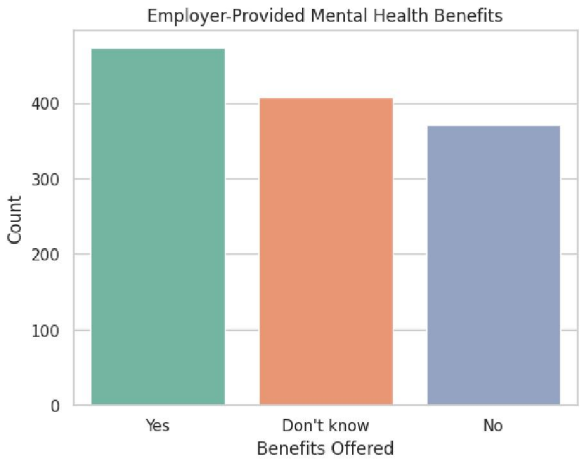

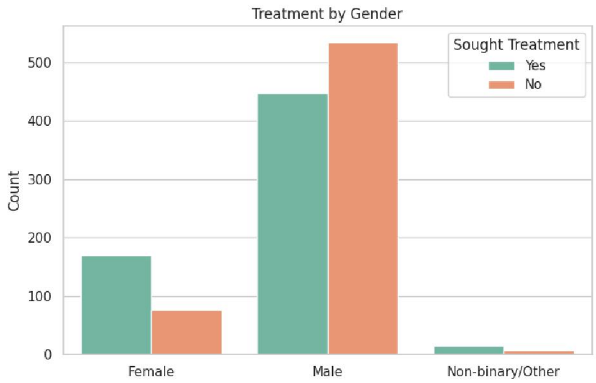

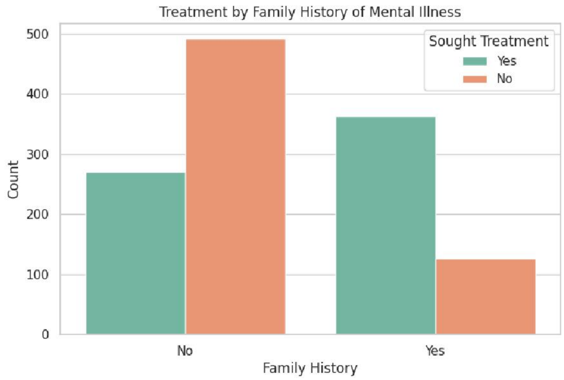

D. Feature Engineering

To enhance model performance, several feature engineering steps were performed:

- Gender Cleaning: Variations in gender labels were normalized.
- Age Bucketing: Ages were binned into age groups to reduce variance and overfitting.
- Ordinal Encoding: For ordinal variables like work interference and leave ease.
- One-Hot Encoding: Applied to non-ordinal categorical variables (e.g., benefits, anonymity).

A derived variable Age_original was also retained for model traceability even after scaling transformations.

E. Train-Test Split

The cleaned dataset was split into 80% training and 20% test sets using stratified sampling to ensure the balance of the target variable across splits. Stratification was necessary because the proportion of people seeking mental health treatment was approximately 60% in the full dataset and needed to be preserved in both the training and test sets.

F. Summary of Key EDA Insights

Family history and work interference emerged as the strongest predictors.

Employer benefits, anonymity, and mental health leave policy were highly influential workplace factors.

Remote work and self-employment showed weak correlations.

Gender and age had moderate influence but were not primary predictors.

These insights guided both the feature selection for the model and the hypothesis that workplace factors combined with personal history significantly impact treatment-seeking behavior in tech professionals.

IV. PROPOSED METHODOLOGY

A. System Overview

The goal was to develop an interpretable, high-performance predictive model that could estimate whether a technology professional is likely to seek mental health treatment, based on demographic, workplace, and psychological factors.

