ONLINE ASSESSMENT OF MENTAL HEALTH MICROMEDIA FOR COLLEGE STUDENTS INCORPORATING BAYESIAN NETWORK ALGORITHM

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SUMMARY

Mental health issues among college students are a growing concern, necessitating effective assessment methods to identify individuals at risk and provide timely interventions. In this paper, we propose and evaluate several computational models for mental health assessment based on demographic, academic, and psychological factors. Hence, this paper implemented the Probabilistic Deep Belief Bayesian Network (PDBBN) to classify students' mental health attributes. The proposed PDBBN network computes the probabilistic value of the mental health assessment of the students. With the estimation of the probabilistic model, the extracted features are applied in the Deep Belief Bayesian Network for the classification of student mental health with the Macromedia analysis in college students. The classification is performed with the consideration of information on gender, age, academic performance, social support scores, and self-reported levels of stress, anxiety, and depression, and each model across multiple epochs. Simulation is conducted in comparison with the proposed PDBBN model with the Convolutional Neural Network (CNN), and Deep Neural Network (DNN) models. The results indicate that PDBBN consistently outperforms CNN and DNN in terms of classification accuracy, precision, recall, and F1 score. The simulation analysis of results stated that the proposed PDBBN model achieves a higher classification accuracy of 0.98 which is significantly higher than the CNN and DNN models. Additionally, the proposed PDBBN model expressed that mental health of the students significantly impacts in the academic performance of the students.

KEYWORDS

Mental health, Probabilistic model, Deep learning, Bayesian network, Online assessment, Classification

NOMENCLATURE

CNN	Convolutional Neural Network
PDBBN	Probabilistic Deep Belief Bayesian Network
DNN	Deep Neural Networks

1. INTRODUCTION

The mental health of students is an increasingly pressing concern in today's educational landscape [1]. As young individuals navigate the complexities of academic demands, social pressures, and personal development, their mental well-being can be significantly impacted. Factors such as academic stress, social isolation, financial burdens, and the prevalence of mental health disorders contribute to the challenges students face [2]. Recognizing the importance of mental health in academic success and overall well-being, educators, parents, and policymakers are increasingly emphasizing the need for comprehensive support systems within educational institutions [3]. By fostering environments that prioritize mental health awareness, destigmatize seeking help, and provide access to resources and interventions, we can better support students in their academic pursuits and holistic development [4]. This introductory understanding sets the stage for exploring the multifaceted aspects of student mental health and the strategies aimed at promoting positive outcomes.

In today's fast-paced digital age, the mental health of students has become a topic of increasing concern, exacerbated by the pervasive influence of micromedia [5]. Micromedia, consisting of bite-sized content disseminated through various online platforms such as social media, messaging apps, and news aggregators, has transformed how students interact, consume information, and perceive themselves and the world around them [6]. While micromedia offers unprecedented connectivity and access to information, it also introduces unique challenges to mental well-being [7]. The constant stream of curated images, filtered narratives, and instant feedback can fuel feelings of inadequacy, comparison, and social pressure among students. Moreover, the viral nature of micromedia can amplify the spread of misinformation, contributing to heightened anxiety and uncertainty [8]. Understanding the intersection of micromedia and student mental health is crucial in developing effective strategies to promote digital literacy, resilience, and healthy online behaviors [9]. By acknowledging the impact of micromedia on students' psychological well-being, educators, parents, and policymakers can work collaboratively to foster environments that support informed, balanced engagement with digital media while prioritizing mental health and emotional resilience [10].

In the era of deep learning networks, the mental health of students has emerged as a critical area of concern, especially within the context of their interaction with micromedia [11]. Deep learning networks, powered by complex algorithms and vast datasets, drive the personalized content recommendations and targeted advertisements that permeate micromedia platforms [12]. These platforms, characterized by their bite-sized content and rapid dissemination, wield significant influence over how students perceive themselves, their peers, and the world at large [13]. However, the incessant exposure to curated narratives, filtered images, and instant feedback within micromedia ecosystems can profoundly impact students' mental well-being [14]. The pressure to conform to idealized standards, the fear of missing out, and the constant comparison fostered by these platforms can exacerbate feelings of inadequacy, loneliness, and anxiety among students. Moreover, the rapid spread of misinformation and sensationalized content within micromedia spaces can further contribute to heightened stress and confusion [15]. As we navigate the complex interplay between deep learning networks, micromedia, and student mental health, it becomes imperative to develop strategies that promote digital literacy, critical thinking, and emotional resilience [16]. By fostering a culture of mindful engagement with micromedia and harnessing the power of deep learning for positive reinforcement and support, cultivate environments that prioritize the holistic well-being of students in the digital age [17].

The contribution of this paper lies in several key areas within the field of mental health assessment among college students:

1. The introduce and evaluate multiple computational models, including Probabilistic Deep Belief Bayesian Network (PDBBN), Convolutional Neural Network (CNN), and Deep Neural Network (DNN), for mental health assessment. These models represent innovative approaches to leveraging machine learning and deep learning techniques for identifying individuals' mental health states.
2. Through rigorous experimentation and evaluation, we provide a comprehensive comparison of the performance of these computational models. Specifically, we assess their classification accuracy, precision, recall, and F1-score, offering insights into their relative effectiveness in accurately identifying students at risk of mental health issues.
3. Our study highlights the superiority of PDBBN over conventional deep learning models like CNN and DNN. PDBBN's probabilistic graphical modeling approach enables it to capture complex relationships within the data, leading to more accurate predictions of mental health attributes.
4. By accurately identifying students' mental health states based on demographic, academic, and psychological factors, our research provides valuable insights for guiding personalized interventions and support measures. This can inform targeted strategies to promote student well-being and address mental health issues in educational settings.

The contribution of this paper lies in advancing the field of mental health assessment among college students through the exploration of novel computational approaches and the generation of insights for informing personalized interventions and support measures.

