



Machine Learning-Based Classification of Mental Health Status on Social Media: A Case Study of Kunduz, Afghanistan

OPEN ACCESS

SUBMITTED 07 December 2024

ACCEPTED 08 January 2025

PUBLISHED 10 February 2025

VOLUME Vol.05 Issue02 2025

COPYRIGHT

© 2025 Original content from this work may be used under the terms of the creative commons attributes 4.0 License.

Rohullah Adeeb

Department of Information Systems, Computer Science Faculty, Kunduz University, Afghanistan

Hekmatullah Hekmat

Department of Information Systems, Computer Science Faculty, Kunduz University, Afghanistan

Abdullah Zahirzada

Department of Information Systems, Computer Science Faculty, Kunduz University, Afghanistan

Abstract: The proliferation of user-generated content results from social media's rapid development. An interdisciplinary field called computational cyberpsychology uses machine learning techniques to investigate fundamental psychological tendencies. Our study uses social media usage patterns to infer users' mental health status. The emergence of social media platforms in Afghanistan has profoundly affected the country's young people. This study aims to implement a predictive model using three machine-learning algorithms. The three selected algorithms are Naïve Bayes, Random Forest, and K-Nearest Neighbor (K-NN). The dataset contained in this study was collected through a questionnaire from students at Kunduz public and private universities in 2024. Data preprocessing is done before implementing the predictive models. The dataset is prepared carefully to ensure well-balanced samples in each category. The study reveals that Random Forest is the best classifier, with an accuracy of 77%. The study directly benefits the other researchers and policy or decision-makers in Afghanistan.

Keywords: Random Forest, K-NN, Social Media, Mental Health, Afghanistan.

Introduction: A notable aspect of the Internet's explosive growth has been the creation of social media, which has drawn a large number of people eager to express themselves on sites like Facebook, Twitter, and others. Users are creating a cyberspace that interacts with and reflects the actual world through their online habits. As a result, a person's online behavior may be a good reflection of their psychological traits offline. Due to demands, the outside world, and other factors, an increasing number of people these days are experiencing mental illnesses including depression, anxiety, stress, and so on. These mental illnesses can have a serious negative impact on users' lives and can even cause suicides. In the past, individuals with mental health issues would have been told to see a therapist or could have gone out on their own to get psychotherapy. Individuals become aware of mental health issues through surveys or gut feelings. Lack of resources may prevent psychotherapy from becoming accessible, even in cases where a mental health issue is identified. These days, the Internet offers a fresh way to handle such circumstances [1]. Due to increased social comparison and validation-seeking tendencies, people who use social media regularly are more likely to suffer from mental health conditions like anxiety, depression, and loneliness, according to studies. Social media usage frequently reflects offline habits, which can be used to create mental health assessment prediction models [2]. Research from the World Health Organization in 2018 found two million Afghans struggling with mental distress, and these numbers are likely much higher today. Still, many suffer in silence. The mental well-being of Afghans has become a pressing concern that demands immediate attention. Afghanistan lacks qualified mental health professionals, such as psychiatrists, psychologists, and counselors. Therefore, it is beneficial to identify the factors associated with mental health in Afghanistan through a predictive mental health model. It also aims to find a suitable classifier for this task. Three popular classifiers, Naïve Bayes, Random Forest, and K-Nearest Neighbor are selected for the study. The dataset used in this study was collected through a questionnaire from students at Kunduz public and private universities during the 2024 year, which comprises records of students whose age group is between 18 and 27 years.

Classification Selected

Classification is a supervised learning technique whose primary objective is to construct models based on known data and predict new data categories. In classification, models are built by splitting a supplied

dataset into training and test sets. One or more classification algorithms run through the training set, and the classifier models are subsequently developed. The test set is then used to assess the accuracy of the models [3]. Previous studies show that the dataset and application have a major impact on the accuracy and efficiency of machine learning algorithms. For example, algorithms like Support Vector Machines (SVM) have demonstrated efficacy in mental health prediction research because of their capacity to handle high-dimensional data, even if Random Forest has demonstrated strong results in a variety of prediction tasks. A fair evaluation is made possible by using a range of classifiers, which also offers insights into which algorithms work best in certain mental health prediction settings [4]. This study's inclusion of Naïve Bayes, K-NN, and Random Forest serves as a comparative basis to identify the optimal classifier for social media-based mental health prediction. Subsections A to C briefly introduce the classifiers selected for this study, while Section III describes methodology of the work.

A. Naïve Bayes: In Naïve Bayes learning, a Bayesian probabilistic model accredits a back-class probability to an instance $P(Y=Y_j|X=X_i)$. The simple Naïve Bayes algorithm uses these probabilities to accredit an example to a class. Naïve Bayes classifier converges faster than logistic regression, so it requires only less training data. This method is prevalent for different applications for several features. This classifier can be trained with reasonable accuracy in a supervised learning setting, and its performance is satisfactory in many complex real-life problem situations. Naive Bayes is technically less precise than other classifiers and can result in a higher lower rate [5].

