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Enhancing Feature Discretization in Alarm and Fire Detection Systems Using Probabilistic Inference Models

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Abstract

Sensors for fire alarms require a high level of predictive variables to ensure accurate detection, injury prevention, and loss prevention. Bayesian networks can aid in enhancing early fire detection capabilities and reducing the frequency of erroneous fire alerts, thereby enhancing the effectiveness of numerous safety monitoring systems. This research explores the development of optimized probabilistic graphic models for the discretization thresholds of alarm system predictor variables. The study presents a statistical model framework that increases the efficacy of fire detection by predicting the discretization thresholds of alarm system predictor variable fluctuations used to detect the onset of fire. The work applies the Bayesian networks and probabilistic visual models to reveal the specific characteristics required to cope with fire detection strategies and patterns. The adopted methodology utilizes a combination of prior knowledge and statistical data to draw conclusions from observations. Utilizing domain knowledge to compute conditional dependencies between network variables enabled predictions to be made through the application of specialized analytical and simulation techniques.

Keywords

Neural Network, Discretization, Alarm Systems, Graphical Models, Machine Learning

1. Introduction

Rapid and effective detection of a fire is essential for battling and monitoring a fire. The precision of fire detection is dependent on a number of factors, the most important of which is the algorithm's accuracy when modelling discretization thresholds. Many residential fire alarm systems currently rely on a single passive sensor system, which presents inherent complications [1]. For instance, sunlight and illumination can affect photosensitive detector-equipped devices. Using threshold and duration-based processing systems, a variety of gases can affect fire detectors. Simple fire alarm algorithms are based on maximal value thresholds, rate of increase thresholds, and the combination of these values from multiple sensors. Using threshold values, alarm techniques are extremely susceptible to signal offsets caused by background concentration changes or delayed calibration drift [2]. Utilizing changes in trend and duration over time has improved the accuracy of fire detection. As a method for fire prediction, image recognition, processing, and feature extraction have also been studied [3]. Due to the unstructured and highly uncertain nature of fire information, a substantial amount of research has been conducted on Bayesian neural networks as a means of accumulating predictor factors for the purpose of generating fire signal decisions using the adaptive, deep-learning capability of neural networks. Bayesian Networks (BNs) are probabilistic graphical models that depict a set of random variables and their conditional interdependence using a Directed Acyclic Graph (DAG) [4]. Deep learning has gained popularity in recent years due to advancements in neural networks, the capacity to analyze vast amounts of data, and significant advancements in the design of network architectures and training methods [5]. Deep learning automates feature extraction by training on vast amounts of data and uses the neural network's learned discriminative characteristics to detect fire or smoke. Numerous researchers have investigated various types of fire detection sensors, including smoke, carbon monoxide temperature, and image recognition [1] [5]. The alarm is only initiated when particles collide with and activate the sensors. For fire alarm system detection, numerous authors have proposed neural networks, multi-sensor data fusion, fuzzy logic decision-making, and image processing technology.

The Bayesian Network has its origins in artificial intelligence and machine learning research, where it was initially identified as a method for analyzing decision strategies in uncertain contexts [6]. This study builds Bayesian Networks to integrate sensor data and other validating evidence for fire scenarios. The network is utilized to graphically represent the causal relationships and conditional probabilities between events such as operational changes and the observable data generated by a fire monitoring system. Bayesian Networks are an efficient technique for removing uncertainties and utilizing accumulated evidence [2]. This study illustrates the application of Bayesian Networks to the development of models that maximize the effectiveness of fire detection in a fire alarm monitoring system. By analyzing the mechanism of fire combustion, discretization thresholds, predictor variables, and its characteristics, as well as applying domain knowledge to a dataset acquired from the fire database of the National Institute of Standards and Technology. The final product consists of model construction and simulation of optimal probabilistic visual taxonomy for alarm system predictor variable discretization thresholds.

2. Related Works

For accurate detection, numerous fire alarm sensors require a substantial number of predictive variables. This extends the detection time, which can result in significant injury and loss [7]. By integrating computer vision algorithms with sensors, numerous researchers have investigated these limitations [8]. Vision-based detectors are typically superior to sensor-based detectors because they can circumvent sensor-based disadvantages. This technology offers numerous benefits, such as scalability and manageability. In recent years, significant advancements have made computer vision for surveillance applications an intriguing research topic. Moreover, vision-based technologies eliminate numerous limitations of conventional fire alarm systems, such as the requirement for human interaction, surveillance coverage, response time, and comprehensive fire reports. Nevertheless, complexity and erroneous triggering remain a concern for numerous reasons. Throughout the years, numerous additional detection methods have been developed and extensively implemented in order to accelerate the detection process while simultaneously enhancing the accuracy of information analysis [9]. Chojnacki *et al.* [6] proposed a color-based identification metric for video-based fire detection. This resulted in exceptionally rapid processing, which made the system useful not only for real-time fire detection, but also for video retrieval, which requires analysis to occur quicker than in real-time. Hradsky *et al.* [8] applied a framework to the problem of detecting real-time wildfires. The proposed adaptive decision fusion method utilized forest stewards' input. Using a large dataset, Khakzad *et al.* [10] identified a system's gap and constraint and proposed a surrogate system for detecting fire and rejecting non-fire motion attributes.