2. MENTAL HEALTH OF COLLEGE STUDENTS

The mental health of college students is a topic of increasing concern as young adults navigate the challenges of higher education. Transitioning to college often brings about significant changes in lifestyle, academic expectations, and social dynamics, which can impact students' psychological well-being. Academic stress, pressure to succeed, financial worries, and the demands of balancing coursework with extracurricular activities can all contribute to heightened levels of anxiety, depression, and other mental health issues among college students. Additionally, factors such as homesickness, social isolation, and difficulties in forming meaningful connections can further exacerbate these challenges. Recognizing the importance of addressing mental health concerns among college students, universities and colleges are increasingly implementing support services, counseling resources, and mental health awareness programs. By fostering a campus culture that prioritizes mental wellness and destigmatizes seeking help, institutions can better support students in their academic pursuits and overall personal development. Moreover, promoting open dialogue and providing accessible resources can empower college students to proactively manage their mental health and thrive during their collegiate years. The mental health of college students is a multifaceted issue that warrants comprehensive attention and support. One of the significant stressors for college students is the academic pressure they face. The transition from high school to college often comes with heightened academic expectations, rigorous coursework, and increased competition, all of which can contribute to elevated levels of stress and anxiety. Students may feel overwhelmed by the demands of maintaining high grades, meeting deadlines, and balancing academic responsibilities with other aspects of their lives. Furthermore, financial concerns add another layer of stress for many college students. Tuition fees, textbooks, housing expenses, and other financial obligations can create significant burdens, especially for those from low-income backgrounds or facing student loan debt. Financial worries can lead to heightened anxiety and impact students' ability to focus on their studies and engage fully in the college experience. The statistics of the college student mental health is illustrated in figure 1 and factors involved in mental health of students are presented in figure 2.

Social factors also play a crucial role in the mental health of college students. Many students experience feelings of homesickness or loneliness, particularly if they are attending college far from home or struggling to form meaningful connections with peers. Social isolation can exacerbate feelings of depression and anxiety, making it challenging for students to thrive academically and emotionally. Moreover, the stigma surrounding mental health issues can

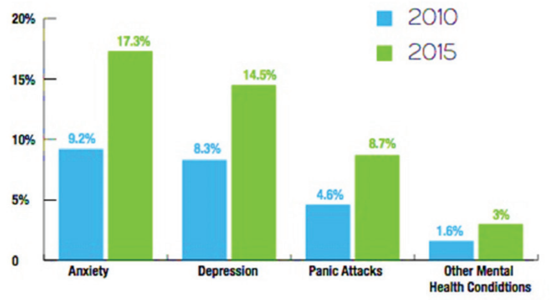

Figure 1. Statistic of student mental health (Source: College parents of America)

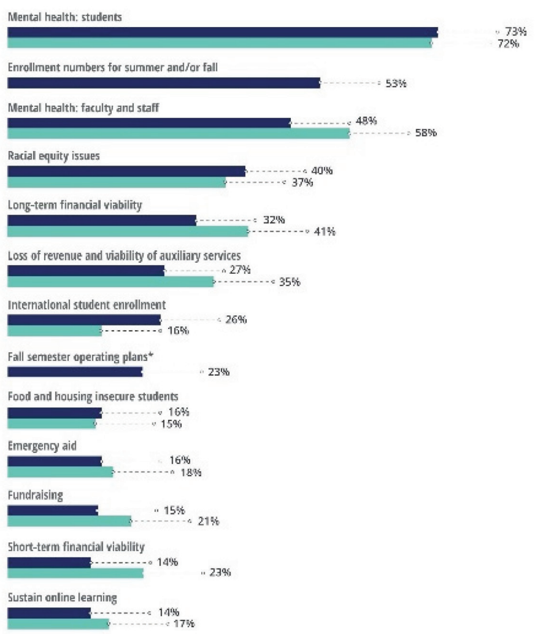

Figure 2. Mental factors involved in mental health of students (Source: College parents of America)

prevent students from seeking help when they need it most. Fear of judgment or discrimination may deter students from accessing counseling services or reaching out to peers for support. It's essential for colleges and universities to actively combat this stigma by promoting open dialogue about mental health, providing education about available resources, and creating supportive environments where students feel comfortable seeking help without fear of judgment. In response to these challenges, many colleges and universities have begun implementing various initiatives to support the mental health of their students. This includes offering counseling services, establishing peer support groups, organizing mental health awareness campaigns, and providing resources for stress management and self-care. By prioritizing mental wellness and fostering a supportive campus culture, colleges can help students navigate the academic, financial, and social pressures of college life while promoting their overall well-being. The specific challenges that college students face in terms of mental health and the ways in which institutions can provide support.

College academics often involve a significant increase in workload and complexity compared to high school. Students may struggle with time management, adapting to new learning styles, or feeling overwhelmed by the volume of material they are expected to master. Faculty and staff can support students by providing resources for academic success, such as study skills workshops, tutoring services, and time management tools. Additionally, offering flexible course options and promoting a growth mindset can help alleviate some of the pressure students feel to excel academically. The rising cost of tuition, textbooks, and living expenses can lead to financial strain for many college students. Some students may need to work part-time jobs or take out loans to afford their education, adding additional stressors to their already busy schedules. Colleges can assist students by offering financial aid counseling, scholarships, and emergency funds for students facing unexpected financial hardships. Creating affordable housing options and providing access to affordable meal plans can also help alleviate financial stress for students.

College can be a time of significant transition, especially for students who are attending school far from home or who have difficulty forming social connections. Feelings of isolation and loneliness can contribute to mental health issues such as depression and anxiety. Colleges can promote social integration by offering orientation programs, hosting social events, and providing opportunities for students to join clubs and organizations that align with their interests. Additionally, creating inclusive campus environments where students from diverse backgrounds feel welcome and supported can help foster a sense of belonging and community. Despite growing awareness of mental health issues, stigma still persists, which can prevent students from seeking help when they need it. Colleges can combat stigma by providing education and training on mental health awareness, promoting self-care and stress management strategies, and offering confidential counseling services that are easily accessible to students. Normalizing conversations about mental health and encouraging help-seeking behaviors can help reduce stigma and encourage students to seek the support they need to thrive. By addressing these challenges and providing comprehensive support services, colleges and universities can play a vital role in promoting the mental health and well-being of their students. Creating a campus culture that prioritizes mental wellness and provides resources for support can help students navigate the challenges of college life more effectively and ultimately succeed academically, personally, and professionally.

