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Deep Learning Mechanism for Pervasive Internet Addiction Prediction

Zon-Yin Shae
Department of Computer Science and Information Engineering
Asia University, Taichung, Taiwan
zshae1@gmail.com

Jeffrey J.P. Tsai
Department of Bioinformatics and Medical Engineering
Asia University
Taichung, Taiwan
jjptsai@gmail.com

Abstract—This paper outlines a visionary approach for Internet addiction prediction mechanism suitable for large scale population deployment. Internet addiction detection and treatment is traditionally an area of psychology research which focus on the Internet addition symptom detection and intervention by way of self-answer questionnaire design and psychologist interview that is not suitable for large scale population. This paper proposes a mechanism from the computer science AI deep learning aspect which evaluates the efficacy of the questionnaire and then transfer the questionnaire into the label data for deep learning model. By way of collecting the users' APP and web browsing behaviors as well as the bioinformatics data sets, AI model can be built not only for the detection, but also for prediction. An extensive discussion about the issues and open questions are also provided.

Keywords—*Internet addiction, Technology addiction, Internet addiction prediction, user web browsing behavior, user APP browsing behavior, bioinformatics, deep learning, AI*

I. Introduction

Internet addiction has become a pervasive problem not only among the adults, but also to the entire young generation during their education process due to the pervasive accessibility of the Internet technology. Currently, the Internet addiction researches mainly focus on the symptom detection and intervention. Moreover, the detection mechanisms are mainly using the self-answer questionnaire with psychologist interview which are not scalable for the large scale population. Prediction is always a better way to treat and prevent a medical problem. This paper outlines a vision of pervasive Internet addiction prediction mechanism using AI deep learning technology for analyzing the user web browsing and APP playing behaviors as well as their corresponding bioinformatics data.

Overuse the Internet technology has emerged as a crucial education and social issue of technology addiction. It will cause counter-effects, such as negative psychological problems, interpersonal relationships, fatigue caused by long-term use, and abnormal physical conditions. Internet addiction refers to individuals who continue to overuse Internet technology and products with various negative psychological behaviors, but cannot reduce or control their use. They even have emotional discomfort and withdrawal reactions when they are unable to use them. In 1996, the concept of Internet Addiction Disorder emerged for the first time [4]. Diagnostic and Statistical Manual for Mental Disorders (DSM-5) [9, 17] described that the individual had to experience a minimum of three of the following symptoms over the period of twelve months: tolerance, withdrawal, lack of control, relapse, large amounts of time spent online, negative consequences, and continuation of use irrespective of problem awareness [5, 9].

Internet addiction can be further categorized into 4 technology addictions: Internet addiction, game addiction [44], social website addiction and mobile phone addiction [45, 46]. For the rest of the paper, we refer all the 4 technology addictions as Internet addiction for the convenient purpose. In Internet addiction, the most worrying thing is the deviation of children's moral concepts and values. Users of any age and status can easily access the Internet for any contents including violent video games and pornographic websites. Accessing these resources on the Internet affects children's moral concepts and values, leading to problems in interpersonal, psychological, or physical problems, affecting children's education and future development.

Internet addiction is an important issue that must be dealt with in a timely manner [6, 7, 8, 47]. Approximately 47% of the developing and 87% of the developed world population is online at 2019 [10]. With 92% of Internet users in South Korea using high-speed Internet connections in comparison to 99% in the UK, and 86% in the USA [11, 12, 13]. Adult spent 144 minutes compared with US teens spent more than 7 hours on average per day on Internet on 2019 [14,15]. This suggests that young adults are the most active Internet users. South Korea and Mainland China reported that if patients develop Internet addiction, it will lead to withdrawal, such as emotional reactions when they cannot use technology products. Patients must spend more time using technology products to get the same stimulation [16]. Taiwanese college students are a high-risk group for Internet addiction. According to the statistics of first-year freshmen at Cheng Gong University, the rate of Internet addiction is 17.9% [17]; in addition, the results of students from 8 Universities in Taiwan also point out that Taiwan's college students have Internet addiction with the prevalence rate of 12.9% [18].