Consideration was also given to the possibility of detecting spurious detections in the presence of significant noise, partial occlusions, and rapid angle change. Jafari *et al.* [9] proposed a fire-flame detection system for use in an early fire detection and warning system that identifies prospective fire locations using background subtraction and colour analysis. The system's algorithm simulated both the fire's behavior using various spatio-temporal characteristics as well as the temporal evolution of pixel intensities in a potential image block using dynamic texture analysis. By introducing the Interval-Message-Ratio (IMR) measure and evaluating their architecture using the IMR metric, Amari *et al.* [11] expanded upon previous research. The researchers discovered that the strategy is applicable not only to fire detection but also to other disaster recovery techniques. Mihaljević *et al.*'s [12] work is an example of a variant of a prior publication. The researcher presented a sensor network strategy for detecting wildfires in urban and forested areas. The network included a temperature sensor and a maximum likelihood algorithm for incorporating sensory data. Muhammad *et al.* [13] investigated the use of wireless sensor networks for early detection of mine fires. The authors described a system consisting of subsystems for data collection, data processing, and monitoring. Their research centered on the network architecture, scheduling mechanism, and communication protocol components. Bayesian networks have been implemented in data analysis and expert knowledge systems, particularly in industries where uncertainty is prevalent. In addition, they have been applied to the development of expert systems that assimilate and represent expert knowledge in complex domains [14]. Bayesian Network approaches have been devised and implemented by machine learning researchers to encode uncertainty in expert knowledge [5]. Bayesian networks (BNs) are well-established probabilistic techniques that have been effectively applied to a variety of problems in a variety of disciplines utilizing a variety of machine learning techniques.

Sensors play a vital role in fire detection systems by detecting and warning of potential flames. Among the most important applications of sensors in fire detection are moisture detection, heat detection, flame detection, and gas detection [15]. Although smoke detectors are the most prevalent form of fire sensors, they utilize optical or ionization sensors to detect the presence of smoke particles in the air, which may indicate a fire. Heat sensors, also referred to as heat detectors or thermal sensors, monitor environmental temperature changes. The temperature sensor can detect significant temperature increases, such as those caused by a fire, and initiate an alarm. The purpose of flame sensors is to detect the presence of flames or specific wavelengths of light emitted by flames [7]. These types of sensors are commonly used in industrial contexts where rapid flame detection is crucial. In general, the use of sensors in fire detection systems allows for early detection, swift response, and enhanced safety measures, thereby reducing the risk of fire-related incidents and protecting lives and property. Fire detection technology is an extremely efficient method for preventing fires. Various fire detection technologies, including smoke, carbon monoxide, and temperature detection, are currently employed to detect fire [6]. Detecting changes in fire-predicting factors such as temperature, smoke concentration, and carbon monoxide (CO) in the environment prior to the onset of a fire is essential for early warning. Conversely, shorter time periods result in more subtle variations in fire parameters, making it more challenging to distinguish between fire signals and environmental disturbances. While the phenomena and products created by various materials during the early phases of flames are distinct, there are some similarities, including the release of heat and the production of smoke. These frequently occurring combustion byproducts (temperature, humidity, smoke, CO_2, CO, etc.) are known as fire prediction factors [4]. The detection and processing of predictor variables is essential for multi-sensor data fusion-based early warning technology [9]. In fire alarm technology, temperature is frequently used as the first and most adaptable signal. In order to avoid false alarms induced by weather fluctuations, the temperature alert threshold is typically set higher than 60˚C. Consequently, temperature is rarely used in isolation. However, it is an acceptable equilibrium metric for algorithms that utilize a multi-sensor data fusion paradigm for early fire warning. A fire's smoke concentration is a crucial characteristic because it can indicate the presence or absence of a fire. Additionally, because the concentration of carbon monoxide in the air remained minimal, it increased rapidly in the event of a fire. Compared to carbon dioxide, few stimuli can generate sufficient CO to activate a fire detector. Carbon monoxide is therefore an effective combustion indicator. While carbon dioxide and humidity are also common combustion byproducts, they are inextricably linked to the environment. The flame's physical properties include flame radiation, flame form, and flame fluctuation [10]. The characteristics of a fire flame include infrared light, ultraviolet light, and flame shape. Infrared sensors, ultraviolet sensors, and image sensors are all used. Combustion products exhibit a variety of properties, including gaseous and solid products as well as variations in temperature, with CO and CO_2 constituting the majority of gaseous products.

