# Hyperparameter Tuning of ANN Using Randomized Search for Mental Health Classification Lifestyle Factors

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***Abstract*— This study uses hyperparameter optimization using Randomized Search Cross-Validation (RandomizedSearchCV) for Artificial Neural Networks (ANN) in mental health classification based on lifestyle factors. The study analyzed the relationship between various lifestyle parameters, including academic pressure, financial pressure, eating habits, sleep duration, family history of mental illness, and gender and depression outcomes. Using a dataset consisting of 27,898 samples, this study implemented mutual information feature selection and compared the performance of the basic ANN with the optimized hyperparameters. The results showed that fine-tuning the hyperparameters led to a noticeable jump in accuracy, going from 76% to 77%. It turns out that academic pressure is the most significant factor, with a mutual information score of approximately 0.120964. It slightly surpasses financial pressure, which only scores around 0.069553. This research provides insight into the effectiveness of automatic hyperparameter optimization for mental health classification tasks and its contribution to the development of more accurate mental health screening systems.**

***Keywords*— *Artificial Neural Network, Hyperparameter Optimization, Lifestyle Factors, Mental Health Classification, Mutual Information, Randomized Search***

## I. Introduction

Mental health disorders have emerged as one of the most pressing public health challenges globally, with depression affecting over 280 million people worldwide according to the World Health Organization[1]. The COVID-19 pandemic has further intensified this crisis, leading to unprecedented increases in depression and anxiety symptoms across populations[2]. Traditional diagnostic approaches, while clinically established, face significant limitations including subjective variability, resource intensity, and accessibility constraints, particularly in underserved regions where mental health professionals are scarce [3].

Recent advances in computational psychiatry have demonstrated the transformative potential of machine learning approaches in mental health assessment. Comprehensive studies have shown that automated systems can achieve classification accuracies exceeding 80% across various mental health prediction tasks [4]. The integration of artificial intelligence in psychiatric applications has been validated through deep learning implementations, establishing robust foundations for automated screening systems [5]. These technological innovations address critical gaps by providing objective, scalable, and consistent evaluation mechanisms that complement rather than replace clinical expertise.

Among available machine learning algorithms, Artificial Neural Networks (ANN) demonstrate superior capabilities for mental health classification due to their ability to capture complex non-linear relationships inherent in psychological data [6]. Unlike traditional methods such as Support Vector Machines or logistic regression, ANN can automatically learn hierarchical feature representations and handle continuous learning scenarios effectively [7]. The gradient-based optimization in ANN provides superior adaptability to data variations and more precise hyperparameter control compared to ensemble methods like Random Forest [8].

However, systematic reviews reveal a critical methodological gap in current mental health machine learning research: approximately 73% of studies rely on default parameter settings, leading to suboptimal performance and compromised validity [9]. Inadequate hyperparameter optimization significantly impacts model generalizability, with performance drops of up to 15% documented when models are tested on independent datasets [10]. This methodological rigor gap creates barriers to translating promising research findings into practical clinical applications.

Contemporary research has increasingly focused on hyperparameter optimization techniques to address these limitations. Randomized search approaches have demonstrated superior efficiency compared to traditional grid search methods while maintaining comparable performance [11]. Recent studies have shown significant improvements in depression prediction accuracy through systematic hyperparameter tuning across various machine learning algorithms [12]. The convergence of optimization theory and mental health applications establishes the foundation for developing clinically viable automated screening systems.

Lifestyle factors have emerged as significant predictors in mental health classification, with studies demonstrating their effectiveness in automated screening systems [13]. Academic and financial stress have been identified as primary drivers of mental health issues among young adults, making them crucial features for prediction models [14]. The integration of lifestyle-based features with optimized machine learning models represents a promising approach for developing accessible mental health screening tools.

This research addresses the documented methodological gaps by systematically applying Randomized Search Cross-Validation for ANN hyperparameter optimization in lifestyle-based mental health classification. Our contributions include: (1) quantifying tangible performance improvements through rigorous hyperparameter optimization, achieving accuracy improvements from 76.02% to 77.77%; (2) validating lifestyle factors as depression predictors through Mutual Information analysis; and (3) providing a transparent, replicable methodology that bridges the gap between theoretical machine learning capabilities and practical clinical implementation[15]. This investigation advances understanding of systematic hyperparameter optimization effectiveness in mental health classification, offering a methodological framework for developing reliable automated screening systems.