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Internet addiction detection is often complex. The Internet offers direct benefits to our society and our daily life, such as conduct research, perform business transactions, social communication, and relaxing in playing game. To isolate the daily life behaviors from the addicted behaviors become complicated. Detection methods for Internet addiction include self-answer questionnaire, psychologist interviews, mental illness diagnostic manuals, EEG brainwaves, fMRI functional magnetic resonance imaging, etc. [19]. Currently, self-answer questionnaire is the most widely used method. The researchers compile the questions to be studied into questionnaires, and tests the subjects to meet the needs of the research topic; however, the data designed and collected in these questionnaires often require the input of multiple psychological experts, then psychologists can conduct interviews to tell whether the test subjects show symptoms of Internet addiction.

There is no international gold standard for the self-answer questionnaires. There existed 21 different assessment instruments has been identified [5]. For examples, smartphone addiction, short version (SA-SV) [20], Chen Internet Addiction Scale (CIAS) [21], Internet Addiction Test (IAT) [1, 2, 3, 4], Internet gaming disorder questionnaire (IGDQ) [22, 23, 24], The 11th version of Barratt Impulsiveness Scale (BIS-11) [25, 26], Chinese Big Five Personality Inventory (CBF-PI) [27], Brief Self Control Scale (BSCS) [28], Self-assessment manikin (SAM) questionnaire [29], Mini International Neuropsychiatric Interview (MINI) [30], Padua Inventory [31], and Adult ADHD Self-Report Scale (ASRS) [32].

The most popular questionnaire is the Internet Addiction Test (IAT) which is developed by Dr. Kimberly Young [1,2,3,4]. It is designed to measure the presence and severity of Internet and technology dependency among adults. The IAT is the first validated [1] test to be used in mental health settings and schools. IAT consists of 20 questions of 5 scales each. The testers will be rated as addicted if the IAT test score is higher 70, possible addicted if 40-69, and not addicted if score is below 39. The criteria include the degree of preoccupation, compulsive use, behavioral problems, emotional changes, and impact on life related to Internet usage. In the Asia University, the psychology research team, led by Professor Huei-Chen Ko, had also developed their own set of questionnaire for the goal of its localized population and targeted studies (e.g., young students at various ages of schools). This paper will make use of the available questionnaire data from the Asia University psychology team. Note that our mechanism described in this paper can be also applied to various other questionnaires.

In a short period of time, takes into account the limit of the number of psychologists and the limitations of the questionnaire itself (for example: sample limit, social preference error, the limitation of the number of test questions, etc.), the self-answer questionnaire method cannot effectively screen out subjects with Internet addiction on a large scale.

Many difficult diseases, such as cancer, cardiovascular diseases, and mental illnesses, still cause heavy losses to society and many families. Early prevention and early medical intervention for underlying diseases will have the opportunity to greatly reduce morbidity and mortality. In recent years, the field of behavior and mental health benefits from advances in artificial intelligence. For example, computing methods that use artificial intelligence (AI) technology for learning, understanding, and reasoning. The AI technology has been used in the fields of behavioral and mental health care, including clinical decision-making, treatment, evaluation, self-care, medical care management and research which can help medical professionals in clinical decision-making, testing, diagnosis, and care management.

