HAPPINESS IN METHOD OF LEARNING PREDICTOR WITH FUSION OF VARIOUS ML ALGORITHMS IN POST COVID SITUATION SCHOOL BOARD EXAM STUDENTS

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ABSTRACT

Covid 19's youngsters are feeling insecure and uneasy during the Pandemic. The most serious source of concern is that, due to the Corona outbreak, students were compelled to attend their classes online and then take their board examinations in person. Use machine learning models to collect data from students once a week to boost student happiness. The youngsters will report information regarding their whereabouts, smartphone usage, and behavioural responses once a week. The model can tell the difference between students who are happy and those who are sad. Depressed students are given extra attention to help them cope with the exam. We looked at a few different machine learning models and discovered that the average categorization accuracy is around 80%.

Keywords: Students, Board Exams, Health, Happiness, Machine learning

INTRODUCTION

Due of the fear of face-to-face tests, depression is common among school-aged board exam students. As a result, it's critical to comprehend the components that influence depression resistance. Overall wellbeing, which includes elements like self-reported happiness, social support, and work engagement, has been found to relate to an individual's resiliency and ability to bear stressful life events without becoming sad in a body of studies. Depression is influenced by physiological causes as well. Numerous studies have found a link between sleep disorders and depression , and physical health is highly linked to depression and happiness.

By examining the interaction between characteristics including sleep, social and physical activity, stress, and happiness, this study increases our understanding of the role of affect in resiliency and wellness. In an ideal world, we'd look at the things that have a positive and negative impact on an individual's overall well-being. We rely on self-reported measures of wellbeing, such as stress, health, and happiness, because wellbeing cannot be evaluated directly. We will focus heavily on happiness because self-reported happiness is strongly correlated with depression measures [6], so we can not only discover factors that contribute to happiness, but also use machine learning methods to build a system that can automatically detect when a college student is becoming vulnerable to depression.

This approach could be used to direct prompt interventions, preventing serious depressionrelated effects such as suicide. We look at a variety of data sources to help us in our investigation: Questions about academic activities, sleep, drug and alcohol usage, and exercise were asked in the survey. Data from phones, including phone calls, SMS, and usage trends Data on location: logged coordinates throughout the day In this study, we will design a machine learning algorithm to distinguish between happy and unhappy college students, analyse which metrics provide the most information about happiness, and evaluate the relationship between happiness, health, energy, alertness, and stress.

DATASET PREPERATION

The information was gathered from a variety of school-aged youngsters in Kumbakonam and the surrounding area. We bypassed the data cleaning phase and went straight to preprocessing because the data was clean, with no missing rows or characteristics. Happiness was chosen as our dependent variable, with the other variables serving as predictors.

HAPINESS MEASURE

Participants self-reported on five factors relating to wellbeing twice a day: stress, health, energy, alertness, and happiness. Although we'd like to be able to forecast overall happiness, the question of how to develop a ground-truth happiness measure from these scales remains unanswered. One instinct might be to create a composite measure from a few of the relevant scales, such as the ratio of happiness to stress.A extremely happy and highly stressed condition, on the other hand, would be treated as similar to a low happiness and low stress state in this schema. Happiness has the strongest association coefficients, implying that focusing our forecasts solely on Happiness would provide the most insight into the other scales. We're also particularly interested in happiness, as it has been linked to depression.

MACHINE LEARNING METHODS

Happiness is the most important factor based on the data collected, so it will be used as the target variable. The data is divided into two groups: happy and sad. The happy category will be reviewed on a regular basis, and the conversion of depression to happiness will be prioritised.





A various ML algorithms are used to check the categorization of splitting such as NB and KNN. Out of which Naïve Bayes gives a very good result in splitting the data into happiness and depressed state.

NAÏVE BAYES

It's a classification method that uses Bayes' Theorem and assumes predictor independence. A Naive Bayes classifier, to put it simply, assumes that the presence of one feature in a class is unrelated to the presence of any other feature. If a fruit is red, round, and roughly 3 inches in diameter, it is believed to be an apple. Even if these characteristics are reliant on one another or on the presence of other characteristics, each of them contributes to the likelihood that this fruit is an apple, which is why it is called 'Naive.' The Naive Bayes model is simple to construct and is especially useful when dealing with huge datasets. Naive Bayes is renowned to outperform even the most complex classification systems, owing to its simplicity. The Bayes theorem allows you to calculate the posterior probability P(c|x) from P(c), P(x), and P(x|c) using P(c), P(x), and P(x|c). Examine the following formula:



$$P(c \mid \mathbf{X}) = P(x_1 \mid c) \times P(x_2 \mid c) \times \dots \times P(x_n \mid c) \times P(c)$$

Above,

- P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes).
- P(c) is the prior probability of class.

• P(x|c) is the likelihood which is the probability of predictor given class.

• P(x) is the prior probability of predictor.

When comparing the aforementioned results to Knn, we discovered that Nave bayes provides a higher level of accuracy. These are the stepladders we've planned to incorporate into our data mining environment and data sets.

1. Gather and evaluate the information.

2. Select relevant data and use a fuzzy set to manipulate it.

3. Train the desired algorithm on a condensed data set by removing attributes that turn out to be uninformative in the data collection and visualisation.

- 4. Using the most helpful data determined in step 4, create an ideal data set for each programme.
- 5. Make an educated guess about the outcome.
- 6. The data set should be randomised.

7. Calculate and compare findings, as well as the performance of algorithms.

RESULTS AND DISCUSSION



Figure 2 Result Comparison of NB and KNN

The results of Naïve bayes and KNN are compared with different number of students each time Naïve Bayes shows good results when compared with KNN.

CONCLUSION

The proposed technique splits the student into two category and the students who are in depression are taken special care so that they don't fall in the stress level. The students who are happy can concentrate on their exams. The Proposed method Naïve Bayes gives around an average of 80% of accurate results.

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