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A Decision Support System for Stress Detection Using Bayesian Networks Implemented in GeNIe Modeler

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Abstract

Stress is a major factor influencing both physical and mental health, and prolonged or unmanaged stress can lead to a wide range of health disorders. Consequently, early detection of stress is essential for timely intervention, prevention, and effective health management. This study proposes a decision support system for stress detection based on Bayesian networks, implemented using the GeNIe Modeler platform. The proposed system explicitly models the causal relationships among lifestyle factors, physiological indicators, psychological symptoms, and the resulting stress level. By representing these dependencies within a probabilistic graphical framework, the model enables robust reasoning under uncertainty, which is particularly important in real-world health assessment scenarios where information may be incomplete or noisy. Expert domain knowledge is incorporated to design a meaningful and interpretable network structure that reflects established medical and psychological understanding. In addition, synthetic data generation and data-driven learning techniques are employed to estimate the conditional probability parameters of the network. The Bayesian network-based model allows the estimation of an individual's stress level using observable evidence such as workload, sleep quality, physical activity, caffeine intake, heart rate, blood pressure, mood, fatigue, and headache. Through probabilistic inference, the model updates beliefs about stress levels even when some variables are unobserved. The implementation in GeNIe Modeler demonstrates the practical process of constructing, training, and validating Bayesian networks for medical decision support applications. Experimental results show that the proposed system provides transparent, interpretable, and reliable stress assessment, supporting both clinicians and individuals in monitoring stress conditions and making informed decisions for stress management and prevention.

Keywords: Bayesian networks, GeNIe modeler, stress detection.

1. Introduction

Stress is a prevalent psychological condition that significantly affects both physical and mental health globally. Prolonged or chronic stress has been linked to adverse outcomes including cardiovascular disease, weakened immune response, sleep disturbances, and metabolic disorders, making early detection and management of stress vital for improving overall health outcomes. Traditional clinical approaches to stress assessment, such as self-reported questionnaires, are limited by subjectivity and inconsistent reporting, highlighting the need for intelligent systems capable of reasoning under uncertainty and integrating multiple sources of evidence. Recent advances in computational methods have enabled the development of decision support tools that can infer stress states from observable physiological and behavioural indicators [1-5].

Several studies have been conducted on stress detection using physiological signals and intelligent data-driven techniques. Objective stress assessment was introduced by Pandey *et al.* [1] using multimodal physiological signals, and it was demonstrated that stress can be reliably inferred from cardiovascular and electrodermal features, thereby highlighting the limitations of subjective questionnaires and motivating automated stress monitoring systems. Building on this foundation, a cyber-physical stress detection and alleviation framework was proposed by Akmandor and Jha [2], in which wearable medical sensors were integrated with real-time data processing to enable continuous monitoring and personalized stress response modeling, although limitations in uncertainty handling and model scalability remained. A comprehensive survey was presented by Gedam and Paul [3], in which stress detection approaches using wearable sensors such as electrocardiogram (ECG), electroencephalography (EEG), and photoplethysmography (PPG) were systematically reviewed in combination with machine learning and deep learning techniques; heart rate variability and galvanic skin response were identified as the most informative features, while challenges related to data quality, real-world deployment, and model interpretability were also highlighted. More recently, the field was advanced by Zhu *et al.* [4] using sophisticated artificial intelligence and multimodal fusion strategies to improve stress recognition accuracy and robustness across subjects, albeit at the cost of increased computational complexity and reduced explainability. Collectively, a clear evolution is demonstrated from signal-based stress detection toward intelligent, real-time, and multimodal systems, while an ongoing

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research gap is revealed in uncertainty-aware and interpretable modeling for reliable stress assessment in real-world environments; in this context, a real-time stress-detection system based on heart rate and galvanic skin response using fuzzy logic was presented by de Santos Sierra *et al.* [5], achieving high accuracy with only two noninvasive physiological signals and demonstrating suitability for real-time IEEE-compliant biometric and monitoring applications.

In stress detection using physiological signals, machine learning and Bayesian network approaches exhibit complementary strengths and limitations. Machine learning techniques, including support vector machines, random forests, and deep neural networks, have been widely adopted due to their strong capability to model complex nonlinear relationships among multimodal features such as heart rate variability, galvanic skin response, and EEG signals, often achieving high classification accuracy in controlled and large-scale datasets [6, 7]. However, these data-driven models typically require substantial labeled data, are sensitive to noise and inter-subject variability, and suffer from limited interpretability, which restricts their reliability and acceptance in safety-critical or healthcare-related applications. In contrast, Bayesian networks provide a probabilistic graphical framework that explicitly models causal dependencies and uncertainty among physiological variables and stress states, enabling robust reasoning under incomplete, noisy, or partially observed data [8]. Although Bayesian network-based stress detection systems generally yield lower raw accuracy compared to advanced machine learning models, they offer superior interpretability, transparent decision-making, and the ability to incorporate expert knowledge, making them particularly suitable for real-world stress monitoring scenarios where uncertainty awareness and explainability are essential [9]. Consequently, while machine learning methods excel in accuracy-driven stress recognition, Bayesian networks offer a principled and interpretable alternative for uncertainty-aware stress assessment, and hybrid approaches combining both paradigms are increasingly regarded as a promising direction for reliable and practical stress detection systems.