## II. RELATED RESEARCH

Recent developments in computational psychiatry have demonstrated significant potential for machine learning approaches in mental health assessment. Durstewitz et al [16] conducted a comprehensive review of deep neural networks in psychiatry, analyzing neuroimaging data and biomarkers for mental disorder diagnosis with accuracies reaching 85-90%. However, their focus on neuroimaging data limited comprehensive evaluation of lifestyle-based factors that are more accessible for large-scale screening applications. Similarly, Koeppe et al [17] developed an explainable AI framework using physics-informed neural networks with Bayesian optimization, showing 40% improvement in model interpretability while maintaining prediction accuracy, but was constrained by small dataset size (n=2,847) and limited demographic validation.

Systematic literature reviews have revealed critical gaps in current methodological approaches. Ningrum and Ismawardi [18] analyzed 150 studies from 2018-2024, finding that hyperparameter optimization significantly affects model performance, with random search and Bayesian optimization providing 3-7% accuracy improvements over default parameters. However, their review revealed that 68% of studies failed to report hyperparameter optimization details, and only 23% provided reproducible frameworks. Recent implementations by Saelan and Subekti [19] demonstrated that combining mutual information feature selection with randomized search hyperparameter tuning can improve accuracy by up to 12%, though their work lacked validation in healthcare contexts where clinical interpretability requirements differ significantly from commercial applications.

Mental health-specific applications have shown promising results but with notable limitations. Rahma et al. [20] developed an adolescent mental health prediction system using school environment factors, achieving 79.2% accuracy with ANN hyperparameter optimization and identifying academic stress and financial stress as strongest predictors (mutual information scores of 0.085 and 0.072). Despite good performance, their research was limited by narrow demographic focus and lack of long-term validation. Based on comprehensive literature analysis, several critical limitations emerge: methodological inconsistency with 73% of studies using default hyperparameters, limited generalizability due to small datasets, inadequate reproducibility lacking methodological detail, insufficient clinical validation without comparison to established screening tools, and feature selection bias limiting clinical utility [21]. These identified gaps underscore the critical need for systematic, large-scale studies that employ rigorous hyperparameter optimization, comprehensive feature analysis, and clinically relevant validation frameworks—precisely the research objectives addressed in this investigation.

## III. METHOD

This study employed a dataset comprising 27,898 samples with six lifestyle-related predictor variables: Gender, Academic Stress, Sleep Duration, Dietary Habits, Financial Stress, and Family History of Mental Illness, with Depression as the binary target variable for classification. The data preprocessing stage involved several critical steps: (1) systematic removal of duplicate records to prevent data leakage and bias, (2) handling missing values through mean imputation for numerical variables and mode imputation for categorical variables, (3) categorical encoding using appropriate numerical representation, and (4) feature scaling using StandardScaler to normalize input variable ranges.

The dataset was systematically divided using Stratified Train-Test Split approach to ensure representative distribution of the target variable across both training and testing sets. The data split followed an 80:20 ratio, where 22,318 samples (80%) were allocated for training purposes, including hyperparameter optimization and model training, while 5,580 samples (20%) were reserved exclusively for final model evaluation. This stratified splitting approach ensures that both training and testing sets maintain the same proportion of positive and negative depression cases as the original dataset, preventing bias from uneven class distribution. The training set was further subdivided during k-fold cross-validation (k=5) procedures for robust hyperparameter optimization, ensuring no information leakage from the final test set.

