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A New Artificial Intelligence-Based Hierarchical K-Means Clustering Technique to Detect Addictive Twitter Activity

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Abstract

To stop the COVID-19 epidemic from spreading among their populations, several countries have implemented lockdowns. Students are being forced to stay at home during these lockdowns, which is causing them to use mobile phones, social media, and other digital technologies more frequently than ever. Their poor utilization of these digital tools may be detrimental to their emotional and mental health. In this study, we implement an Artificial Intelligence (AI) approach named Hierarchy-based K-Means Clustering (HKMC) algorithm to group individuals with comparable Twitter consumption habits to detect addictive Twitter activity during the epidemic. The effectiveness of the suggested HKMC is evaluated in terms of accuracy, precision, recall, and f1-score in respect to the association between students' mental health and mobile phone dependency. Additionally, this study offers a comparative examination of both the suggested and existing procedures.

Keywords- *Digital Technology, Mobile Phones Dependency, Mental Health, Artificial Intelligence (AI), Hierarchy-based K-Means Clustering (HKMC)*

I INTRODUCTION

The cell phone has revolutionized our lives in only a few short decades, changing the way we interact with others, acquire knowledge, do business, and even unwind. The expansion of smartphone usage may be related to the device's development throughout time, as newer models provide capabilities that are more advanced, faster memory and processing speeds, and almost continuous internet access [1]. The rapidity of change and the resulting variations in exposure patterns have sparked worries about their potential effects on human health. There is worry that extended exposure to the radio waves given out by mobile phones might be detrimental to human health. The health effects of being around mobile phones' radiofrequency electromagnetic fields have not been conclusively established. The World Health Organization (WHO) is compiling a book on the impact of radiofrequency electromagnetic fields on human health as part of its Environmental Health Criteria Series [2]. Researchers have looked at the physiological, psychological, and behavioral effects of mobile phone use. The cell phone has rapidly surpassed all other forms of ICT as the most widely used device due to its pervasive impact on modern culture. Academics in the fields of psychology, sociology, and education have all recognized cell phone addiction as modern technological phenomena associated with irreparable harm to the mind [3]. An unhealthy preoccupation with one's cell phone might be seen as a kind of technological dependency.

Many people with a mobile phone addiction suffer from poor self-esteem and strained social connections, which drives them to feel an urgent need to be continuously in touch with others. Symptoms of cell phone withdrawal include anxiety, irritability, sleep disturbances, shaking, insomnia, and digestive problems [4]. Excessive use of mobile phones has been related to a number of negative outcomes, including anxiety, insomnia, depression, mental pain, and an unhealthy way of life. Many people believe they cannot live without their mobile gadgets because of the emotional attachment they have developed to them. Several studies have shown the negative effects of cell phone use on the emotional and physical well-being of pupils. Researchers have shown that using a mobile phone is detrimental to users' health. Studies have shown that using a mobile phone for long periods of time can have negative effects on your health, including changes in gene regulation, hearing loss, vision problems, increased acid pressure on the cornea and lens tissue, headaches, neck pain, a feeling of warmth in the ears, memory loss, and fatigue [5]. Research has also linked heavy mobile phone use to an increased risk of developing brain tumors. According to studies in psychology, the growing use of electronic communication technology has a detrimental effect on social ties and general well-being, leading to a rise in loneliness, depression, and isolation [6]. The use of information and communication technologies (ICT) has been connected to social anxiety and sleep issues in both adults and children, according to study by the researcher.

As has been stated, it seems that there is a link between excessive use of mobile devices and negative health outcomes. Acceptance and adaptation to one's social surroundings, as well as the ability to manage one's own needs, are crucial for psychological well-being. Optimal mental health is defined by the World Health Organization as the ability to achieve one's own potential, cope with the normal stresses of life, make a positive contribution to one's community, and play an energetic role in social situations [7]. Because of this, an individual's mental health is crucial to the success of both themselves and of society as a whole. Staffordshire University psychologists found that 16.0% of smartphone users exhibit harmful behavior. Their research proved that the stress of coping with behavioral disorders brought on by excessive mobile phone use was the last straw. Despite mobile phones' pervasiveness, research suggests that excessive use might have negative effects on one's personal life. According to a review of the related literature, being too dependent on one's cell phone is a kind of technology dependence [8]. According to researchers, a large majority of college students use their mobile phones on a daily basis [9]. There is sufficient evidence to support mandatory, voluntary, or dependent cell phone use, but far less evidence to support compulsive, addictive mobile phone use.