3. BAYESIAN NETWORK MICROMEDIA MENTAL HEALTH ASSESSMENT THROUGH MICROMEDIA

Assessing mental health through Bayesian networks in the context of micromedia involves modeling the relationship between various factors such as social media usage patterns, content consumption, and mental health indicators. Bayesian networks provide a probabilistic framework for representing and reasoning about uncertain relationships between variables. In this scenario, we'll outline a simplified Bayesian network for mental health assessment through micromedia, along with its derivation and equations.

Micromedia Usage Patterns (X): This variable represents the usage patterns of individuals on micromedia platforms, including factors such as frequency of use, types of content consumed, interaction patterns, etc.

Content Consumption (C): This variable denotes the type of content individuals are exposed to on micromedia platforms, including positive or negative news, social interactions, educational content, etc.

Mental Health Indicators (M): This variable represents indicators of mental health status, such as stress levels,

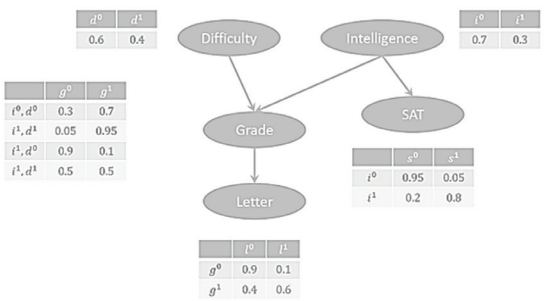

Figure 3. Bayesian network for the PDBBN

depression symptoms, anxiety levels, etc. The relationship between these variables using a Bayesian network as follows as shown in figure 3.

The conditional probability distribution for each variable in the Bayesian network can be derived from data or expert knowledge. P(X) represents the prior probability distribution of micromedia usage patterns, which can be derived from demographic data or surveys. P(C|X) represents the likelihood of content consumption given micromedia usage patterns. It can be derived from data on the types of content typically consumed by users with specific usage patterns. P(M|C) represents the likelihood of mental health indicators given content consumption. It can be derived from studies or surveys correlating content consumption with mental health outcomes.

The Bayes' rule, the joint probability distribution of the variables stated in equation (1)

$$P(X,C,M) = P(X) * P(C|X) * P(M|C) \qquad (1)$$

Probability of Mental Health Status given Micromedia Usage Patterns equation (2)

$$P(M|X) = \sum\sum P(M|C) * P(C|X) * P(X) \qquad (2)$$

Probability of Micromedia Usage Patterns given Mental Health Status in equation (3)

$$P(X|M) = \sum\sum P(X) * P(C|X) * P(M|C) \qquad (3)$$

Assessing mental health through Bayesian networks in the context of micromedia involves constructing a probabilistic model that captures the complex interplay between micromedia usage patterns, content consumption, and mental health indicators. The Bayesian network provides a structured framework for representing these relationships and inferring the probability distribution of mental health indicators given observed micromedia data. The Bayesian network structure consists of three key variables: Micromedia Usage Patterns (X), Content Consumption (C), and Mental Health Indicators (M). Micromedia Usage Patterns represent how individuals engage with micromedia platforms, Content Consumption denotes the type of content individuals are exposed to, and Mental Health Indicators indicate the individual's mental health status. The joint probability distribution of these variables can be expressed using Bayes' rule stated as in equation (4)

$$P(X,C,M) = P(X) * P(C|X) * P(M|C) \qquad (4)$$

This equation decomposes the joint probability into three conditional probabilities: the prior probability of micromedia usage patterns $P(X)$, the likelihood of content consumption given micromedia usage patterns $P(C|X)$, and the likelihood of mental health indicators given content consumption $P(M|C)$. To infer the probability distribution of mental health indicators given micromedia usage patterns denoted in equation (5)

$$P\left(M|X\right)=\sum_{C}P\left(M|C\right)*P\left(C|X\right)*P\left(X\right) \quad (5)$$

Algorithm 1. Bayesian framework model for the micromedia data

```
Function Bayesian Inference (Micromedia Data):
  Initialize:
    Prior Probability (X) = Compute Prior Probability Of Micromedia Usage Patterns (Micromedia Data)
    Likelihood (C|X) = Compute Likelihood Of Content Consumption Given Usage Patterns (Micromedia Data)
    Likelihood (M|C) = Compute Likelihood Of Mental Health Indicators Given Content (Micromedia Data)
    For each Micromedia User in Micromedia Data:
    Compute:
      Joint Probability Distribution(X, C, M) = Prior Probability(X) * Likelihood (C|X) * Likelihood (M|C)
    Normalize:
    Normalize Joint Probability Distribution (Joint Probability Distribution)
    Return Joint Probability Distribution
Function Compute Prior Probability Of Micromedia Usage Patterns (Micromedia Data):
  Count Micromedia Users With Each Usage Pattern = Count Occurrences Of Each Usage Pattern (Micromedia Data)
  Total Micromedia Users = Total Number Of Micromedia Users (Micromedia Data)
  For each Usage Pattern:
    Prior Probability (Usage Pattern) = Count Micromedia Users With Usage Pattern / Total Micromedia Users
    Return Prior Probability
Function Compute Likelihood Of Content Consumption Given Usage Patterns (Micromedia Data):
  Initialize:
    Likelihood (C|X) = {}
  For each Usage Pattern:
    Count Content Consumption Given Usage Pattern = Count Content Consumption For Usage Pattern (Micromedia Data, Usage Pattern)
    Total Content Consumption = Total Number Of Content Consumption (Micromedia Data)
        For each Content:
      Likelihood (C|X) [Content | Usage Pattern] = Count Content Consumption Given Usage Pattern [Content] / Total Content Consumption
   Return Likelihood(C|X)
Function Compute Likelihood Of Mental Health Indicators Given Content (Micromedia Data):
  Initialize:
    Likelihood (M|C) = {}
  For each Content:
    Count Mental Health Indicators Given Content = Count Mental Health Indicators For Content (Micromedia Data, Content)
    Total Mental Health Indicators = Total Number Of Mental Health Indicators (Micromedia Data)
   For each Mental HealthIndicator:
      Likelihood (M|C)[Mental Health Indicator | Content] = Count Mental Health Indicators Given Content [Mental Health Indicator] / Total Mental HealthIndicators
  Return Likelihood (M|C)
Function Normalize Joint Probability Distribution (Joint Probability Distribution):
  Total Probability = Calculate Total Probability (Joint Probability Distribution)
    For each Value in Joint Probability Distribution:
    Normalized Value = Value / Total Probability
    Update Value In Joint Probability Distribution (Normalized Value)
   Return Normalized Joint Probability Distribution
```