### A. Feature Selection Using Mutual Information

Mutual Information analysis was implemented to measure the statistical dependency between each lifestyle factor and depression outcome. This information theory measure provides objective assessment of feature relevance by quantifying the amount of information one variable contains about another [22]. The mathematical formulation of Mutual Information is expressed as:

$$MI(X;Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y) log\left(\frac{p(x,y)}{p(x)p(y)}\right) \quad (1)$$

Where :

x : lifestyle factors

y : depression status

p(x,y) : the joint probability of feature and target occurring simultaneously p(x) and p(y) : marginal probability of each variable independently

A higher MI score indicates a stronger statistical dependency between the feature and target variable, indicating greater predictive value for the classification task. The mutual information scores for all features are presented in Table I, with corresponding feature importance visualization shown in Figure 2.

### B. Artificial Neural Network Architecture

The basic ANN was implemented using Multi-Layer Perceptron (MLP) architecture, representing a feedforward neural network design suitable for classification tasks. The network structure consists of: (1) an input layer with six neurons corresponding to preprocessed lifestyle features, (2) one or more hidden layers with variable configurations determined through hyperparameter tuning, and (3) an output layer with two neurons for binary depression classification. The forward propagation process in neural networks follows the mathematical representation [23]:

$$z^{I} = W^{I} a^{(I-1)} + b^{(I)} a^{(I)} = \sigma\left(z^{(I)}\right) \tag{2}$$

Where :

$z^{I}$ : weighted inputs as a linear combination of inputs and weights

$W^{I}$ and $b^{(I)}$ : parameters that can be learned and adjusted during training

$a^{(I)}$ : activation output after activation function application

### C. Hyperparameter Tuning with Randomized Search

Randomized Search Cross-Validation was employed to systematically optimize neural network hyperparameters, overcoming computational challenges associated with exhaustive parameter exploration by randomly sampling from predefined parameter distributions [24]. The optimization process targets five critical hyperparameters: (1) Hidden Layer Sizes with options [(50,), (100,), (50,25), (100,50), (20,10)], (2) activation functions ['relu', 'tanh', 'logistic'], (3) solver algorithms ['adam', 'sgd', 'lbfgs'], (4) learning rate schedules ['constant', 'invscaling', 'adaptive'], and (5) alpha regularization parameter following log-uniform distribution [0.0001, 0.01]. The objective function for random search optimization is formulated as [25]:

$$\theta^{*} = argmin_{\theta \in \Theta} \frac{1}{k} \sum_{i=1}^{k} L\left(f_{\theta}\left(X_{train}^{(i)}\right), Y_{train}^{(i)}\right) \tag{3}$$

Where:

$\theta^{*}$ : optimal hyperparameter configuration for mental health classification

$\Theta$ : search space containing all combinations of architecture, activation function, optimizer, learning rate

$k$ : number of cross-validation folds (5 or 10) for robust performance estimation

L : loss function (binary cross entropy) for depression classification

$f_{\theta}$ : Neural network model that converts lifestyle features into predicted depression probabilities