The current literatures on applying traditional machine learning on Internet addiction mostly in the area of data pre-processing and classification. For examples: (1) Naive Bayes, Support Vector Machine (SVM) and Radial Basis Function Neural Network (RBFN) are used to perform data preprocessing on the Smartphone addiction-short version (SA-SV) questionnaire to remove data noise, and is used to understand the impact of mobile phone addiction on the academic performance; A total of 222 Indian college students participated in the questionnaire. The survey questionnaire consisted of demographic information, internet access pattern and smartphone addiction pattern. The results find the correlation between smartphone addiction and academic performance [33]. (2) SVM, C-SVM, and ν-SVM are used to perform parameters optimization and classification to detect the degree of Internet addiction among Chinese college students. Dataset consisting of 2397 Chinese college students from the University are collected. The questionnaires included Brief Self Control Scale (BSCS), the 11th version of Barratt Impulsiveness Scale (BIS-11), Chinese Big Five Personality Inventory (CBF-PI) and Chen Internet Addiction Scale (CIAS). The best detection performance of Internet addiction is 96.32% which was obtained by C-SVM in the 6-feature dataset [34]. (3) Ioannidis et. al. recruited 1749 participants aged 18 and above via media advertisements in an Internet-based survey at two sites, one in the US, and one in South Africa; Utilized Lasso regression for the analysis. The analysis results show many types of online behavior (e.g. shopping, pornography, general surfing) bear a stronger relationship with maladaptive use of the internet than gaming [35]. (4) Mak, et. al., provides a systematic review of the applications of machine learning methods in addiction research, including substance addiction and non-substance Internet addiction. Results suggest that machine learning methods, particularly supervised learning are increasingly used in addiction psychiatry for informing medical decisions [36]. (5) Mi Jung Rho, et. al., identified a total of 511 participants to the problematic Internet game user group according to the *Diagnostic and Statistical Manual of Mental Disorders* Internet gaming disorder criteria. According to the CHAID algorithm, six important predictors for gaming addiction were found: gaming costs (50%), average weekday gaming time (23%), offline Internet gaming community meeting attendance (13%), average weekend and holiday gaming time (7%), marital status (4%), and self-perceptions of addiction to Internet game use (3%) [37]. (6) Singh, et. al., exploited the unique features of Bayesian Network to explore the influence of causal symptoms on the probability of occurrence of Internet Addiction Disorder (IAD). The model measured through six parameters of IAT (Salience, Excessive use, Neglect work, Anticipation, Lack of control, Neglect Social Life) [38]. (7) Problematic internet use was identified using the Internet Addiction Test (IAT). Konstantinos Ioannidis Using Logistic Regression and Naïve Bayes produced a classification prediction of problematic internet use was possible using specific measures of impulsivity and compulsivity in a population of volunteers [43].

Most of the researches on Internet addiction so far has focused on the development of questionnaire, the symptoms and causes, the treatment and medical intervention of Internet addiction. The early detection and prevention of Internet addiction are rarely discussed. The research on early detection of Internet addiction by digital technology is even rarer. At present, no research has proposed how to use deep learning technology to construct a personalized early warning mechanism of Internet addiction symptoms to detect early symptoms of Internet addiction.

The contribution of this research is to explore how to use deep learning technology to outline a visionary approach to construct a personalized early detection and warning mechanism of Internet addiction symptoms. Our project will conduct research on Internet addiction prediction from the perspective of computer science. In this project, we will study how to collect data and investigate the required technologies to derive from data the behavioral characteristics, physiological responses, and networking behavior of subjects with and without addiction. Feature characteristics such as time spent, frequency, changes in web and APP browsing behaviors, and the bioinformatics characteristics (blood pressure, heart rate, sleep pattern, etc.) will be captured. Guided by AI deep learning technology, a personalized early warning mechanism of Internet addiction symptoms will be constructed to detect early symptoms of Internet addiction and achieve early prevention on a large scale of population.

This paper is organized as follow. A system architecture of the Internet prediction is provided at section 2, in which the data sets required and the label data for model training will be described, followed by efficacy analysis of the questionnaire at section 3, in which an auto encoder is used evaluate the efficacy of the questionnaire under study. An extensive discussion will be provided at section 4.

II. System Architecture

The overall system architecture is shown in Figure 1. The data set we consider to collect including the users' web browsing behavior, APP usage behavior, bio sensor for the bioinformatics pattern, as well as the validated questionnaire functioned as the labelled data. The APP usage behavior can be collected and report from a customer designed APP. This approach is possible from the Android phone environment, but could be difficult from the IoS phone environment due to its security control. In the IoS phone environment, the customer designed APP will capture and analyze the screen shot to obtain user's APP usage behavior. Both IoS and Android APP usage pattern can be also captured and analyzed from the data traffic of wireless Internet access point or from the data log of data center of enterprise or University.

