e-ISSN:2582-7219

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

Volume 7, Issue 7, July 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.521

6381 907 438 6381 907 438 ijmrset@gmail.com www.ijmrset.com

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| Monthly, Peer Reviewed & Referred Journal|

| Volume 7, Issue 7, July 2024 |

| DOI:10.15680/IJMRSET.2024.0707083 |

A Holistic Approach to Addressing Mobile Phone Addiction through Social Networks

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ABSTRACT: A recent report noted that 93.4% of Peruvian citizens own a smartphone and that this has impacted positively in society for different purposes. Although prior research has examined user preferences across a range of topics, there is a study gap in the use of machine learning techniques to predict OS preferences on mobile phones. Despite its advantages, scholars and practitioners have been investigating human-technology interaction, psychological processes, and their possible negative effects. Previous studies have investigated Problematic Mobile Phone Use as a dysfunctional interaction concerning the excessive use of smartphone activities that results progressively in negative consequences such as lack of control, preoccupation, withdrawal, relapse, and conflict. These studies have primarily relied on obtrusive techniques, such as self-reporting surveys, or called for user involvement to establish rules for regulating addiction. Although several research studies employed unobtrusive techniques, they only looked at a small subset of addiction-related issues. Mobile addiction problems are growing at associate around the world at an alarming rate. Problems due to mobile phone addiction like sleep disturbance, anxiety, stress, and, to a lesser extent, and depression require immediate action. The proposed Long Short-Term Memory (LSTM) classification method can be used effectively. The lower computational complexity property is obtained from the approach of LSTM classification that does not require a feature space to be constructed. Social media platforms such as Facebook, Snap chat, and Instagram produce the same neural circuitry that is caused by gambling and recreational drugs to keep consumers using their products as much as possible includes challenges among users. They might challenge each other, keep disconnected and earn points. Challenges might be done by two remote users. In this study several symptoms, effects, and causes of smartphone addiction are summarized.

I. INTRODUCTION

Mobile phones are an inseparable part of our lives. the number of active mobile numbers in the United States exceeded 327 million, which is greater than the US population. According to another research project, as of January 2014, 90% of American adults have a mobile phone and 65% of them use smartphones. On average, people check their mobile phones 150 times a day for different purposes. Information systems literature examines different phases of IT use, such as adoption and continuous use. Adoption of technology is widely studied where several models have been proposed in the literature to explain users' technology adoption behaviors. After adoption, researchers focus on how continuous use of technology is embedded or routinized in users' life. Several IS continuance models explain post-adoption behavior and identify the factors affecting their usage intentions. Repetitive usage of a technology artifact, in medium or long-term scenarios, can lead to forming automatic usage behaviors. This phenomenon is defined as habit in the IS literature. These IS habits by themselves can have some positive or negative consequences. Moreover, in the specific case of mobile phone addiction, there is no consensus even on the independent existence of such addiction. Some researchers consider mobile phone addiction as a kind of technology addiction characterized by technology addiction symptoms (i.e. conflict, withdrawal, relapse, and behavioral salience). Others strongly believe that mobile phone addiction is some other kind of behavioral addiction (e.g. Addiction to game, shopping, gambling, etc.) Manifested through excessive mobile phone usage. Thus, to the second group, individuals are not addicted to the mobile device, but through the device by experiencing addiction to the applications.

The main purpose of this research is to differentiate between "addiction to the device" (simply referred to as mobile addiction) and "addiction through the device" (i.e. Application addiction) for mobile phones. The investigate the role of application addiction in the formation of mobile addiction to illustrate that even though they both may occur in high degrees simultaneously, it is also likely that each can exist at high degrees absent the other one. In this study the pursue two main objectives: 1) to investigate antecedents of mobile phone addiction as a kind of technology addiction; and 2) to demonstrate the differentiation between mobile addiction and application addiction signifying that addiction to the mobile device does really exist and is likely to happen in high degrees apart from