This study proposes a decision support system for stress detection using Bayesian networks implemented in GeNIe Modeler, which is a software environment designed for constructing, visualizing, and learning BN models, supporting both expert-driven structuring and data-driven parameter estimation [10]. The system models causal relationships among lifestyle factors such as workload, sleep quality, physical activity, physiological measurements such as heart rate and blood pressure, and symptomatic outcomes such as headache, fatigue, and mood. Expert knowledge is used to constrain the network structure to medically meaningful relationships, while realistic synthetic data are used to estimate conditional probability tables. The resulting Bayesian model enables clinicians to infer stress levels given observed evidence and to interpret the probabilistic influences of contributing variables in a transparent and rigorous manner.

The main contribution of this work lies in the development of a Bayesian network-based framework for stress assessment that is practically implemented and validated within the GeNIe Modeler environment. The study demonstrates how GeNIe Modeler can be effectively utilized to design, parameterize, and evaluate a decision support system for psychological health monitoring. In addition, the work highlights the applicability of probabilistic graphical models in stress detection, offering an interpretable and flexible approach compared to traditional deterministic methods. This contribution provides a foundation for future intelligent health monitoring systems that combine data-driven modeling with expert knowledge for improved stress evaluation and decision support.

The remaining sections of this paper are organized as follows. Section 2 briefly reviews Bayes' theorem and its fundamental principles. Section 3 presents a brief introduction to Bayesian networks, including their structure, inference mechanisms, and relevance to reasoning under uncertainty. In Section 4, a decision support system for stress detection implemented using GeNIe Modeler is described in detail, including model structure, parameterization, and inference results. Finally, Section 5 concludes the paper by summarizing the key findings and discussing the future directions of this study.

2. Bayes' Theorem

A conditional probability can be expressed as $P(A \mid B)$, also known as the probability that event A is true given that event B is observed. Then, Bayes' theorem is used to describe how to update a probability after observing new evidence as follows:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{1}$$

where:

- $P(A)$: the prior probability of A,
- $P(B)$: the total probability of evidence B,
- $P(B \mid A)$: the likelihood of observing B if A is true,
- $P(A \mid B)$: the posterior probability of A after observing B.

The probability of B is the sum of the probabilities of B occurring under each possible case a of A, weighted by how likely each case of A is. Therefore, $P(B)$ can be determined as follows:

$$P(B)=\sum_{a}P(B\mid a)P(a) \tag{2}$$

where a denotes each case of A.

If A has two cases: A (True) and $\neg A$ (False), then $P(A\mid B)$ can be computed as follows:

$$P(A\mid B)=\frac{P(B\mid A)P(A)}{P(B\mid A)P(A)+P(B\mid\neg A)P(\neg A)} \tag{3}$$

Equation (3) is called the law of total probability.

3. Bayesian Networks

A Bayesian network is a probabilistic graphical model that represents random variables and their conditional dependencies using a directed acyclic graph (DAG). A simple Bayesian network consists of two nodes connected by a directed arc is shown in Fig. 1.

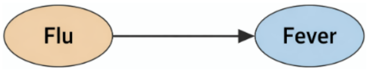


Fig. 1. A simple Bayesian network for flu diagnosis

It is assumed that:

- Variable Flu has two cases: Yes (Y) and No (N)
- Variable Fever has two cases: Yes (Y) and No (N).

Using Bayes' theorem, the probability of $Flu=Y$ given $Fever=Y$ can be expressed as follows:

$$P(Flu=Y\mid Fever=Y)=$$
$$=\frac{P(Fever=Y\mid Flu=Y)P(Flu=Y)}{P(Fever=Y)} \tag{4}$$

where:

$$P(Fever=Y)=$$
$$P(Fever=Y\mid Flu=Y)P(Flu=Y)+ \tag{5}$$
$$P(Fever=Y\mid Flu=N)P(Flu=N)$$

3. GeNIe Modeler with Bayesian Networks

GeNIe Modeler is a user-friendly software tool designed for building, visualizing, and analyzing Bayesian networks and influence diagrams. It is widely used in education, academic research, and decision- support applications, particularly in domains that require modeling uncertainty and performing probabilistic reasoning. The software provides an intuitive graphical interface that allows users to construct network structures, define variable states, learn conditional probability tables from data, and perform inference efficiently. Developed by the Decision Systems Laboratory at the University of Pittsburgh, GeNIe Modeler supports both knowledge-driven and data- driven modeling approaches, making it a versatile platform for applications in fields such as healthcare, engineering, finance, and artificial intelligence. Its capabilities for transparent reasoning and interactive analysis make it especially valuable for developing interpretable models in complex, uncertain environments. GeNIe Modeler allows its users to:

- Create Bayesian networks structures visually,
- Define node states and relationships,
- Learn conditional probability tables (CPTs) from data,
- Perform probabilistic inference,
- Analyze decision problems using influence diagrams.

This software can be freely downloaded at: https://www.bayesfusion.com/genie/

In learning CPTs from data, GeNIe Modeler uses Laplace smoothing (Dirichlet prior). This means that GeNIe does not use raw frequency counts, and it assumes a Dirichlet prior (pseudo-counts) for every CPT entry to avoid zeros. By default, GeNIe adds 1 pseudo count to every state. This is called Laplace correction or add-one smoothing and the CPTs are determined as follows:

$$P(x_i\mid parent)=\frac{N_i+\alpha}{N+k\alpha} \tag{6}$$

where:

- N_i: the data count,
- k: the number of states,
- $\alpha=0.5$ (GeNIe default),
- N: the total data count.