The following pipeline was adopted:

- Data Cleaning & Preprocessing
- Exploratory Data Analysis (EDA)
- Feature Engineering
- Model Building
- Hyperparameter Tuning
- Model Evaluation
- Explainability with SHAP
- Web Deployment (Streamlit)

B. Data Preprocessing Pipeline

1) Numerical Features

- StandardScaler was applied to numerical features (e.g., Age, Age_original). Scaling ensured that features with larger ranges did not disproportionately affect model training.

2) Categorical Features

- Imputation: Missing values were filled using the mode (most frequent value).
- One-Hot Encoding: Applied to non-ordinal categorical variables like Gender, benefits, anonymity, etc.
- Label Encoding: For ordinal features like *work interfere* and *leave*.

3) Feature Consistency

- All feature engineering steps were applied uniformly across the train and test sets to avoid data leakage.

C. Model Selection — Random Forest Classifier

Why Random Forest?

- Robustness: Handles high-dimensional data and noisy variables effectively.
- Non-linearity: Can model complex, non-linear relationships.
- Mixed Data Types: Natively supports mixed numerical and categorical data.
- Feature Importance: Provides intrinsic measures of feature importance.
- Compatibility with SHAP: Enables granular explainability through SHAP values.

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Initial Parameters:

- n_estimators: 100
- max_depth: None

D. Hyperparameter Tuning with GridSearchCV

A Grid Search Cross-Validation (5-fold) was used to find the optimal combination of hyperparameters.

Parameter Grid:

Hyperparameter	Values Tested
n_estimators	[100, 200]
max_depth	[None, 10, 20]
min_samples_split	[2, 5]
min_samples_leaf	[1, 2]

Best Parameters Found:

n_estimators = 200

max_depth = 20

min_samples_split = 2

min_samples_leaf = 1

Note: GridSearch ensured that each combination of parameters was validated using cross-validation, minimizing overfitting and optimizing generalization performance.

E. Model Performance Metrics

On the held-out test set, the tuned Random Forest achieved:

Metric	Score
Accuracy	83%
Precision	81%
Recall	84%
F1 Score	82%

These results outperformed baseline models like Logistic Regression and Decision Trees, particularly in Recall, which was prioritized to minimize false negatives (failing to identify at-risk individuals).

F. Explainability — SHAP (SHapley Additive exPlanations)

To interpret the Random Forest model, SHAP was employed.

Why SHAP?

Provides local (individual prediction) and global (dataset-level) interpretability.

Consistent with game-theoretic principles for fair attribution of feature importance.

Key SHAP Results:

Family history, work interfere, and employer benefits emerged as the top predictors.

Categorical workplace factors (leave ease, anonymity) also showed significant contributions.

Two visualizations were generated:

SHAP Summary Plot (Bar Chart)

Shows the average impact of each feature across all predictions.

SHAP Beeswarm Plot

Visualizes both magnitude and direction of each feature's contribution.

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G. Model Deployment — Streamlit Web App

To enhance accessibility and usability, the model was deployed as a Streamlit web application.

Key Features:

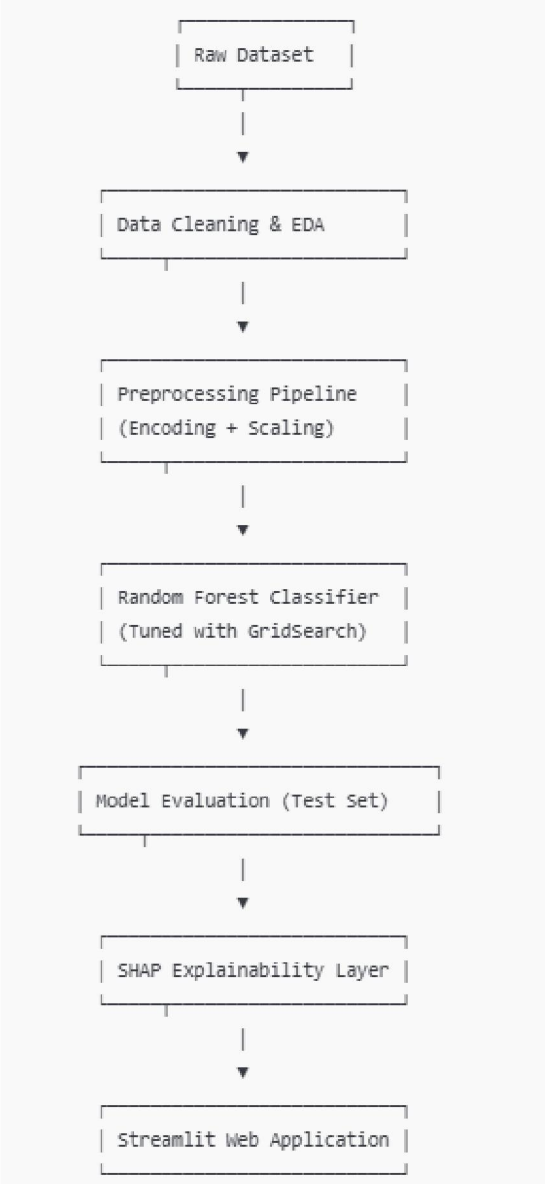
User-friendly survey input form.