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other addictions. The remainder of this paper is as follows: in the next section mobile addiction and application addiction are discussed and definitions are provided. Following that our model, hypotheses, and method are discussed. The last two sections discuss the results and implications of the study. The excessive usage of technology artifacts is reported in the literature to lead to some negative consequences such as decreasing social quality of life, reduced productivity, tardiness for appointments, insomnia, financial losses, family issues and risky and illegal behaviors like using mobile phones while driving . One of the critical negative consequences of this excessive usage identified in the literature is technology addiction which can encompass many of the mentioned consequences and affect various aspects of a person's life and even require treatment. Technology addiction is a special type of behavioral addiction that encapsulates a psychological dependency on the use of an IT artifact. Based on this, most of the definitions proposed for technology addiction are mainly based on a number of symptoms just like the symptoms of substance addictions despite how much they vary. In one of the most accepted definitions, define technology addiction as a psychological state of maladaptive dependency on the use of technology to such a degree that the following symptoms arise: salience (i.e. domination of users' thoughts and behaviors by the technology), withdrawal (i.e. arising negative emotions if a person cannot use the technology), conflict (between the use of technology and other personal tasks), relapse and reinstatement (inability of the technology user to voluntarily reduce her use), tolerance (the need to use the technology to a greater extent to produce thrill), and mood modification. This inconsistent conceptualization of technology addiction has bred two different conceptualizations: technology addiction as a zero-or-one phenomenon where an individual is either an addict or not or viewed as a spectrum with different levels of severity. Theemploy the latter view as thebelieve it is not possible to define a specific threshold for such a subjective phenomenon.

II. RELATED WORK

Addiction can be manifested in different ways for different individuals where some of the symptoms might not develop at all like with substance addiction where some of the highly addictive substances do not develop all the symptoms in the addict. The believe that behavioral addictions must be viewed as a spectrum with different levels of severity where the emergence of the symptoms to any degree should be considered as addiction. [1-2] The believe that behavioral addictions, just like any other psychological state (e.g. depression, self-efficacy, self-regulation, etc.) exist in every individual in variable degrees. What is known as addiction for ordinary people is in fact the "higher-than-norms" degree of this state manifested in one's behavior. While the existence of a general concept of technology addiction seems to be accepted in both IS and neuroscience, there is still a debate over the sensibility of addiction to some specific kinds of technology like the Internet and mobile devices. Some researchers believe that addiction to the internet or mobile phones does not make much sense as most of the individuals who excessively use these technologies are not addicted to the physical device but use them as a medium to fulfill other addictions (e.g. Social networking, gambling, shopping, porn, gaming, etc.) While others acknowledge this, they believe that these technologies themselves can be addictive as well.

In this study the propose a model to investigate this issue in the specific case of mobile phones. To this end, the first distinguish between addiction "to" and "through" the mobile phone. Based on the previous arguments, for both concepts, the adapted the mentioned definition of technology addiction proposed by with some slight alterations. The following two sections provide our specific definitions. The other addiction concept the deal with in this study is addiction through a mobile phone. As there focusing on smartphones with complex applications they consider mobile phones supported by an operating system (e.g. Windows, Android, iOS, etc.). In recent years almost all of the operating systems provided to the market by mobile manufacturers have an application-based framework. A mobile application can be defined as a software program that resides on mobile devices, which provides users with a specific experience and a set of supporting functions (e.g. A specific game, getting banking services from a specific bank, shopping from a specific website, etc.). The define application addiction as a psychological state of maladaptive dependency on a specific dominant life activity context (i.e. DLAC) to such a degree that some of the following behavioral addiction symptoms arise to any degree: salience, withdrawal, conflict, relapse and reinstatement, tolerance, and mood modification. For example, if an individual's highest level of addiction is to gaming (i.e. her DLAC is gaming), 'application addiction' for this particular person refers to her psychological dependency on gaming and not to other life activity contexts (LAC). Similar definitions are also proposed in the literature for other life activity contexts. For instance propose a definition (based on their original technology addiction definition) for 'online auction addiction' as a life activity context.

