Early Detection System for Gas Leakage and Fire in Smart Home Using Machine Learning

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***Abstract* — Making houses more inclusive, safer, resilient and sustainable is an important requirement that must be achieved in every society. Gas leakage and fires in smart houses are serious issues that are causing people's death and properties losses. Currently, preventing and alerting systems are widely available. However, they are generally individual units having elementary functions without adequate capabilities of multi-sensing and interaction with the existing Machine-to-Machine (M2M) home network along with the outside networks such as Internet. Indeed, this communication paradigm will be clearly the most dominant in the near future for M2M home networks. In this paper, we are proposing an efficient system model to integrate the gas leakage and fire detection system into a centralized M2M home network using low cost devices. Then, through machine learning approach, we are involving a data mining method with the sensed information and detect the abnormal air state changes in hidden patterns for early prediction of the risk incidences. This work will help to enhance safety and protect property in smart houses.**

Keywords — smart home, gas leakage detection, fire detection, machine-to-machine, wireless sensor network, machine learning.

I. Introduction

Gas leakage and fires in houses are causing many victims and property damages. For example, the natural gas leaks, which is highly flammable, increase the risk of fire and can even provoke explosion. Furthermore, exposure to gas leak in home or smoke inhalation can cause very serious respiratory complications. Indeed, the use of an early warning system results in significant reduction in losses. The sooner a gas or smoke is detected, the better the outcome for saving lives and properties. Practically, smoke and fire detection devices are considered the first line of defense against these issues. On the current market, most of these devices are standalone (individual units) and typically used as an immediate indicator of fire incidence that generally issues a local audible or visual alarm from the detector itself announcing that there is an emergency for evacuation [1,2].

Comparing to industrial domains where usually the gas leakage and fire detectors are permanently monitored and connected to local fire station, the current solutions in residential houses are very basic and work separately from any communication to other systems, and satisfied only giving a local warning to anyone in the nearby place, with the assumption that someone will be around and can hear the sound of the alarm [3]. However, with many residential housing life style cases such as for couples and single residents who are almost outside home in work or in travel, as well as, for people with special needs and elder people, a remote notification system must be implemented to automatically alert the relevant persons, such as the householder, his neighbors and the necessary emergency services. Indeed, it should be great to have gas leakage and fire detection systems connected to Machine-to-Machine (M2M) home networks as we can obtain more additional services such as having automated pre-planned action and remote warning systems.

Opportunely, with the drastic penetration of low cost embedded devices and Wireless Sensor Networks (WSN) technologies, M2M communications may play a key role that can handle the previous cases preventing many incidences. WSN is a current trend which is deployed to control and monitor the physical environment by using sensor nodes [4]. M2M connects between devices through WSN without (or with minimum) human intervention. The devices collect useful information and then autonomously flow the data between other devices up to the gateway. This can offer a panoply of new innovative services through the interaction with other smart home systems (e.g. aeration system, smart gas, etc.), and furthermore provides Internet of Things (IoT) for wide range of services.

In this paper, we propose a novel approach in which we first deploy an M2M system prototype and collect the data from devices. We then apply machine learning methods in order to correlate data between them and propose methods to early detect disaster scenario with imminent fire or gas leakage, etc.

The rest of the paper is organized as follows. In Section II, we introduce our Architecture and describe the dataflow structure. Section III describes our experimental set up and scenario, while Section IV presents the results of our experiments. Section V surveys the related work, and finally, Section VI conclude the paper and present some perspectives.

II. SYSTEM OVERVIEW

A. Architecture

In our system proposal, we considered that smart home architecture (or home automation and control) includes pre-integrated M2M solutions such as smart metering, lightning control, door openers for example [5,6,7]. Furthermore, an M2M data exchange among smart devices is guaranteed without human intervention.

The objective of our system is to collect efficiently the useful data and save it in a central point for farther prediction analysis. As shown in Fig.1, the general system architecture in our methodology consists of three main logical parts: node layer, gateway layer, and application layer.

- Node layer: Two basic operations are provided in this layer. First, sensors measure physical data in their indoor environment, and send the various inputs data for aggregation. The aggregation node combines the data into a unique entity then send it through a low-power wireless network (LPWN) such as ZigBee, Z-Wave, and Bluetooth. This will help for minimizing the number of transmissions and optimizing the energy consumption [8].