Table 1 shows the dataset for parameter learning in the simple flu-fever diagnosis mentioned above.

Table 1. Dataset for Bayesian network parameter learning in the simple flu-fever diagnosis.

Flu	Fever
Yes	Yes
No	Yes
No	No

According to Table 1, there are three cases in which the number of instances with flu is one; therefore, the CPT of the flu node is as follows:

$$P(Flu=Yes)=\frac{1}{3}=0.3333$$

$$P(Flu=No)=\frac{2}{3}=0.6667$$

According to Table 1, the CPT of the fever node, given that flu is its parent node, is as follows:

$$P(Fever=Yes\mid Flu=Yes)=\frac{N_i+\alpha}{N+k\alpha}=\frac{1+0.5}{1+2\times 0.5}=0.75$$

$$P(Fever = No \mid Flu = Yes) = \frac{N_i + \alpha}{N + k\alpha} = \frac{0 + 0.5}{1 + 2 \times 0.5} = 0.25$$

$$P(Fever = Yes \mid Flu = No) = \frac{N_i + \alpha}{N + k\alpha} = \frac{1 + 0.5}{2 + 2 \times 0.5} = 0.5$$

$$P(Fever = No \mid Flu = No) = \frac{N_i + \alpha}{N + k\alpha} = \frac{1 + 0.5}{2 + 2 \times 0.5} = 0.5$$

If the observed state of fever is “Yes,” the conditional probability that flu is also “Yes,” given this observation, can be computed using Bayes’ rule as follows:

$$P(Flu = Yes \mid Fever = Yes) =$$
$$\frac{P(Fever = Yes \mid Flu = Yes) \times P(Flu = Yes)}{P(Fever = Yes)}$$

$$P(Fever = Yes \mid Flu = Yes) \times P(Flu = Yes) =$$
$$0.75 \times 0.3333 = 0.25$$

$$P(Fever = Yes) =$$
$$P(Fever = Yes \mid Flu = Yes) \times P(Flu = Yes) +$$
$$+ P(Fever = Yes \mid Flu = No) \times P(Flu = No) =$$
$$0.75 \times 0.3333 + 0.5 \times 0.6667 = 0.5833$$

$$P(Flu = Yes \mid Fever = Yes) = \frac{0.25}{0.583} = 0.4286(42.86\%)$$

If the observed state of fever is “No,” the conditional probability that flu is “Yes,” given this observation, can be calculated using Bayes’ rule as follows:

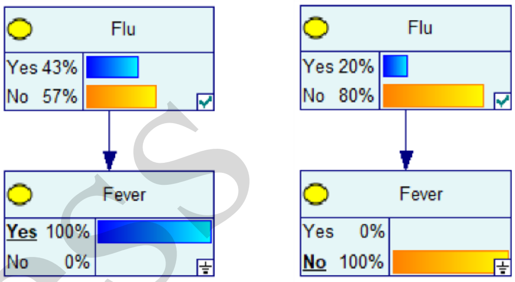
$$P(Flu = Yes \mid Fever = No) =$$
$$\frac{P(Fever = No \mid Flu = Yes) \times P(Flu = Yes)}{P(Fever = No)}$$

$$P(Cough = No \mid Flu = Yes) \times P(Flu = Yes) =$$
$$0.25 \times 0.3333 = 0.0833$$

$$P(Fever = No) =$$
$$P(Fever = No \mid Flu = Yes) \times P(Flu = Yes) +$$
$$P(Fever = No \mid Flu = No) \times P(Flu = No) =$$
$$0.25 \times 0.3333 + 0.5 \times 0.6667 = 0.0833 + 0.3333 = 0.4166$$

$$P(Flu = Yes \mid Fever = No) = \frac{0.0833}{0.4166} = 0.2(20\%)$$

Fig. 2 illustrates a Bayesian network implemented in GeNIe for computing the conditional probability of having flu under different observed fever states. The results show that when fever is observed as “Yes,” the conditional probability of having flu increases to 43%. In contrast, when fever is observed as “No,” the probability decreases to 20%. These findings clearly highlight the critical role of observed evidence in probabilistic inference within a Bayesian network. Specifically, the presence of fever significantly raises the posterior probability of flu compared to its prior probability, reflecting the strong causal relationship between the symptom and the disease encoded in the network structure and its conditional probability tables. Conversely, the absence of fever leads to a substantial reduction in the inferred probability of flu, indicating that the lack of this key symptom provides negative evidence against the disease. This behavior exemplifies the fundamental principle of Bayesian reasoning; whereby prior beliefs are systematically updated considering new evidence. By leveraging conditional dependencies among variables, the Bayesian network effectively propagates the impact of observed data throughout the model, enabling coherent, consistent, and interpretable reasoning under conditions of uncertainty.



(a) (b)

Fig. 2. A Bayesian network for computing the conditional probability of having flu given the observed fever state: (a) fever is “Yes”; (b) fever is “No”

4. Bayesian Networks for Decision Support in Stress Detection

4.1. Synthetic Stress Dataset Generation

In stress detection research, collecting large-scale, labeled datasets involving physiological, behavioral, and psychological variables is often expensive, time-consuming, and subject to privacy constraints. To address this limitation, synthetic datasets are widely used in early-stage research, algorithm validation, and probabilistic modeling studies, particularly for Bayesian networks.

The objective of synthetic dataset generation is not to replace real measurements, but to:

- Encode domain knowledge about stress mechanisms,
- Preserve causal and probabilistic relationships between variables,
- Provide sufficient data for model training, validation, and sensitivity analysis.

