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Machine Learning Model for Predicting Insomnia Levels in Indian College Students

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***Abstract*— Insomnia is a widely prevalent sleep disorder that has an adverse effect on the lifestyle of millions across the world. This paper proposes a novel probabilistic approach to identify insomnia. The proposed technique makes use of the positive predictive values of the Insomnia Severity Index and Athens Insomnia Scale to provide a stochastic measure of the existence of insomnia in a college student. A machine learning model for prediction of these levels on the basis of the Depression, Anxiety and Stress levels and their Social Adjustment level has been developed. The dataset was created with 158 samples collected from students by conducting online surveys based on standardizes tests. A neural network model was developed to predict the probability of insomnia. The results predicted by the neural network were compared with their actual values, giving a RMSE value of 0.13, which is deemed viable. The important contributions of this paper are creation of a new dataset, analysis and a probabilistic modelling of insomnia scores which should provide a significant improvement to the current class-based approach of classification.**

Keywords— Insomnia. Probabilistic Modelling. Indian College Students. Artificial Neural Network. Survey-based testing.

I. Introduction

Insomnia is a sleep disorder that causes disturbance in a normal sleep pattern, resulting from the difficulties to fall sleep or to stay asleep. [1] The prevalence of insomnia in the population varies between 10 to 60%. It is associated with poor mental and medical health, and significant consequences. [2] Chronic insomnia is associated with a shorter life span, and it is a common early feature of certain neurological disorders like Parkinson's disease. [*3*] It affects the human body psychologically and physiologically.

Insomnia is associated with several mental health parameters like depression, anxiety, stress, and social adjustment. *[4-8]*.These disorders and issues are widely prevalent amongst the youth of today. In several studies conducted across the world, disturbing trends of widespread mental health disorders have been seen. As per a study conducted in India, [11] depressive symptoms were present in 18.5% of the population, anxiety in 24.4%, and stress in 20% of the population studied.

College students are associated with insomnia. As per studies, up to 60% of all college students suffer from a poor sleep quality, and 7.7% meet all criteria of an insomnia disorder. [9] Keeping this aspect in mind, and to improve as well as understand the mental health conditions of college students, the dataset was generated by information collected from college students.

This study aims at depicting the current existence of insomnia and mental health disorders amongst Indian college students. It develops a probabilistic model for the insomnia levels. This modelling will assist by automating the diagnosis process, as well as by associating a probability before the onset of the disease. This probability makes it easier for the common man to understand the implications of the disorder. Associating probabilities will allow an understanding of the population, provide a measure for risk, and can be used in the future to suggest measures to improve the situation.

A. Causes of Insomnia

Insomnia exhibits high levels of interdependency. It is affected by medical conditions, substances consumed, mental disorders, sleep disturbance, and other such events. [10] Thus, its exact cause is generally difficult to determine. Insomnia is a subjective clinical diagnosis. [11] Several studies have been performed to determine the causes. Insomnia has been related to age, gender, and to comorbidity with psychiatric conditions like depression. [12] It is associated with stress, mental health disorders, pre-existing hormonal or medical conditions, and vices like nicotine or caffeine. [13] Insomnia with a short-sleep duration is associated with physiological hyperarousal, cardiometabolic morbidity, neurocognitive impairment, and a persistent course. [14] While these studies show that insomnia can be related to mental health parameters, they do not quantify the defined relationship.

B. Insomnia and Mental Health

There is a strong association between mental health parameters and insomnia. Mental health parameters have been defined as subjective parameters, as they are measured with respect to an individual's associations with society. Due to their interdependencies, they are strongly related to the sleep disorder, insomnia. By using these subjective factors as inputs, the experience and mental health status of an individual is used to generate a probabilistic diagnosis for the occurrence of the disorder. Studies have shown that people with insomnia had greater depression and anxiety levels than people not having insomnia. [15] Chronic insomnia is a marker of anxiety and depression, [16] and stress negatively impacts sleep. [17] These bidirectional relationships [7] provided an impetus to study the prediction of one factor on the basis of the other.

