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Smart sensor-based system for campus fire detection and control using a Naive Bayes classifier

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Abstract

Emergency incidents relating to fire control and recovery systems require urgent attention to detect fire explosions quickly and to speed up the control process in order to allow escape. In gigantic buildings and large-scale environments like a university campus, data transmission to the control panel for signal processing may be obstructed; the inability to provide accurate analytical sensor data could cause excessive false alerts. Security monitoring of campus to protect lives and property through immediate response to pre-empt fire outbreak is the objective of this study. This study adopts a quantitative and experimental design by incorporating smart sensor being integrated into portable devices like personal digital assistants (PDA) or internet enabled smart phone; with the use of supervisory trained Naive Bayes classifier for intelligent reasoning and decision-making through possibility approximation analysis of environmental observations as a machine learning model for fire detection. An improved model (Fire-DC) for implementing a fire detection and control system in a campus environment was developed using smartphone sensors and a Naive Bayes classifier. Seventy-five percent (75%) of the dataset was provided as sensor values and experimental observations to the model (Fire-DC) for training, while twenty-five percent (25%) of the dataset was later used for testing in scientific experimentation. Performance of the improved system (Fire-DC) was evaluated through a web-based application program implemented in HTML, Bootstrap, XML, PHP, MySQL, Google Maps API, and integrated sensors in internet-enabled smartphones, and compared with previous techniques in existing systems using accuracy, sensitivity, precision, and confusion matrix as yardsticks. Prototype development and experimental performance of the improved system (Fire-DC) recorded higher accuracy of ninety percent (90%) for its classification algorithm; as well as good sensitivity of seventy one percent (71%) for smart sensors in sophisticated mobile phones to detect presence of fire in immediate surroundings, with visual description of incidence location through geographic positioning system (GPS) coordinates being fetched from sensor nodes.

Keywords: Control system, Dataset, Fire detection, Naïve Bayes, Smart sensor

1. Introduction

Fire explosions are disastrous incidents that often occur in our environment due to human negligence or other sources, thereby destroying private and/or public properties. Inferno kind of emergency incident, and control measures require urgent attention to detect fire explosions quickly and to speed up the control process to allow escape (Aslan et al., 2022). The need for an innovative entity that can handle escalation and notification of fire explosions is quite germane to ensure timely control to avert severe consequences (Mishraet et al., 2023). Precautionary measures and safety are the key to healthy and peaceful co-existence in our neighbourhood. Disastrous incidents are relatively unpredictable, and as such it could bring about untimely death and destruction of valuable resources (Okokpujie et al., 2021).

Communication is very important in this era of digitalization and the knowledge economy, so that groups of people within and outside a settlement can share updates and live reports to avert hazards with urgency (Ayeni &

Soyemi, 2016). In disaster situations, information and concurrent communication with rescue teams in a typical society and academic environment are essential. A campus, as a citadel for higher learning, is such a large community of a university or other tertiary institutions which embodied various buildings, laboratory complexes, lecture rooms, administrative blocks, among other infrastructural elements needed for academic activities. The need to forestall an inferno or disasters is germane to avoiding the destruction of valuable properties like infrastructure or learning resources and loss of lives (Prabhuram et al., 2020). Every campus must be adequately secured to protect lives and property through immediate response to pre-empt fire outbreaks. Bayesian inference engine is specifically applied to a huge amount of data. Besides its simplicity, Naive Bayes is generally regarded as having the best performance in classification accuracy, even beyond some sophisticated and popular classification techniques (Alese et al., 2023).

Dong and Tinh (2023) established an inference and reasoning pattern that requires complete probability estimates, including joint probabilities, to ascertain its conclusions and the correctness of the extracted ruleset to draw inferences in their developmental research. Meanwhile, extensive data collection and validation processes may be capital intensive. However, complexity bounds and implementation issues accompany most data mining techniques for problem solving in real-time because it considers single hypothesis in the context of the union of multiple symptoms (Noel et al., 2020; Muralidharam & Joseph, 2024).

Asifet et al. (2024) developed a fire detection framework to function in real time but only provides a standalone interface while providing users with the reasoning tendency as a fire alarm system. More often than not, firefighting officers use their experience to determine the fire intensity and infer it based on the smoke colour and the burning sound. Firefighters sometimes need infrared (IR) cameras to detect the temperature of the burning place, because the lack of remote monitoring limits the analysis of sensor data on a back-end server only (Ann-Ganesh, 2023).