II LITERATURE REVIEW

Thomée S. (2018) conducted this study with the aim of conducting a review of observational studies that take into account correlations between mobile phone use and mental health from a psychological or behavioral perspective. For articles published up till 2017, systematic literature searches in PubMed and PsycINFO were conducted. Papers that looked at radiofrequency fields, attention, safety, relational repercussions, sexual behavior, cyberbullying, and reviews as well as qualitative and case or experimental research were excluded. Title and abstract screening resulted in a total of 4738 papers; 404 of those were retrieved in full text, and 290 were eventually included. Only 5% of the designs were longitudinal. The most common measurement method was self-reporting. Children or youth were included in one-third of the research. University students and/or volunteers who choose to participate themselves made up the majority of the adult populations. The primary research findings were relationships between frequent mobile phone use and outcomes related to mental health, including depressed symptoms and sleep issues. Use of a mobile device before bed has been linked to poorer sleep quality and shorter sleep duration, among other things. Dependency and "problematic use" were linked to a number of undesirable effects. In conclusion, studies that approach the exposure from a psychological or behavioral viewpoint find links between mobile phone use and poor mental health outcomes. However, more high-quality research is required before we can draw reliable conclusions regarding the mechanisms and directions of connections' causality.

This work by Jingmin Li (2022) investigates the impact of wireless network mobile devices on college students' labor concept education under the environment of artificial intelligence in order to cultivate correct labor values and good labor quality in college students and effectively promote the development of their labor concept education. First, a questionnaire survey is employed to learn more about 400 college students' views on the labor market. Second, by contrasting group A (college students using artificial intelligence APPs for wireless network devices to learn about labor concepts) with group B, the effect of wireless network mobile devices on college students' labor education is determined. Approximately 20% of college students agree, according to statistical survey results, that "if they have enough money to live, they do not have to work," while less than 50% concur that "they cannot be admitted to civil servants and senior managers in the company and are willing to engage in ordinary labor in the future." Additionally, between 50% and 60% of college students believe that "housework has nothing to do with me and is all the responsibility of parents." Only approximately 50% of college students are willing to clean actively in response to the question, "What would you do when you discover the public area is poor and dirty, but it's not your turn to be on duty?" Comparing the data from groups A and B reveals that group A's perception of the world of work is more biased than group B's, and group A students are more pessimistic and sluggish in their attitudes toward and behaviors related to their work. This indicates that wireless network mobile devices have a significant detrimental effect on college students' perception of the world of work as a whole. As a result, it is made clear in this work that the proper application of artificial intelligence technology to the notion of labor education has a crucial impact on the thoughtful development of educational approaches.

Concerns have been raised concerning the potential impact of the growing usage of mobile phones (MP) and other wireless devices (WD) on the wellness of children and adolescents. Given the continued rise in use of these devices since the COVID-19 outbreak, it is more important than ever to understand if they have beneficial or negative effects on children's and teenagers' mental health. to evaluate the empirical data on the relationships between MP/WD usage and adolescent and child mental health. For research published before July 15, 2019, a systematic review of the literature on Medline, Embase, and PsycINFO was conducted. Observational studies published between January 1, 2011, and 2019 were also evaluated (ten were cohort studies, 15 were cross-sectional). The estimated mean age of all participants was 14.6 years, and 47% of participants were female. Our ability to draw broad generalizations was hindered by the significant between-study variability in the design and measurement of MP/WD usage and mental health outcomes. Observed effects varied with usage duration and MP/WD type. Girela-Serrano et al. (2022) discovered intriguing but scant evidence that higher MP/WD use may be linked to worse mental health in kids and teenagers. For 16 research, the risk of bias was graded as "high," for 5 studies, "moderate," and for 4 studies, "low." To better understand the impact of sleep and the types of MP/WD use (such as social media) on the trajectories of mental health in children and adolescents, more high-quality longitudinal studies and mechanistic research are required.

For a number of years, there has been growing interest in using smartphone applications (apps) and other consumer technologies in mental health care. However, due in part to the complicated issues associated with the use of smartphones and other consumer technology in psychiatry, the vision of data from apps seamlessly returning to and integrated in the electronic medical record (EMR) to assist both psychiatrists and patients has not been widely realized. Utilization of consumer technology in therapeutic settings, commercialization, and advancing consumer technology are some of these issues. The role of consumer technology in psychiatry will be determined by technological, legal, and commercial factors as well as by medical factors. In this article, Bauer et al. offer suggestions for a more fruitful direction for consumer technology use in psychiatry (2020).