C. Detection of Insomnia, Particularly on the Basis of Surveys

The methods used to determine insomnia are subjective perceptions of the patients. Additionally, the sleep of a patient is judged for a pre-determined time range. These time-ranges have not been standardized internationally yet. As a result, the categorization or diagnosis of insomnia uses a subjective method instead of an objective, mathematical, deterministic approach.

The research regarding the appropriate surveys to be used for developing a deterministic approach involved the works of earlier researchers. The Insomnia Severity Index is a reliable, clinically useful tool that can be used for an insomnia screening test. [18] The Athens Insomnia Scale additionally measures the intensity of the sleep related problems. [19].These surveys perform categorization based on the answers of the patients. They are still limited by the fact that there is no quantitative or continuous result. Prediction of insomnia is essential for its prevention. Using the known associated cognitive and metacognitive factors, a stepwise multiple regression model has been developed. [20] However, this is limited by the fact that it depends on a purely mathematical model, which is inherently incapable of learning. A mathematical model for the ISI test was developed, which mapped this score to the EuroQI-5D health utility score, using generalized linear models. [21] While this serves as an estimation for the result of the survey, it neglects the other factors associated with insomnia. It assumes that only the ISI is a proper representation of the person's sleep routine. This score is also a conversion of encoded information, and cannot provide an accurate description of the obtained results.

D. ANNs in the Study of Insomnia, and Mental Health

In order to introduce these imperative characteristics to the study of insomnia, the use of modelling is essential. Since, no mathematical relation has been discovered, but insomnia frequently occurs with mental health issues, artificial neural networks (ANNs) were used to develop a functional model. By using ANNs, the model is flexible, and constantly learning, thereby accounting for the diverse combinations of mental health statuses that exist in society.

Neural networks for determination of sleep stages have been created. [22,23] Quality of sleep has been studied on the basis of CNNs and deep learning methods. [24] As presented in the work by Aarthi Satyanarayana et al, deep learning could be used for categorization of sleep. However, this approach presented a binary classification of sleep, and did not present any significant relation with sleep disorders. Also, the deep learning model presented was a black box, and thus its measure for efficiency could not be established clearly.

Depression [25] and anxiety [26] can also be predicted using ANNs. The relationships between these mental health parameters and insomnia have not been studied using artificial intelligence. These studies are limited by their small, localized data set. It does not take into account any of the other existing large scale research values available. In the work presented, the results of extremely large scale research projects have been accommodated for while designing the model.

Using multivariate logistic regression, it was found that insomnia could be used as a marker for depression and anxiety. [8] This study excluded the patients that had high levels of anxiety, insomnia or depression, to induce underestimation. The data points used for comparison and relative determination of these values are several years apart.

Thus, while works have extensively studied the relationships between insomnia and mental health parameters, the stochastic prediction of insomnia has not been performed earlier.

E. Innovation of Current Paper

The innovation in this current paper is to convert this class-based categorization of insomnia into a continuous probabilistic equivalent. Using the existing dependencies, and standardized surveys, scores for the college students are collected. The positive predictive values from large-scale surveys are utilized to create the best-fit estimate, from which a mathematical function relating the survey score and probability of insomnia was derived. Using this probability as the required output, an ANN model was developed, which uses the scores from the DASS-21 and WSAS tests as inputs, and gives the probability of insomnia as the predicted output.

The rest of this paper is organized and reported as follows. Detailed description of the methodology and proposed method is given in section 2. Section 3 presents the results, and their detailed analysis. Section 4 deals with a comparative study of the current model, against the existing forms. Section 5 provides a brief conclusion, as well as the future scope of this research.

II. DATA ACQUISITION AND ANALYSIS

A. Developing Data Set

The constraints decided for the dataset were that they would belong to Indian college students. This was done as the challenges faced by college students have been observed to lead to mental health disorders and insomnia. Since this dataset was not available, the required surveys had to be conducted.