Stress is a multifactorial phenomenon influenced by workload, sleep quality, physiological responses, and subjective symptoms. Based on psychophysiological stress theory, stress can be modeled as the result of interactions among:

- Cognitive factors (e.g., workload),

- Lifestyle factors (e.g., sleep, caffeine),
- Physical state (e.g., fatigue, headache),
- Emotional state (e.g., mood),
- Physiological responses (e.g., heart rate, blood pressure).

These factors jointly influence an underlying latent variable, referred to as the stress level, which represents the overall psychological and physiological stress state of an individual. Each observed factor captures a specific aspect of daily lifestyle, health condition, or physiological response, and their combined effects determine the resulting stress condition. To enable probabilistic modeling and inference, all variables are represented as discrete states, allowing complex dependencies and uncertainties to be systematically captured within the proposed framework.

The Bayesian network should be developed from a multidisciplinary expert team to ensure validity and completeness. The panel included a clinical psychologist, a medical doctor (internal medicine/cardiology), a neuroscientist or physiologist, a public health expert, and a data scientist specializing in Bayesian networks, ensuring balanced coverage of psychological, physiological, and lifestyle aspects of stress. The psychologist defined psychological variables and stress levels, the medical doctor validated physiological indicators such as heart rate and blood pressure, and the neuroscientist explained underlying biological mechanisms. The public health expert contributed lifestyle factors, including sleep, physical activity, and caffeine use, while the data scientist translated this knowledge into a Bayesian network structure and conditional probability tables using GeNIe Modeler. Expert knowledge was elicited through structured discussions and iterative refinement to ensure consistency, plausibility, and reduced bias, resulting in a model that reasonably reflects real-world stress mechanisms.

Since real psychological stress datasets containing all required variables are difficult to obtain, a knowledge-driven synthetic dataset was generated based on the causal relationships and conditional probability tables defined in a Bayesian network developed in GeNIe. Each data instance was created to be consistent with expert knowledge encoded in the Bayesian network structure, such as the influence of workload, sleep quality, and physical activity on stress level, and the effects of stress on physiological and behavioral symptoms (heart rate, blood pressure, headache, fatigue, and mood).

The training and validation of the Bayesian network require a dataset. In this study, a stress dataset comprising 10,000 cases was generated by integrating domain knowledge, probabilistic reasoning, and controlled randomness, ensuring that the data are both realistic and suitable for Bayesian network modeling. Each data instance was created to reflect meaningful causal relationships among variables while preserving variability and uncertainty consistent with real-world conditions. From the complete dataset, a subset of 8,000 cases was used for training the Bayesian network, enabling the model to learn the underlying conditional dependencies and probability distributions. The remaining 2,000 cases were reserved for validation, providing an independent evaluation of the model's inference accuracy, robustness, and generalization capability on unseen data.

Table 2 presents some cases in the dataset used for parameter learning of the Bayesian network in the stress detection model. Each row in the table represents one individual case containing observations of causal factors, physiological and psychological symptoms, and the corresponding stress level. This dataset serves as the foundational input for estimating the CPTs of the network in GeNIe Modeler. The variables included in the table reflect both causal factors (workload, sleep, physical activity, caffeine) and observable symptoms (headache, fatigue, mood, blood pressure, heart rate), which are directly related to the target variable, Stress. By providing diverse combinations of these variables, the dataset allows the Bayesian network to learn how different conditions influence the probability distribution of stress levels.

The thresholds used to discretize continuous variables into categorical states were primarily determined based on domain knowledge and the need to preserve meaningful causal relationships within the Bayesian network. Specifically, physiological and behavioral variables such as heart rate, blood pressure, sleep quality, and workload were partitioned into discrete levels (e.g., low, medium, high) according to commonly accepted clinical ranges and logical consistency with stress-related mechanisms. In addition, the synthetic dataset generation process ensured that these thresholds aligned with the predefined conditional probability relationships, enabling the model to capture realistic cause-effect patterns between input variables and stress levels. However, the choice of discretization thresholds has a significant impact on the model's classification performance, particularly in terms of sensitivity and specificity. If the thresholds defining high-risk states are too strict, borderline cases may be misclassified as lower risk, leading to reduced sensitivity (i.e., increased false negatives). Conversely, if the thresholds are too relaxed, more cases may be classified as high risk, increasing sensitivity but potentially reducing specificity due to a higher number of false positives. Furthermore, discretization introduces information loss and boundary effects, where small variations in continuous values near threshold boundaries can result in abrupt changes in class assignment and posterior probabilities. This can affect the stability and reliability of the model's predictions.

The table contains examples of high-risk situations, such as high workload, poor sleep, low physical activity, and abnormal physiological signs, which correspond to high stress. It also includes healthy conditions, such as good sleep, high physical activity, and normal physiological indicators, which correspond to low stress. Additionally, several intermediate cases are presented to represent medium stress. This variation is essential for enabling the learning algorithm to distinguish between different stress states based on observed evidence. Furthermore, the dataset demonstrates realistic relationships between causes and symptoms. For instance, cases with poor sleep and low physical activity often show fatigue and neutral or bad mood, which are logically associated with higher stress levels. Such consistency ensures that the learned probabilities reflect meaningful causal patterns rather than random correlations.