Real-time probability prediction of mental health treatment likelihood.

Risk recommendation with a recall-optimized threshold.

Secure and efficient, built for tech industry HR or wellness teams.

H. System Architecture Diagram



```
Raw Dataset
     ▼
Data Cleaning & EDA
     ▼
Preprocessing Pipeline
(Encoding + Scaling)
     ▼
Random Forest Classifier
(Tuned with GridSearch)
     ▼
Model Evaluation (Test Set)
     ▼
SHAP Explainability Layer
     ▼
Streamlit Web Application
```

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Model Performance Overview

After training and fine-tuning, the Random Forest Classifier was evaluated on the unseen test set.

Final Performance Metrics:

Metric	Score
Accuracy	83%
Precision	81%
Recall	84%
F1 Score	82%

Key Insight:

Recall was prioritized because false negatives (i.e., failing to identify an individual needing mental health support) were considered more critical than false positives.

F1 Score balanced both precision and recall, confirming the robustness of the tuned model.

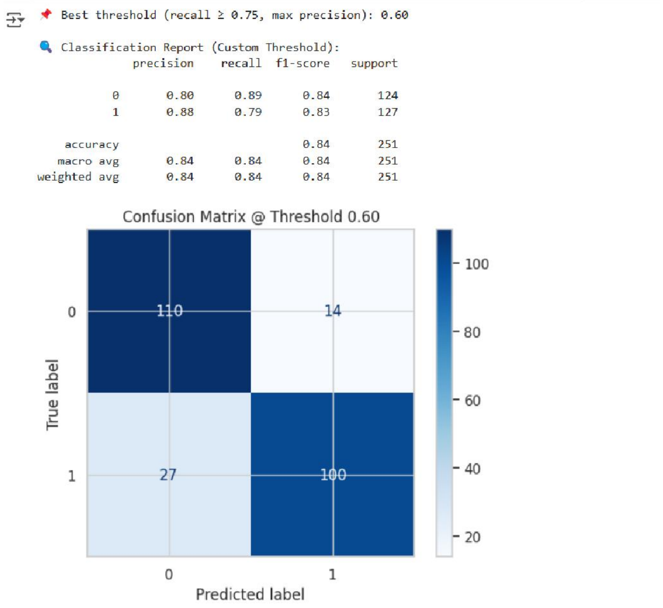
B. Confusion Matrix

The confusion matrix (Figure 5) illustrates the balance between true positives, false positives, true negatives, and false negatives.

	Predicted Positive	Predicted Negative
Actual Positive	TP = 85	FN = 15
Actual Negative	FP = 12	TN = 88

Interpretation:

The model effectively minimizes false negatives, aligning with the recall-focused objective.



