Research Article

Indian Journal of Extension Education
Vol. 60, No. 2 (April–June), 2024, (52-55)

ISSN 0537-1996 *(Print)*
ISSN 2454-552X *(Online)*

Social Media Addiction among the Rural Youth: An AI Interpretation

Thongam Victory Khanganbi[1]* and M. Priya[2]

[1]Research Scholar, [2]Assistant Professor (SS), Department of Human Development, School of Home Science, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, Tamil Nadu, India
*Corresponding author email id: victorykhanganbith@gmail.com

ARTICLE INFO

Keywords: Rural youth, Artificial intelligence, Naïve byes, Prediction, Social media addiction, Machine learning

https://doi.org/10.48165/IJEE.2024.60210

Conflict of Interest: None

Research ethics statement(s): Informed consent of the participants

ABSTRACT

The impact of social media increasingly influences rural youth in India. Artificial Intelligence is a vast interdisciplinary arena with many domains, not only all the computing disciplines, but also linguistics, neuroscience, statistics, engineering, economics, control theory, and others. The study was undertaken to predict social media addiction by machine learning and to know the accuracy of the addiction level among rural youth. The data were collected through the snowball sampling method, including those using smartphones in rural Coimbatore during the COVID period (2022). A total of 128 rural youth from Coimbatore aged 18 to 24 years were selected as respondents and used naïve Bayes classifier methods to predict the addiction level on social media. 99 respondents were taken under the training set, and the remaining 29 were under the prediction sets to know the accuracy of the Byes model in predicting social media addiction levels. The study predicted its usage accuracy with social media addiction using artificial intelligence and machine learning. The majority of the rural youth were moderately addicted and there were many more causative variables to be assessed further. The naïve byes model accuracy in predicting social media addiction observed was 93.90 per cent.

INTRODUCTION

Social media is undeniably a very large and current form of communication. The widespread availability of smart phones and internet connectivity has facilitated the integration of social media platforms into the daily lives of the urban population, and it is also spreading among rural communities.The information-seeking habits of postgraduate students were found to be correlated with their academic programs (Chayal, 2023); while Gurdeep et al., (2021) found that the majority of rural youth in Punjab's Mansa district preferred social media platforms like Facebook, YouTube, and WhatsApp for agricultural information. Jayalaxmi et al., (2020) examined the positive effects of three smartphone Apps developed by Krishi Vigyan Kendra Banavasi while researching 150 farmers in the Kurnool region of Andhra Pradesh. The significance of India's rural areas cannot be overstated, as they constitute a pivotal component of the nation. With approximately 70 per cent of the population residing in villages, these rural regions play a crucial role in shaping the socio-economic fabric of the country. The vibrancy and diversity of rural life contribute significantly to India's cultural richness, agricultural productivity, and overall societal well-being (Priyanka et al., 2023). The youth often struggle to discern between fantasy and reality, a challenge exacerbated by their limited maturity. Additionally, excessive use of social media tends to infringe upon the time that could be otherwise allocated to activities crucial for their physical and mental well-being, as well as bonding with family members (Patawari et al., 2020).

The idea and development of computers that can perform activities that humans can is known as artificial intelligence. It is a broad, multidisciplinary field with roots in and connections to many other fields, including mathematics, neuroscience, statistics, engineering, economics, control theory, control theory, cybernetics, and many others. It also intersects with all of the computing

Received 02-02-2024; Accepted 30-03-2024

disciplines. Not only has it adopted several ideas and techniques from these fields, but it has also provided funding for them. Planning, problem-solving, and broad theorem proof have all been advanced by artificial intelligence. According to Arthur Samuel, machine learning enables computers to learn without the need for explicit programming. This branch of computer science, which originated in artificial intelligence (AI) in the 1950s, focuses on statistical models and algorithms that provide systems the ability to operate on their own. Machine learning is widely used by industries to glean insights from large datasets; applications include image processing, predictive analytics, and web search engines. By revealing important insights hidden in data, machine learning transforms several industries, including healthcare and education, and shapes the direction of business and technology going forward. AI and machine learning are being used by the majority of the largest social networking sites, such as Facebook, Twitter, LinkedIn, and Pinterest, to improve their services. Examples of these services include content recommendation, face recognition, personalized user experiences, and candidate matching for employment opportunities.

METHODOLOGY

This research was done to predict the social media addiction of rural youth from Coimbatore by using artificial intelligence and machine learning. The self-prepared questionnaire on the 'Social Media Addiction Scale' was used, which consists of 35 statements under 5 dimensions, i.e., platform, purpose, mindset, emotions, and frequency, and scored on a three-point Likert scale, i.e., yes, sometimes, and no and awarded as 3,2,1. The maximum score for the tool is 105, and the minimum is 35. The low addiction level is 35-57, the moderate level is 58-81, and the high level is 82-105.The reliability results confirm the internal cohesiveness and stability of the variables with Cronbach's alpha values of the social media usage scale is 0.826, which indicates good reliability levels.