However, most of the existing frameworks require sophisticated external sensors, which are capital-intensive, and cannot perform reasoning and monitoring simultaneously (Christopher & Shanti, 2024). Lack of a coordinating mechanism for multi-agent systems causes overwhelming false and non-relevant alerts to be generated. The inability to provide exact analytical sensor data, thereby causing excessive flooding of false alerts, is the focus of this study.

2. Materials and methods

The research design adopts a developmental and experimental approach by incorporating smart sensors embedded in portable devices like internet enabled smart phones being the in-built sensors of mobile phones, with the use of supervisory trained Naive Bayes classifier for intelligent reasoning and decision-making through possibility approximation analysis of environmental observations as a machine learning model for fire detection. Bayesian approach was adopted as the logical composition of smart sensor nodes: a Naive Bayes technique called classifier and inference /notification module, with a synchronized mechanism for functionality.

The implementation and experimental process of the model involves observable environmental data, which were collected as a training set from sensor nodes, and technical understanding of data distribution, which paves the way for memory- and energy-efficient training, with testing in real time. Multifactor observations were used to define input variables through some parameter values for major traits of explosion through a generic classifier as an inference mechanism, while fire is being identified by the target output variable, which not only classifies raw observations from localized sensor nodes into fire classes but can explicitly send descriptive information about the incidence location through a geographic information system (GIS).

The inference engine of the detection system initializes the Naive Bayes classifier to compute the expected posterior probability of a fire outbreak on campus by approximating the probability distribution of prior selectors in observation yardsticks, as shown in Figure 1, and the highest likelihood or tendency becomes return the output. The input data for the intelligent reasoning and inference phase contains the nominal values, which are being converted according to labelled ranges of likelihood values.