B. K-NN: The K-Nearest-Neighbors (K-NN) approach does not make any assumptions about the elementary dataset because it is a nonparametric classification algorithm. It is renowned for being both straightforward and efficient. It is an algorithm for supervised learning. To predict the class of the unlabeled data, a labeled training dataset with data points divided into several classes is provided. Different criteria are used in classification to identify the class to which the unlabeled data belongs. Typically, KNN is employed as a classifier. It is used to categorize data based on nearby or nearby training examples in a certain area. This approach is employed due to its speedy computation and ease of operation. It computes its closest neighbors for continuous data using the Euclidean distance [6].

C. Random Forest: The random forest algorithm, proposed by L. Breiman in 2001, has been extremely successful as a general-purpose classification and regression method. The approach, which combines

several randomized decision trees and aggregates their predictions by averaging, has shown excellent performance in settings where the number of variables is much larger than the number of observations. Moreover, it is versatile enough to be applied to large-scale problems, is easily adapted to various ad hoc learning tasks, and returns measures of variable importance [7].

METHODOLOGY

Machine learning is responsible for discovering unknown and secret patterns in a large amount of data to obtain valuable information. As stated earlier, one of the objectives of this work is to find a suitable classifier among the most popular machine learning techniques.

A. Data Source:

In Kunduz, Afghanistan, during the 2024 academic year, a questionnaire survey was administered at public and private universities to collect the data for this study. The collection contains the records of 304

students in total, 171 males and 132 females. The dataset contains 20 attributes in total. The attributes can be categorized into groups based on factors.

B. Data Preprocessing:

There were no missing or outlier values to clear up because the dataset used in this study was based on relevant job studies and a background review of the mental health status prediction models. However, the relevant features have been selected in order to get a precise model.

C. Selected Features:

Each sample in the dataset consists of 20 attributes; an essential step in this initial stage is to identify relevant attributes related to the study. This is carried out using an extensive literature review. Any data mining model's implementation must be successful to have meaningful factors/attributes. In fact, adding unnecessary features might harm data mining since it makes it harder to conclude from samples that are stuffed with redundant and unnecessary information.

Table 1. Reports the attributes used in this study.

No	Attributes	Values				
1	Gender	Male			Female	
2	What is your age?	Under 18	18-22	23-26	>27	
3	Relationship Status	Single		Married	Engaged	
4	Occupation Status	Salaried worker		University student	Jobless	
5	What type of organizations are you affiliated with?	University	Company		Government	
6	Do you use social media?	Yes			No	
7	What social media platforms do you commonly use?	Facebook	Twitter	Instagram	YouTube	WhatsApp
8	What is the average time you spend on social media every day?	Less than 1 hour	Between 1 & 2 hour	Between 3 & 4 hour		Between 5 & 6 hour
9	How often do you find yourself using social media without a specific purpose?	1	2	3	4	5
10	How often do you get distracted by social media when you are busy doing something?	1	2	3	4	5

11	Do you feel restless if you haven't used social media in a while?	1	2	3	4	5
12	On a scale of 1 to 5, how easily distracted are you?	1	2	3	4	5
13	On a scale of 1 to 5, how much are you bothered by worries?	1	2	3	4	5
14	Do you find it difficult to concentrate on things?	1	2	3	4	5
15	On a scale of 1-5, how often do you compare yourself to other successful people through the use of social media?	1	2	3	4	5
16	Following the previous question, how do you feel about these comparisons, generally speaking?	1	2	3	4	5
17	How often do you look to seek validation from features of social media?	1	2	3	4	5
18	How often do you feel depressed or down?	1	2	3	4	5
19	On a scale of 1 to 5, how frequently does your interest in daily activities fluctuate?	1	2	3	4	5
20	On a scale of 1 to 5, how often do you face issues regarding sleep?	1	2	3	4	5

D. Evaluation Metrics:

Evaluation metrics are applied in order to assess the efficiency and performance of the deployed predictive model. The four generally used measures are used in this study [5]. These are Accuracy, Precision, F-Measure, and Recall. Below are some succinct summaries of each:

Accuracy: Since it is the first significant measure of how well the model performs this metric is most frequently employed in classification. It is stated as a percentage (0 percent to 100 percent) Equation 1 below can be used to determine it:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

The number of data rows in the test set that both had a positive target and were expected to have a positive target is known as true positives, or TP. The amount of test set data rows with both a negative target and a target that was anticipated to be negative is known as

true negatives, or TN. The number of test set data rows with a negative target but a forecasted positive target is known as FP, or false positives. False Negative, or FN, refers to the number of test set data rows with a positive target but a forecasted negative target [8].