This dataset is important as it has not been created for Indian college students, as per prior publications. The availability of this dataset would allow a complete understanding of the actual existence of insomnia, as well as other disorders. This data is essential to perform any form of analysis about the current situation, or to take steps to improve these conditions. Additionally, the data collected was from reliable sources, and distributed across various fields of study and regions. This diverse dataset is currently a sample for the distribution of these disorders. An extended dataset can be developed to provide a complete understanding. The developed dataset can directly be used to improve basic research in the field, and extended at a later date.

In order to acquire this information, an online survey was used. This forms a relatively reliable method of acquiring information. Additionally, the entire design of the survey is designed to be from the patients' subjective and personal view of their current mental status. By performing these tests remotely, it ensures that the data obtained is not influenced. This survey contained the combined questionnaires for ISI, AIS, DASS and WSAS (explained in section 2.B).

The survey was completed by 158 students, from different educational streams. Students who have taken up the survey are pursuing their undergraduate degrees, and lie in the age range of 18 to 23 years. This data was initially collected as their responses to answers, and then converted to the mathematical equivalent by using the standard scoring schemes that have been issued for each of these tests.

Thus, for every individual participating in the survey, the three scores of the DASS, the WSAS scores, as well as the AIS and ISI scores were calculated. ISI and AIS were used for the design of the output parameters, while DASS and WSAS formed the input parameters for the model.

The DASS provides 3 scores, one for depression, one for anxiety and one for stress. The shortened version of this test having 21 questions was used. For each patient, the disorder level is classified as normal, mild, moderate, severe and extremely severe. The scores used as boundary values are determined on the basis of existing research and established international norms designed by the test creators [27]. In a similar fashion, the scores for WSAS were calculated. This categorizes the students into people with moderately severe or worse psychopathology, people with significant functional impairment, and subclinical populations [28].

For future subjects that would use the model, this combination of tests is convenient. It creates an effective self-supplied record, on the basis of 26 questions in total. (21 for the DASS 21 and 5 from the WSAS). Thus, the input will be simple to procure and utilize for future studies and models. The reliability of such online surveys has been investigated in further studies. As per their results, surveys form a reliable basis for the testing with sufficiently high sensitivity and specificity.

B. Feature Selection

All the surveys used were self-report questionnaires. These allowed the patient to provide their understanding of their current mental state, and self-assess the difficulties they face due to these conditions.

1) Insomnia Severity Index (ISI)

It is a 7-item questionnaire that assesses the nature and severity of insomnia. It records severity of sleep onset, sleep maintenance, and early morning awakening problems, sleep dissatisfaction, interference of sleep difficulties with daytime functioning, noticeability of sleep problems by others, and distress caused by the sleep difficulties [29]. Each problem is rated on a scale of 0 to 4, giving a maximum score of 28. The total score is interpreted as follows: absence of insomnia (0–7); sub-threshold insomnia (8–14); moderate insomnia (15–21); and severe insomnia (22–28). [30]

2) Athens Insomnia Scale (AIS)

This test is used for the quantification of sleep difficulty. It consists of eight items: the first five pertain to sleep induction, awakenings during the night, final awakening, total sleep duration, and sleep quality; while the last three refer to well-being, functioning capacity, and sleepiness during the day. [31]. Each question is evaluated on a scale of minimum 0 to maximum as 3, thus yielding a total score of 24.

3) Depression Anxiety and Stress Scale (DASS)

The DASS-21 is a set of three scales, designed to measure the extent of depression, anxiety and stress. Each scale consists of 7 items. Depression is tested on the basis of inertia, self-deprecation and devaluation of life. Anxiety is determined on the basis of situational anxiety, autonomic arousal, and a subjective experience. Stress can be evaluated based on difficulty in relaxing, being easily upset, irritable, impatient or over reactive. Each question is rated from 0 (did not apply to me) to 3 (applied to me very much or all the time).

