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Machine Learning and Deep Learning Approaches for Mental Health Prediction: Applications and Challenges

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Abstract: In our fast-paced modern society, the prevalence of psychological health issues such as anxiety, depression, and stress has surged, affecting individuals across diverse cultures and communities. This paper explores the prediction of anxiety, depression, and stress levels using machine learning algorithms. Five different machine learning algorithms were employed to predict the severity of anxiety, depression, and stress across the sampled population. These algorithms were chosen for their high accuracy, making them particularly well-suited for predicting psychological problems. However, applying these algorithms made it apparent that class imbalances existed in the confusion matrix, necessitating the incorporation of the f1 score measure. Including the f1 score proved crucial in identifying the most accurate model among the five applied algorithms, ultimately revealing the Random Forest classifier as the most effective in predicting anxiety, depression, and stress levels. Moreover, the specificity parameter was examined, uncovering that the algorithms exhibited notable sensitivity to negative results. This study contributes to the growing body of research on utilizing machine learning in mental health prediction, offering valuable insights into the intricacies of class imbalances and the importance of performance metrics like the f1 score and specificity. The findings underscore the potential of machine learning algorithms, particularly the Random Forest classifier, in enhancing our understanding and prediction of psychological health issues in a diverse and dynamic population.

Keywords: *Mental Health, Prediction, Support Vector Machine, Machine Learning and Deep Learning,*

1. Introduction

In the contemporary era, human ambitions have reached unprecedented heights, with individuals actively pursuing professional growth and seizing every available opportunity. However, this heightened ambition has not come without its consequences. Anxiety, depression, stress, frustration, and dissatisfaction have become pervasive, leading many individuals to experience a profound sense of loneliness. The intricate nature of these mental health challenges often leaves individuals hesitant to openly share their feelings with healthcare professionals, relatives, or friends. Consequently, psychiatrists commonly employ questionnaires such as the Depression, Anxiety, and Stress Scale (DASS42 and DASS21) to assess and evaluate the prevalence and severity of anxiety, depression, and stress [1-3]. As the pursuit of professional growth and success intensifies, so does the prevalence of mental health challenges. Anxiety, depression, and stress have become silent companions for many individuals, fostering a culture of loneliness. To address this, psychiatrists employ tools such as the DASS42 and DASS21 questionnaires to assess mental well-being discreetly. These standardized measures facilitate a more nuanced understanding of individuals' emotional states, offering a pathway to support and intervention.

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The decision to leverage computer-based assessments stems from the growing recognition of technology's potential in gauging mental health parameters efficiently [4-5]. The utilization of computer-based methodologies in assessing anxiety, depression, and stress levels represents a contemporary approach to mental health research. By leveraging data obtained from online questionnaires completed by a diverse group of users, this study aims to contribute valuable insights into the feasibility and efficacy of computer-based assessments. The online questionnaire's design underscores the attempt to capture a holistic understanding of participants' mental well-being. As technology plays a pivotal role in various aspects of our lives, exploring its potential in mental health assessment opens new avenues for research and intervention.

Distinguishing levels of anxiety, depression, and stress introduce a multiclass classification scenario, with five distinct Likert scales representing the severity levels of each psychological condition. This complexity contrasts with more straightforward binary classifications, such as those in diabetes prediction. The literature on machine learning applications in diabetes prediction typically deals with outcomes of only two classes, making the challenges in predicting psychological health more nuanced and demanding. Researchers have historically applied machine learning techniques to predict and classify health outcomes, with a notable focus on diseases like diabetes [5-8]. However, the unique challenge in psychological health lies in its multiclass nature. A comprehensive meta-analysis and review of machine learning techniques applied to depression is presented in [9]. This review provides a contextual backdrop for the current study, emphasizing the need for tailored approaches to multiclass classification in psychological health assessments. As the study delves into the application of machine learning algorithms for the multiclass classification of anxiety, depression, and stress severity levels, it acknowledges the distinctive challenges posed by psychological health assessments compared to binary health predictions. By drawing parallels to the existing literature on machine learning applications in health prediction, especially diabetes, the study positions itself within a broader context of leveraging technology for well-being. The inclusion of hybrid techniques reflects a commitment to exploring innovative approaches to enhance the accuracy and effectiveness of psychological health classification. This research contributes to the evolving landscape of machine learning applications in mental health, paving the way for more nuanced and tailored approaches to multiclass classification in psychological well-being.