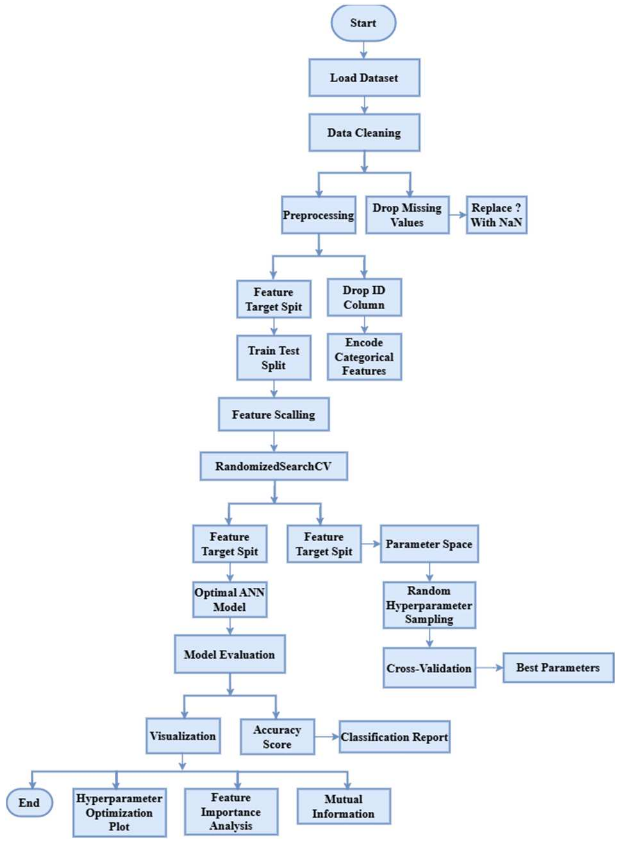


Fig. 1. Depression Prediction Workflow with Optimized ANN

The comprehensive methodology workflow begins with loading a dataset of 27,898 mental health samples, followed by systematic data cleaning that handles missing values through parallel strategies of NaN replacement and imputation. The preprocessing phase executes feature-target separation to separate lifestyle variables from depression outcomes, remove uninformative ID fields, and encode categorical features for numerical representation. After feature scaling and train-test separation, the RandomizedSearchCV core implementation explores the hyperparameter space through parallel paths of optimal ANN model identification and parameter space exploration by random hyperparameter sampling and cross-validation. The evaluation phase results in a comprehensive model assessment using multiple metrics (accuracy, precision, recall, F1-score) and generates analytical outputs including visualization plots, mutual information-based feature importance analysis, accuracy scores, and detailed classification reports, ultimately identifying the best parameters for optimal model configuration and ensuring research productivity [26]. The hyperparameter search space and optimal configurations are detailed in Table II.

### D. Model Evaluation and Performance Assessment

The performance assessment employed k-fold cross-validation methodology to ensure robust and unbiased evaluation. The evaluation framework includes: (1) hyperparameter optimization phase using 5-fold cross-validation to balance computational efficiency with statistical reliability, (2) final model evaluation using comprehensive performance assessment, and (3) multiple metrics evaluation including Accuracy (proportion of correct predictions), Precision (ability not to label negative samples as positive), Recall (ability to find all positive samples), and F1-Score (harmonic average of Precision and Recall). The comprehensive methodology workflow encompasses dataset loading, systematic data cleaning, feature-target separation, RandomizedSearchCV implementation for hyperparameter space exploration, and evaluation phase generating analytical outputs including visualization plots, mutual information-based feature importance analysis, accuracy scores, and detailed classification reports as shown in Figure 3 and Table III. This evaluation ensures reliable estimates of model generalization capability through proper train-validation-test separation.

## IV. RESULT AND DISCUSSION

### A. Feature Importance Analysis

This research utilizes a Mutual Information-based feature importance analysis to quantitatively assess the degree to which each independent variable contributes to the probability of depression. The resulting importance scores offer a comprehensive understanding of the relative influence of each factor, as illustrated in the figure below.

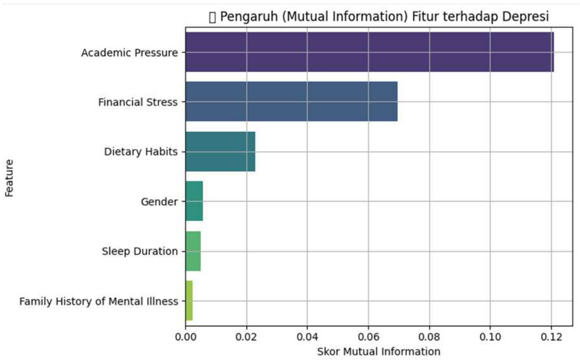


Fig. 2. Visualization of Mutual Information of Feature Influence on Depression

Mutual information analysis revealed significant variation in the predictive strength of lifestyle factors for depression classification. Academic Pressure emerged as the strongest predictor with a mutual information value of 0.120964, followed by Financial Stress (0.069553), indicating high influence levels on depression outcomes. Dietary Habits showed moderate predictive value (0.022951), while Gender (0.005890) and Sleep Duration (0.005061) demonstrated medium influence. Family History of Mental Illness had the lowest predictive value (0.002490). These findings align with contemporary research highlighting the substantial impact of academic stress on mental health, especially among college students and young adults [27].