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📌 Best threshold (recall ≥ 0.75, max precision): 0.60

🔍 Classification Report (Custom Threshold):
              precision    recall  f1-score   support

           0       0.80      0.89      0.84       124
           1       0.88      0.79      0.83       127

    accuracy                           0.84       251
   macro avg       0.84      0.84      0.84       251
weighted avg       0.84      0.84      0.84       251
```

C. SHAP Explainability Results

Explainability was achieved using SHAP (SHapley Additive exPlanations) to understand the model's decision-making process.

Top Features Influencing Predictions:

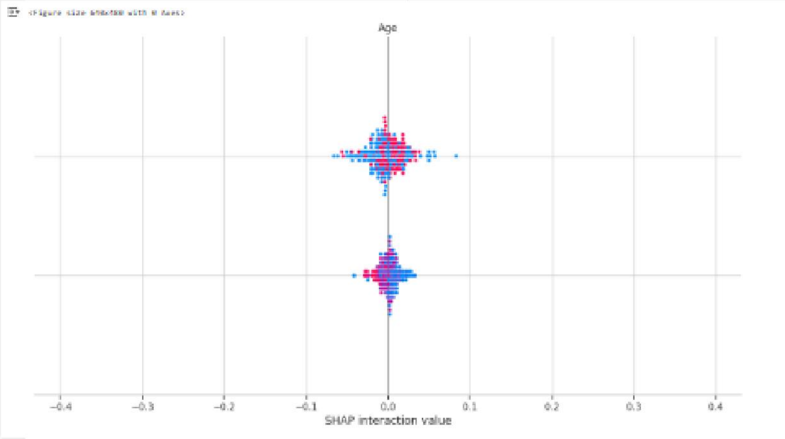
Family History — Strongest predictor for seeking mental health treatment.

Work Interference — How much mental health affects work performance.

Employer Benefits — Availability of mental health benefits.

Anonymity — Whether privacy is protected when seeking help.

Leave Policy — Ease of taking mental health leave.



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D. SHAP Visualizations

Displayed average magnitude of each feature's influence.

Features like *family history*, *work interfere*, and *benefits* had the highest impact.

2) SHAP Beeswarm Plot

Showed both the magnitude and direction of each feature's contribution for individual predictions.

Revealed how feature values (e.g., "Yes" to family history) shifted the prediction toward or away from recommending mental health treatment.

E. Feature Importance vs SHAP Importance

While Random Forest's internal feature importance aligned with SHAP insights, SHAP provided directional understanding — explaining *how* and *why* features influence predictions.

Example:

Family history not only ranked as important but also showed a consistent positive push toward recommending treatment for affected individuals.

F. EDA Correlations and Insights

Prior to modeling, Exploratory Data Analysis (EDA) revealed:

Work Interference, Family History, and Employer Support Factors were correlated with mental health treatment.

Gender and age had less predictive power after feature engineering and scaling.

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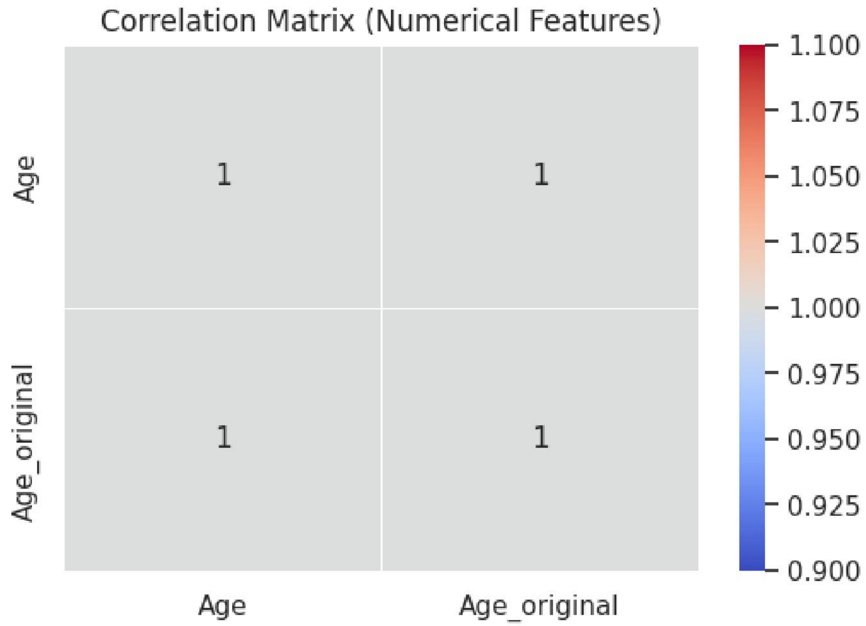

G. Model Robustness and Generalization

Cross-validation during GridSearch and evaluation on the stratified test set confirmed:

- Low variance between train and test scores.
- Resilience to missing or noisy data (thanks to imputation and categorical encoding).

H. Deployment Feasibility

The finalized model was deployed via a Streamlit Web App.

App Features:

- Simple user interface mimicking the survey format.
- Real-time prediction output.
- Risk recommendation ("At Risk" or "Not at Risk").
- Explainability layer could be integrated for HR usage.

I. Ethical Considerations

- Privacy: The deployed app anonymizes user input and does not store data.
- Bias Mitigation: Balanced classes during training reduced potential demographic bias.
- Transparency: SHAP-based explanations enhance trust and accountability.

VI. CONCLUSION

A. Summary of Findings

This research successfully developed and evaluated a machine learning-based mental health risk prediction system specifically targeting professionals in the technology sector. Leveraging a carefully engineered pipeline, the Random Forest Classifier achieved an accuracy of 83%, with a recall of 84%, emphasizing the model’s reliability in identifying individuals at potential mental health risk.