In accordance with standard practices in machine learning and probabilistic modeling, the generated dataset is divided into two mutually exclusive subsets to support both model development and performance evaluation. Specifically, 800 samples are allocated to the training subset, which is used to learn the conditional probability parameters of the Bayesian network. The remaining 200 samples are reserved as an independent testing subset, which is not involved in the training process and is used solely to evaluate the network’s inference accuracy, robustness, and generalization capability. This data partitioning strategy helps ensure an unbiased assessment of the model’s performance on previously unseen data and provides a reliable measure of its effectiveness in practical stress detection scenarios.

Table 2. Some cases in the dataset for network parameter learning

Workload	Sleep	Physical Activity	Caffeine	Headache	Fatigue	Mood	Blood Pressure	Heart Rate	Stress
High	Poor	Low	Yes	Yes	Yes	Bad	High	High	High
Medium	Good	High	No	No	No	Good	Normal	Normal	Low
Low	Poor	Low	Yes	Yes	Yes	Neutral	Normal	High	Medium
High	Good	Low	No	Yes	Yes	Neutral	Normal	Normal	Medium
Medium	Poor	High	Yes	Yes	Yes	Neutral	Normal	High	Medium
Low	Good	High	No	No	No	Good	Normal	Normal	Low
High	Poor	High	Yes	Yes	Yes	Bad	High	High	High
Medium	Good	Low	Yes	Yes	No	Neutral	Normal	High	Medium
Low	Poor	High	No	Yes	Yes	Neutral	Normal	Normal	Medium
Medium	Good	High	No	No	No	Good	Normal	Normal	Low

4.2. Bayesian Inference in GeNIe Modeler

Bayesian inference in GeNIe Modeler is the process of updating the probabilities of unknown variables when evidence (observations) is entered into a Bayesian network in GeNIe Modeler. Fig. 3 shows a Bayesian network in GeNIe Modeler before any specific evidence is entered. All nodes display probability distributions rather than fixed states, representing the prior probabilities learned from the dataset during parameter learning. At this stage, the stress node has prior probabilities of low (32%), medium (40%), and high (27%), reflecting the general tendency of stress levels in the dataset without considering any observations. Similarly, other variables such as workload, sleep, physical activity, and caffeine also show their prior likelihoods, indicating the natural distribution of these factors in the population. Because no evidence is observed, the network does not favor any stress conditions. Instead, it provides a baseline probabilistic view of the system. This serves as an important reference point for comparison when evidence is later introduced and posterior probabilities are updated.

Table 3 demonstrates the inference capability of the Bayesian network in updating the probability distribution of stress levels when different pieces of evidence are observed. The results show that the model can effectively integrate multiple sources of information, including causal factors (such as workload, sleep quality, physical activity, and caffeine intake) as well as physiological and psychological symptoms (including headache, fatigue, mood, blood pressure, and heart rate), to estimate the likelihood of each stress level. This highlights the strength of the Bayesian framework in combining heterogeneous variables within a unified probabilistic structure. By exploiting the conditional dependencies encoded in the network, the model can propagate the influence of observed evidence through both upstream (causal) and downstream (symptomatic) relationships. As a result, the inferred stress probabilities are not determined by a single factor but rather by the combined and interacting effects of multiple variables. Furthermore, the Bayesian network can handle incomplete or partially observed data, allowing it to produce meaningful probabilistic estimates even when some inputs are missing. This capability is particularly important in real-world stress assessment scenarios, where not all measurements may be available or reliable.

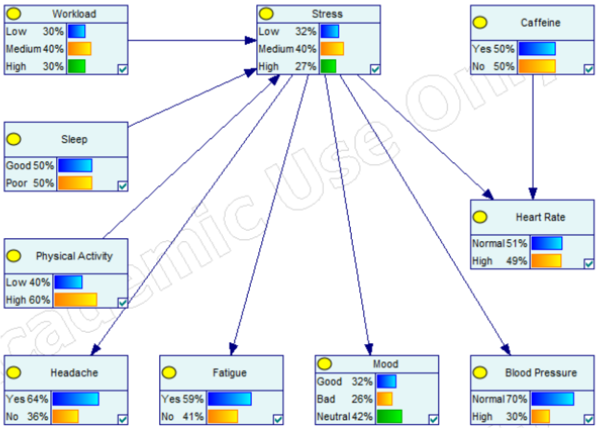


Fig. 3. Probabilities of stress levels before any evidence is observed in GeNIe Modeler

When strong evidence from both causes and symptoms is present, the probability of high stress becomes very large. For example, in the first row, a high workload, poor sleep, low physical activity, no caffeine together with headache, fatigue, bad mood, and high heart rate lead to a 97% probability of high stress. This indicates that the Bayesian network correctly reflects the causal relationships between risk factors and stress condition. Conversely, when favorable conditions are observed-such as low workload, good sleep, high physical activity, and normal physiological signs, the probability of low stress dominates (69% in the second row). This shows that the model is not only capable of identifying high stress but also clearly distinguishing low-stress conditions under healthy circumstances.