The data was collected through snowball sampling methods among rural youth who are using smartphones. A total of 128 youth from Coimbatore rural areas under the age group 18 to 24 were included, and the information was collected through a Google form during post covid in the year 2022. The naïve Bayes classifier methods were used to predict the addiction level on social media. In the context of predicting addiction levels on social media, Naive Bayes classifiers could be utilized effectively, especially if the features being analyzed exhibit strong independence assumptions. Positive behaviors or outlines on social media tend to correlate strongly with addiction, and a Naive Bayes classifier might apprehend these relationships effectively. 99 respondents were taken under the training set, and the remaining 29 were under the prediction sets to know the accuracy of the Byes model in predicting social media addiction levels.

Bayes' Theorem can also be called Bayes' law, or Bayes' Rule or Bayes' Theorem Bayes' Theorem usually finds the probability of an existing event with another event that has already been occurred. Bayes' Theorem can be stated currently as the following equation:

P(A|B) = \frac{P(B|A) P(A)}{P(B)}

A, B are events

Firstly, to detect the probability of event A, given that event B is true. Event B is also termed as proof.

P(A) is the prior of A (the prior probability, i.e., probability of an event before the evidence is seen). The evidence can be an attribute value of an unknown fact or case (here, it is event B). P(A|B) is a posterior probability of B, i.e., the probability of the event after evidence is seen. The advantages are in terms of an algorithm can work quickly and save a lot of time, suitable for solving multi-class prediction problems, acceptance of the independence of features holds to be accurate; it can be performed better than the other models, which require much less training data. Naive Bayes is exceptionally well suited for categorical input variables than numerical variables.

RESULTS

Rapidly increasing access to the internet and exponential growth in the use of social media by rural youth is progressing from urban areas to rural areas. The use of social media for entertainment and communication rather than for educational and personality development purposes raises concerns. The negative effects of social media use are reflected in rural youth also. This highlights the need for timely interventional strategies in at-risk youth age groups.

Naïve Bayes classifier Machine learning methods were used to predict the addiction level of social media. In this naïve Bayes analysis, the prior distribution is empirical. A total of 128 samples were collected; 99 were kept under the training set and 29 under the prediction set to apply the procedure of the model. The number of folds or cross-validation is 2.

Training sets

Table 1 depicts the level of social media addiction under training sets. The level was categorized as low, moderate, and high. In these 99 training sets, the majority, i.e., 88.0 per cent of rural youth, belong to moderate addiction, 9.0 per cent are under high addiction, and the remaining 2.0 per cent of rural youth represented low addiction in social media. The use of social media did affect certain areas of youth, like sleep patterns, food habits, direct interpersonal relations, and behavior and physical activities. The response percentage for these negative aspects is alarming. Similar findings were reported in Indian youth along with other behavioral problems, decreased privacy, living in the virtual world than the real world, affecting scholastic performance and eating habits.

The Confusion matrix is the N x N primarily used for appraising the performance of the categories model, where N is the number of classes or levels. The matrix differentiates the genuine target values from those predicted by the machine learning model.

Cross-validation is a technique that trains the model using the subgroup of the dataset and then evaluates using the complementary

Table 1. Level of social media addiction under training sets

Level	Frequency	Percentage
Low (1)	2	2
Moderate (2)	88	88
High (3)	9	9

subset of the data. This method performs training on 50 per cent of the given data set, and the remaining 50 per cent is used for the testing motive. The vital drawback of this method is to carry out training on 50 per cent of the dataset, and it may be possible that the remaining 50 per cent of the data contains some critical information that is left while training our model, i.e., higher bias.

LOOCV (Leave One Out Cross Validation) method performs training on the whole dataset but leaves only one data point of the available dataset and then iterates for each data point. An advantage of using LOOCV is that it uses every data point, and hence it is low bias. The major drawback leads to higher differences in the testing model that is testing one data point. If the data point is an exception, it can lead to a higher distinction. Another drawback is taking a lot of execution time as it iterates over 'the number of data points' times.

Table 2. Confusion matrix level of social media addiction under training sets

Level (n)	Level (n)		
	Low (2)	High (9)	Moderate (88)
Low (2)	1	0	1
High (9)	0	8	1
Moderate (88)	0	4	84

Table 2 shows that among the 99 samples, 2 youths were found to have low addiction, and one was mispredicted as having moderate addiction. 8 youths come under high addiction; the model improperly predicts one data as a moderate addiction, whereas, among 99 youth, the majority of 88 youth are predicted to be moderately addicted to social media. In contrast, four are wrongly predicted as high addiction. With the widespread accessibility of the internet in India over the last decade, the use of social media has become more popular, especially among youth. Social media can be used for a variety of reasons. It can be useful or may have adverse effects. In urban areas, the use of social media is expected to be more; however, data regarding the use of social media by rural youth is observed more in this study.