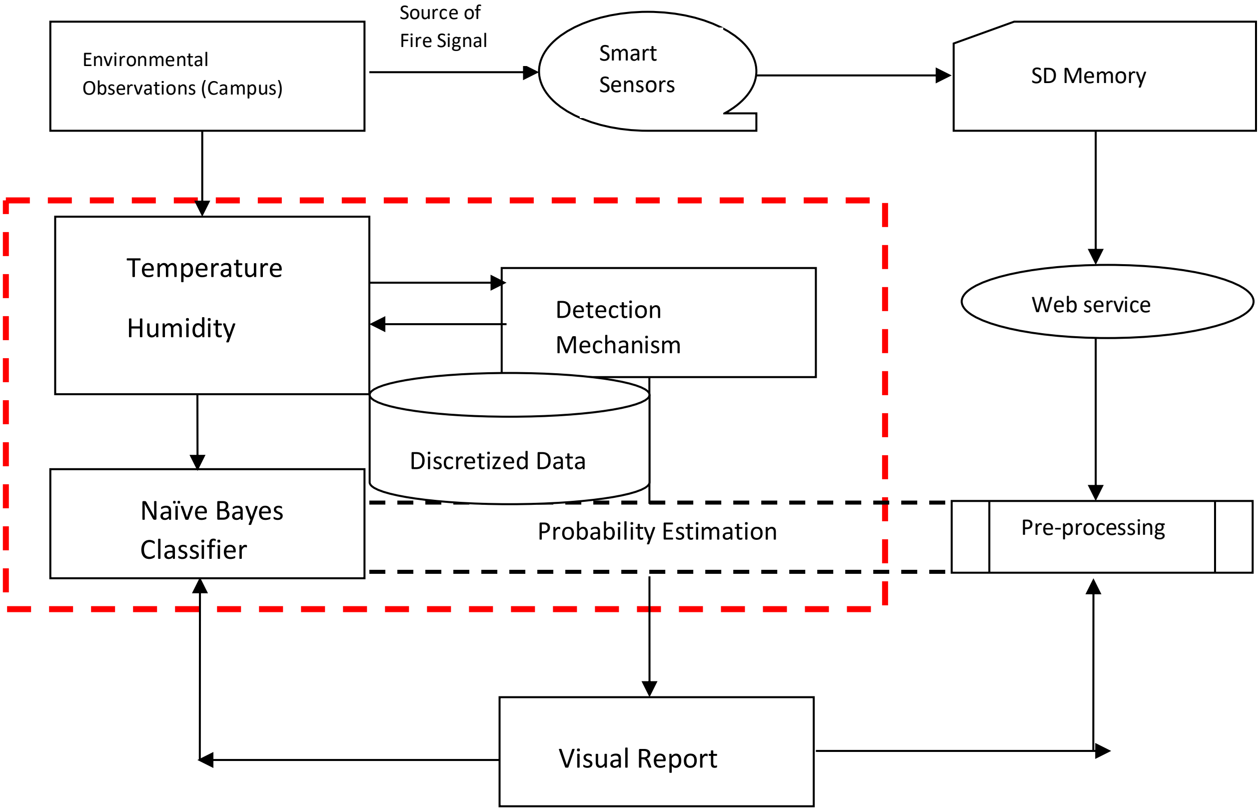

Figure 1: Architecture of Smart Fire-DC System

Figure 1 depicts how environmental observations consider multi-class perception or multiple elements for parameter observations. Temperature which determines the degree of hotness, humidity which indicate the level of water moisture or atmospheric air and light which indicate possible cloudy or presence of smoke, are all provided as fire signals from smart sensors being the digital source integrated in smart phones. While the temperature sensor monitors and record momentum changes as numeric data that emanates from atmospheric heat in the campus environment, humidity and light sensors perform similar functions on changes in water vapour and cloud intensity. The recorded values are initially stored as numeric data in SD memory or in-built storage of the mobile device, and thereafter transferred to a back-end remote database via web service. Pre-processing is handled by a special function deployed to the database server to convert numeric data to nominal data, because the detection mechanism called the Naive Bayes classifier only operates on nominal data for fire prediction; discretized data are fetched from the dataset repository or knowledge base of fire signals into the classification routine for manipulation and decision-making.

The operational flow of data during input and output processes, which are executed by a server-side script as the middleware mechanism operating at the intermediate layer, is initially stored as localized observations or sensors' values in the internal memory (built-in) or external SD memory of the client's smartphone or internet-enabled device. The computational process is handled by the Naive Bayes algorithm or a detection mechanism known as a classifier, incorporating data fusion with variance to reduce false alarms and to de-noise environmental interference that could affect the classification target, when estimating the probability tendency in order to escalate true fire presence.

Naive Bayes principle and its probability algorithm are supervised learning methods, which require training prior to performing a classification task. Hence, the training set and/or validation data contain several factual data as domain knowledge for the subjective hypothesis and the predictor class. It uses the target variable as a dependent element on observable selectors or values to determine environmental traits for a fire signal or otherwise; just as the training set conveyed in Table 1 showed values of three yardsticks, namely temperature, humidity, and light (T, H, L), and a likely predictor with target output being determined by a sequence of observation data.

The classification algorithm for detection computes all the relational possibilities for visual analysis by conversion; data instances acquired about environmental observations from monitoring sensors in smartphones cannot be used directly by the Bayesian method. Hence, it is imperative to convert the continuous input data of specified parameters, which appear in numeric form in temporary log or buffer storage of the smart mobile device (for example, an Android phone), to corresponding nominal discrete data (for instance, extracted features) according to labelled ranges being defined as shown in Table 1.

The pre-processing is to be performed following onward relay of incidence values to the back-end database server. Labelled ranges are defined in accordance with data distribution for process and efficacy of intelligent reasoning.

Parameter	**Low**	**Mild**	**High**
Temperature (**^oC**)	0-34	35-74	75-170
Humidity **(%)**	0-49	50-79	80-100
Light **(Lux)**	0-999	1000-9999	10000-60000

Table 1: Labelled Range for Converting Observation Parameters

2.1. Experimental data acquisition

Experimental design in this study used the combination of open-source and local datasets with five thousand, five hundred and fifty (5550) data instances and six (6) attributes. In all cases of fire data, the data samples are multivariate in nature with more categorical characteristics. While five thousand (5000) instances of localized fire data were obtained from sophisticated smartphones with built-in sensors, the readings of environmental observations include geographic positioning locations, which imply GPS coordinates of specific places/user's proximity on campus. Five hundred and fifty (550) instances of open-source fire data (OSFD) were acquired from the publicly available machine learning repository of the University of California, Irvine (UCI), at the following uniform resource locators (URLs):
https://archive.ics.uci.edu/ml/machine-learning-databases/
https://archive.ics.uci.edu/ml/machine-learning-databases/

The fire detection system was subjected to scientific experimentation and integration testing through internet enabled smart phone. Web-based programming languages like XML and PHP/MySQL were chosen as development tools, with the embedded Google Maps application programming interface (API) for intelligent systems and/or machine learning. It runs on typical smartphones and web platforms, especially with cross-platform mobility that meets the required functional specifications.