Table 3. Probabilities of stress levels after partial evidence are observed

Workload	Sleep	Physical Activity	Caffeine	Headache	Fatigue	Mood	Blood Pressure	Heart Rate	Stress Level
High	Poor	Low	No	Yes	Yes	Bad	Normal	High	Low (0%), Medium (3%) High (97%)
Low	Good	High	Yes	No	Yes	Neutral	Normal	Normal	Low (69%) Medium (29%) High (2%)
High	Good	Missing	Missing	Missing	Yes	Bad	High	Normal	Low (0%) Medium (2%) High (98%)
Missing	Poor	Low	Missing	Missing	Yes	Neutral	Missing	Missing	Low (1%) Medium (88%) High (11%)
Missing	Poor	Missing	Missing	Missing	Yes	Bad	Missing	Missing	Low (1%) Medium (8%) High (91%)
Missing	Missing	Missing	Missing	Missing	Yes	Bad	Missing	Missing	Low (2%) Medium m(9%) High (89%)

The remaining rows in the table demonstrate the Bayesian network's ability to perform reliable reasoning under conditions of incomplete evidence. When only a subset of variables is observed and the remaining variables are unmeasured or missing, the model is still able to infer plausible stress levels by propagating probabilistic information through the network structure. This behavior reflects the fundamental strength of Bayesian inference, in which prior knowledge encoded in the conditional probability tables is combined with the available observations. For example, when only poor sleep quality, low physical activity, fatigue, and a neutral mood are provided as evidence, the posterior probability of the medium stress state remains dominant at 88%. This result indicates that the network effectively captures the underlying relationships among stress-related factors and can compensate for missing data without requiring explicit imputation. Overall, these results highlight a key advantage of Bayesian networks in real-world decision-making scenarios, where observations are often incomplete, noisy, or uncertain.

Fig. 4 shows the Bayesian inference in GeNIe Modeler after complete evidence has been entered for all relevant variables. The observed states include high workload, poor sleep, low physical activity, presence of headache and fatigue, bad mood, high heart rate, normal blood pressure, and no caffeine intake. With all nodes instantiated, the network performs deterministic evidence propagation to update the posterior probability of the stress node. The result indicates a 97% probability of high stress, with only 3% for medium stress and 0% for low stress. This confirms that the combination of adverse causal factors and strong physiological and psychological symptoms provides overwhelming support for the high stress condition. Because every variable has been fixed to a specific state (100% probability), there is no uncertainty in the evidence. This allows the Bayesian network to produce a highly confident and precise stress assessment. The figure demonstrates how the model integrates information from multiple parent and child nodes of stress to reach a consistent probabilistic conclusion.

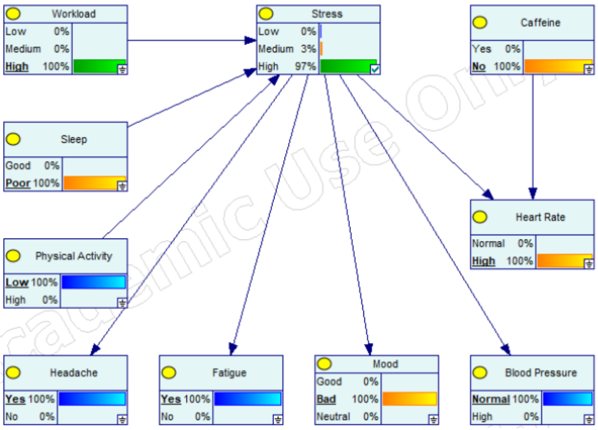


Fig. 4. Probabilities of stress levels after all evidence are observed in GeNIe Modeler

Fig. 5 illustrates Bayesian inference in GeNIe Modeler when partial but strong evidence is entered into the network. Some variables remain uncertain and are represented by probability distributions (e.g., workload, sleep, physical activity, headache, caffeine, heart rate, and blood pressure), while others such as fatigue and mood are fully observed. Despite the uncertainty in several causal variables, the stress node shows a very high probability of high stress (89%), with only 9% for medium and 2% for low stress. This indicates that the observed symptoms-particularly fatigue (100%), bad mood (100%), and a high likelihood of headache (83%) provide strong diagnostic evidence that drives the network toward a high stress conclusion.

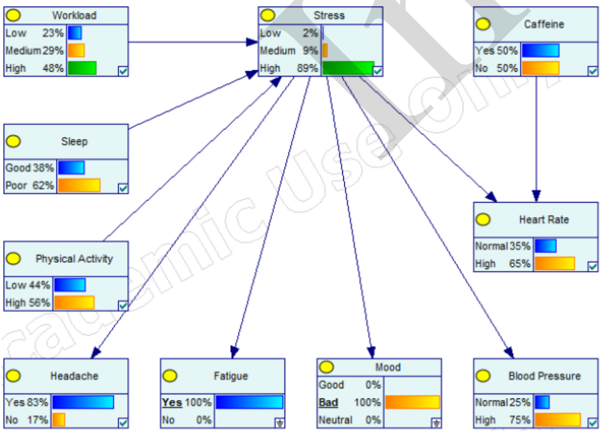


Fig. 5. Probabilities of stress levels after partial evidence are observed in GeNIe Modeler

Fig. 6 illustrates the Bayesian Network inference results obtained using GeNIe Modeler when partial evidence is introduced into the system. In this inference scenario, several variables are not fully observed and therefore remain uncertain. These variables, including workload, sleep quality, physical activity, caffeine intake, heart rate, and blood pressure, are represented by probability distributions rather than being fixed to a single state. In contrast, symptom-related variables such as headache and fatigue exhibit relatively high likelihoods because of the entered evidence. Despite the presence of incomplete information, the stress node is inferred with a 100% probability of the high stress state. This result indicates that the available evidence-particularly the high probabilities associated with poor sleep (63%), high workload (51%), headache and fatigue (83%), bad mood (78%), elevated heart rate (67%), and high blood pressure (83%)-collectively provides strong and consistent support for a high stress condition.