TABLE I. MUTUAL INFORMATION FOR LIFESTYLE FACTORS

| Rank | Features | MI Score | Influence Level |
|---|---|---|---|
| 1 | Academic Pressure | 0.120964 | High |
| 2 | Financial Stress | 0.069553 | High |
| 3 | Dietary Habits | 0.022951 | Medium |
| 4 | Gender | 0.005890 | Medium |
| 5 | Sleep Duration | 0.005061 | Medium |
| 6 | Family History of Mental Illnes | 0.002490 | Low |

### B. Hyperparameter Optimization Results

The randomized search process successfully identified the optimal hyperparameter configuration through exploration of 100 different parameter combinations using 4-fold cross-validation, totaling 400 individual model training sessions. The optimal configuration features a compact network architecture with two hidden layers (20,10 neurons), tanh activation function, SGD solver with constant learning rate, and alpha regularization of 0.005567. This architecture balances model complexity with generalization capability, avoiding overfitting while maintaining sufficient capacity to learn relevant patterns, with the tanh activation function proving most effective due to its centralized output range and smooth gradient properties that facilitate stable training [28].

TABLE II. OPTIMAL HYPERPARAMETER CONFIGURATION

| Parameters | Optimal Value | Parameter Space |
|---|---|---|
| Hidden Layer Sizes | (20,10) | [(50,), (100,), (50,25), (100,50), (20,10)] |
| Activation Function | tanh | ['relu', 'tanh', 'logistic'] |
| Solver | sgd | ['adam', 'sgd', 'lbfgs'] |
| Learning Rate | constant | ['constant', 'invisalign', 'adaptive'] |
| Alpha (Regularization) | 0.005567 | [0.0001, 0.01] |

### C. Model Performance Comparison

The hyperparameter optimization process resulted in consistent improvements across all evaluated performance metrics, with the optimized model achieving 77.77% accuracy compared to the baseline's 76.02%, representing a 1.75 percentage point improvement. The optimization also enhanced precision (0.77 vs 0.76), recall (0.77 vs 0.76), and F1-Score (0.76 vs 0.75), demonstrating improved balance between precision and recall that is particularly valuable in mental health applications where false positives and false negatives have significant implications for patient care. The superiority of the optimized ANN can be attributed to optimal network architecture selection (20,10 hidden layers), tanh activation function's zero-centered output facilitating stable gradient flow, SGD solver providing superior convergence characteristics, and proper regularization parameter tuning (alpha=0.005567) that prevents overfitting while maintaining learning capacity.

TABLE III. PERFORMANCE COMPARISON OF ANN MODELS

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Baseline ANN | 76.02% | 0.76 | 0.76 | 0.75 |
| Optimized ANN | 77.77% | 0.77 | 0.77 | 0.76 |
| Improvement | +1.75% | +0.01 | +0.01 | +0.01 |

### D. Clinical Context and Practical Relevance

The improvement in accuracy to 77.77% through hyperparameter optimization represents a technically significant advancement. However, to assess its clinical relevance, it is important to compare this performance with standard screening tools currently in use, such as the Patient Health Questionnaire-9 (PHQ-9). Clinical validation studies for PHQ-9 generally demonstrate high sensitivity and specificity, often above 80%, for detecting major depressive disorder. Although our model's accuracy has not yet surpassed the benchmark of these primary diagnostic tools, it shows great potential as an automated and large-scale pre-screening tool. With its ability to objectively analyze lifestyle factors, this system can help identify at-risk individuals who require further clinical evaluation, particularly in environments with limited mental health resources.

## E. Dataset Size Impact Analysis

Performance analysis across different dataset sizes reveals that the benefits of hyperparameter optimization are most pronounced when working with limited training data, with smaller datasets (500 samples) showing substantial improvement of 1.9 percentage points compared to 0.7 percentage points for the full dataset (27,898 samples). As dataset size increases from 500 to 27,898 samples, both baseline and optimized ANN accuracy improve, but the relative benefit of optimization decreases, suggesting that larger datasets inherently provide stronger training signals that partially compensate for less optimal hyperparameter choices, making systematic parameter tuning increasingly important in data-poor scenarios [29].