In summary, to enhance the precision and efficiency in alarm and fire detection systems, the integration of feature discretization and probabilistic inference models is essential. Through the process of discretizing features and employing probabilistic inference models, it is possible to augment the system's capacity to recognize pertinent patterns and generate precise prognostications. The objective of feature discretization in alarm and fire detection systems is to transform features that are continuous or have real values into discrete representations that can be utilized by the detection algorithms [9]. This enhances the capacity to streamline issues and makes them more amenable to scrutiny and strategic determination. The utilization of probabilistic inference models, such as Bayesian networks or Hidden Markov Models, can be utilized to improve feature discretization in these systems [5]. The utilization of models enables the capture of interrelationships among diverse variables and establishes a structure for generating probabilistic deductions grounded on the data that has been observed. This study aims to address a practical issue related to enhancing the precision and dependability of alarm and fire detection systems. The utilization of probabilistic inference models in feature discretization can enhance the differentiation between ordinary occurrences and hazardous circumstances.

3. Method

Bayesian probability and inference are fundamental concepts in Bayesian statistics, a branch of statistics that uses probability theory to quantify uncertainty and update beliefs based on new evidence. The theoretical composition of Bayesian probability and inference revolves around key principles and mathematical frameworks. This work adopts the Hierarchical Models [11]. The Bayesian inference methodology allows for the specification of hierarchical models, which capture dependencies and allow for borrowing of information across different levels. Hierarchical models are particularly useful when dealing with complex data structures or when data are scarce. The National Institute of Standards and Technology (NIST) [16] is the principal data source for this study. The institution upholds a National Fire Research Laboratory that is outfitted with calorimetry instruments for quantifying the thermal energy generated by fires and the byproducts of their oxidation. The database comprises a range of examples, such as singularly combusting items, furnished spaces, regulated burners, thoroughly characterized fuels, and composite fuels with unknown compositions. The validation of the model was conducted through the utilization of twenty experimental tests and 1500 fire datasets that were incorporated into the dataset. A diverse array of flammable substances, including but not limited to cotton rope, polyurethane plastic, ethanol, and wood, were encompassed by the twenty chosen tests. As argued by some authors that a large number of variables would not influence the predictive capability of feature discretization [8] [11], this works aims to minimize the number of variables utilized in our model to achieve the optimal set that yields the highest forecast accuracy. This is done to reduce the computational complexity of our prediction mechanism and account for the minimal contribution of most variables to our method's predictive powers. In this specific situation, the technique of iterative variable reduction is employed. Initially, we shall assess the precision of the prediction by employing the aggregate count of factors that were entered. Subsequently, the least significant variable in terms of prediction accuracy is identified and subsequently eliminated from the input variable set. Subsequently, we conduct a comprehensive reassessment of the entire procedure. The accuracy of the prediction can be enhanced by eliminating conflicting input variables during the prediction process. The aforementioned pattern is expected to persist until the subset of input variables that remain is sufficiently limited, such that any additional decrease in the number of variables would result in a decline in accuracy. The variables under consideration for the intermediate node were the flame, the products of combustion, and the sound of burning. However, after careful evaluation, the flame was ultimately selected. Ultimately, the output node is assigned the fire variable.

4. Results and Simulations

Bayesian inference employs Bayes' theorem to infer characteristics of probability distributions from data. Thus, Amari *et al.* [11] argued that establishing the conditional probability distribution for each node generates an exhaustive probability model. Bayesian networks must apply probability distributions to each node following the construction of nodes and connections. The Conditional Probability Table (CPT) describes the relationship between a child node and all its parents. CPT calculates the likelihood of a state given parent state values. Thus, each variable's CPT size is the product of the child node's state count and the total of its parent nodes' state counts. A probability distribution $P(X \mid pa(X))$ is required for each node X in a Bayesian network. The Bayes server implements a variety of methods for determining the conditional probability of nodes in a Bayesian Network. Probabilities can be calculated using expert knowledge. A belief network specifies a factorization of the joint probability distribution in which the conditional probabilities form multiplicative factors. A belief network, also known as a Bayesian network, is a directed acyclic graph with random variable nodes [17].

4.1. The Conditional Probability Table

The CPT developed in this study is based on directly observed data from cases and expert knowledge elicitation (Table 1). The node Flame has three progenitor nodes (Infrared, Ultraviolet, and Burning Picture), and the probability distribution of the Flame node is shown on the right. Consequently, an illustration of the probability distribution P (Flame|Infrared, Ultraviolet, Burning Image) is required. This is referred to as a conditional probability distribution, and when discrete variables are involved, the sum of each entry in the table is 1.0. The evaluation of the output reliability of a Bayesian belief network can be achieved through subjecting it to a sensitivity analysis concerning its conditional probabilities. The assessments of a Bayesian belief network's numerous conditional probabilities will invariably be erroneous which will affect the reliability of the network's output. It is possible to conduct an investigation into the dependability of the network's output by first putting the network to a sensitivity analysis with regard to its conditional probability. Unfortunately, even a basic sensitivity analysis of a belief network can take a significant amount of time.