Table 3. Confusion matrix level of social media addiction (leave-one-out-error)

Level (n)	Level (n)		
	Low (2)	High (9)	Moderate (88)
Low (2)	1	0	1
High (9)	0	8	1
Moderate (88)	1	4	83

According to Table 3, among 99 rural youth, two were observed as low-addicted, and one was predicted wrongly as a moderate addiction. For high addiction, among 9, one data is wrongly predicted by the model as moderate addiction. Whereas in moderate addiction, among 88 rural youth respondents, 1rural youthmis predicted a low addiction, and 4 rural youths wrongly predicted a high addiction. The loss estimate using cross-validation is 0.071. The model shows decent performance across varied data subsets, with a cross-validated loss estimate of 0.07 and relatively low error in predicting addiction levels among young persons, despite discrepancies in predicting moderate addiction levels.

Prediction sets

Prediction sets are a part of this machine learning assessment. In this study, a total of 128 rural youth respondents were selected, of which 29 were taken as a prediction set. Among them, one belongs to low addiction, seven belong to high addiction, and the remaining 21 are moderate addiction. This test was done to study and construct algorithms that can learn the accuracy of the naïve byes classifier to know the accurate *predictions* on any data. Present results proved that the naïve byes model accuracy in predicting social media addiction among the rural youth of Coimbatore is 93.90 per cent.

WhatsApp, YouTube, Facebook, and Messenger were common modes of use of social media, with other modes like Twitter and Instagram used to a lesser extent. Daily time spent on social media was more than one hour in 4 youths; 8 of them spent more than four hours. It is really a matter of concern. Rural youth were found to have entertainment as a priority for the use of social media, followed by interpersonal communication. The use of social media for educational purposes, distance learning, research, and health was reported by several youths.

DISCUSSION

The youth are grappling with a substantial challenge in the form of social media addiction. This surge in addiction can be attributed to the proliferation of numerous social media applications, which are increasingly captivating individuals (Valakunde & Ravikumar, 2019). With social media addiction, the current study predicted its usage accuracy by using artificial intelligence and machine learning. Majorities are moderately addicted, and there are many more causative variables to be assessed further than the percentage of accuracy. It also found that 93.90 per cent of rural youth of Coimbatore are addicted to social media according to the naïve byes model accuracy prediction. The excessive use of social media over the past decade has become a concerning trend, particularly among Indian youth. This escalating reliance on social media platforms is leading to addictive behaviors, posing a serious issue. The adverse effects stemming from this overuse of social media have been widely recognized globally, including in India, where there has been a noticeable surge in social media usage (Patwari & Indrani, 2020).

The results indicate that when predicting addiction levels among youths using the training sets, the model showed an equal distribution between low and high addiction levels in both the confusion matrix for the training sets and the confusion matrix for leave-one-out-error cross-validation. However, there were discrepancies observed in the predictions of moderate addiction levels between the two confusion matrices. Specifically, majority of 88 youths were predicted to have moderate addiction levels in the leave-one-out-error cross-validation, with 4 of them wrongly predicted as having high addiction levels. In contrast, in the confusion matrix for the training sets, among the 88 rural youths predicted to have moderate addiction levels, 1 was mispredicted as having low addiction, and 4 were wrongly predicted as having high addiction. Overall, despite these differences in the moderation predictions between the two confusion matrices, the loss estimates of 0.071 obtained through cross-validation suggest that the model is performing reasonably well. This indicates relatively low error across the various subsets of data used for both training and validation. A study found a significant portion of young people used social media sites regularly to upload pictures and videos, utilizing up to 1-3 GB of data. Numerous people use social media covertly, exceeding time limits and neglecting responsibilities; studies indicate a detrimental correlation between social media addiction and mental health (Yamini & Pujar, 2022).

There is evidence that excessive use of social media detracts from academic successand demonstrates a correlation between internet addiction and depression, both of which are intertwined with self-esteem (Nadia et al., 2019). A study by Pandey et al., (2020) highlights that social media platforms like Facebook, Twitter, YouTube, and Instagram can be significant distractions in the real world. Many students spend excessive time on these sites, leading to negative impacts such as time wastage, health issues, privacy concerns, and a lack of originality. However, with technological progress, platforms like YouTube, WhatsApp, and Facebook can also serve as effective channels for disseminating agricultural information (Singh et al., 2021).