Once the scores are obtained, they are doubled to make the scores out of a total of 42. This is important since most research has been done on the original 42-point scale. The categories for depression, anxiety and stress are then allotted on the basis of score ranges as shown in Table 1. [32]

TABLE I. CATERGORIZATION OF DASS 21 SCORES

	Depression	Anxiety	Stress
Normal	0-9	0-6	0-10
Mild	10-12	7-9	11-18
Moderate	13-20	10-14	19-26
Severe	21-27	15-19	27-34
Extremely Severe	28-42	20-42	35-42

4) Work and Social Adjustment Scale (WSAS)

This test is used as a measure of impaired functioning. Since this is a frequently correlated factor with insomnia, it was taken into consideration. It consists of 5 questions, rated on a 0 (no impairment) to 8 (very severe impairment) scale [33]. A score above 20 is for people with moderately severe or worse psychopathology, in the range of 10-20 is for people with significant functional impairment, and below 10 represents subclinical populations. [28]

C. Analysis of Survey Results

The mean age of students observed was 19.9±1.169. The distribution of students included 76.8% from engineering backgrounds, 9.1% from medicine and dentistry, 7.3% from business, and the rest from other fields.

The distribution of college students as per their ISI scores revealed that 40.88% did not show clinical insomnia, while the others showed varying degrees. The distribution of the ISI scores is shown in figure 1.

Since the AIS merely categorizes the individuals into those having insomnia or not having insomnia, the distribution for this test was not graphically constructed. However, the mean score obtained was 8.06±4.14. Using 6 as the cut-off score, 71.69% of the participants were categorized as having insomnia. Thus, ISI and AIS showed considerable difference in the categorization and mathematical models from both of these tests were considered while finally categorizing the students.

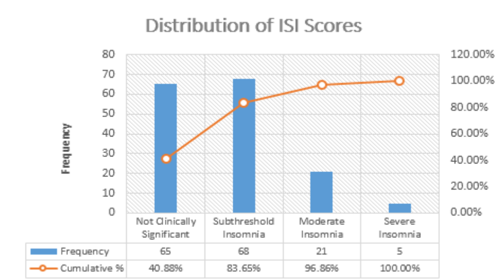

Figure 1: Distribution of Insomnia by ISI

The distribution of the depression, anxiety, stress, and work and social adjustment scores are shown in Figure 2. A discussion for the categorization of the scores is found in section 3.C. For the DASS, a summary is found in Table 2. This distribution of input parameters and categorization of students helped to understand how these parameters are affecting them. In this study, the pre-determined categorizations have not been used while developing the mathematical models and the prediction model. The absolute scores of the tests were used as inputs to the model as each of these surveys have been carefully developed and studied by earlier researchers. Also, this would allow for a continuous variation of the data, which would make a stochastic estimation of the output values effective. It makes the input data comparatively less sparse, increases variability at the input, and is expected to make the developed model more robust to external environmental influences.

III. Probabilistic Modelling

A. *Positive Predictive Values*

Positive predictive values are a representation of the probability that the disease is present when the test result it positive. [34]

Thus, if a person has a score of zero, then the probability that they have the disease is also zero. If the score is the maximum possible (28 for ISI and 24 for the AIS), then the probability that they have the disease in this case is one. For an intermediate case, if the positive predictive value for score 'x' is given as 'y', then the probability that the person has insomnia for that score is given by the value of 'y'.

The main limitation to the usage of this estimator is that it is dependent on the prevalence of the disease in the region. However, since insomnia may be present and simply not diagnosed, and by using high amounts of input data, the positive predictive values are used as estimators for the same.

The positive predictive values were originally calculated using the formula represented in equation 1. These have been calculated for a particular cut off score, and hence can be used as a representative for the probabilities of insomnia at this particular score.

$$Positive\ Predictive\ Value = \frac{True\ Positive + False\ Positive}{True\ Positive}$$

From existing research papers, [35-39] the positive predictor values were collected. It was assumed that the minimum score represents no insomnia, i.e. probability of insomnia as 0, and a maximum score (28 for ISI, 24 for AIS) represents that the patient definitely has insomnia i.e. probability is one.