The Bayesian Maximum Entropy (BME) reduction for spatial analysis and mapping provides explicit principles for incorporating prior knowledge, as well

Table 1. Current belief of fire alarm network.

	High	**Medium**	**Low**
CO_2	2.4404e−07	2.3671e−07	1
CO	2.4952e−07	2.3342e−07	1
	High	**Low**	
Temperature	0.5	0.5	
	Present	**Absent**	
Burning_Gas	0.61111	0.38889	
Burning_Picture	0.5	0.5	
Burning_Product	0.52778	0.47222	
Burning_Sound	0.5	0.5	
Electrostatic	0.5	0.5	
Fire	0.51389	0.48611	
Flames	0.5	0.5	
Infrared	0.5	0.5	
Smoke_Picture	0.5	0.5	
Solid_Product	0.5	0.5	
Ultraviolet	0.5	0.5	

as hard and soft data, into the mapping process. The BME for Sensitivity of target "ultraviolet" is shown in Table 2. Bayesian Networks provide a straightforward methodology for conducting scenario testing, allowing users to define a predetermined distribution at a node by providing input evidence [18]. The analysis of the impact of a particular scenario can be conducted by evaluating its effect on other interconnected nodes through the distribution of probabilities. The rapid distribution of data throughout the network is a notable advantage of utilizing Bayesian Networks. This phenomenon can be attributed to their capacity to enable expeditious evaluation of the consequences of choices and observed circumstances at a singular point on the whole system.

4.2. Simulation and Probabilistic Inference

Bayesian Networks are an effective method for scenario testing, as they enable the user to incorporate evidence into a node by specifying a fixed distribution at that node. The determination of the outcome of a scenario is based on the impact it has on other nodes through probability propagation. The capacity of Bayesian Networks to rapidly depict the influence of decisions and observed conditions at a singular node on the entire system is considered a significant advantage [9].

The Bayesian theory offers a comprehensive and coherent framework for dealing with uncertainty that is applicable across various domains. The presence of ambiguity often complicates decision-making in everyday situations, and the

Table 2. Sensitivity of target "ultraviolet".

Variable	Mutual Information	% Entropy Reduction
Ultraviolet	0.87767	100
Flames	0.00003	0.00373

Node	Mutual Info	Percent
Ultraviolet	0.87767	100
Flames	0.00003	0.00373

Variable	Mutual Information	% Entropy Reduction	Variance of Beliefs	% Variance of Beliefs
Ultraviolet	0.87767	100	0.2088159	100
Flames	0.00003	0.00373	0.0000095	0.00455
Fire	0.00000	0	0.0000000	1.58e−05

% Entropy Reduction	Node
100	Ultraviolet
0.00373	Flames

ability to draw upon past experiences can prove to be advantageous when faced with challenging choices. The aforementioned principle is equally applicable in scenarios where machines are required to acquire knowledge and adapt to situations characterized by unpredictability. Various methods exist for acquiring knowledge from prior experience, including but not limited to classification, regression, and density estimation. The modelling of flame is considered a critical element in the progression of a fire. The node box analysis indicates that the combustion process is influenced by the presence of a burning product that exhibits both gaseous and solid properties, as well as a corresponding temperature change, resulting in an increased likelihood of fire occurrence. This implies that the existence of a solitary flammable substance can lead to numerous supplementary sources of fire. The detection of fire in a fire alarm system can be achieved through the utilization of various observable characteristics present at the site of the fire. The network model illustrated in **Figure 1** assumes that the indicative variable is the concentration of Burning Gas CO_2. If the concentration of CO_2 present in the environment surpasses the established threshold, the finding node's status is deemed to be elevated. The process of forecasting necessitates the computation of the posterior probability of supplementary node variables contingent on the obtained results. In Bayes Server modeling, the CO_2 variable is assigned a high state (High = 100%) to signify that the state of the finding variable is established.

The process of gaining knowledge from past experiences can take on diverse manifestations, such as classification, regression, and density estimation. The diagram presented and the regression analysis utilised both entail the examination of the probability distribution pertaining to a given output variable. The output variable is considered a stochastic variable when given a set of input variables. Likewise, the input parameter could potentially be susceptible to imprecision.