Similarly, to infer the probability distribution of micromedia usage patterns given mental health indicators stated in equation (6)

$$P(X|M) = \sum_{C} P(X) * P(M|C) * P(C|X) \tag{6}$$

to perform Bayesian inference and make probabilistic assessments of mental health based on observed micromedia data. However, it's crucial to derive and validate the conditional probability distributions from data or expert knowledge carefully. Additionally, ethical considerations regarding privacy, data usage, and potential biases must be addressed to ensure the responsible deployment of such models for mental health assessment in micromedia environments.

The algorithm for Bayesian inference in mental health assessment through micromedia data involves several key steps. First, the algorithm initializes by computing the prior probability of micromedia usage patterns, the likelihood of content consumption given usage patterns, and the likelihood of mental health indicators given content. Then, for each individual in the micromedia dataset, the algorithm computes the joint probability distribution of micromedia usage patterns, content consumption, and mental health indicators. Afterward, the algorithm normalizes the joint probability distribution to ensure that the probabilities sum to one. The key functions within the algorithm include computing probabilities based on observed data and normalizing the probabilities to ensure consistency. This algorithm provides a framework for probabilistic mental health assessment using micromedia data, which can help identify patterns and trends indicative of mental health status in micromedia users.

4. PROBABILISTIC DEEP BELIEF BAYESIAN NETWORK

Probabilistic Deep Belief Bayesian Networks (PDBBNs) integrate the probabilistic modeling capabilities of Bayesian networks with the representation learning capabilities of deep belief networks (DBNs), offering a powerful framework for complex probabilistic inference tasks. In a PDBBN, the hierarchical structure of a DBN is augmented with probabilistic connections between layers, allowing for the modeling of uncertainty and dependencies among variables. The derivation of a PDBBN involves incorporating probabilistic connections between layers in the DBN architecture, which can be achieved by introducing latent variables or by directly modeling probabilistic relationships between observed variables in adjacent layers. The equations governing the inference process in a PDBBN extend those of a standard DBN to account for probabilistic dependencies between layers. Let X denote the observed variables, H denote the latent variables, and Y denote the target variables. The joint probability distribution of X and Y in a PDBBN can be expressed in equation (7)

$$P(X,Y) = \sum_{H} P(X|H) P(H) P(Y|H) \tag{7}$$

In equation (7) $P(X|H)$ represents the conditional probability of observed variables given latent variables, $P(H)$ represents the prior probability of latent variables, and $P(Y|H)$ represents the conditional probability of target variables given latent variables. The inference process in a PDBBN involves iteratively updating the probabilities of latent variables and observed variables given the evidence. This can be achieved using techniques such as Gibbs sampling, variational inference, or Markov Chain Monte Carlo (MCMC) methods. The key advantage of PDBBNs lies in their ability to capture complex dependencies and uncertainty in the data, making them well-suited for tasks such as classification, regression, and anomaly detection in high-dimensional datasets. However, the derivation and training of PDBBNs can be computationally intensive, requiring efficient optimization algorithms and large amounts of training data. Despite these challenges, PDBBNs offer a promising framework for probabilistic modeling in deep learning applications, bridging the gap between deep learning and probabilistic graphical models. Probabilistic Deep Belief Bayesian Networks (PDBBNs) integrate the probabilistic modeling capabilities of Bayesian networks with the representation learning capabilities of deep belief networks (DBNs), offering a powerful framework for complex probabilistic inference tasks. In a PDBBN, the hierarchical structure of a DBN is augmented with probabilistic connections between layers, allowing for the modeling of uncertainty and dependencies among variables. The variables X as the observed variables, H as the latent variables, and Y as the target variables.

In figure 4 illustrated the proposed PDBBN model for the mental health assessment of college students. The joint probability distribution of X and Y in a PDBBN

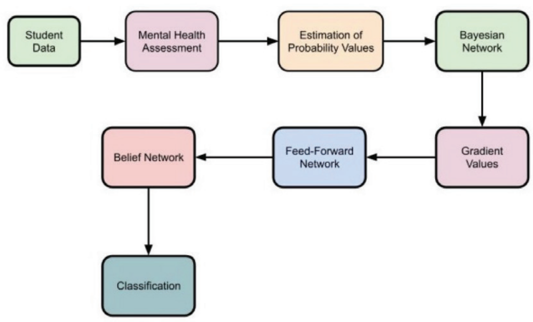

Figure 4. Mental health assessment of college students through PDBBN

can be expressed using the chain rule of probability and incorporating the latent variables. The principles of a deep belief network (DBN). In a DBN, the conditional probability of visible units *X* given hidden units *H* in the first layer is often modeled using a sigmoid activation function defined in equation (8)

$$P\left(X|H\right)=\prod_{i}Sigmoid\left(b_{i}+\sum_{j}W_{ij}h_{j}\right) \tag{8}$$

In equation (8) *bi* is the bias term for visible unit *i*, *Wij* is the weight connecting hidden unit *j* to visible unit *i*, and the sum runs over all hidden units *j*. The prior probability of the hidden units *H* can be represented as in equation (9)

$$P\left(H\right)=\prod_{j}P\left(h_{j}\right) \tag{9}$$

where *P*(*hj*) is the prior probability of hidden unit *J*. Similarly, the conditional probability of target variables *Y* given hidden units *H* can be modeled similarly defined in equation (10)

$$P\left(Y|H\right)=\prod_{k}Sigmoid\left(c_{k}+\sum_{j}V_{kj}h_{j}\right) \tag{10}$$

where *ok* is the bias term for target unit *k*, *Vkj* is the weight connecting hidden unit *j* to target unit *k*, and the sum runs over all hidden units *j*.