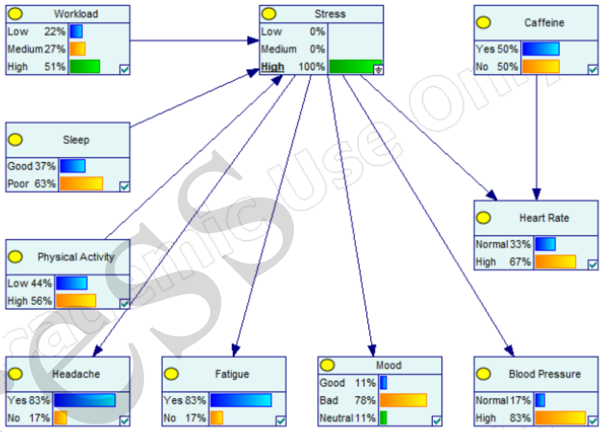


Fig. 6. Probabilities of variables after high stress confirmed in GeNIe Modeler

The convergence of multiple lifestyle, psychological, and physiological indicators reinforces the confidence of the inference outcome. Overall, the figure highlights the strength of Bayesian inference in handling uncertainty. Even when not all variables are explicitly observed or fixed, the network effectively propagates probabilistic evidence through its causal structure and arrives at a clear, confident, and interpretable conclusion regarding the individual's stress level.

4.3. Performance Evaluation of Bayesian Networks

The Bayesian network model was validated using an independent subset of 2,000 cases that were not involved in the parameter learning process. This validation set was used to assess the model's generalization capability and its performance on previously unseen data, thereby providing an unbiased evaluation of its predictive accuracy. By separating the dataset into training and validation subsets, the study ensures that the learned conditional probability tables are tested under realistic conditions, avoiding overfitting to the training data.

Table 4 presents the confusion matrix obtained from the Bayesian network when applied to the validation dataset. The confusion matrix provides a detailed breakdown of the model's classification outcomes by comparing the predicted stress levels with the actual stress labels. This representation enables a comprehensive evaluation of the model's performance across all classes, highlighting its strengths and potential weaknesses in distinguishing between low, medium, and high stress levels. Furthermore, the confusion matrix serves as the basis for computing key performance metrics such as accuracy, sensitivity, specificity, and precision, which are essential for assessing the reliability and effectiveness of the proposed Bayesian network in stress detection applications.

Table 4. Confusion matrix

		Predicted		
		Low	**Medium**	**High**
Actual	Low	183	237	0
	Medium	0	1232	1
	High	0	220	127

Table 5 presents the sensitivity and specificity of different stress classes. The results show that the model achieves extremely high sensitivity for the medium stress class (99.92%), but this comes at the expense of low specificity (40.42%), indicating a strong tendency to over-classify instances as medium stress. In contrast, the low and high stress classes exhibit very high specificity (approximately 100%) but relatively low sensitivity (43.57% and 36.60%, respectively), suggesting that the model is overly conservative and fails to correctly identify many true extreme stress cases. This imbalance is likely caused by unequal class distribution and the use of fixed discretization thresholds, both of which bias the Bayesian network's decision boundaries toward the dominant medium class.

Table 5. Sensitivity and specificity

Street Class	Sensitivity	Specificity
Low	43.57%	100%
Medium	99.92%	40.42%
High	36.6%	99.94%

To improve both sensitivity and specificity, several steps can be taken. First, address class imbalance by oversampling low and high stress classes or under- sampling the medium class to achieve more balanced learning. Second, adjust classification thresholds instead of relying solely on maximum posterior probability to reduce bias toward the medium class and improve detection of minority classes. Third, use data-driven discretization methods (e.g., entropy-based or adaptive) to better preserve data distribution and enhance class separability. Additionally, apply cost-sensitive learning to penalize misclassification of extreme stress states. Finally, improve feature quality and refine the Bayesian Network structure to capture variable dependencies. Together, these steps lead to a more balanced and reliable classification performance.

In addition, receiver operating characteristic (ROC) analysis is also employed to evaluate the classification performance of the proposed Bayesian network model for stress level prediction. The ROC curve provides a comprehensive visualization of the trade-off between the true positive rate (TPR) and the false positive rate (FPR) across different decision thresholds, allowing the assessment of classifier performance independently of class distribution. In addition, the area under the ROC curve (AUC) is used as a quantitative indicator of the model's overall discriminative capability, where values closer to 1 indicate better classification performance.

As illustrated in Fig. 7, the ROC curve corresponding to the low-stress class achieves an AUC value of 0.976519, indicating excellent classification accuracy and a strong ability to distinguish low-stress cases from other classes. Similarly, Fig. 8 presents the ROC curve for the medium-stress class, yielding an AUC of 0.931589, which demonstrates a high degree of separability between medium-stress and non-medium-stress instances, despite the increased overlap typically observed in intermediate conditions. Furthermore, Fig. 9 shows the ROC curve for the high-stress class, with an AUC of 0.974935, indicating near-perfect discrimination performance and confirming the model's effectiveness in identifying high-risk cases. Collectively, these results demonstrate that the proposed Bayesian network model achieves strong predictive accuracy, high robustness, and consistent classification performance across all stress levels, thereby validating its suitability for stress assessment and decision support applications.