A polynomial function was fit onto the graph obtained. The equation of the curve would then represent the probability of the patient having insomnia on the basis of their ISI and AIS scores. It also allows for approximation for the scores that do not have corresponding positive predictive values.

B. *Graphical Modelling*

A polynomial function was then fit to the values obtained. This is shown for ISI in Figure 2.

While constructing the polynomial graph, the average regions were considered. This is to ensure that the probability is not skewed towards the result of any one particular test. In order to decrease the dependence on the population, only papers having large sample sizes were considered while obtaining the positive predictive values. Additionally, all values of the function were restricted between 0 and 1 in the result, as this represents a probabilistic model.

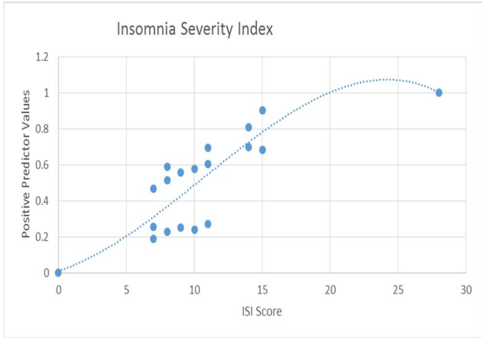

Figure 2: Probability of Insomnia by ISI

This fitting of the polynomial curve generated an equation which was indicative of the student having insomnia. The ISI score was given as an input 'x' to the equation, and the corresponding values of 'y' were calculated.

$$y = -0.0001x^3 + 0.0035x^2 + 0.0238x + 0.012 \ldots\ldots (2)$$

The graph was fit to the given data with an R-squared value of 0.7067.

A parallel model for AIS was drawn. (Shown in Figure 3) [40-43]

This fitting of the polynomial resulted in equation 3, and resulted in an R-squared value of 0.4895

$$y = -1E - 05x^3 - 0.0009x^2 + 0.0681x + 0.047 \ldots\ldots (3)$$

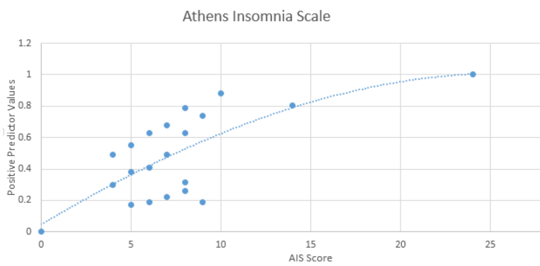

Figure 3: Probability of Insomnia by AIS

The fitting of the graphs was done by using polynomial-fitting software, and then by deciding the visually best-fitting polynomial. This approach may be further optimized by using mathematical model building. However, the fitting of data should not be made optimal. Each point of the plot represents one resultant positive predictive value of one of the tests. This means, that using the points from a single study would make the model localized to that specific study only. All the studies used for the generation of the plot points have a large data set. They have been created with data from various countries. By using such a vast store of input information for the estimation of the positive predictive values, it is ensured that the resulting polynomial is as general as possible.

This resulted in a function that determined the probability of the patient having insomnia for both the ISI and AIS test. These values were averaged, and used as the expected output values for the model. This value considered as the probability of the individual having insomnia.

C. Neural Network Model for Insomnia Prediction

A sequential model was created in Keras. It consists of three major layers: the input layer with 4 neurons, and the ReLU activation function, a hidden layer of 2 neurons, using linear activation, and a single-neuron output layer, which also uses the linear activation. The loss function to be minimized was set as the mean squared error, and Adam was selected as the required optimizer.

The dataset was split 75-25 for training and testing. A supervised model was developed using the Keras package in Python. Once the inputs and outputs were prepared, they were imported into Python as a data frame. As discussed in section 2.1, the results of the DASS and WSAS formed the input parameters for the neurons, which the averaged probability from the ISI and AIS estimated the required output value.

Optimization was performed to allow for smaller differences between the results, so that they may be used for diagnostic purposes. Additionally, this choice of architecture would allow the neural network to converge to optimum weights quickly, even when the size of the dataset is increased.