Model and Hypotheses Within the Technology Usage literature, habit is defined as the extent to which people tend to use technology automatically because of learning, and is known in the IS literature as the main factor in

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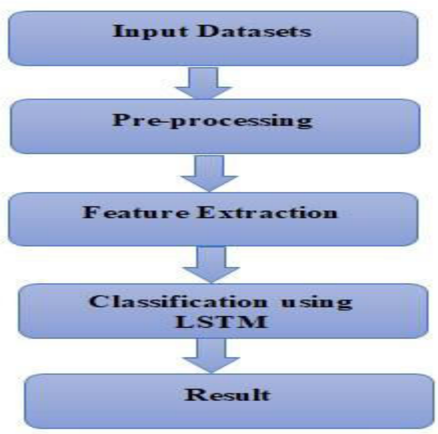
developing technology addiction. Even some researchers believe that habit and addiction are both on the same continuum where addiction is the extreme, out of control mode of usage. Considering habit and addiction as the two ends of the same continuum it then makes sense to consider antecedents of habit as antecedents of addiction as well. Nevertheless, some other factors seem to be required to shift an individual along this continuum from a habit towards an addictive behavior. Demonstrating habit's effect on mobile phone use, have demonstrated that when habit is beyond normal control it increases negative consequences due to deficient self-regulation . They argue that mobile phone habit and self-regulation (i.e. overriding one's action tendency in order to attain another goal) can be considered as the reflexive and reflective systems of a dual-system respectively. The characteristics they describe for the two systems of thinking in their dual-systems perspective (unconscious vs. Conscious, shared with animals vs. uniquely related to human, rapid and parallel vs. the use of smartphones in our daily lives has grown steadily, especially with hardware improvement and effective programming capabilities. More specifically, smartphones are used to perform activities, such as sending emails, trans ferrying money via mobile Internet banking, making calls, texting, surfing the Internet, viewing documents, storing medical, confidential, and personal information, shopping online, and playing games. For instance, Deloitte Mobile Consumer Survey (2018) demonstrates that 95% of the owner of smart phones use their devices daily in the UK. Furthermore, the UK market penetration by device type, which showed clearly that mobile, is gradually increased compared with a laptop (Deloitte Mobile. In addition, with the advent of the increasing features of smartphones, mobile applications have been evolved and become ubiquitous and widely used by smartphone owners.

III. IMPLEMENTATION PROPOSED METHOD

Mobile addiction identification is influenced by societal and environmental factors as well as individual factors. The scope of this study is to understand the effectiveness of these algorithms for preventing future mobile addictions. Data description is a best solution used for a visually impaired people who are unable to comprehend visuals. The proposed prediction of mobile addictions can help in making governing decisions in the affected regions such as promoting education and reworking existing facilities. The features in the study refer primarily to the part of the population which are affected most by mobile addictions. The decoder to process semantic information from the collecting data.

Fig 3.1 show the semantic information obtained from the hidden state of the layer is used as the primary information of the semantic information generated. The combination of LSTM is considered as the best solution for this project; the main target of the proposed study work is to obtain the perfect caption for a data. After obtaining the description, it will be converted into data and the data into a text. To early predict the presence of mobile addiction ideation and further prevent the behavior of mobile addiction are essential and important. With the technology improvement and the availability of various kinds of real-world big data, artificial intelligence (AI) grows fast accordingly.

The academics have made great efforts on the computerized algorithms to deal with big data. Machine learning, a combination of AI and computations, could provide accurate diagnosis of diseases and predict the outcomes. To extract various global spatial features and the adaptive attention module helps to decide whether to attend to the data. It gives more accuracy compare to other existing methods.



3.1 Implementation Diagram LSTM

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3.1 Long Short-Term Memory (LSTM) for Mobile addiction Analysis

The proposed Long Short-Term Memory (LSTM) proficiently creates information from auto-learning capabilities. Work out diminished highlight maps involving LSTM for quicker handling. Profound learning is a diverse learning strategy that can be utilized to address various degrees of information deliberation. LSTM models can find new highlights in view of info information or fundamental portrayals of past informational indexes with next to no earlier information. The profundity highlights of each addiction test can then measure up to the recalculated addiction dataset. Since LSTM has a fixed-size input boundary list, the information plots should be pre-handled. The proposed new method can be utilized to productively and obviously catch addiction designs and go back over clicked addiction pictures with loud foundations.