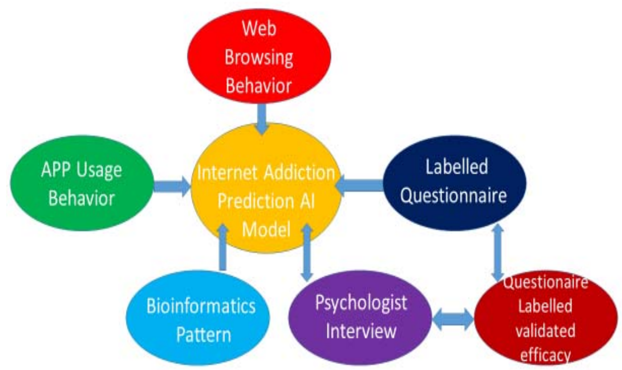

Figure 1: System Architecture

The Web browsing behavior can be obtained and analyzed from the data traffic of Internet access points. This will require a specially design access points resided in each household. From this Internet data traffic, we can detect the user's web browsing behavior, for examples, the top 10 URL or applications/games, at what time (midnight or regular hour), and how long to stay on each web site and application/game. Note that from the time duration alone, one can not tell the user's addiction tendency, since people rely on Internet for most of their regular work, search for information, and research. We will need to discosver special psychology features, e.g. eager, anxiety, etc. Face expression might be the most direct measurement for detecting these psychology features, but will have invaded person privacy. We will also collect and analyze the user's bioinformatics pattern by collecting the data generating from the bio sensors. For the first step, we will collect the bioinformation data (e.g., blood pressure, sleep pattern, living style, etc.) from electronic wrist watches [39, 40].

The data sets will be used for training a deep learning AI model for the Internet addiction detection and prediction. All AI supervised learning model need precise lableled data for model training. The accuarcy of the trained model wholly depends on the amount of training data and accuracy of the lablelled data. This is a traiditional delima of the AI deep learning since large amount of accurate labelled is really hard to come by in most of the cases. This project will provide a resoulation for this issue. First, we will make use unsupervised model to validate the efficacy of the questionaire (detailed in next section) based on psychologist interview. Then, make available this questionnaire to Internet web site to collect large amount of the questionaire responses from general population. We can then use this as the labelled data set to train the AI detection and prediction model. Note that, these questionnaire data set is generated from huam responses such that errors could happened. However, the GAN [41, 42, 43] approach has demonstarted that if the labelled data can be similar to the real data in characteristics, then GAN generated data trained resulting model can be even better than using the real data for training. We argue that since these questionnaire is valided by the psychologist such that it can have the similar correct characteristics labeling property. The final trainned model will need to be examed by the psychologist and fine tuning for improving its accuracy.

This mechanism will be pervasively available and can be applied for the large population since the system is all automatic. One can view that this system is very useful in screening the risk person out of the general poupulation which is currently not possible. The identifed high risk person then can be gone through the regualr psychologist interview process to confirm and get early treatment.

III. Efficacy of the Questionnaire

Given a set of Internet addiction questionnaire, one needs to study its validity from the psychologist point of view, for example, there has been validity study on the IAT questionnaire [1]. This paper is approaching from the computer science and AI technology point of view. We need to derive a set of creditable feature characteristics for a given data set. We will first investigate the efficacy of the questionnaire that is the power of separation of its questionnaire under study.

The current questionnaire data is obtained from our colleague of department of psychology of Asia University. This study recruited 9,112 students from elementary (2656), junior (4771) and senior high schools (1685). There are a total of 9 questions in the questionnaire described below: (it is a direct translation from the Chinese original version).

1. Although I am not using the Internet, I often think about going online or when I want to go online.
2. When I want to reduce or stop using the Internet, or when I cannot use the Internet, I feel restless, tantrums, irritable, angry, nervous or frustrated
3. In order to get the same excitement as in the past, I need to spend more time online or do more online activities
4. Although my family and teacher told me that I should reduce the time I use the Internet, I still cannot reduce it
5. In order to use the Internet, I give up or reduce the time I spend with my family and friends in real life, chatting, reading and doing homework or favorite activities in the past
6. I know that spending too much time on the Internet has many disadvantages (for example: lack of sleep, being late for class, spending too much money, arguing with others or neglecting important things), but I continue to use it
7. I have lied to my family, teachers, friends or other people without letting them know how long I actually use the Internet
8. I use the Internet to forget about my personal problems, to express uncomfortable feelings such as anxiety, helplessness or depression
9. Because of my excessive use of the Internet, my relationship with family and friends, work or academic performance deteriorated

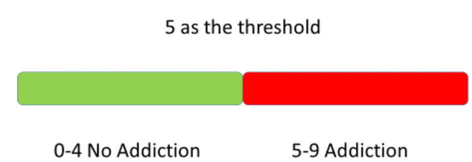

Figure 2: Labelling Scheme

After the test subjects have completed the questionnaire report, they will be divided into two groups, one is addicted and the other is not addicted, based on the score on the report. Each yes answer from each of the 9 questions will count as 1 point. If the total number of the points exceed or equal to 5, they will be labelled as addicted and will be classified into the addicted group. The labelling scheme is illustrated in Figure 2.