The architecture of the model used is shown in Figure 4. It indicates the change in dimensionality as data moves through the network, and thus enables the estimation of the probability of a student having insomnia on the basis of the associated factors.

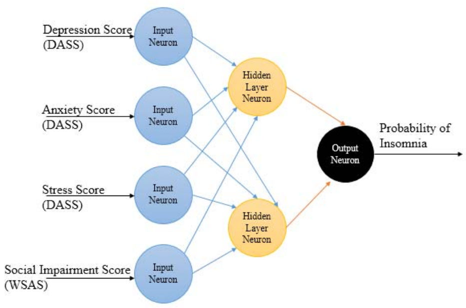

Figure 4: Architecture of the Neural Network Model Used

IV. RESULTS AND DISCUSSION

For validation, the model was run on testing data, and results obtained were recorded. The MSE and RMSE values for the same were calculated. This testing returned an RMSE value of 0.1309. Thus, the developed neural network returned viable results for prediction.

The distribution of the actual and predicted values is shown in figure 5.

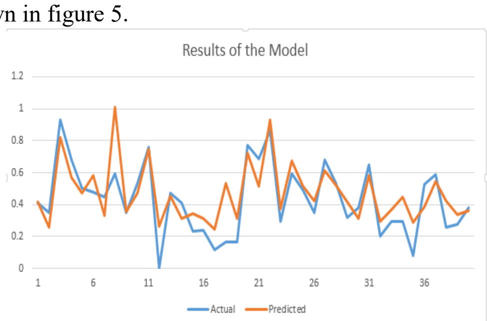

Figure 5: Distribution of Actual and Predicted Values

In places where the graph is showing high disparity, the predicted value is much higher than the actual value. This refers to the individuals who show signs of mental distress, but not of insomnia. In this case, the network seems to predict that they may develop insomnia. It merely acts as a warning sign for the individual. Additionally, the cut-off positive predictive values were experimentally supplied for more values in the lower end of the score spectrum. As a result, the polynomial fit expects a continuous variation in the data for higher scores, which may not be true for the population that is being studied.

These results show that a viable neural network has been developed. This provides an impetus for research, and also suggests that similar methods can be used to predict insomnia. However, clinical validation of this methodology is yet to be completed. Additionally, the study is restricted due to its limited sample size. Although the results are positive, there is scope for improvement of the model, and thereby its applications.

The benefits of this model lie primarily in the fact that it converts an abstract set of classes into a continuous form. This makes it easier for the patients to understand their diagnosis, and for doctors to estimate the probability of progression of the disease. Additionally, by converting the scores generated by these surveys to a mathematical model, it makes it easier for researchers to analyze their results and improve predictions. The relationships between the mental health status of an individual and their probability of insomnia has been modelled, showing that the high correlation between these two features can be used for diagnosis. By modelling one in terms of the other, the causative factors of these disorders may be studied in further detail.

V. CONCLUSION AND FUTURE SCOPE

This paper has presented the development of a basic ANN model for the prediction of insomnia on the basis of depression, anxiety, stress and the social adjustment of an individual. It proposes a novel probabilistic model for insomnia, returning a probability of a person having insomnia on the basis of their survey results and the existing positive predictive values.

The designed ANN had a sufficiently low RMSE, which is indicative of the fact that this neural network is viable. With an increased sample size, the flexible nature of the network will allow it to keep learning. Thus, the model can accommodate for advancements in society and in trends.

Prediction of insomnia, and assigning a probability of having insomnia plays an essential role in creating awareness amongst people. Developing a thorough understanding of the interrelations of insomnia and mental health parameters would allow further research as well as remedies for this field.

Insomnia shows a clear relation with mental health. On this basis, it is expected that there is a strong correlation between insomnia and the generated signals in the brain of any afflicted individual. Further studies can be conducted using EEG values for insomnia patients, studying their prediction of these probability values, and the interdependencies with the various mental health parameters.

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