- Gateway layer: The gateway plays an important role in the system. First, it collects the data from sensor devices (node layer); Second, the Gateway can be accessed remotely by end-user as control and monitoring system. Data is then analyzed by application layer.

- Application layer: This layer serves as the interface between M2M home network and M2M devices. The main functionality of this layer is to analyze and correlate data received from Gateway layer in order to detect anomalous pattern and to predict gas leakage and fire incidences in smart home environment. Application layer can provide additional services such as local remote notification.

Several applications can be included offering a user-friendly interface with some typical services such as monitoring, local alerting and remote notification. An emergency operations plan implement is required to prevent disasters and maintain safety in house. This will involve the autonomous interaction with: (1) local systems such as smart aeration and smart gas, (2) the relevant persons such as the householders and the neighbors, (3) the emergency services such as local fire station and hospitals in case of imminent incidents.

B. Data flow system

We are going to focus on the trend of the relevant factors related to gas leakage and fire incidences in smart home. In the figure below (Fig. 2), we are detailing the dataflow model

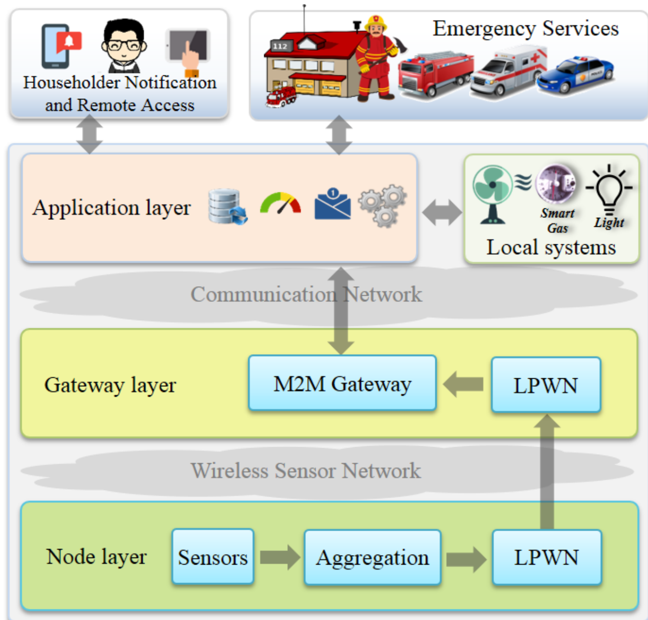


Fig. 1. General System Overview

among the three layers of our architecture as well as with remote entities. The parameters for data acquisition step that we considered in our study are: Air Temperature, Air Humidity, Liquefied Petroleum Gas (LPG), Smoke, Carbon monoxide (CO), Flame, and Carbone dioxide (CO_2). After sequentially receiving the sensed data, the aggregation node merges the data and transmits them to the Gateway. Getting multi-sensing information at each period of time about the environment is very important for an efficient analysis.

Afterward, we will proceed to the data analytics for predicting change of environment and anomalous scenarios. One straightforward method for detecting incidences is to rely on predefined threshold values for our considered parameters. However, in real-world environment, samples are often incomplete data set and some attribute values can be missing or inconsistent because of data collection process issues (packet lost, noise, etc.). Note that there is also a data preprocessing step to improve its quality, and we will discuss further this point in the Discussion Section. For being more efficient and improve the performances over time, we are going to use a supervised machine learning for patterns recognition [9-11]. Then, our main objective consists of predicting unseen information and deciding the level of risks.

In order to achieve the next logical step in case of predicting any irregular pattern, a warning system must be activated to notify the relevant persons that some actions are advised. In case of estimating a high risk of incidence or an imminent disaster the level of alert became more important. As result, an action plan will be immediately initiated and M2M local systems will be trigged. It will be time to notify the necessary relevant persons and emergency services for evacuation.