After data cleaning some incomplete data points, as a result, in elementary schools a total of 115 students are classified as addiction and 2,081 students without addiction; in junior high schools a total of 520 students as addiction and 3,528 students without addiction; in high school a total of 159 students as addiction and 1,308 people without addiction. A total of 794 students are classified as addiction and 6,917 students are not.

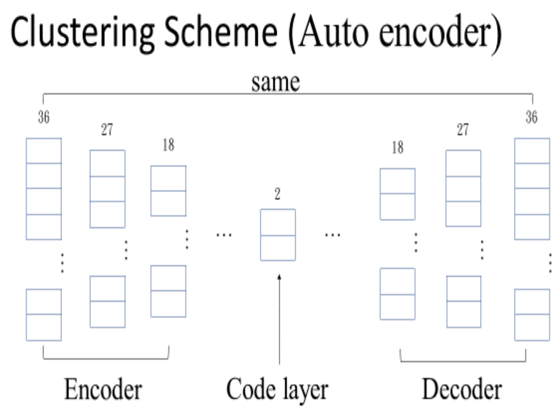

Figure 3: Unsupervised Model for Efficacy measurement

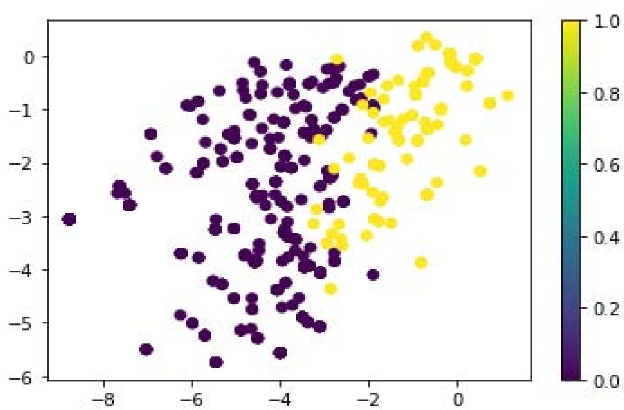

Figure 4: Questionaire Efficacy

Note that this is the classification results purely based on the questionnaire. We try to evaluate the efficacy of the separation power of the questionnaire using the AI deep learning technology. We design and build an unsupervised AI model that is able to visualize and measure the separation of the two groups only from the questionnaire data and not using the labelled data. We build an auto encoder AI model shown in Figure 3 for the task. It is well known that in order to get a good model training, the balance of the training data points in two groups are important. Currently, we have an unbalance addiction and not addition data set. We randomly sampling data points from the not addition data group to create a balance data for auto encoder training. The results are shown in Figure 4.

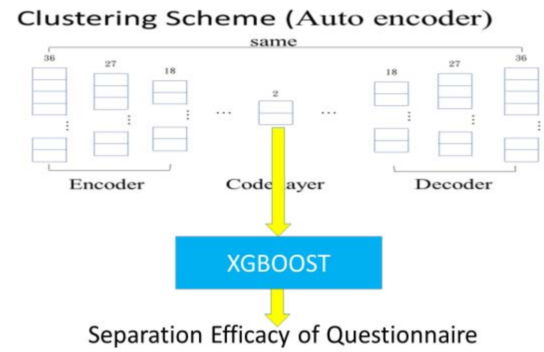

Figure 5: AI unsupercised model for Questionaire

The two groups of the data points can be separated clearly in the model to illustrate the efficacy of the questionnaire design. Given this high degree of power of separation efficacy, we easily design a supervised AI learning model (XGBOOST [48]) to achieve 100% accuracy in detecting the Internet addiction simply based on the questionnaire. The training system architecture is shown in Figure 5.

A validated efficacy questionnaire can be used much pervasively since one can make it available as a web page from Internet and people can access to report their own assessment. However, the correctness of the questionnaire data set is not always trustable. The questionnaire data is generated from human and can be most likely under personal factors: misunderstanding, viewed as a game and not serious, stress or bad mode of testing environments and scenarios. As such, the faithfulness of the reported value sometimes could be questionable due to human factors. As such, we should not solely rely on the questionnaire data for the Internet addiction detection and prediction. Nevertheless, validated questionnaire data can be used as one of the feature for detection and prediction purpose.