Hence, at middleware initialization a subroutine is invoked to convert numeric value to nominal value as pre-processor for Naive Bayes classifier as shown in figure 2. The operational flow of data during input and output processes which are executed by server-side script being the middleware mechanism operating at intermediate layer is initially stored, as localized observations or sensors' values in the internal memory (built-in) or external SD memory of client's smart phone or internet enabled device.

The classifier is trained to classify sequence of nominal values into appropriate fire class by likely predictor and yield a corresponding output. Accordingly, observed incidence for predictor with the highest nominal value and likelihood range must be selected or chosen for probable outcome. Classification algorithm usually makes reference to the training instances, to compute probabilities of every class based on the possibility distribution in the training dataset.

In the first instance, when computing the possibility of the fire class TRUE, the classifier will count the number of data cells in which TEMPERATURE scale equals HIGH when the observation sequence in data cells is classified as TRUE. Only four (4) data cells exist with this yardstick; meanwhile, there are five (5) data cells in which the TEMPERATURE equals or is greater than MILD, and the data cell is classified as TRUE.

Therefore, the relative possibility of TEMPERATURE equals HIGH given TRUE equals 4/5, while the relative possibility of TEMPERATURE equals MILD given TRUE equals 1/5. From a similar perspective, when computing the possibility of the fire class FALSE, the classifier will count the number of data cells in which TEMPERATURE scale equals LOW when the observation sequence in the data cell is classified as FALSE. Only one (1) data cell exists with this yardstick; meanwhile, there are three (3) data cells in which the TEMPERATURE equals or is less than MILD, and the data cell is classified as FALSE.

Therefore, the relative possibility of TEMPERATURE equals MILD given FALSE equals 2/3; while the relative possibility of TEMPERATURE equals LOW given FALSE equals 1/3. In the second instance, when computing the possibility of the fire class TRUE, the classifier will count the number of data cells in which HUMIDITY scale equals to LOW when the observation sequence in the data cell is classified as TRUE. Only two (2) data cells exist with this yardstick; meanwhile, there are five (5) data cells in which the HUMIDITY equals or is less than MILD and the data cell is classified as TRUE.

Therefore, the relative possibility of HUMIDITY equals MILD given TRUE equals 3/5, while the relative possibility of HUMIDITY equals to LOW given TRUE equals 2/5. From a similar perspective, when computing the possibility of the fire class FALSE, the classifier will count the number of data cells in which HUMIDITY scale equals to LOW when the observation sequence in the data cell is classified as FALSE. Only one (1) data cell exists with this yardstick; meanwhile, there are three (3) data cells in which the HUMIDITY equals or is less than HIGH, and the data cell is classified as FALSE.

Therefore, the relative possibility of HUMIDITY equals HIGH given FALSE equals 1/3; the relative possibility of HUMIDITY equals MILD given FALSE equals 1/3, and the relative possibility of HUMIDITY equals LOW given FALSE equals 1/3. In the third instance, when computing the possibility of the fire class TRUE, the classifier will count the number of data cells in which LIGHT scale equals LOW when the observation sequence in the data cell is classified as TRUE. Only one (1) data cell exists with this yardstick; meanwhile, there are five (5) data cells in which LIGHT equals or is greater than LOW, and the data cell is classified as TRUE.

Therefore, the relative possibility of LIGHT equals LOW given TRUE equals 1/5; the relative possibility of LIGHT equals MILD given TRUE equals 2/5; and the relative possibility of LIGHT equals HIGH given TRUE equals 2/5.

From a similar perspective, when computing the possibility of the fire class FALSE, the classifier will count the number of data cells in which LIGHT scale equals LOW when the observation sequence in the data cell is classified as FALSE. Only one (1) data cell exists with this yardstick; meanwhile, there are three (3) data cells in which the LIGHT equals to or less than HIGH and the data cell is classified as FALSE. Therefore, the relative possibility of LIGHT equals HIGH given FALSE equals 1/3; the relative possibility of LIGHT equals MILD given FALSE equals 1/3; and the relative possibility of LIGHT equals LOW given FALSE equals 1/3.