The use of smartphones has become ubiquitous in the twenty-first century. The present study has commenced an exploration of the relationship between these three variables in the Malaysian higher education context because there has been little research exploring the relationship between mobile addiction, interpersonal relationship, and academic behavior among young adults in tertiary institutions. The information was gathered and analyzed using a descriptive correlational study design from 150 young individuals who answered to an online Google form that was sent out via a WhatsApp link. The questionnaire's questions were modified from a number of doctoral research. Descriptive and inferential statistics, such as the mean and standard deviation, correlation, and multiple regression, were used to analyze the data. According to this study by Fook et al. (2021), young adults in Malaysian tertiary institutions had a case of mild mobile addiction. The findings also showed a relationship between the three variables—mobile addiction, interpersonal relationships, and academic behavior. The research found that while mobile addiction had a detrimental effect on young adults' academic behavior in tertiary institutions, interpersonal relationships had a favorable impact on the variance of academic behavior.

Smartphones and other personal and ubiquitous sensing devices have made it possible to collect data continuously and covertly. Continuous sensor data has been subjected to machine learning techniques in order to forecast user contextual information such as location, mood, physical activity, etc. Utilizing ubiquitous sensing technologies for mental health care applications has recently attracted increasing interest. This will enable the automatic continuous monitoring of various mental conditions like depression, anxiety, stress, and other similar conditions. In this publication, Garcia-Ceja et al. (2018) review recent research on sensor data and machine learning-based mental health monitoring systems (MHMS). The authors concentrated on studies on mental illnesses/disorders as depression, anxiety, bipolar disorder, stress, etc. They present the overall phases of MHMS and suggest a classification taxonomy to direct the review of relevant publications. Additionally, the field's research problems and potential future opportunities are highlighted.

The internet of things (IoT) has improved medical facilities, according to early study. It is now possible to detect routine parameters in isolated COVID-19 patients in remote locations where patients cannot access a doctor. Using sensors, cloud storage, data transmission, and IoT mobile applications, the doctors and families will be able to monitor the patient's health outside of the hospital. The major goal of Muhammad Zia Ur Rahman et alplanned .'s research-based project (2022) is to create a remote health surveillance system using local sensors. The suggested solution additionally offers GSM texts, real-time location, and the ability to email a doctor in an emergency. In the absence of a doctor, an automatic injection system will administer the dose to the patient's body in an emergency. This action is based on artificial intelligence. Only ECG monitoring, SpO2 level detection, body temperature, and pulse rate measurement are relevant metrics for our study. In the event of a sudden change in the parameters, the doctor will be able to see some of the parameters remotely through the Blynk application. The IoT system will notify the emergency team and family members of the location if the doctor is unavailable. A system based on artificial intelligence (AI) will evaluate the parameters and inject the dose.

The goal of this study was to look into the mechanisms by which college students become addicted to their mobile phones. The whole group sample approach was used to pick 9406 students from 35 colleges in four regions of Jiangsu Province, ranging in age from freshmen to seniors. A number of questionnaires were given out, including the Positive Psychological Capital Scale (PPQ), the Social Adjustment Diagnostic Questionnaire (SAFS), the Mobile Phone Addiction Index Scale (MPAI), and the International Physical Activity Questionnaire—Long Form (IPAQ). Physical activity was found to be a poor predictor of mobile phone addiction among university students by Chen H et al. in 2022. Among university students, social adaptation partially mediates the relationship between mobile phone addiction and physical activity, with no indirect contribution from a separate mediation of psychological capital. The relationship between physical activity and cell phone reliance among college students is mediated by psychological capital and social adjustment. According to their research, physical exercise has a significant external influence on college students' use of mobile phones. It also has an indirect impact on students' use of mobile phones through social adaption and psychological capital. College students can avoid cell phone addiction by increasing their level of physical exercise, building their psychological capital, and fostering greater social skills.