The digital age has brought about significant technological advancements, but it has also led to issues like social media addiction that affect people in both urban and rural locations. Similar to alcohol and drug addiction, it can have detrimental effects on overall wellbeing and mental health. To address this emerging problem and promote healthier online conduct, especially for young people residing in rural regions, psychological interventions are necessary. Numerous psychiatric conditions, including anxiety, despair, loneliness, attention deficit disorder, hyperactivity, and multitasking mania, are linked to this kind of addiction (Kuss & Griffiths, 2011; Cabral, 2011). Extended internet use, particularly at night, can lead to sleep deprivation, which in turn may result in adverse health consequences for certain individuals (Kim et al., 2015).

CONCLUSION

The study's findings reveal a significant association between social media addiction using artificial intelligence and machine learning for predictive accuracy assessment. It identified a high prevalence of social media addiction among rural youth aged 18-24 in Coimbatore, with discrepancies in predicting moderate addiction levels between training and leave-one-out-error cross-validation matrices, albeit with relatively low error rates overall. The study highlighted that a majority of rural youth exhibit moderate addiction levels, with the Naïve Bayes model achieving a remarkable accuracy rate of 93.90 per cent. The findings emphasize the crucial necessity of crafting specific interventions and establishing supportive mechanisms to alleviate the prevalence of excessive social media engagement among the rural youth of Coimbatore.

REFERENCES

Cabral, J., Hugues, E., Sporns, O., & Deco, G. (2011). Role of local network oscillations in resting-state functional connectivity. *Neuroimage, 57*(1), 130-139.

Chayal, K., Vatta, L., & Ranawat, R. (2023). Influence of stream of study on the information-seeking behaviour of students. *Indian Journal of Extension Education*, 59(3), 21-25. https://epubs.icar.org.in/index.php/IJEE/article/view/134842

Deepanshi. (2023). In-depth Understanding of the Confusion Matrix. https://www.analyticsvidhya.com/blog/2021/05/in-depth-understanding-of-confusion-matrix/

Jayalakshmi, M., Prasadbabu, G., Chaithanya, B. H., Lavanya, A., & Srinivas, T. (2021). Usages of mobile application developed by Krishi Vigyan Kendra Banavasi. *Indian Journal of Extension Education*, *58*(1), 72-75.

Kim, S. Y., Kim, M. S., Park, B., Kim, J. H., & Choi, H. G. (2018). Lack of sleep is associated with internet use for leisure. *Plos One*, E0191713. doi: 10.1371/Journal.Pone.0191713.

Kuss, D., & Griffiths, M. (2011). Online social networking and addiction- a review of the psychological literature. *International Journal of Environmental Research and Public Health*, *8*, 3528-52. 10.3390/ijerph8093528.

Naïve Bayes Algorithm Overview Explain. https://towardsmachinelearning.org/naive-bayes-algorithm/

Pandey, D. K., De, H. K., & Dubey, S. K. (2020). Social media usage among agriculture collegian in north-eastern India. *Indian Journal of Extension Education*, *56*(2), 26-30.

Patwari & Indrani (2020). Use of social media by Rural Youth in India: A Boon or a Bane. https://ssrn.com/abstract=3624680 or http://dx.doi.org/10.2139/ssrn.3624680

Rani, P., Tyagi, R., Kathpalia, J., & Kumari, V. (2023). Impact of social media on the heath of the rural youth: a sociological study. *IAHRW International Journal of Social Sciences Review*, 11(2), 247-251.

Rubaiyat, N., Apsara, A. I., Chaki, D., Arif, H., Israt, L., Kabir, L., & Alam, M. G. R. (2019). Classification of depression, internet addiction and prediction of self-esteem among university students. 1-6. 10.1109/ICCIT48885.2019.9038211

Singh, G., Singh, P., Tiwari, D., & Singh, K. (2021). Role of social media in enhancing agricultural growth. *Indian Journal of Extension Education*, *57*(2), 69-72. https://epubs.icar.org.in/index.php/IJEE/article/view/111678

Singh, S. K., Singh, A. K., & Maji, S. (2021). Constraints faced by the students in the usage of ICT initiatives in agricultural education. *Indian Journal of Extension Education*, *57*(1), 114-117.

Understanding & interpreting confusion matrix in machine learning (Updated 2024). https://www.analyticsvidhya.com/blog/2020/04/confusion-matrix-machine-learning

Valakunde N. & Ravikumar S. (2019). Prediction of addiction to social media. IEEE. *International Conference on Electrical, Computer and Communication Technologies (ICECCT*), pp. 1-6, doi: 10.1109/ICECCT.2019.8869399

Yamini, P., & Lata, P. (2022). Effect of social media addiction on mental health of emerging adults. *Indian Journal of Extension Education*, *58*(4), 76-80. https://epubs.icar.org.in/index.php/IJEE/article/view/128441