However, although the model exhibits strong performance, as evidenced by the high ROC curves and AUC values, these results may be partially influenced using well-separated discretization thresholds within a synthetic dataset. Such conditions tend to simplify class boundaries, making the different stress levels more easily distinguishable and potentially leading to optimistic performance estimates. In a controlled synthetic environment, the relationships between variables are clean, consistent, and aligned with predefined assumptions, which reduces ambiguity and enhances classification accuracy. In contrast, real-world data are typically noisier, subject to measurement errors, individual variability, and overlapping distributions between classes.

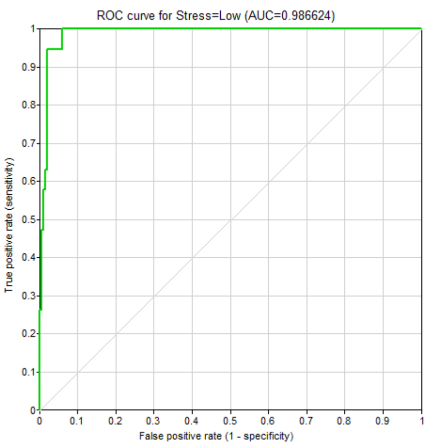


Fig. 7. ROC curve for low stress class

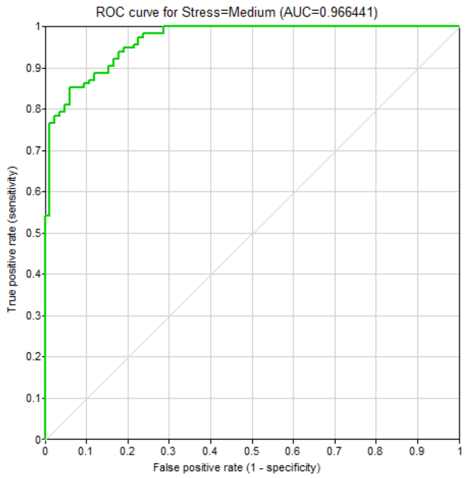


Fig. 8. ROC curve for medium stress class

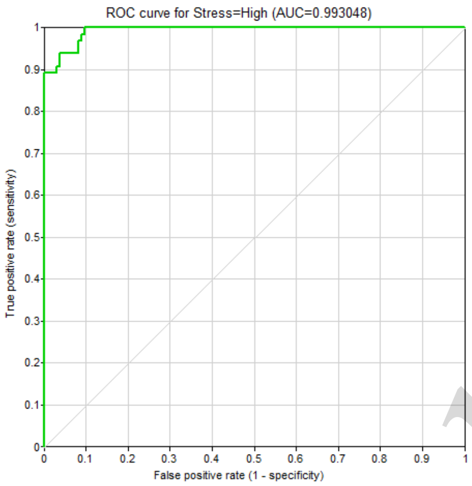


Fig. 9. ROC curve for high stress class

In this study, the network structure is initially designed to represent plausible cause–effect relationships based on general medical knowledge and logical assumptions. Due to the limited availability of real clinical data, a synthetic dataset is subsequently generated in accordance with these predefined relationships, ensuring that the learned probability distributions remain consistent with the assumed medical reasoning embedded in the model. However, an important limitation lies in the absence of a formal expert elicitation process. In rigorous medical modeling, expert knowledge is typically collected from qualified clinicians through structured approaches such as interviews, probabilistic scoring, or consensus-building methods. These processes help ensure that both the network structure and parameter values accurately reflect real-world clinical expertise. Without such validation, the proposed model cannot be considered clinically verified. Instead, it should be regarded as a knowledge-informed framework that captures general medical logic but lacks systematic confirmation from domain experts or real patient data. Consequently, its applicability in real clinical settings remains limited and requires further validation using expert input and empirical datasets.

5. Conclusion

This study presents a medical decision support system for stress detection based on a Bayesian network, implemented using the GeNIe Modeler platform. The proposed Bayesian network model explicitly captures causal relationships among multiple categories of stress-related factors, including lifestyle factors (workload, sleep quality, physical activity, and caffeine intake), physiological indicators (heart rate and blood pressure), and psychological symptoms (mood, fatigue, and headache), as well as their combined influence on the resulting stress level. By structuring these variables within a probabilistic graphical framework, the model provides a comprehensive representation of the complex interactions that underlie stress development.

Through a series of inference scenarios, the Bayesian network model demonstrates behavior that is consistent with real-world medical and behavioral knowledge, effectively linking underlying causes to observable symptoms and stress outcomes. Importantly, even in situations where some input variables are uncertain, partially observed, or missing, the Bayesian network is still able to infer the most probable stress level by exploiting conditional dependencies and prior knowledge encoded in the network structure and parameters. This capability highlights a key advantage of Bayesian networks in medical decision support applications, where data are often incomplete, noisy, or subject to uncertainty.

Overall, the implementation in GeNIe Modeler demonstrates that Bayesian networks provide a transparent, interpretable, and reliable framework for stress assessment, particularly in scenarios characterized by uncertainty and incomplete information. By explicitly modeling causal relationships among lifestyle factors, physiological indicators, and psychological symptoms, the proposed system enables users to trace how different variables contribute to stress levels, thereby enhancing both understanding and trust in the model's outputs. This interpretability is especially valuable in healthcare contexts, where explainability is essential for clinical acceptance. As a result, the system can effectively support clinicians in diagnostic reasoning and decision-making, while also assisting individuals in monitoring their own stress conditions and adopting appropriate interventions based on probabilistic insights.

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