2.1 Mental health and mobile dependence using AI

The researcher shown how using a mobile phone may lead to dependency, addiction, and habit formation. Addiction to mobile devices was shown to affect a negligible portion of Pakistani university students, less than 18.50%. Due to the naturalistic conditions in which they used their phones, the participants in this study were less likely to display addictive behaviors associated with excessive mobile phone use [10]. Multiple studies have revealed that students who are addicted to texting are more likely to struggle with introversion, extroversion, and anxiety. Furthermore, the frequency of text message addiction varied widely among student subgroups. Furthermore, new studies have linked texting often with feeling powerless and anxious in social situations. The researcher identified a significant relationship between depressed symptoms and the three features of mobile phone addiction—compulsive use, withdrawal, and escape—in a study of 519 American college students [11]. Then people went on to say that women were more prone than men to show indications of cell phone addiction. The problem of over-reliance on technology, and on mobile phones in particular, must be addressed for a variety of reasons. Technology has unquestionably benefited and is essential to human society. The stimulating effects of these innovations, however, might lead to compulsive usage and eventually addiction. Addiction to mobile devices is common among young people owing to frequent use [12]. Young people's mental health, their addiction to and motivation for mobile phones, and the importance of having a strong social network are all major topics of research in the fields of psychology and sociology.

A person's emotional, psychological, and social well-being all contribute to what is known as their "mental health [13]." One's thinking, feeling, and responding capacities are all impacted. Positive mental health reduces the mental and emotional strain that comes with giving 100% and realizing one's full potential. Maintaining a healthy mental state is crucial from early infancy all the way into old age. Anxiety, social phobia, sadness, panic disorder, substance abuse, and other illnesses may all contribute to mental health problems.

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The ability to spot the early warning symptoms of mental illness is becoming more important for maintaining a healthy work-life balance. Both their present emotional state and their unique character influence the mental well-being of an individual. Most cases of mental illness may be traced back to a chemical imbalance in the brain. In order to effectively treat people who are experiencing abnormal mental activity, it is necessary to do extensive research on their mental health [14].

The degree of success in treating mental illness may be gauged by how effectively patients are cared for. Keeping an eye on the mental health characteristics of different groups is essential for predicting health issues. Most of the residents are either high school students, recent college graduates, or young professionals. It's possible for anyone from any background or circumstance to experience tension or unhappiness. There are occasions when the emotional well-being of a certain demographic is very vital in averting a pandemic illness. It will be more important over the next years for healthcare practitioners to take patients' mental health into account in order to deliver more effective care and speed their patients' recoveries. The impact of prescriptive medical modeling on the international healthcare industry was studied by Winters-Miner and colleagues [15].

For the most part, psychologists' professions center upon providing psychotherapy and behavioral therapies for those struggling with emotional and mental health issues. Psychologists are trained to assess mental health in addition to identifying and addressing any problems that may arise. Professionals will be able to forecast a person's mental health based on the results of psychological sampling. The subject's clinical and behavioral issues are addressed together by the psychologist and the psychiatrist. Therapists and doctors specializing in mental health are vital to improving people's mental and emotional well-being. There is undeniable need for enhanced community monitoring due to the fact that all but the most serious psychiatric treatment is delivered in an outpatient environment. In the event the issue was identified and steps were made to prevent a recurrence, the result may have been very different. Patients' written records may be used to track their emotional and mental health even when they are not in a therapeutic environment [16]. There is a natural tension between this method and the potential for warped recollections and noncompliance. Applications that encourage users to provide information about their feelings, sleep habits, and other important areas have been created despite comparable challenges.

Artificial intelligence (AI) methods are being used all around us, often undiscovered. Because of their widespread use, several AI-based applications are now taken for granted. Emerging smartphone applications and wearable gadgets that monitor mental health using artificial intelligence may supplement or perhaps render the role of a psychologist obsolete. It demonstrates how AI has the ability to aid in medical diagnostics. Technology advancements in AI are also helping the domains of behavioral medicine and mental health therapy. In fields like healthcare administration, testing, and diagnosis, as well as care coordination, it is possible that the use of computer tools for teaching and thinking will be beneficial to healthcare practitioners [17]. Self-care technologies with the potential to enhance people's lives might be developed using artificial intelligence (AI) techniques, such as user-participatory mobile wellness applications (apps) that learn from users' behaviors and preferences. By aiding in the diagnosis of health problems and the implementation of appropriate solutions, AI is enhancing public health.