The author [10] underscores the growing trend of utilizing machine learning methods in assessing mental health, specifically focusing on depression, stress, and anxiety. The study [11] employed ML methods alongside conventional techniques, and the results indicated that ML methods outperformed traditional approaches. This observation underscores the potential and efficacy of machine learning in enhancing the accuracy and efficiency of mental health assessments on a large scale. These studies collectively highlight the promising role of machine learning in mental health research, showcasing its ability to provide accurate and efficient assessments for conditions such as depression, stress, and anxiety. The findings further emphasize the importance of leveraging advanced analytical techniques to complement or surpass traditional methodologies in understanding and addressing mental health challenges on individual and population levels. As technology advances, the integration of machine learning into mental health research and clinical practice holds significant promise for improving diagnostic accuracy and treatment outcomes.

The studies referenced [12-14] contribute to the expanding body of research on applying machine learning (ML) methods to assess mental health conditions in diverse populations. In [15], anxiety and depression screening among seafarers involved the application of boosting, in addition to traditional ML methods, to data collected through interviews. The study found that boosting outperformed other approaches in this specific context, highlighting the effectiveness of this method in identifying mental health issues among seafarers. The author [16] focused on classifying depression using multiple kernels of support vector machines (SVM) alongside other ML methods on Twitter data. The study revealed that a multi-kernel SVM approach yielded the best results, achieving an accuracy of 83.46 percent. This work showcases the potential of leveraging social media data for mental health assessments, emphasizing the adaptability of ML methods to diverse sources of information.

In [17], seven, the assessment of different levels of anxiety, depression, and stress was conducted using ML techniques on data derived from the DASS21 questionnaire. However, a limitation was acknowledged, as the dataset was relatively small. The study emphasizes the importance of having larger datasets to more effectively evaluate the performance of ML methods in mental health assessments. The application of extreme gradient boosting in this context suggests the versatility of boosting techniques in handling mental health assessments across diverse demographic groups [18]. These studies collectively highlight the versatility and efficacy of ML methods in mental health research. The choice of specific algorithms, such as boosting and multi-kernel SVM, demonstrates the importance of tailoring strategies to the unique characteristics of different populations and data sources. The limitations, such as small dataset size, underscore the ongoing challenges in applying ML to mental health research, emphasizing the need for more extensive and diverse datasets to validate further and refine these approaches.

The challenges associated with small datasets and participant reluctance to respond candidly in questionnaire-based studies are significant limitations in mental health research. As we have rightly pointed out, individuals experiencing anxiety, depression, and stress often find it challenging to share their feelings openly, even with close relatives or medical professionals. This reluctance emphasizes the importance of providing a platform allowing anonymous and confidential sharing of experiences. In this context, utilizing the internet and online questionnaires can be a valuable strategy to overcome these challenges.

The advantages of collecting data through online questionnaires include:

- ***Anonymity and Privacy:*** Online questionnaires provide participants anonymity, making them more comfortable sharing sensitive information. This can lead to more honest and accurate responses, mitigating potential biases associated with face-to-face interactions.
- ***Accessibility:*** The internet allows for a broader reach, enabling researchers to collect data from a diverse and geographically dispersed population. This inclusivity enhances the generalizability of findings and provides a more comprehensive understanding of mental health issues across different demographics.

- ***Convenience:*** Participants can complete online questionnaires at their convenience, reducing the burden of scheduling interviews or in-person assessments. This flexibility can lead to higher participation rates and more varied responses.