Algorithm steps for Long Short-Term Memory (LSTM)
Phase 1: Input the values
Phase 2: Pre-processing the dataset
Phase 3: If values not found
Phase 4: Re-enter another value
Phase 5: If value is found represent the abstraction of multi-level data
Phase 6: Detecting new features of input data or previous datasets
Phase 7: Each addiction sample with the recomputed addiction dataset with LSTM
Phase 8: Testing the value
Phase 9: If (Test the values) ==ok)
Phase 10: Solution found
Phase 11: Else
Phase 11: Solution not found

3.2 Data Pre-processing

Information pre-handling is a term that depicts procedure on information at an exceptionally low degree of deliberation. These tasks don't build the data content of the information, yet on the off chance that entropy is a proportion of data, they diminish the data content of the information. The motivation behind preprocessing is to work on the information by smothering undesirable contortions or to further develop a few information qualities pertinent to additional handling or investigation errands.

3.3 Feature selection

Highlights are the traits that effect or are helpful in the issue. Choosing significant highlights to show is called include determination. Albeit the cycles of component determination and element extraction fill similar need, they are very unique. The primary distinction between them is that highlight determination chooses a subset of the first list of capabilities, while include extraction produces new elements. Highlight determination is a strategy to diminish model info factors, utilizing just significant information to decrease model overfitting.

3.4 Data Classification

Information characterization is the errand of allocating marks or classes to the entire arrangement of information. Each profile is supposed to have just a single class. Information characterization might be the main piece of computerized information investigation. Ordering Information Utilizing LSTM Characterizing information between objects is a complicated undertaking, which makes information characterization a significant errand in the field of PC vision. Information grouping alludes to marking information into one of various predefined classes. There might be n classifications into which a given item is grouped.

IV. RESULT AND DISCUSSION

In the first place, we portray the dataset and the handling subtleties. Then, we measure the proposed strategy against the traditional models. Simultaneously, a progression of end tests was done to concentrate on the viability of the technique. To start with, the product prompts the client to enter data about the addiction that should be recognized. This program adds picture pixels to a framework and concentrates variety boundaries. Then, the shape boundaries will be extricated. The determined boundaries are contrasted and all recently recognized preparing profile leaves in the vault utilizing the base distinction measure and the best addiction is shown. Compared with existing classical models

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Compared to the existing methods, the model of this method can get better results for analysis. We compared the proposed model by LSTM with previous models using CNN and NB. A graphical bar method is used to compare and analyze the percentages of existing classic models, as shown in the figure below.

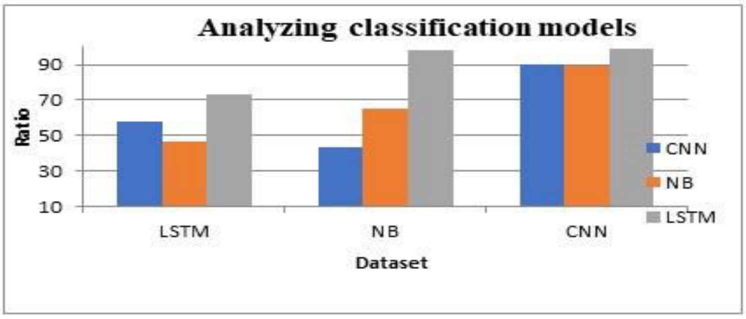

Fig .1. Analyzing the classical models %

Figure 1 shows that the analysis rate of the classic model LSTM is 90.5% and NB is 89%, while the analysis rate of the proposed LSTM method in this article is 99%. CNN has higher accuracy as compared to other existing models. Therefore, this method has a large data set and can easily identify mobile addiction substances.