IV. Discussions

1. How to detect and measure the anxiety and eager and control? The Internet addiction has been defined as the individual had to experience a minimum of three of the following symptoms over the period of twelve months: tolerance, withdrawal, lack of control, relapse, large amounts of time spent online, negative consequences, and continuation of use irrespective of problem awareness. The large amount of time spent online is only one of the symptoms. It is a necessary condition, but not a sufficient condition for Internet addiction. The amount of the time spent online can be easily measured (e.g., APP and web browsing time), but the other 4 symptoms are related to the psychology factors, e.g., to measure the anxiety and eager and control. We propose in this paper to measure

and infer indirectly these symptoms by the bioinformatics data collected by biosensors. Moreover, build AI model to detect user's APP and web browsing behaviors, and then combine the bioinformatics data to detect the anxiety and eager and control for Internet addiction prediction.

2. If the questionnaire alone can be used to detect the Internet addiction accurately, since this questionnaire mechanism can be deployed and accessed pervasively, is the problem of the Internet addiction detection problem solved already? Some of the questionnaire has been officially validated, e.g., IAT. However, it is validated for the adult only and not for particular type of addiction, e.g., young students or game addiction. Currently, Internet addiction issues are more severe in the young students. If the problem can be detected earlier, the intervention can be more easily to apply and fix the issue. Further, the questionnaire is used only for the detection, that is, it is only to measure the current status, it cannot be used for the prediction of the Internet Addiction. Moreover, questionnaire is a users' initiative mechanism, that is, users' have to take the efforts to go to web site to answer the questionnaire. We propose in this paper is to automatically detect and predict the Internet addiction by automatically collecting the user's related data.
3. How is the AI model prediction accuracy using the questionnaire as the label data for training? It is well known that the AI model accuracy mainly depends on the large amount of training data and the accuracy of the labelled data. In the Internet addiction cases, both are hard to come by. We propose to make use the questionnaire mechanism to collect the large amount of the data as label data. Although we acknowledge that this label data mechanism cannot be fully precise. However, the great extent of psychologist research and knowledge is embedded in the questionnaire design. The AI GAN technology has been applied to the Amazon's unman store and other application use cases and achieve great success. It trains the object models based on the GAN generated objects, and not the real objects. The result shows the GAN generated objects can even build much better AI model due to its large amount of GAN generated data, even they are not exactly correct in look and feel, but with similar characteristics properties. We argue that the large amount of questionnaire generated data might not be entirely precise individually, but the characteristics property similarity from the psychologist knowledge should exist to train a good AI model of Internet addiction prediction.
4. What is the optimized threshold for the questionnaire? Our efficacy study uses 5 as the threshold for the separation of addiction and non-addiction. Although value 5 seems logical, but it is rather arbitrarily. Is there an optimal line of the decision remaining to be further investigated? Moreover, any question in the 9 questions carries more detection information than other questions in the addiction detection is another topic of research in the questionnaire design area.
5. Can the bioinformatics data reflect the psychological mind status? The APP playtime and the Internet browsing time itself cannot show too much of user's psychological mind status for Internet addiction. The APP data includes user's playtime, which APP, time of use (day time or night time), how much times, etc. which can be used to derive the model of user's APP browsing behavior. User browsing behavior can be more important in the AI modeling than the raw play time. Bio sensors, e.g., electronic wrist watch, can measure user's blood oxygen, heartbeat, blood pressure, sleep time, heart rate variability (HRV), etc. which can be more directly related to user's psychological status when using the APP, play games or browsing the Internet. By adding more users' bioinformatics data as the basis for AI model can improve the accuracy of detection and prediction. However, the privacy issues have to be seriously considered in the bioinformatics data collection. For example, the face expression data can be very useful, but requires the face photo captures which can raise the privacy considerations.
6. There are many open and hard questions in the Internet addition detection and prediction which deserve further investigations. For examples, Statistical Manual for Mental Disorders described that the individual had to under observation over the period of twelve months. Can the AI detection model dramatically reduce this observation period? Detection model is different from the prediction model. How much time ahead can we predict before the actual symptom appear? What is the feature vectors for the AI models for detection and prediction?

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