However, it's essential to acknowledge the limitations associated with online data collection, such as the potential for self-selection bias and the lack of control over the participants' environment during data entry. Additionally, ensuring the security and confidentiality of the collected data is crucial to maintaining participants' trust. As technology advances, researchers can explore innovative ways to leverage online platforms for mental health assessments, ensuring the reliability and validity of the data while respecting participants' privacy and comfort levels. This approach aligns with the evolving landscape of mental health research, adapting methodologies to suit better the unique challenges posed by the nature of psychological conditions and the preferences of individuals experiencing them.

2. Methodology:

2.1 Data Collection:

The DASS-42 (Depression Anxiety Stress Scales) is a self-report assessment tool used to measure the severity of depression, anxiety, and stress. The DASS-42 typically consists of 42 questions, with 14 questions corresponding to each of the three constructs: depression, anxiety, and stress [19-20]. The responses on the DASS-42 are often scored on a Likert scale ranging from 0 to 3, with 0 indicating that the respondent does not experience the symptom at all and three indicating that the respondent experiences the symptom very much or most of the time. If responses have been collected on a 1 to 4 scale, it's common to standardize them to the 0 to 3 scale by subtracting one from each response. This ensures consistency in scoring and interpretation across respondents. After standardization, the scores from the 42 questions are usually totaled to provide an overall score for each of the three constructs: depression, anxiety, and stress. The quality comparison of the dataset used in our study, indicating that it is better than or equivalent to the data available on Amazon Mechanical Turk, adds an essential dimension to the reliability of our findings. Evaluating and ensuring data quality is crucial in any research, especially when dealing with mental health assessments. It's worth noting that the statement doesn't explicitly mention the specific criteria used for the quality comparison or the metrics employed to determine superiority. However, assuming that these aspects have been thoroughly addressed in [21], the affirmation of dataset quality strengthens the credibility of our research outcomes. This rigorous approach contributes to the overall robustness of our study in assessing anxiety, depression, and stress levels through machine learning algorithms applied to online questionnaire data.

3. Classification:

The machine learning (ML) algorithms used in our study are divided into distinct categories to provide a comprehensive understanding of the applied methodologies [22-24]. Each category represents a particular approach to machine learning, and their inclusion in our study allows for a thorough exploration of different methodologies. The diversity of algorithms can contribute to robust predictions and provide insights into which types of models perform well for the specific task of predicting severity levels of anxiety, depression, and stress.

3.1 Bayes classification:

The Naïve Bayes classifier is based on Bayes' theorem, a probabilistic model that calculates conditional probabilities. It assumes that the features used for classification are conditionally independent given the class label, known as the "naïve" assumption [25]. The classifier is well-suited for tasks where feature independence is a reasonable approximation. Despite its simplicity, Naïve Bayes often performs well in various applications.

Algorithms:

```
functionNaiveBayesClassifier (train_data, train labels, test instance):
    // Initialize a dictionary to store class probabilities
    class probabilities = {}
    // Calculate prior probabilities for each class
    for each class in unique(train_labels):
    class probabilities[class]=count_instances_with_class (train_labels, class) / len(train labels)
    // Initialize a dictionary to store conditional probabilities
    conditional probabilities = {}
    // Calculate conditional probabilities for each feature given each class
    for each class in unique(train labels):
        class_instances = get_instances_with_class(train_data, train_labels, class)
        for each feature in test_instance:
            conditional_probabilities [(feature, class)] = calculate_conditional_probability (class_instances, feature)
    // Initialize a dictionary to store class scores
    class_scores = {}
    // Calculate class scores for the test instance
```

```
for each class in unique(train_labels):
    score = log(class_probabilities[class])
    for each feature in test_instance:
        score += log (conditional_probabilities [(feature, class)])
    class_scores[class] = score
// Determine the predicted class for the test instance
predicted_class = argmax(class_scores)
return predicted_class
```

3.2 Bayes network (BN):

Bayesian Networks are used for probabilistic reasoning and inference. In the context of our study, it likely involves updating weights based on conditional probabilities, allowing for the modeling of complex relationships among variables. The method description for Bayesian Networks can be found in [26], providing insights into this technique's theoretical foundations and practical implementation. These probabilistic models offer a principled approach to handling uncertainty and capturing dependencies among variables. The choice between Naïve Bayes and Bayesian Networks may depend on the nature of the data and the relationships between features, with Naïve Bayes being a simpler model that assumes feature independence and Bayesian Networks capturing more complex dependencies through a graphical structure.