This study tend to synthesize the existing literature on intelligent automation and to shed light on its most salient contributions and challenges to HRM [18]. Health problems are exacerbated by the rising prevalence of mental illnesses like depression. By evaluating patients' historical clinical, social media, and behavioral data, newly created AI systems are being used to help professionals in the area of mental health care, in particular psychiatrists and clinicians. Ignoring the underlying mental health problems that many adolescents face may lead to more significant problems in the road. The computational capabilities of AI platforms may one day help us understand the complex biology behind mental diseases and more precisely target our therapeutic interventions. The doctor-patient relationship is vital in mental health treatment, yet restricted medical visits might be a barrier to progress. AI technologies enable the automation of tasks that don't need "human interaction," freeing up doctors to focus on more humane practices and "civilizing" the healthcare system [19]. In this study, the CF-KNN method is used for the first time to the task of using AI to predict teenagers' mental health. During the pre-processing stage, the obtained raw data is standardized and balanced using a normalization approach [20]. Once the data has been standardized, the VAE method is used to convert values into characteristics.

III PROPOSED METHODOLOGY

This study employs Hierarchy based KMC for evaluating the performance of the proposed model. The study focus on evaluating the relationship between mobile addiction and mental health of the college students.

KMC

The traditional clustering technique KMC has been employed extensively in data analysis. The primary purpose of this algorithm is to group the patterns from a training sample into a predetermined set of clusters. Generally speaking, an objective function including such, among many others, the total of the square of the Euclidean distance between every pattern and its centroid may be used to evaluate the quality of the clustering produced by traditional KMC:

$$f = \sum_{K=1}^{K} \sum_{i=1}^{n_k} \left| x_i^k - \omega_k \right|^2 \tag{1}$$

Here, K=cluster, $\omega = centroid$

$n = number\ of\ patterns$, $x_i^k = ith\ pattern\ belonging\ to\ kth\ cluster$

The fundamental steps of the traditional KMC are described below to divide "N" patterns to "K" groups:

Step-1: Choose K patterns as randomly from the primary data to serve as the centroids.

Step-2: Determine the distance between every centroid and every pattern, and afterwards arrange every pattern in the nearest cluster.

Step-3: The following formula should be used to adjust every centroid, namely the kth centroid.

$$\omega_k = \frac{1}{n_k} \sum_{i=1}^{n_k} x_i^k \tag{2}$$

Step-4: The method should be stopped with the present K groups if the convergence requirement is met; else, proceed to Step-2.

Step-4's convergence condition may be established in a variety of ways, such as a predetermined iteration, centroids stability, an allowed range of the objective function value, and so on.

For big datasets, the computational performance of traditional KMC is often quick. The reliability of the grouping outcomes, however, is dependent on the original centroids and may be compromised by the problem of local best solution. The section outlines a HKMC as a solution to these problems.

3.1 Hierarchy-based KMC (HKMC)

The end outcomes of conventional KMC are greatly influenced by the quality of the initial centroids that are provided. However, the likelihood that the KMC will locate the high-quality initial centroids among the patterns decreases as the number of patterns in the dataset increases. Our suggested HKMC's core idea is as below.

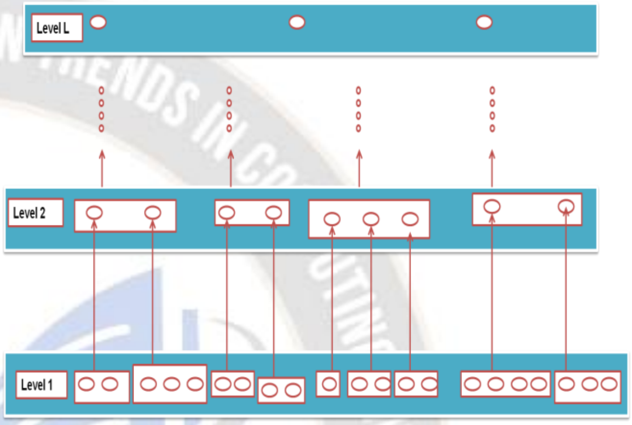

Figure 1: Hierarchy configuration

The complete dataset is depicted as a small number of features made up of numerous representative-patterns with a similar distribution to the original one for a specific dataset if a group of patterns that are near to one another are treated as one representative-pattern through their centroid. From this vantage point, a hierarchical structure is constructed (as depicted in figure 1) for the original data, where the user or other requirements determine the number of levels (L), the first level is made up of the original data, and every succeeding level is made up of a scaled-down version of the level before it. The steps of the HKMC can be broken down into the following categories based on this multilevel configuration:

Phase-I: Creating a hierarchy organization

Step-1: Start with i=2 and make the initial data the first-level dataset.