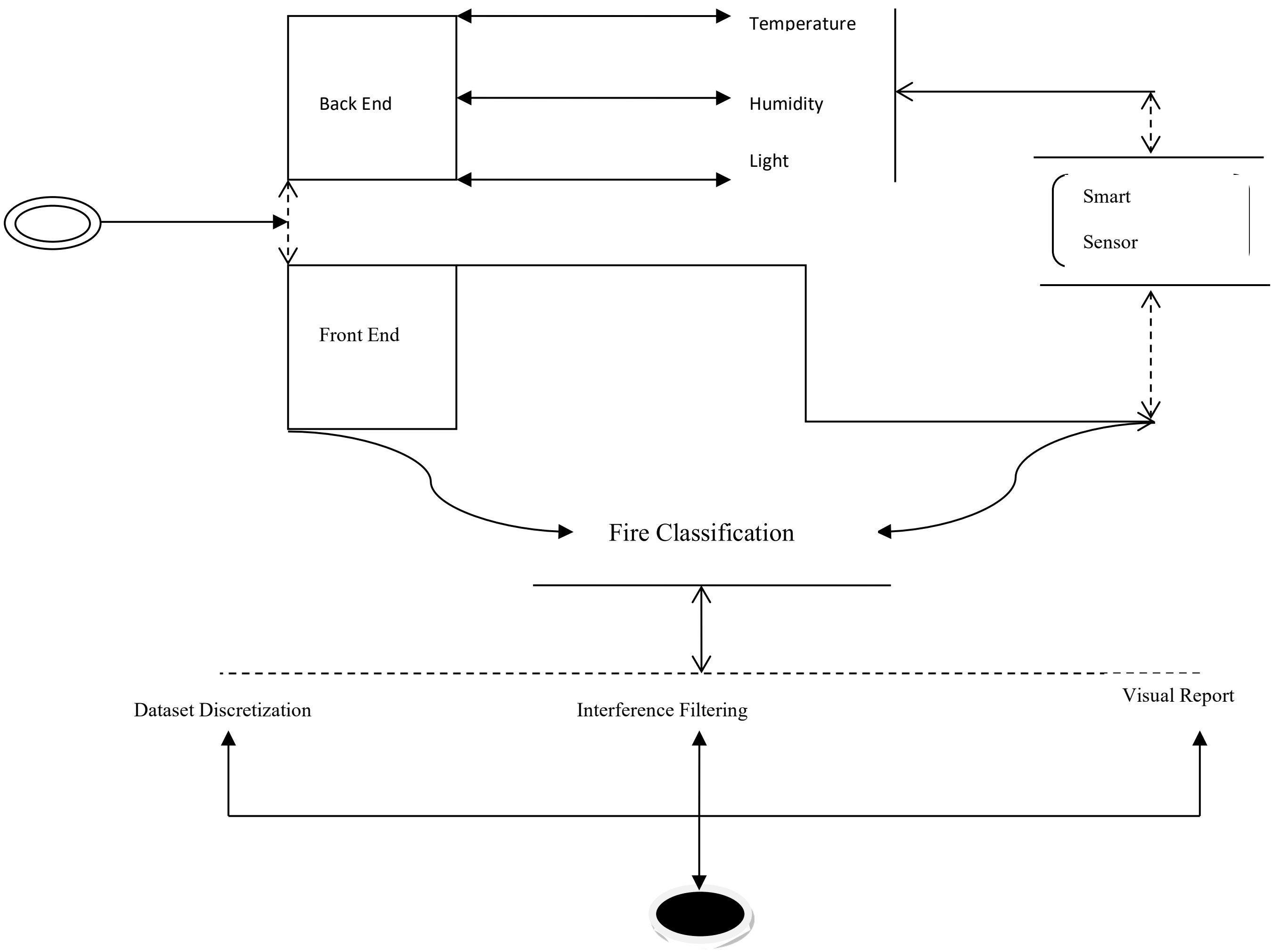

Figure 2: Dataflow Diagram of Smart Fire-DC System

2.2. Adapted Mathematical Model

For fire disaster and emergency escalation in which fire signal is to be detected, thus;

$P(vLocation)$ (1)

is the tendency (prior probability) of campus as target hypothesis

$P(FireHx)$ (2)

is the tendency (prior probability) of fire signal as observable selectors

$P(vLocation|FireHx)$ (3)

is the tendency of campus disaster *(as target hypothesis)* given fire signal *(as observable selectors)* based on posterior probability

$P(FireHx|vLocation)$ (4)

is the tendency of fire signal *(as observable selectors)* given campus disaster *(as target hypothesis)* based on likelihood

Meanwhile, observable selectors and symptom attribute '*FireHx'* is quite subject to likelihood yardsticks or parameter changes like light, heat, flame, humidity, because the conditional possibility of observable selectors given the target hypothesis is tantamount to the production of conditional possibilities of each observable trait in fire signal given in the specified environment as the target.