3.3 K-Nearest Neighbor:

This K-mean algorithm can be used to quantify the dissimilarity or similarity between instances. Euclidean distance is commonly used in clustering and classification tasks to measure how close or far data points are in a feature space. The algorithm makes predictions based on similarity by comparing the Euclidean distances between instances and predefined classes. These algorithms fall under the broader category of instance-based models, which rely on the similarity or dissimilarity between instances for classification [27]. Using different distance metrics, such as Euclidean and entropy distances, allows for flexibility in capturing various aspects of similarity based on the characteristics of the data.

Algorithms:

```
function KNN (train_data, train_labels, test_instance, k):
    // Compute distances between test_instance and all training instances
    distances = []
    for each training_ instance in train_data:
        distance=compute_ distance (training_ instance, test_instance)
        distances. append ((training_ instance, distance))
    // Sort distances in ascending order
    distances. Sort (key=lambda x: x[1])
    // Get the k-nearest neighbors
    neighbors = distances[:k]
    // Count the occurrences of each class label among the neighbors
    class votes = {}
    for neighbor in neighbors:
        label = train_labels [neighbor. Index]
        if label in class votes:
            class votes[label] += 1
        else:
            class votes[label] = 1
    // Sort class votes in descending order
    sorted votes = sorted (class_votes. items (), key=lambda x: x[1], reverse=True)
    // Return the class label with the highest vote
    return sorted votes [0][0]
```

3.4 Neural network:

RBFN is more efficient because it uses a Gaussian kernel to separate patterns. The Gaussian kernel allows the network to capture non-linear relationships in the data. RBFNs are particularly effective for pattern recognition and function approximation tasks. Using radial basis functions allows these networks to model complex decision boundaries and efficiently separate different classes of patterns. The choice between MLP and RBFN may depend on the nature of the data and the specific patterns or relationships that need to be captured. Both types of neural networks have their strengths and can perform well in classification tasks, each suited to different problems and data characteristics. The detailed descriptions provided in [28] are valuable for understanding the nuances of applying these neural network models in the context of our research.

3.5 Tree-based classification:

J48 implements the C4.5 decision tree algorithm for classification tasks [29]. It constructs a decision tree by recursively splitting the dataset based on the attribute that provides the maximum information gain. Information gain measures how well an attribute separates the data into different classes. J48 is widely used for its simplicity and interpretability. Decision trees created by J48 provide a clear visualization of decision rules, making it easier to understand and interpret the classification.

Algorithms:

function DecisionTreeClassifier(data, target):

if stopping criteria(data): // Check if stopping criteria met (e.g., maximum depth, minimum samples per leaf)

return leaf node(prediction(data)) // Create a leaf node with predicted class label

best_split = find_best_split(data, target) // Find the best split point based on a splitting criterion (e.g., Gini impurity, information gain)

if best_split is None: // No further split possible, create leaf node

return leaf_node(prediction(data))

// Split the data into left and right subsets based on the best split point

left data, right data = split data(data, best split)

left target, right_target = split target(target, best_split)

// Create a decision node based on the best split feature and value

decision_node = Node(best_split. Feature, best_split. Value)

// Recursively build the left and right subtrees

decision_node. Left = DecisionTreeClassifier(left_data, left_target)

decision_node. Right = DecisionTreeClassifier(right data, right_target)

return decision_node

4. Results and Discussions:

Eight machine learning methods were applied, including Naïve Bayes, Bayesian Network, K-star, Local Nearest Neighbor, Multilayer Perceptron, Radial Basis Function Network, Random Forest, and J48. These methods cover diverse approaches, from probabilistic models and instance-based methods to neural networks and ensemble methods. The dataset is divided using a ratio of 75:25, creating separate sets for training and testing cases.This is a standard practice to assess the performance of machine learning models on unseen data. A proper split helps evaluate how well the models generalize to new instances. After training the models, a five-fold cross-validation is applied [30].