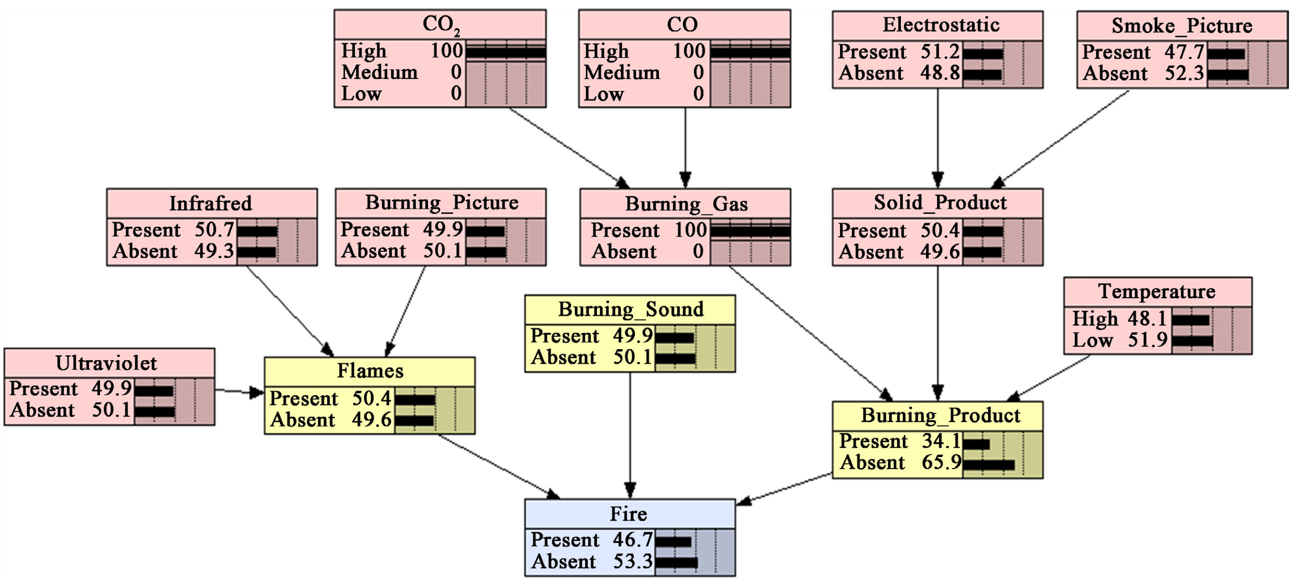

Figure 1. Fire forecast based on both CO_2 and CO predictive variants with other average indicative values.

The acoustic phenomena of crackling and burning sounds produced by a fire are commonly ascribed to the liberation of localised steam pockets. As per the simulation presented in Figure 2, the discrete variable "Ultraviolet" and "Infrared" simulated as presence with "Burning_Sound" infers an increased likelihood of a fire. As shown in Figure 3, the Burning_Product node box indicates that the occurrence of a burning product at full concentration, along with the characteristics of gas and solid product, and a corresponding alteration in temperature, is accountable for the escalation of fire presence. The aforementioned statement implies that the existence of a solitary combusting item has the potential to result in a plethora of diverse fire instigators.

By utilising the updating function, the probability of the entire network is automatically modified. The model presented suggests a correlation between the concentration of carbon monoxide and the probability of a fire occurrence. The

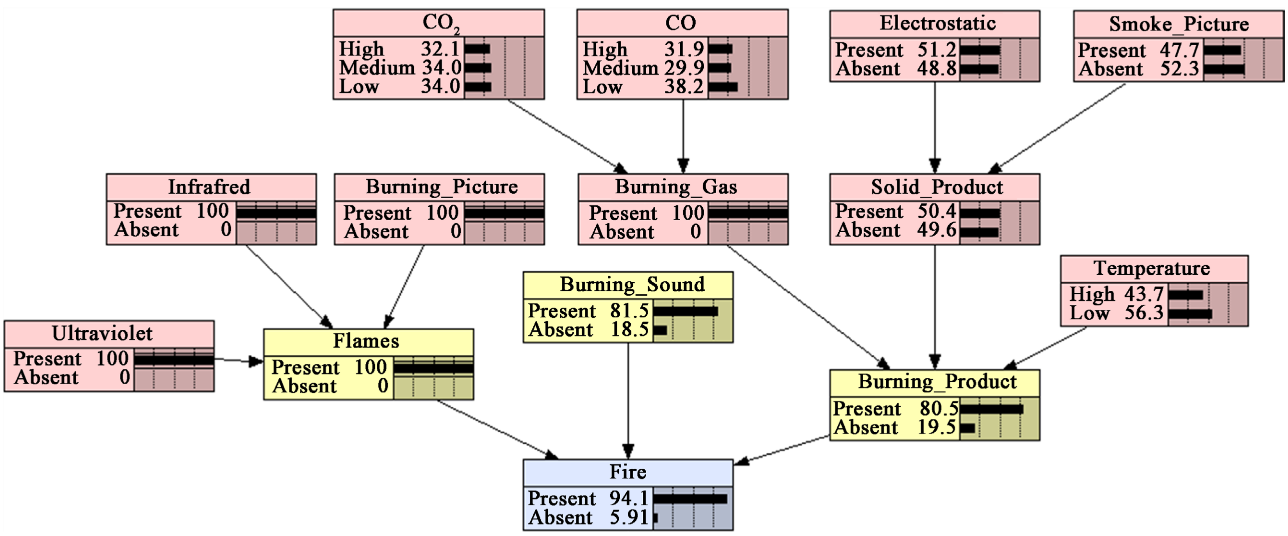

Figure 2. Estimating Bayesian probability with presence of burning sound.