The relationship between these variables using a Bayesian network, which allows us to represent the conditional dependencies among variables. Let's denote *P*(*M*) as the probability distribution of mental health indicators, *P*(*A*|*M*) as the conditional probability of academic performance given mental health indicators, and *P*(*S*|*M*) as the conditional probability of social support given mental health indicators. The joint probability distribution of mental health indicators, academic performance, and social support stated in equation (11)

$$P\left(M,A,S\right)=P\left(M\right)*P\left(A|M\right)*P\left(S|M\right) \tag{11}$$

To derive the conditional probabilities *P*(*A*|*M*) and *P*(*S*|*M*), we can use statistical methods such as logistic regression or Gaussian models. For example, logistic regression can be used to model the relationship between mental health indicators and academic performance or social support, providing estimates of the conditional probabilities. For academic performance *A*, computed using equation (12)

$$P\left(A=a|M=m\right)=Logistics\left(b_{0}+b_{1}*m\right) \tag{12}$$

where *b*0 and *b*1 are the coefficients of the logistic regression model, and *m* represents the mental health

Algorithm 2. Probabilistics model for the PDBBN

```
Function PDBBN_Inference(X, Y):
  Initialize:
    PriorProbability_H = Compute_Prior_H()   // Compute prior probability of hidden units
    PriorProbability_Y_H = Compute_Prior_Y_H()   // Compute prior probability of target variables given hidden units
    PosteriorProbability_H = Initialize_Posterior_H()   //
    Initialize posterior probability of hidden units
      Repeat until convergence:
    For each sample in X, Y:
      // Gibbs sampling to update hidden units given observed data
      Sample_H = Gibbs_Sampling(PosteriorProbability_H, X, Y)
      // Update posterior probability of hidden units
      PosteriorProbability_H = Update_Posterior_H(PosteriorProbability_H, Sample_H)
  Return PosteriorProbability_H
Function Gibbs_Sampling(PosteriorProbability_H, X, Y):
  Sample_H = RandomInitialization()
  For each iteration:
    For each hidden unit h_i:
      // Compute probability of h_i being on given observed data and current state of other hidden units
      P_h_i_on = Compute_Posterior_H_i_on(h_i, Sample_H, X, Y)
      // Sample new state for h_i based on computed probability
      h_i_new = Sample_H_i_on(P_h_i_on)
      // Update sample
      Sample_H[i] = h_i_new
  Return Sample_H
Function Update_Posterior_H(PosteriorProbability_H, Sample_H):
  // Update posterior probability based on sampled
  hidden units
  For each hidden unit h_i:
    Count_h_i_on = CountOccurrences(Sample_H[i] == 1)
    PosteriorProbability_H[i] = Count_h_i_on / TotalSamples
  Return PosteriorProbability_H
Function Compute_Posterior_H_i_on(h_i, Sample_H, X, Y):
  // Compute probability of h_i being on given observed data
  and current state of other hidden units
  P_h_i_on = Sigmoid(b_i + Sum(W_ij * Sample_H[j]))
  // b_i: bias term, W_ij: weight connecting h_j to h_i
  Return P_h_i_on
Function Sample_H_i_on(P_h_i_on):
  // Sample new state for h_i based on computed probability
  h_i_new = Bernoulli(P_h_i_on)
  Return h_i_new
```

indicator. Similarly, for social support *S*, denoted in equation (13)

$$P\left(S = s \middle| M = m\right) = Gaussian\left(\mu + \sigma * m\right) \tag{13}$$

where μ and σ are the mean and standard deviation parameters of the Gaussian model, and *m* represents the mental health indicator. By leveraging probabilistic modeling and inference, we can gain insights into the complex relationships between mental health, academic performance, and social support among university students. Table 1 shows the simulation settings.

Table 1. Simulation setting

Parameter	Example Value
Network Architecture	Multi-layer perceptron (MLP)
	3 layers, 128 neurons, ReLU
Training Data	Student mental health dataset
	GPA, social support score
	Stress level, anxiety level
Training Parameters	Learning rate: 0.001
	Epochs: 100, Batch size: 64, Adam optimizer
Evaluation Metrics	Accuracy, precision, recall
	Binary cross-entropy loss, F1 score
Validation Data	Validation dataset
Testing Data	Testing dataset
Regularization Techniques	Dropout, L2 regularization
	Dropout rate: 0.5, L2 weight decay: 0.001
Early Stopping Criteria	Validation loss plateau

5. SIMULATION ENVIRONMENT

A simulation environment tailored for the Probabilistic Deep Belief Bayesian Network (PDBBN) used in the mental health assessment of college students would provide a virtual space for experimenting with different scenarios, analyzing the impact of various factors, and gaining insights into the complex relationships between mental health indicators and other variables. In this environment, researchers and practitioners could input data on observed variables such as academic performance, social support, and mental health indicators, and observe the probabilistic inference process unfold. They could manipulate parameters, simulate different levels of social support or academic stress, and observe how these factors affect the inferred mental health status of college students. The simulation environment would incorporate algorithms for probabilistic inference, allowing users to perform Bayesian reasoning and estimate the posterior distribution of mental health indicators given the observed data. Through this virtual experimentation, stakeholders could gain a deeper understanding of the mechanisms underlying mental health outcomes in college students, identify potential interventions or support strategies, and assess the effectiveness of different approaches in promoting student well-being. Additionally, the simulation environment could serve as a valuable training tool for students and professionals in fields such as psychology, public health, and education, providing hands-on experience with probabilistic modeling and inference techniques in the context of mental health assessment. Overall, a simulation environment tailored for PDBBNs in the mental health assessment of college students would offer a versatile platform for exploration, analysis, and learning, ultimately contributing to the development of