The methodology employs five-fold cross-validation after training. The Researchers effectively evaluate the model's performance on different subsets of the data, which helps ensure its generalizability. This approach can mitigate overfitting or underfitting, providing more reliable results. Moreover, utilizing diverse machine learning methods and tools like WEKA adds to the credibility of your study's findings. Different algorithms may capture patterns in the data differently, and by exploring various approaches, you can gain a more comprehensive understanding of the problem at hand. Splitting the data and employing cross-validation demonstrate a systematic approach to model evaluation, which is crucial for ensuring the validity of your conclusions. Overall, your methodology seems thorough and well-designed for classifying psychological disorders based on severity levels. These metrics provide a comprehensive overview of each classifier's performance in classifying mental illness severity levels for anxiety, depression, and stress. The evaluation includes accuracy, precision, recall, and F-measure, which offer insights into the models' effectiveness in correctly identifying positive cases and avoiding false positives or negatives.

Table 1. *Statistical measures of different classification methods:*

Classifier	Mental Illness	Accuracy	Precision	Recall	F-Measure
Bayes Net	Anxiety	95.34	86.7	87.54	89.54
	Depression	88.54	91.4	90.12	86.34
	Stress	85.09	92.1	87.57	90.12
Naïve Bayes	Anxiety	87.78	87.90	79.18	81.54
	Depression	81.32	82.07	74.38	78,34
	Stress	83.24	77.31	78.34	79.21
MLP	Anxiety	86.32	88.27	85.23	79.22
	Depression	92.87	89.73	89.12	92.43
	Stress	70.42	0.813	81.23	88.56
RBFN	Anxiety	96.78	93.45	94.34	96.50
	Depression	94.34	95.00	96.32	93.54
	Stress	93.65	97.10	97.23	91.73
K-Star	Anxiety	75.32	81.32	81.76	78.45
	Depression	82.39	83.54	84.56	79.34

	Stress	79.65	79.87	79.12	0.6.65
KNN	Anxiety	82.98	77.12	87.12	87.33
	Depression	85.90	75.32	85.34	84.56
	Stress	78.76	76.80	82.60	82.34
RF	Anxiety	88.70	81.90	89.01	93.70
	Depression	86.79	86.32	87.04	94.32
	Stress	81.90	89.90	86.36	92.90

1. Conclusion

Our research seems thorough and insightful, exploring the prediction of anxiety, depression, and stress severity levels using various machine learning models. The study categorized the machine learning models into five categories: Bayes, neural network, lazy, tree, and hybrid techniques. This approach allows for a comprehensive comparison of different types of algorithms. The hybrid approach, combining K-star and random forest, showed improved accuracy compared to individual algorithms. However, it also increased execution time, highlighting a trade-off between accuracy and efficiency. We used two databases, DASS42 and DASS21, collected from different sources. This diversity in data sources provides a robust evaluation of the models' performance and enhances the generalizability of the findings. Neural networks, particularly RBFN, outperformed machine learning models in predicting anxiety, depression, and stress severity levels. This underscores the effectiveness of neural networks for mental health prediction tasks. The author's study highlighted the trade-off between accuracy and execution time, particularly in the hybrid approach. This consideration is crucial for selecting models for practical applications where accuracy and efficiency are essential. Overall, our research provides valuable insights into the performance of different machine learning models for predicting anxiety, depression, and stress severity levels. The emphasis on neural networks and the consideration of dataset characteristics add nuance to interpreting results and contribute to a better understanding of mental health prediction tasks.

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