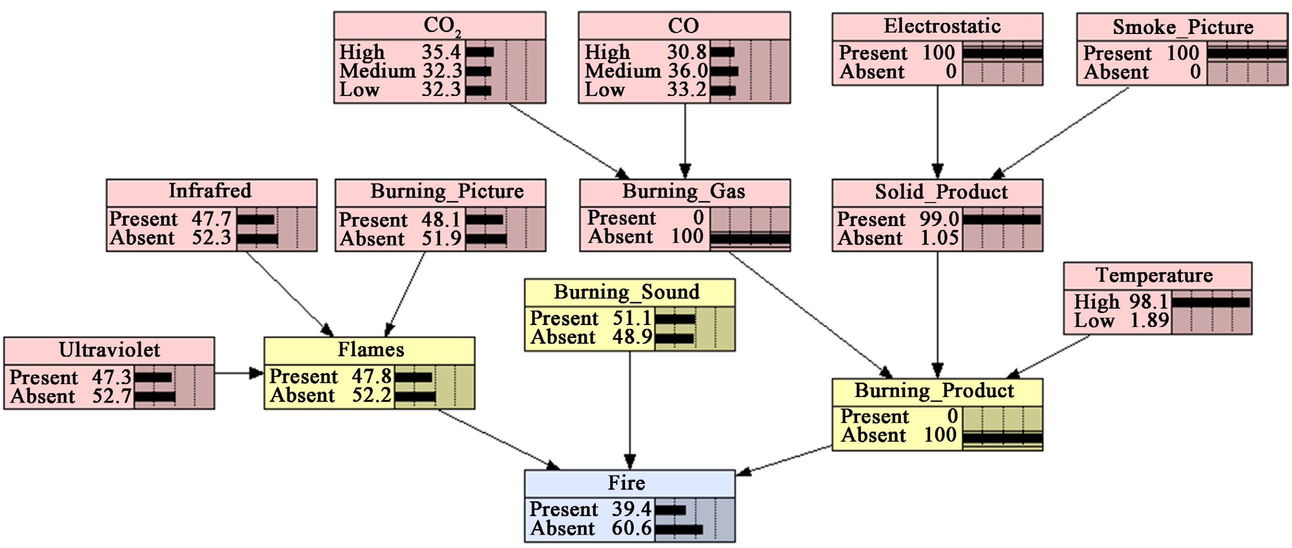

Figure 3. Estimating Bayesian probability with presence of burning product.

findings indicate that there is a positive correlation between the concentration of CO and the likelihood of burning gases, burning products, and fire. The likelihood of combustion of gases experienced a rise from 61.1% to 99.9%, while the probability of combustion of products increased from 52.8% to 100%. Additionally, the probability of fire escalated from 51.4% to 100%. In addition to carbon dioxide, it is anticipated that levels of carbon monoxide will surpass the established threshold. The results indicate that there is a positive correlation between the probability of fire and the likelihood of fire, as evidenced by the escalation of both variables to 87.5%. The Bayesian theory provides a systematic and consistent framework for handling uncertainty. The presence of ambiguity is a prevalent characteristic of routine decision-making, and antecedent familiarity frequently functions as a valuable asset in directing our selections. The aforementioned approach is applicable in scenarios where machines encounter the task of acquiring knowledge and handling ambiguity.

Validating the model of the fire and alarm detection systems requires evaluating their performance, precision, and dependability via model training and simulations. Using supervised learning, the probabilistic inference models are trained on a subset of the collected dataset. Each instance of the labelled training data is associated with a known alarm or fire condition in supervised learning. The probabilistic inference models modify their parameters based on the labelled data to make accurate predictions. In addition to the supervised learning method, maximum likelihood estimation and maximum a posteriori estimation is used to train models using labelled data. Figure 4 depicts the simulation of absence of fire using maximum a posteriori estimation. Cross-validation is used to divide the dataset into training sets in order to evaluate the performance of the model. To evaluate how well the models perform in detecting alarms and fires, the defined performance metrics on the test set are measured. A comparison between the performance of the probabilistic inference model and the baseline