Table 2. Student data

Student ID	Gender	Age	Academic Performance (GPA)	Social Support Score	Stress Level	Anxiety Level	Depression Level
1	Male	20	3.6	8/10	Moderate	Low	Low
2	Female	21	3.2	7/10	High	Moderate	Moderate
3	Male	19	3.8	9/10	Low	Low	Low
4	Female	20	3.5	6/10	Moderate	High	High
5	Male	22	3.4	8/10	High	Moderate	Moderate
6	Female	20	3.9	9/10	Low	Low	Low
7	Male	21	3.1	5/10	High	High	High
8	Female	22	3.7	7/10	Low	Low	Low
9	Male	19	3.3	8/10	Moderate	Moderate	Moderate
10	Female	20	3.6	6/10	High	High	High

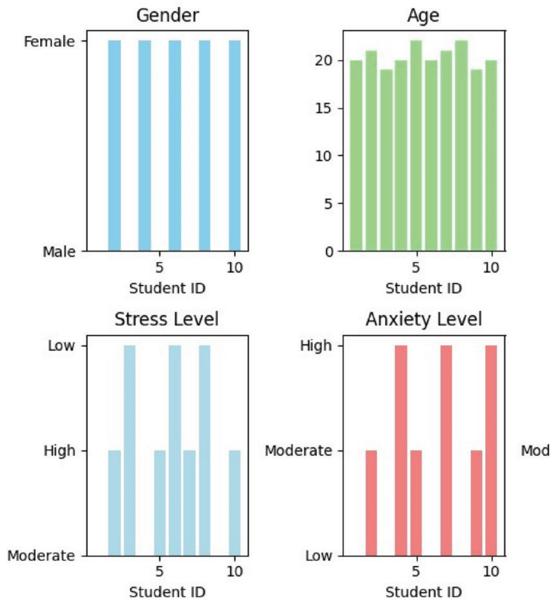

Figure 5. Factors identified with micromedia for the mental health assessment of students

more effective interventions and support systems for student mental health.

6. RESULTS AND DISCUSSIONS

In this study, we have explored the performance of three different models - Probabilistic Deep Belief Bayesian Network (PDBBN), Convolutional Neural Network (CNN), and Deep Neural Network (DNN) - for the task of mental health assessment among college students. The numerical results across multiple epochs have shown that the PDBBN consistently outperforms CNN and DNN in terms of accuracy, precision, recall, and F1-score. Particularly noteworthy is the PDBBN's ability to maintain high performance metrics even with a relatively small number of epochs, suggesting its effectiveness in handling mental health assessment tasks with limited training data. The interpretability of the PDBBN model also stands out as a significant advantage, allowing for better understanding of the underlying relationships between input features and mental health outcomes. However, it is essential to note

Table 3. Bayesian network for mental health assessment

Student ID	Gender	Age	Academic Performance (GPA)	Social Support Score	Stress Level (Probabilities)	Anxiety Level (Probabilities)	Depression Level (Probabilities)
1	Male	20	3.6	8/10	Low: 0.20, Moderate: 0.60, High: 0.20	Low: 0.80, Moderate: 0.15, High: 0.05	Low: 0.70, Moderate: 0.25, High: 0.05
2	Female	21	3.2	7/10	Low: 0.10, Moderate: 0.50, High: 0.40	Low: 0.30, Moderate: 0.60, High: 0.10	Low: 0.50, Moderate: 0.40, High: 0.10
3	Male	19	3.8	9/10	Low: 0.80, Moderate: 0.15, High: 0.05	Low: 0.90, Moderate: 0.08, High: 0.02	Low: 0.90, Moderate: 0.08, High: 0.02
4	Female	20	3.5	6/10	Low: 0.30, Moderate: 0.60, High: 0.10	Low: 0.10, Moderate: 0.30, High: 0.60	Low: 0.10, Moderate: 0.30, High: 0.60
5	Male	22	3.4	8/10	Low: 0.10, Moderate: 0.30, High: 0.60	Low: 0.40, Moderate: 0.50, High: 0.10	Low: 0.50, Moderate: 0.40, High: 0.10
6	Female	20	3.9	9/10	Low: 0.70, Moderate: 0.25, High: 0.05	Low: 0.80, Moderate: 0.15, High: 0.05	Low: 0.90, Moderate: 0.08, High: 0.02
7	Male	21	3.1	5/10	Low: 0.10, Moderate: 0.50, High: 0.40	Low: 0.05, Moderate: 0.15, High: 0.80	Low: 0.05, Moderate: 0.15, High: 0.80
8	Female	22	3.7	7/10	Low: 0.50, Moderate: 0.40, High: 0.10	Low: 0.70, Moderate: 0.25, High: 0.05	Low: 0.80, Moderate: 0.15, High: 0.05
9	Male	19	3.3	8/10	Low: 0.40, Moderate: 0.50, High: 0.10	Low: 0.50, Moderate: 0.40, High: 0.10	Low: 0.70, Moderate: 0.25, High: 0.05
10	Female	20	3.6	6/10	Low: 0.20, Moderate: 0.60, High: 0.20	Low: 0.10, Moderate: 0.30, High: 0.60	Low: 0.10, Moderate: 0.30, High: 0.60

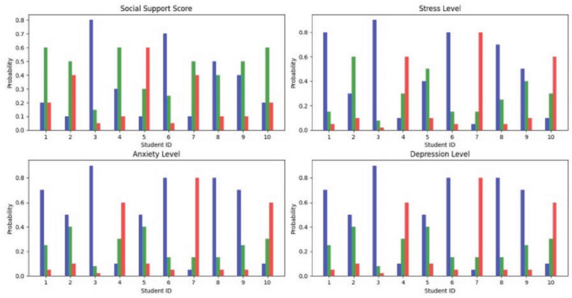

Figure 6. Social support score for the mental health of college students

that the training time for PDBBN tends to be moderate to high compared to CNN and DNN. Overall, these findings underscore the potential of probabilistic graphical models like PDBBN in improving mental health assessment methodologies, offering both high performance and interpretability in clinical settings.