$P(FireHx_1|vTemperature)$ (5)

Implies predictor *fire signal* subjected to temperature

$P(FireHx_2|vLight)$ (6)

Implies predictor *fire signal* subjected to light

$P(FireHx_3|vFlame)$ (7)

Implies predictor *fire signal* subjected to flame

$P(FireHx_n|vHumidity)$ (8)

Implies predictor *fire signal* subjected to humidity

Hence,

$$P(FireHx|vLocation) = P(FireHx_1|vLocation) \ldots * \ldots P(FireHx_n|vLocation) \quad (9)$$

3. Results and Discussion

Model training is quite necessary for the chosen data mining and classification algorithm; hence, data instances from real fire scenarios were used to form the training set before experimental analysis. Three additional values were created from sensors' data by calculating the temperature variance, humidity variance, and light variance for temperature, humidity, and light, respectively. This is an important step to determine if a significant change in sensor value is continuous, as well as ensuring the stability of selected parameters for measuring environmental observations and the rationale for difference ratio or periodic changes in the situation.

Similarly, the calculated values for arithmetic mean and variance are useful in forming the needed intervals for the discretization process. This size and grouping, or number of intervals for parameter values, also has a direct impact on the accuracy of the classification mechanism, which determines the presence or absence of fire by probability approximation of sequential value input.

The parameter values are obtained from sensor nodes (for example, integrated sensors in the client's smartphone) as numeric data, but are in turn converted to nominal data through discretization, which is a special function incorporated in the classifier module because the Naive Bayes algorithm works with nominal values for predictors' probability distribution and posterior estimation.

Figures 3 and 4, as well as Figures 5 and 6, show the tendency to classify parameter values at escalating intervals to fire class, based on experimental data from a web repository, which was considered as input elements for dependent variables in this study.

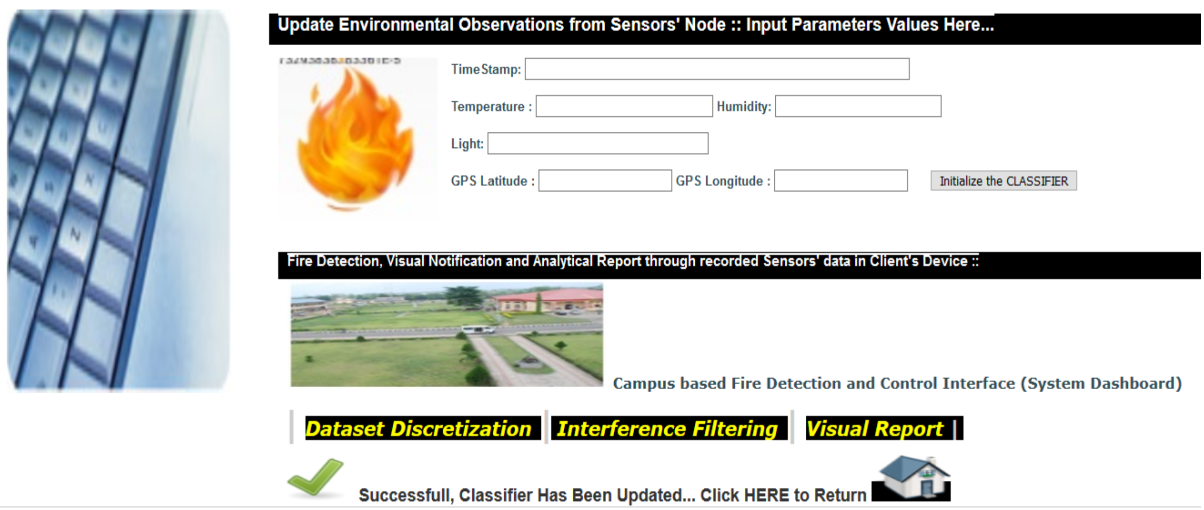

Figure 3: System Dashboard – Successful Insertion of New Values for Sensor Data

Host: localhost
Database: firedb
Generation Time: Feb 15, 2021 at 03:59 AM
Generated by: phpMyAdmin 3.2.0.1 / MySQL 5.1.36-community-log
SQL query: SELECT * FROM `fire report` LIMIT 0, 30 ;
Rows: 5

TimeDate	Temperature	Humidity	Light	GPS_Latitude	GPS_Longitude	Temperature_Variance	Humidity_Variance	Light_Variance
2020-10-09 08:10:00	23.18	27.272	426	58.3353	8.5754	2	2	2147483647
2020-10-09 08:11:00	23.21	28.292	328	48.3353	8.5753	2	3	2147483647
2020-10-09 08:12:00	23.29	28.274	498	58.3353	7.5753	2	3	2147483647
2020-10-09 08:13:00	23.41	29.274	521	68.3353	9.8752	2	0	22
2020-10-09 08:14:00	24.47	32.26	521	78.4353	11.874	3	7	22

Figure 4: Frequency View by SQL query for in Environmental Observation

CHECKING THE INFLUENCE OF ENVIRONMENTAL NOISE AND PARAMETERS' STABILITY:

Temperature Variance: 58

Humidity Variance: 7

Light Variance: 9897

Click Here to Return...