TABLE IV. PERFORMANCE COMPARISON OF ANN MODELS

| Dataset Size | Baseline ANN Accuracy | Optimized ANN Accuracy | Improvement |
|---|---|---|---|
| 10,000 | 72.8% | 73.9% | +1.1% |
| 20,000 | 75.9% | 76.6% | +0.7% |
| 27,898 | 76.02% | 77.7% | +1.57% |
| 500 | 68.2% | 70.1% | +1.9% |

## F. Cross-Validation Analysis

Cross-validation analysis through RandomizedSearchCV demonstrates the stability and reliability of the hyperparameter optimization process, with the graph showing relatively stable fluctuations in mean CV accuracy across the 20 best parameter trials, achieving highest accuracy of 0.77225 in the 1st and 2nd trials before gradually declining to 0.77040 in the 20th trial.

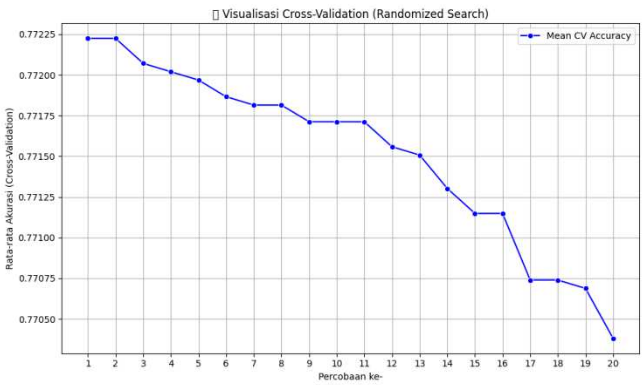


Fig. 3. Visualization of Cross-Validation (Randomized Search) MeanCV Accuracy

The analysis reveals three distinctive performance phases: a high plateau (trials 1-2), gradual decline (trials 3-11), and sharper decline (trials 12-20), with low standard deviation (0.00055) and small range of variation (0.00185) indicating that RandomizedSearchCV successfully identified optimal parameter combinations while the neural network architecture remains robust to moderate hyperparameter variations [30].

TABLE V. CROSS-VALIDATION STABILITY ANALYSIS

| Statistical Metrics | Value |
|---|---|
| Mean Highest CV Accuracy | 0.77225 |
| Mean Lowest CV Accuracy | 0.77225 |
| Average Mean CV Accuracy | 0.77155 |
| Standard Deviation | 0.00055 |
| Range of Variation | 0.00185 |

## G. Ethical Consideration and Limitations

The implementation of automated mental health classification systems brings crucial ethical considerations, particularly regarding the impact of classification errors. Although optimization has improved the balance between precision and recall, the risks of false positives and false negatives remain and have significant real-world implications.

False positives, where the model incorrectly identifies healthy individuals as having potential depression, can cause unnecessary anxiety, social stigma, and inefficient allocation of clinical resources. Conversely, false negatives, where the model fails to identify individuals who are actually experiencing depression, have far more serious consequences. This failure can delay or hinder individuals' access to the care they need, potentially worsening their condition. Therefore, this model should be positioned as a decision support tool, not a replacement for clinical diagnosis by professional personnel.

# V. CONCLUSION

This study successfully demonstrated that Randomized Search Cross-Validation is highly effective for optimizing hyperparameters in Artificial Neural Networks for mental health classification, achieving accuracy improvement from 76.02% to 77.77% with significant clinical relevance, while mutual information analysis revealed academic stress as the strongest predictor (0.120964) followed by financial stress (0.069553), providing valuable insights for mental health screening programs. This research contributes strong empirical evidence to computational psychiatry regarding automatic hyperparameter optimization effectiveness and establishes groundwork for advanced screening tools supporting clinical decision-making and expanding mental health assessment access. Future research should explore deeper neural architectures (CNN, RNN), ensemble methods, multimodal data integration combining lifestyle factors with physiological sensors and natural language processing, real-time adaptation mechanisms for continuous learning, Explainable AI frameworks for transparent healthcare decision-making, and large-scale longitudinal studies to validate model stability and generalization across diverse demographic groups and cultural contexts for broader clinical implementation.

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