Step-2: Create the $(i\text{-}1)^{th}$-level data as the underpinning for the i^{th}-level data.

Step-3: When i=L, move on to Phase-II; if i=i+1, move on to Step-2.

Phase-II: Grouping by weights

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Step-4: When i=L, choose K patterns as randomly from the i^{th}-level data; alternatively, just use K centroids acquired in Step-5.

Step-5: Utilize KMC for such i^{th}-level data and the first centroids should be the patterns provided by Step-4. Compute the cluster centroids, let's assume the kth group, at the beginning of every KMC cycle.

$$\omega_k = \frac{\sum_{p=1}^{n_k}(r_p \cdot x_p)}{\sum_{p=1}^{n_k} r_p} \tag{3}$$

Here, $n_k = size\ of\ the\ kth\ cluster\ in\ the\ ith\ level\ data$

$x_p = pth\ pattern\ of\ this\ cluster$

The amount of (i-1^{th}-level patterns described by x_p is equivalent to r_p if i>1, else, r_p represents 1.

Step-6: The procedure should be stopped if i=1 and the grouping outcomes should be produced in Step-5 like the end outcomes; else, i=i-1, and Step-4 should be taken.

IV RESULTS AND DISCUSSION

In this research, the proposed HKMC method is analyzed and compared with existing methods like logistic regression-LR, random forest-RF, and naïve bayes-NB [21]. A model's ability to correctly classify data may be evaluated using a number of different performance criteria. The article used a wide variety of measures, not only Accuracy, Precision, Recall, and F1-Score. For the purpose of argument, let's say that the values of the class variables in a binary classification job may be thought of as either positive (P) or negative (N). "Cases that the model correctly classified as positive (P) are called true positives (TP), whereas those classified incorrectly as negative (N) are called false negatives (FN).True negative (TN) cases are those that the model properly identifies as negative (N) cases, whereas false positive (FP) cases are those that a model incorrectly identifies as positive (P) cases." The findings of popular and proposed strategies are shown in table 1. Results for various performance metrics, including accuracy, precision, recall, and F1-score, may be given in equations (4)–(7).

$$\text{Accuracy} = \frac{(B + A)}{(B + A + D + C)} \tag{4}$$

$$\text{Precision}=\frac{A}{A + C} \tag{5}$$

$$\text{Recall}=\frac{A}{A+D} \tag{6}$$

$$\text{F1 score} = 2*\frac{precision * recall}{precision + recall} \tag{7}$$

Where,

A=True Positive

B=True Negative

C=False Positive

D=False Negative

Table 1: Results of existing and proposed methodologies

	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR	72	66	88	67
RF	63	71	63	88
NB	84	82	71	77
HKMC [Proposed]	96	93	90	98

Accuracy is used to evaluate a classifier based on how well its predictions match the target label. You may also express this idea by looking at the percentage of correct answers across all examinations. The equation (4) displays the accuracy. Figure 2 shows a comparison between the accuracy of the conventional and suggested approaches. When compared to the standard method, the one proposed yields better results. Accuracy for LR is at 72%, RF at 63%, NB at 84%, and the proposed HKMC at 96%.

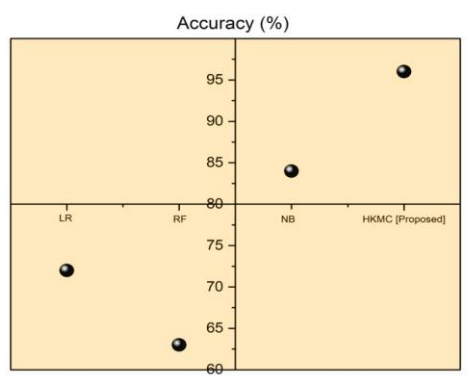

Figure 2: Accuracy

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As a result, it is important to enact regulations that help college students make responsible cell phone choices. Physical activity and positive interactions between teachers and students can help with smartphone dependency. For this reason, it is crucial to monitor and intervene on college students' mental health by providing them with more extensive physical training arrangements and more reasonable aid. Accuracy is measured in many ways, but one of the most crucial is precision. As stated in the equation (5), it is calculated as the proportion of properly classified instances to the total number of occurrences of predictively positive data. Figure 3 displays the results of a comparison between the precision of the conventional and the suggested approaches. Compared to the proposed technique, the accuracy of previous approaches like LR, RF, and NB ranged from 66% to 82%. We obtain a 93% degree of precision in the proposed HKMC.