Figure 5: De-noising the detection parameters from environmental influence

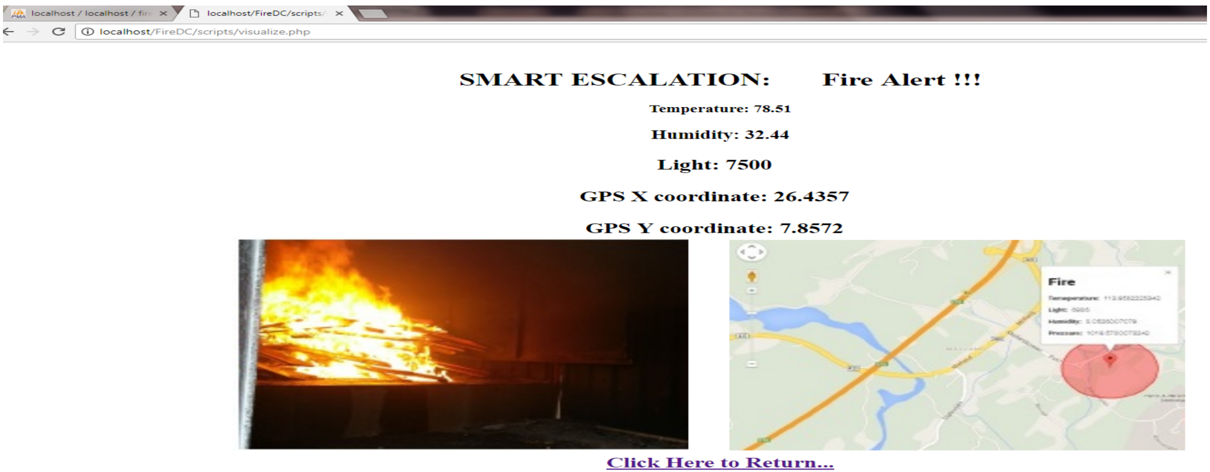

Figure 6: Variance Values for Parameters Due to Environmental Observation

The prior probability of each parameter element and input interval is computed from the frequency distribution generated from the record set of environmental observations stored at every given time stamp through sensors' nodes in the client's device or integrated sensors in a smartphone. Consequently, several situations were created to ascertain confidence in the detection engine (Fire-DC) to discover fire incidence, as shown in Table 2, and to forestall likely explosions that could lead to loss of lives and property; by sending visual notifications to the campus security team and external emergency agency for necessary control or recovery actions; positive signals were received by environmental interference, which generated false alarm.

TEMP	HUMIDITY	LIGHT	GPS_LAT	GPS_LNG	TEM_VR	HUD_VR	LIT_VR	PRECS
22.61	63.29	428	58.57	9.46	2	2	214	No Fire
38.42	51.34	560	51.32	18.06	3	3	215	No Fire
75.93	39.07	875	53.76	20.15	9	9	236	Fire
85.91	49.07	875	53.76	20.15	9	9	236	Fire
65.73	38.07	875	53.76	20.15	9	9	236	Fire
78.93	39.07	875	53.76	20.15	9	9	236	Fire
65.91	29.07	875	53.76	20.15	9	9	236	Fire
75.93	19.07	875	53.76	20.15	9	9	236	Fire
95.03	29.07	875	53.76	20.15	9	9	236	Fire
65.92	49.01	875	53.76	20.15	9	9	236	Fire
85.43	39.27	875	53.76	20.15	9	9	236	Fire
73.93	49.47	875	53.76	20.15	9	9	236	Fire
95.30	35.08	875	53.76	20.15	9	9	236	Fire
55.93	39.07	875	53.76	20.15	9	9	236	Fire
80.93	28.07	875	53.76	20.15	9	9	236	Fire
71.93	39.07	875	53.76	20.15	9	9	236	Fire
75.9	17.07	875	53.76	20.15	9	9	236	Fire

Table 2: Extract from Fire-DC Experiment Results

Table 2 shows environmental observations which served as fire signals and detection parameters. The result was presented in a tabulated manner, showing five columns representing temperature, humidity, light, latitude, longitude, temperature variance, humidity variance, light variance, and the precision for the classification algorithm. Longitude and latitude values were obtained as Global Positioning System (GPS) coordinates that indicate the exact location where incidence fire occurs.