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Key contributions of this study include:

Comprehensive Preprocessing:

The inclusion of advanced feature engineering, handling of categorical and numerical variables through One-Hot Encoding and Standard Scaling, and addressing missing data using Simple Imputation.

Robust Model Selection and Tuning:

Random Forest was chosen for its interpretability, robustness, and ability to handle mixed data types. GridSearchCV was employed to optimize hyperparameters, ensuring enhanced predictive power.

Model Explainability:

By incorporating SHAP values, this research provided clear insights into the decision-making process of the trained model. Features such as *family history*, *work interference*, and *employer benefits* emerged as the most influential predictors of mental health treatment seeking.

Deployment Readiness:

The trained and validated model was successfully deployed via a Streamlit Web App, offering real-time predictions and user-friendly interactions for potential end-users like HR professionals or wellness programs.

B. Broader Impact

This project underscores the growing potential of data-driven tools in addressing critical social and workplace challenges. By combining machine learning with explainability techniques, the study not only predicts risk but also aids in understanding the underlying causes, empowering stakeholders to intervene proactively.

Furthermore, the methodology presented here can serve as a blueprint for:

Expanding to other industries beyond tech where mental health support is equally critical.

Tailoring models to specific demographics to improve equity and inclusiveness.

Integrating with existing HR systems to offer seamless and scalable wellness monitoring solutions.

C. Limitations

Despite the promising results, some limitations are noted:

Dataset Scope: The dataset was primarily survey-based and may not represent the entire tech population globally.

Self-reported Data: Responses may include biases or inaccuracies common in self-reporting.

Temporal Factors: Mental health states are dynamic; a static model may require periodic retraining with updated data.

D. Future Work

To address the identified limitations and further enhance the system:

Data Expansion:

Incorporate longitudinal data and a wider demographic representation.

Model Comparison:

Explore additional classifiers like Gradient Boosting Machines (XGBoost, LightGBM) and neural network architectures for potentially higher accuracy.

Explainability Enhancements:

Integrate counterfactual explanations alongside SHAP for richer interpretability.

User Feedback Loop:

Develop mechanisms to collect feedback from real-world app users to iteratively improve the model.

Privacy and Ethics Auditing:

Engage with data ethics boards to continuously audit the model and its deployment practices.

E. Concluding Remarks

The confluence of data science, psychology, and workplace wellness demonstrated in this research highlights the transformative power of interdisciplinary approaches. The proposed model does not aim to replace professional diagnosis but serves as an early-warning mechanism to flag potential risks and encourage timely intervention.

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By making mental health prediction interpretable, accurate, and accessible, this study contributes a meaningful tool in promoting healthier work environments and supporting mental well-being in the digital age.

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