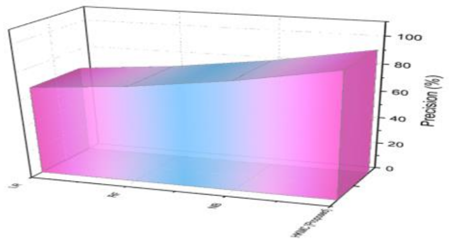

Figure 3: Precision

A classifier's "Recall," or the percentage of instances accurately labeled "positive," is a useful metric to have. Recall is used as an indicator of performance to choose the best model. Figure 4 shows a contrast between the recall of currently used and suggested methods. The suggested technique offers more recall than the standard approach. LR has a 88%, RF has an 63%, NB has a 71%, and the proposed HKMC has 90%. Higher education students' daily mobile phone use averaged nearly eight hours. This could be due to the growing interest in engaging in educational pursuits by way of an online training module, as well as the growing interest in accessing timely information on the pandemic via mobile devices. Their level of mobile dependence was inversely related to their mental health, and it contributed to issues like anxiety and sadness.

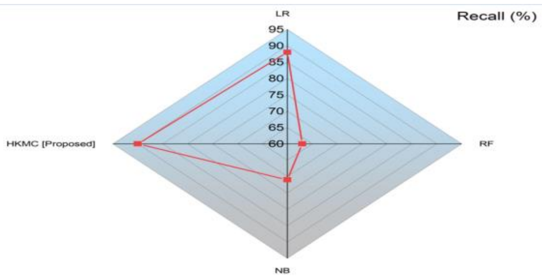

Figure 4: Recall

By averaging the accuracy and recall ratings, we get the F1-score. This calculation will help find out how many false positives and negatives there are. Figure 5 displays the F1-score difference between the conventional and proposed methods. The proposed method outperforms the state-of-the-art strategies on the F1-score. The F1-score for the existing approaches was 67 percent for LR, 88 percent for RF, and 77 percent for NB. The F1-score for the recommended HKMC is 98%.

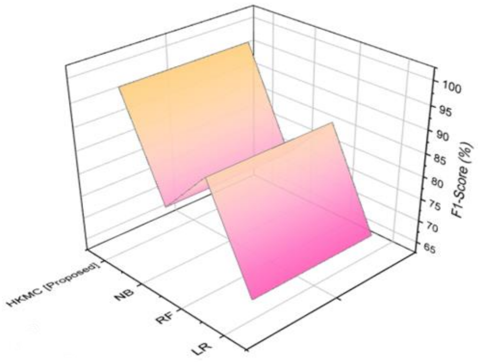

Figure 5: F1-score

During the COVID-19 pandemic, for instance, college students in Shanghai used their phones for an average of 7.39 hours per day. It suggested that these pupils had a little cell phone dependency. This study provided support for the significant effects of mobile dependence in reducing mental health among college students in Shanghai after correcting for variables in the logistic regression analysis. The importance of cell phone use time as a contributor to college students' mental health was also made crystal clear. These results will be useful for schools looking to curb students' disruptive cell phone use in the classroom. Higher levels of mobile dependence were connected with worse mental health, suggesting that those pupils with higher mobile dependence are at a larger risk for developing psychological difficulties. It suggested that college students who engage in an excessive amount of mobile dependence are more likely to suffer from mental health disorders such sadness, anxiety, and stress. This research added to the body of evidence supporting mobile dependence.

V CONCLUSION

Several nations have gone into lockdown in an effort to halt the spread of the COVID-19 virus. During these lockdowns, students are staying at home and using their phones, social media, and other forms of digital technology more frequently than ever before. They risk harming their mental and emotional health through inefficient use of these

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technologies. In this research, we present a method for identifying addictive Twitter behaviour during pandemics by using a machine learning technique called the Hierarchy-based K-Means Clustering (HKMC) algorithm to classify Twitter users into groups with similar consumption patterns. Using measures including accuracy, precision, recall, and f1-score, the HKMC is assessed for its ability to predict the correlation between students' mental health and mobile phone use. The research also provides a contrast between the proposed and established methods.

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