The first column contained recorded values for temperature ranges from a smart sensor as numeric data at different time intervals, and in accordance with different scenarios or environmental changes. For instance, the first data cells and input row from the signal source depict 22.61 centigrade of temperature, 428 lux of light, 58.27 of latitude, 9.46 of longitude, while the precision for these environmental observations and/or classification parameters appears as NO FIRE, having ascertained parameter consistency through measured variance.

3.1. Performance evaluation

TRUE POSITIVE indicate the rate of system precision on received signals that were truly valid or number of test cases for fire signal that were real; TRUE NEGATIVE indicate the rate of system precision on received signals that were truly invalid or number of test cases for fire signal that were not real; FALSE POSITIVE indicate the rate of system precision on received signals that were falsely valid or number of test cases for fire signal that were wrongly escalated;

FALSE NEGATIVE indicates the rate of system precision on received signals that were falsely invalid or the number of test cases for fire signals that were not escalated. Hence, the Fire-DC system was tested to be ninety per cent (90%) accurate and seventy-one point four per cent (71.4%) sensitive to signal precision, which is a great improvement upon existing systems with higher precision, as shown in Tables 3 and 4, compared with other techniques in this problem domain.

Performance Metric	Existing System	Proposed System
True Positive (TP)	1800	3700
True Negative (TN)	1200	1200
False Positive (FP)	2200	300
False Negative (FN)	300	300
Accuracy	70 %	90 %
Sensitivity	50 %	71 %
Precision	65%	85%

Table 3: Performance Evaluation

		True Sentiment	
		Positive	Negative
Classified Sentiment	Positive	3700 (TP)	300 (FP)
	Negative	300 (FN)	1200 (TN)

Table 4: Confusion Matrix

4. Contributions to knowledge and recommendations

The findings from this study have contributed to the body of knowledge through insight into an easily available and efficient approach for ameliorating improper escalation, false alarms, or even negative signals about fire incidence, which could create abrupt panic among the occupants of the concerned area and residents of the academic community at large. The development of an intelligent fire detection and monitoring system for campus environments by combining environmental sensing, machine learning, and GPS-based location tracking.

The proposed Fire-DC framework used a Naive Bayes classifier to analyse sensor data and identify potential fire incidents, and integrated fire detection with location-aware reporting, allowing emergency responders to respond quickly by identifying the source of an incident. A practical framework (Fire-DC) that integrates smartphone-based smart sensors with probabilistic reasoning for campus fire detection and notification through prototype implementation and provides experimental results demonstrating the feasibility of the proposed approach.

It also provided a more economical and location-aware model with responsive mobility for detecting fire; lightweight sensors that are integrated into smartphones were designated as sensor nodes to obtain environmental observations and create an XML log for storage. Usability simplicity helps to minimize false-positive alerts with minimal computational cost for the classifier.

Hence, it is hereby recommended for quick detection of fire, explosion, and emergency management, as quite germane to timely decisions for recovery and control action. The use of intelligent agents and control mechanisms can escalate any disastrous incident on a university campus or other academic communities once it is sensed by intelligent agents mounted in critical locations. It comes as a panacea to incessant fire alarms being escalated wrongly due to environmental noise by conventional fire detectors. However, due to dependency on computational complexity for detection accuracy, multiple sensors with a more simplified algorithm were the focus of wireless sensor networks (WSNs).

5. Conclusion

Experimental analysis involves valid and invalid data in order to ascertain the sensitivity of the proposed system (Fire-DC) in responding to environmental observations and reasoning accuracy. The improved model (Fire-DC), which was provided in this study, was trained and validated with data discretization, showing that the classifier output is in close range of the target inference of fire incidence, with 90% accuracy and 71.4% sensitivity.

Fire explosions could manifest other traits like heat and light, apart from conventional smoke detectors, which lack dependability to escalate fire signals in large-scale environments. The complexity of modern buildings makes it imperative to incorporate fire detection and control mechanisms in structural design. Computational intelligent models and machine learning algorithms are widely projected for data mining applications for functional stability, scalability tendency, and performance accuracy.

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