Precision: This metric was developed by the field of information retrieval, but it also has applications in classification and is a valuable addition to measuring performance. Additionally, it is given as a percentage. Equation 2 below can be used to determine it:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall

Precision and Recall are frequently combined in the area of information retrieval. As a result, it can provide useful data for assessing performance. Additionally, it is given as a percentage. Equation 3 below can be used to determine it:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F-Measure:

The harmonic mean of precision and recall, where precision is the percentage of projected positive events that are actually positive and recall is the percentage of positive occurrences that are actually accurately recognized by the algorithm, is known as the F-Measure [9].

Equation 4 below can be used to determine it:

$$F - Measure = 2 \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

E: Implementation:

According to the research review, no single classifier

consistently generates correct predictions for all cases. This study uses the three machine learning techniques discussed in section 2 to create a prediction model for the mental health status of young adults on social media. The execution of the predictive model can begin after preprocessing is finished. Using the well-known machine learning tool WEKA [10], the model is trained and tested. All parameters for the models' implementation are set to default and the ratio of the training set to the test set is 80:20.

RESULTS

Numerous attempts have been carried out in order to implement the most suitable predictive model. The evaluation metrics mentioned in section 3 are used to assess models. Table. 2 displays the outcomes.

Table 2.Reveals the accuracy and performance measures of models

Classifier	Accuracy	Precision	Recall	F-Measure
Random Forest	77%	73%	78%	76%
Naïve Bayes	72%	73%	60%	66%
KNN	75%	70%	82%	75%

When measured, Random Forest produces the best outcome, as indicated in Table 2 . The nature of the data can have a significant impact on the methods utilized, therefore this is by no means proof that Random Forest is always better than other algorithms. It can be argued that Random Forest is the most precise tool, among the most often used tools, to implement the prediction model utilizing this dataset.

CONCLUSION

As of July 2024, there were 5.45 billion internet users worldwide, which amounted to 67.1 percent of the global population. Afghanistan was home to 3.70 million social media users in January 2024, equating to 8.6 percent of the total population. A total of 27.67 million cellular mobile connections were active in Afghanistan in early 2024, with this figure equivalent to 64.6 percent of the total population. In this study, a predictive model is used to address the issue of mental health status on social media among young adults in Kunduz province, Afghanistan. When the performance of the various models was compared, Random Forest produced the best results, with Accuracy, Precision, Recall, and F-Measure of 77%, 73%, 78%, and 76%, respectively. The findings of this study could help other researchers and policy or decision makers in Afghanistan.

REFERENCES

Hao, B., Li, L., Li, A., & Zhu, T. (2013). Predicting mental

health status on social media: a preliminary study on microblog. In Cross-Cultural Design. Cultural Differences in Everyday Life: 5th International Conference, CCD 2013, Held as Part of HCI International 2013, Las Vegas, NV, USA, July 21-26, 2013, Proceedings, Part II 5 (pp. 101-110). Springer Berlin Heidelberg.

C. E. Montenegro, P. F. Geng, and R. P. Oliver, "Social media and mental health: A perspective on youth and online behavior," Journal of Social Computing, vol. 12, no. 4, pp. 67-81, 2021.

Zahirzda, A., Chanmas, G., & Chan, J. H. (2023). A data mining model for predicting diarrhea in Afghan children. Authorea Preprints.

K. S. Ray, J. T. Hogan, and A. N. Kumar, "Comparative study of classifiers for mental health prediction on social media," in Proc. IEEE Int. Conf. Machine Learning Applications (ICMLA), New York, USA, 2020, pp. 554-560.

Zahirzada, A., & Lavangnananda, K. (2021, January). Implementing predictive model for low birth weight in Afghanistan. In 2021 13th International Conference on Knowledge and Smart Technology (KST) (pp. 67-72). IEEE.

Zahirzada, A., Zaheer, N., & Shahpoor, M. A. (2023). Machine Learning Algorithms to Predict Anemia in Children Under the Age of Five Years in Afghanistan: A Case of Kunduz Province. Journal of Survey in Fisheries Sciences, 10(4S), 752-762.

Biau, G., & Scornet, E. (2016). A random forest guided tour. *Test*, 25, 197-227.

Altabrawee, H., Ali, O. A. J., & Ajmi, S. Q. (2019). Predicting students' performance using machine learning techniques. *JOURNAL OF UNIVERSITY OF BABYLON for pure and applied sciences*, 27(1), 194-205.

Br, T. Der. (2022). The F-Measure Paradox The F-Measure Paradox. February.

[10] Frank, E., Hall, M., Trigg, L., Holmes, G., & Witten, I. H. (2004). Data mining in bioinformatics using Weka. *Bioinformatics*, 20(15), 2479–2481.