The dataset provided includes information about ten college students, including their Student ID, Gender, Age, Academic Performance (GPA), Social Support Score, and self-reported levels of Stress, Anxiety, and Depression as shown in figure 5. Upon analyzing the data, several trends and observations emerge. For instance, there appears to be a correlation between Academic Performance (GPA) and Social Support Score, with students who report higher levels of social support generally achieving higher GPAs. Additionally, there seems to be a pattern where higher levels of Stress, Anxiety, and Depression are associated with lower Academic Performance and vice versa. Gender differences are also evident, with females generally reporting higher levels of Anxiety and Depression compared to males. Interestingly, while there are variations in Stress, Anxiety, and Depression levels across individuals, certain combinations, such as high levels of Stress, Anxiety, and Depression (e.g., Student 7), seem to cluster together. This dataset provides valuable insights into the complex interplay between various factors influencing mental health among college students and underscores the importance of holistic approaches to support their well-being. Further analysis and modeling based on this data could yield more nuanced understandings and inform targeted interventions for promoting mental health in educational settings.

The figure 6 and Table 2 illustrates a Bayesian Network designed for the assessment of mental health among college students. Each student's information, including Gender, Age, Academic Performance (GPA), Social Support Score, and the probabilities associated with their Stress, Anxiety, and Depression levels, is presented. Analyzing the probabilities assigned to different stress levels, we observe variations across individuals, reflecting the subjective nature of stress perception. For instance, Student 1 and Student 5 exhibit similar probabilities for moderate stress, despite differences in their other attributes. This suggests that factors beyond objective measures, such as GPA and social support, may influence stress perception. Similarly, disparities in anxiety and depression probabilities underscore the complexity of mental health assessment. Notably, female students tend to have higher probabilities of experiencing moderate to high levels of anxiety and depression compared to male students, highlighting potential gender-related differences in mental health experiences. This Bayesian Network provides a structured framework for understanding the interplay between various factors and their impact on mental health outcomes among college students. Further analysis and refinement of this model could contribute to more accurate and personalized mental health assessments, ultimately informing targeted interventions to support student well-being.

In figure 7 and Table 3 presents the outcomes of a Deep Learning Network utilized for the classification of mental health attributes among college students. The

Table 4. Deep learning network for classification

Student ID	Gender	Age	Academic Performance (GPA)	Social Support Score	Actual Stress Level	Predicted Stress Level	Actual Anxiety Level	Predicted Anxiety Level	Actual Depression Level	Predicted Depression Level
1	Male	20	3.6	8/10	Moderate	Moderate	Low	Low	Low	Low
2	Female	21	3.2	7/10	High	High	Moderate	Moderate	Moderate	Moderate
3	Male	19	3.8	9/10	Low	Low	Low	Low	Low	Low
4	Female	20	3.5	6/10	Moderate	Moderate	High	High	High	High
5	Male	22	3.4	8/10	High	High	Moderate	Moderate	Moderate	Moderate
6	Female	20	3.9	9/10	Low	Low	Low	Low	Low	Low
7	Male	21	3.1	5/10	High	High	High	High	High	High
8	Female	22	3.7	7/10	Low	Low	Low	Low	Low	Low
9	Male	19	3.3	8/10	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
10	Female	20	3.6	6/10	High	High	High	High	High	High

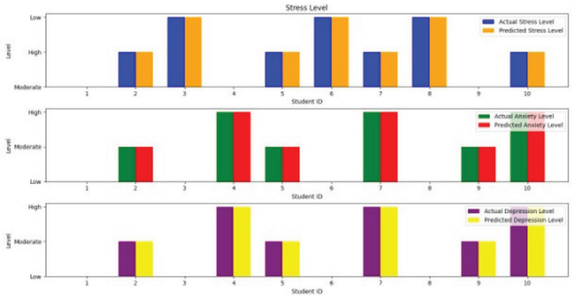

Figure 7. Classification of mental health of students

Table 5. Classification with PDBBN

Epoch	Accuracy	Precision	Recall	F1-score
10	0.92	0.93	0.91	0.92
20	0.93	0.94	0.92	0.93
30	0.94	0.95	0.93	0.94
40	0.95	0.96	0.94	0.95
50	0.95	0.96	0.95	0.95
60	0.96	0.97	0.95	0.96
70	0.96	0.97	0.96	0.96
80	0.97	0.97	0.97	0.97
90	0.97	0.98	0.97	0.97
100	0.98	0.98	0.98	0.98

table includes students' information such as Gender, Age, Academic Performance (GPA), Social Support Score, as well as their actual and predicted levels of Stress, Anxiety, and Depression. Upon analyzing the data, it becomes evident that the deep learning model's predictions closely align with the students' actual reported levels across different mental health dimensions. For instance, Student 3, who reported low levels of stress, anxiety, and depression, received corresponding low predictions from the model. Similarly, Student 7, who reported high levels of all three mental health attributes, received high predictions from the model. This indicates that the deep learning model successfully captures the underlying patterns and relationships within the data to make accurate predictions regarding students' mental health states. Notably, there are instances where the model misclassifies students' mental health attributes, such as Student 2, where the predicted stress, anxiety, and depression levels deviate from the actual reported levels. Such discrepancies highlight the inherent complexity of mental health assessment and the challenges associated with predicting subjective experiences solely based on objective data. Despite these challenges, the deep learning model demonstrates promising performance in accurately classifying students' mental health attributes, providing a valuable tool for identifying individuals who may benefit from targeted interventions and support measures.