A.Comparison of Accuracy with existing Methods:

We compare the accuracy of existing models with the proposed method, which examines the model's processing, understanding, and prediction ability. CNN and NB are existing models, and here is a proposed method called LSTM for comparison. The graph above shows the true positive accuracy observed from various techniques and different datasets, while the proposed implementation gives higher performance than other techniques.

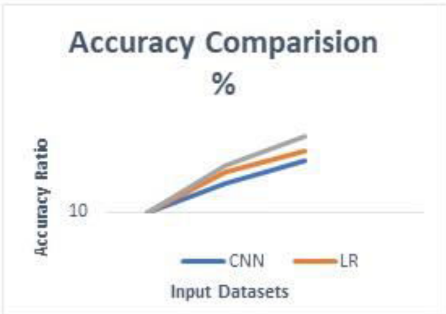

Fig .2. Accuracy Comparison in %

Figure 2 shows the precision of this method. The average is 67% for CNN and 78% for NB. In comparison, the proposed model LSTM 95%. Thus, the proposed model LSTM provides more accurate results compared to previous mobile addiction datasets methods.

B.Evaluating Time Complexity

Time intricacy is characterized as the time expected for a calculation to create an outcome in view of the length of the information. It estimates the time expected to handle the spice addiction distinguishing proof outcome at the hour of origination. Here, the time intricacy of the proposed model is assessed utilizing existing models CNN and NB. The assessment of the time issue is addressed graphically as follows.

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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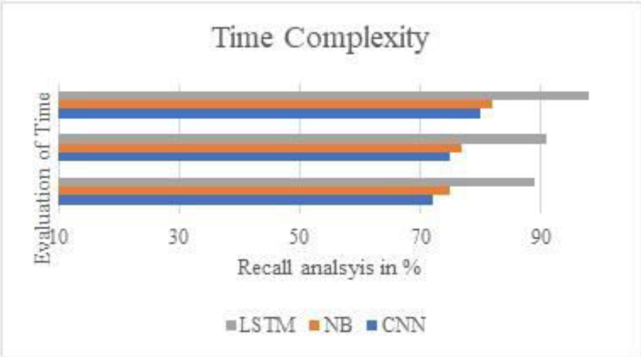

Fig .3. Recall analysis performance.

Figure 3 shows the timing calculation problem in s. Among them, CNN takes 80 s, NB takes 82 s, and the proposed LSTM method takes 98 s. The time complexity of the proposed model is excellent and the execution time remains the same irrespective of the input size. This is a necessary feature as long as you have enough memory and can handle the input size correctly.

C.Performance of herb Identification

The focus mechanism can improve the performance of herbal mobile identification model in complex scenes. It is important to analyze the specific ratio of the herbs. Hence, we compare the proposed method with existing methods such as CNN and NB. It is used to visualize the reasons for the model predictions and to create the mobile addiction analysis.

V. CONCLUSION

This is a limitation in this study as all possible number of epochs were not tested for and hyper parameter optimization to determine the hyper parameters for optimum better prediction performance due to limited computing. For future work, this study can be extended using the attention mechanism to bridge the gap between the data and text modalities by mapping the texts to specific data regions during word translation to lead to further increase in semantic correctness of the generated captions. Evaluation metrics able to compare reference and generated captions based on semantic meaning and not just based on n-gram matches can also be developed and adopted for more complete evaluation. Aiming to produce semantically richer data for mobile addiction prediction data, this study adopts a novel approach investigating to what extent a combination of data scene features and bidirectional in an encoder-decoder architecture can improve the semantic meaning of automatically generated data predict data. It is also found out that introducing scene features unidirectional LSTM inhibits the performance thus the need to improve model learning capacity by introducing the LSTM approach. As part of the outlined objectives, an approach framework is designed, and experiments are conducted using analyses dataset. The main finding of this study is the indication that the proposed approach using scene features and LSTM prediction improved the generated mobile addiction prediction as was evident from the results thereby answering the study question. This can be attributed to the ability of scene features to capture background context between the objects in the data. The use mobile addiction prediction of LSTM also impacted the results positively as they are able to take into consideration past and future.

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