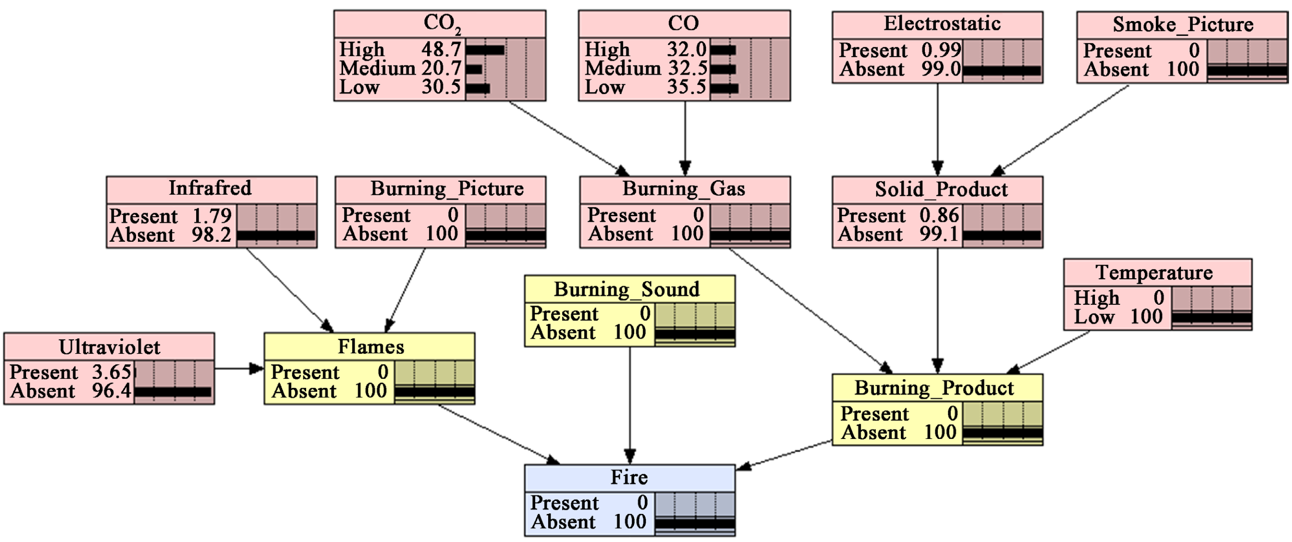

Figure 4. Model validation for fire prediction with "absence" predictive dataset.

of existing methods used in alarm and fire detection confirms whether the probabilistic inference models offer enhancements over the baseline methods in terms of accuracy, false alarm rate, or other pertinent metrics.

5. Discussion

This research provides significant contributions by shedding light on the association between various characteristics and identifying the most impactful features that augment the accuracy of fire detection in a fire alarm surveillance system. The set of sensors that has been identified is deemed to be optimal for detecting fires with high efficiency and reliability, as per reference [19]. The current research centers on the implementation of a suggested technique for identifying fires that integrates a multisensory strategy and numerous inputs to augment the accuracy and reliability of the results. This study presents an analysis of the efforts made to utilize data analysis methods for the purpose of investigating the unpredictability of fire alarm systems. The precise forecasting of fire incidence for identification in a fire detection system is a crucial element in the prospective advancement of surveillance systems. The current study utilized datasets obtained from fire calorimeters to perform data analysis. The utilization of a Bayesian network was employed to analyze the behaviors and trends of fire alarms in the datasets mentioned. The efficacy and practicality of Bayesian network methodologies have been demonstrated in various contexts, surpassing alternative conventional models. Moreover, the manipulation of data improves the accuracy of predictions.