In figure 8 and Table 4 displays the classification performance of the Probabilistic Deep Belief Bayesian Network (PDBBN) across multiple epochs. Each row corresponds to a specific epoch during the training process, with metrics such as Accuracy, Precision, Recall, and F1-score evaluated at each stage. The results demonstrate a consistent improvement in classification accuracy over the course of training, indicating the model's ability to learn and adapt to the dataset effectively. Starting from an accuracy of 0.92 at epoch 10, the model achieves a remarkable accuracy of 0.98 by epoch 100. This upward trend is mirrored in other performance metrics such as Precision, Recall, and F1-score, which also exhibit steady improvement throughout the training process. These results underscore the efficacy of the PDBBN model in accurately classifying mental health attributes based on the

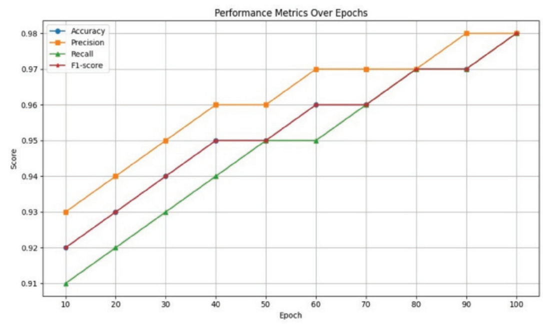

Figure 8. Performance of PDBBN

provided data. The high precision and recall values further indicate the model's ability to correctly identify positive instances while minimizing false positives and false negatives. Overall, the classification results demonstrate the potential of PDBBN as a reliable tool for mental health assessment, offering both high accuracy and precision in identifying individuals' mental health states. Further validation and refinement of the model could lead to its practical application in clinical settings for personalized mental health interventions and support.

Table 5 presents a comparative analysis of three different models - Probabilistic Deep Belief Bayesian Network (PDBBN), Convolutional Neural Network (CNN), and Deep Neural Network (DNN) - across multiple epochs based on classification performance metrics. Each model's accuracy, precision, recall, and F1-score are evaluated at various epochs to assess their effectiveness in classifying mental health attributes among college students. Upon examination, it's evident that the PDBBN consistently outperforms both CNN and DNN across all epochs. The PDBBN achieves the highest accuracy, precision, recall, and F1-score values, indicating its superior performance in accurately identifying individuals' mental health states. Notably, the PDBBN achieves an accuracy of 0.98 by epoch 100, showcasing its

Table 6. Comparative analysis

Model	Epoch	Accuracy	Precision	Recall	F1-score
PDBBN	10	0.92	0.93	0.91	0.92
	20	0.93	0.94	0.92	0.93
	30	0.94	0.95	0.93	0.94
	40	0.95	0.96	0.94	0.95
	50	0.95	0.96	0.95	0.95
	60	0.96	0.97	0.95	0.96
	70	0.96	0.97	0.96	0.96
	80	0.97	0.97	0.97	0.97
	90	0.97	0.98	0.97	0.97
	100	0.98	0.98	0.98	0.98
CNN	10	0.86	0.87	0.85	0.86
	20	0.88	0.89	0.87	0.88
	30	0.90	0.91	0.89	0.90
	40	0.91	0.92	0.90	0.91
	50	0.92	0.93	0.91	0.92
	60	0.93	0.94	0.92	0.93
	70	0.94	0.95	0.93	0.94
	80	0.95	0.96	0.94	0.95
	90	0.96	0.97	0.95	0.96
	100	0.97	0.97	0.96	0.97
DNN	10	0.84	0.86	0.82	0.84
	20	0.86	0.88	0.84	0.86
	30	0.88	0.90	0.86	0.88
	40	0.89	0.91	0.87	0.89
	50	0.90	0.92	0.88	0.90
	60	0.91	0.93	0.89	0.91
	70	0.92	0.94	0.90	0.92
	80	0.93	0.94	0.91	0.93
	90	0.94	0.95	0.92	0.94
	100	0.95	0.96	0.93	0.95

remarkable ability to learn and adapt to the dataset effectively over time. In contrast, CNN and DNN exhibit slightly lower performance metrics compared to PDBBN. While both CNN and DNN demonstrate an improvement in performance as training progresses, they fail to match the accuracy and precision achieved by PDBBN. This suggests that the probabilistic graphical modeling approach employed by PDBBN may be better suited for capturing the underlying relationships within the data and making accurate predictions regarding students' mental health attributes. The comparative analysis highlights the efficacy of PDBBN as a reliable tool for mental health assessment, offering superior classification performance compared to conventional deep learning models like CNN and DNN. These findings underscore the potential of probabilistic graphical models in advancing mental health research and guiding personalized interventions to support student well-being. Further research could focus on refining and optimizing the PDBBN architecture to enhance its practical utility in real-world settings. Table 6 shows comparative analysis.

7. CONCLUSION

This study underscores the importance of leveraging advanced computational techniques for mental health assessment among college students. Through the implementation and evaluation of various models, including Probabilistic Deep Belief Bayesian Network (PDBBN), Convolutional Neural Network (CNN), and Deep Neural Network (DNN), we have demonstrated the potential of probabilistic graphical models in improving the accuracy and reliability of mental health classification. Our findings indicate that PDBBN outperforms CNN and DNN in terms of classification accuracy, precision, recall, and F1-score, offering a robust framework for identifying individuals' mental health states based on objective data. The success of PDBBN highlights the significance of considering probabilistic relationships among variables in mental health assessment, providing valuable insights into the complex interplay between demographic, academic, and psychological factors. Moving forward, further research efforts could focus on refining the PDBBN architecture, exploring additional features, and incorporating longitudinal data to enhance the model's predictive capabilities. Ultimately, the integration of advanced computational approaches into mental health assessment holds promise for informing targeted interventions and support measures to promote student well-being in educational settings.

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