The utilization of the Bayesian network model, as suggested, for fire detection on the optimal set has produced empirical findings that exhibit a significant degree of precision in fire detection. Fire alarm systems serve as a method of safeguarding against fires by identifying and evaluating signals from the fire location to ascertain the presence of a fire. The prevalence of false alarms poses a significant obstacle to the widespread adoption of alarm monitoring systems. The main objective of the study concerns the creation of a fire detection mechanism that employs a variety of sensors. The identification of a fire outbreak can be accomplished by observing alterations in the parameters of fire sensors as the system transitions from a state of absence of fire to a state of fire. Therefore, the optimization of output value fitting to the expected values during the transition phase can result in a noteworthy decrease in the duration needed for fire detection, while also guaranteeing the accuracy of fire alert. The Bayesian inference technique outlines a systematic approach for expressing and revising beliefs through the utilization of Conditional probability and Marginal probability. The conditional independence of a node's non-descendants in a Bayesian network is contingent upon the presence of that node's parents. Consequently, the joint probability distribution of all stochastic variables in the graphical model can be expressed as a product of conditional probability distributions of the variables conditioned on their respective parent variables. Thus, it is possible to construct a comprehensive probability model solely by defining the conditional probability distribution at each node [1]. Conditional probability refers to the likelihood of an event occurring given that another event has already occurred. It is calculated by dividing the probability of the intersection of the two events by the probability of the given event. This concept is widely used in various fields such as statistics, mathematics, and engineering to make predictions and decisions based on available data. The concept of conditional probability pertains to the likelihood of a specific variable or set of variables, given another variable or set of variables. This is commonly represented by the notation P(A|B). An instance of probabilistic reasoning involves determining the likelihood of a Fire burning being True, given the presence of Flame being True, which may result in a probability of 50%. The probability of P (Fire = True|Flame = True) is 50%. The CPT delineates the likelihood of an entity being in a particular state, based on a set of parent state values. The size of the CPT for a given variable is determined by multiplying the number of states of the child node by the number of states of all its parent nodes. The assignment of a probability distribution P(X | pa(X)) is a necessary requirement for each node X in a Bayesian network. The absence of a parent node, or pa(X), for a given node X, indicating that it is a root node, leads to the determination of the requisite distribution as P(X), commonly known as the prior. This distribution can be probabilistically characterized by a marginal probability distribution. The unidirectional orientation of a link within a Bayesian network does not impose any limitations on the transmission of information between nodes, but it does alter the necessary probability distributions. This is due to the fact that a node's distribution is contingent on the presence of its parent nodes, as previously explained. The CPT applied in this research work integrates on secondary data from cases and from elicitation of expert knowledge, as shown in the figures above. The Bayesian network exhibits that the node Flame is influenced by three parent nodes, namely Infrared, Ultraviolet, and Burning Picture. The corresponding states' combination of the nodes is presented on the left side, while the probability distribution of the Flame node with respect to the states' combination of its parent nodes is displayed on the right side. Thus, it is necessary to determine the probability distribution P (Flame|Infrared, Ultraviolet, Burning Picture), as illustrated by the models and simulations.

6. Conclusion

The Bayesian data analysis utilizes a statistical model that integrates probability to represent uncertainty in all its constituents. The model's effectiveness is assessed by utilizing the test dataset, which consists of data from fire scenarios conducted under diverse experimental conditions, as presented in this paper. The study employs the complete fire process data as a unit of analysis and sequentially inputs the test data into the model based on the order of fire incidence, which is a noteworthy aspect of the research. The study provides an analysis of the relationship between various characteristics and identifies the most crucial factors that facilitate the attainment of precise fire detection in a fire alarm monitoring mechanism. The work also expounds on a methodology for fire detection that integrates a multi-sensor system and leverages multiple inputs to augment the accuracy and reliability of the results. One area for further research on feature discretization in alarm and fire detection systems includes a comparison of different feature discretization techniques in the context of alarm and fire detection systems. Exploring both traditional methods, such as equal-width or equal-frequency binning, as well as more advanced techniques like entropy-based or information gain-based discretization to determine their impact on the accuracy and efficiency of the detection system. Another area for further research is identified as the study to investigate the effectiveness of different feature selection methods, such as correlation analysis, mutual information, or feature ranking algorithms, in identifying the most relevant features for detection.

7. Availability of Data and Material

The data utilized in this study are sourced from the NIST public data catalogue, which provides access to the NIST public data repository resources. The repository serves as a centralized location for data pertaining to various scientific domains, such as information systems, mathematics, statistics, and many others. The URL is specified at https://data.nist.gov/od/id/43A15F2DF1A65F6FE0531A5706810D411515 titled Data on Smoke Alarm Performance: A Compilation to NIST TN 1947 by Thomas Cleary for open access with document Identifier: *doi:10.18434/mds2-1515*. The data files include tabulated summary smoke alarm response results for smoke box and room experiments, as well as individual experiment data files containing smoke beam obscuration, MIC current, gas species concentration, temperature, and relative humidity measurements as a function of time for each experiment. On the data landing page, descriptions of the file name structure, data file contents, and uncertainty estimates for each reported metric are provided.

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Author's Contributions

The research utilises fundamental fire process data as a unit of analysis and systematically introduces the test data into the model in accordance with the order of fire incidence, which is a significant feature of the study. The present research offers an examination of the correlation among diverse attributes and determines the pivotal elements that enable the achievement of accurate fire detection in a fire alarm surveillance system. I attest that the author of the article has reviewed and provided their consent for the final iteration of the manuscript that is currently being presented for submission. The author affirms that the manuscript is an original work of their own initiative, has not been previously published, and is not presently being evaluated for publication elsewhere.

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Conflicts of Interest

The authors whose names appear below certify that they have no affiliations with, competing interests or involvement in any organisation or entity with any financial interest (such as honoraria, educational grants, participation in speakers' bureaus, membership, employment, consultancies, stock ownership, or other equity interest, and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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List of Abbreviations

BME	Bayesian Maximum Entropy
BNs	Bayesian Networks
CO	Carbon Monoxide
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
IMR	Interval-Message-Ratio
NIST	National Institute of Standards and Technology