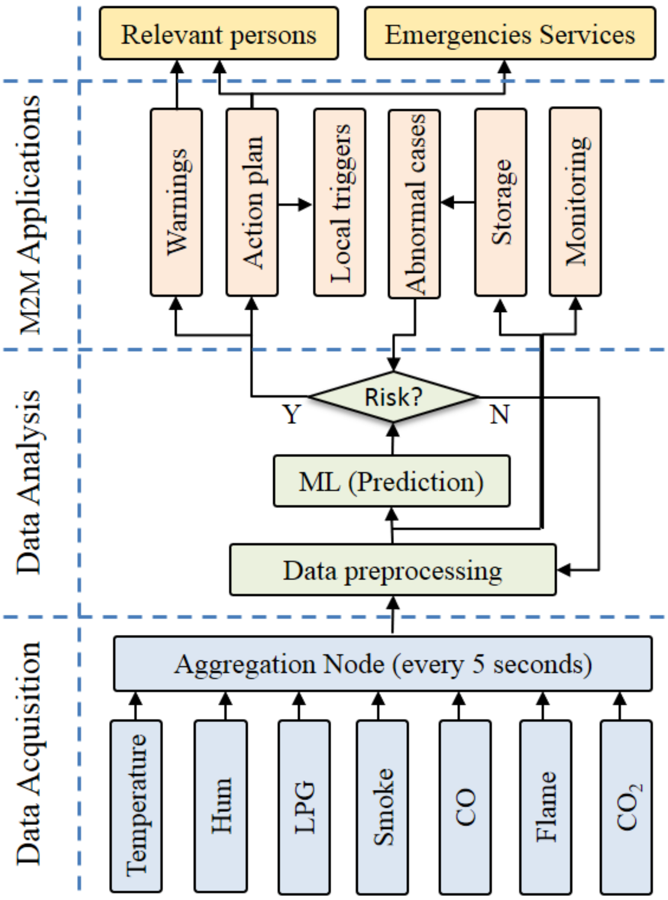


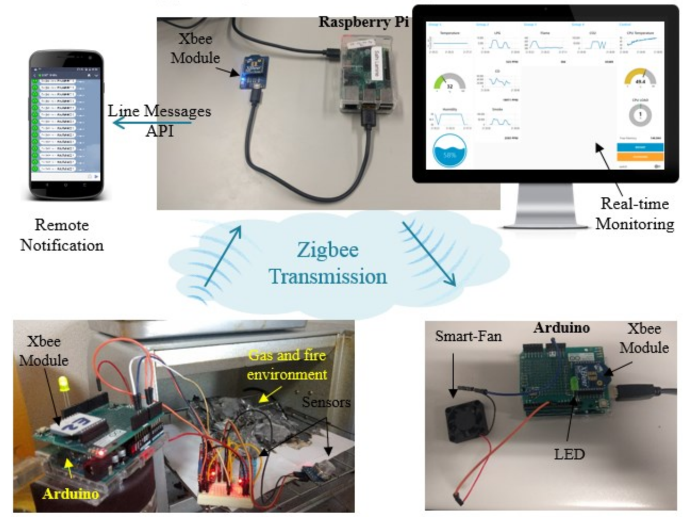
Fig.2. Data flow model for our experimental study

III. Experiment

We implemented a prototype for our early-detection system in smart-home environment. Our prototype collects data through four sensors. This included air temperature, air humidity, smoke, LPG, CO, flame and CO_2.

- As shown in Fig.3(a), an Arduino Uno R3 device [12] is used to aggregate the data from sensors. The Zigbee protocol [13] is also used for communications among devices.
- Then, a Raspberry Pi 3 Model B device [14] is used as M2M gateway to receive the sensed information as depicted in Fig.3(b). Zigbee interface is used for joining the corresponding WSN nodes. The data received is handled by creating topics and using publish/subscribe methods through Message Queuing Telemetry Transport (MQTT) protocol [15]. A graphical user interface (GUI) for monitoring as well as a (local/remote) notification systems are built.
- Finally, a second Arduino Uno R3 device, as shown in Fig.3(c), is used for emulating the triggered functions ordered by the gateway in case of incidence.

(b) Analytics and M2M applications



(a) Sensing and aggregation (c) Local actions after alerts

Fig. 3. The devices and steps of our prototype system during experiment

Table I summarizes the low cost and low energy consumption sensors used during our experiments.

TABLE I. THE USED DEVICES AND PROTOCOLS

N^0	Measurements	Sensors	Units
1	Temperature	DHT-11	^0C
2	Humidity		%
3	Smoke	MQ-2	PPM (Parts per million)
4	LPG		PPM (Parts per million)
5	CO		PPM (Parts per million)
6	Flame	LM35	Flame level
7	CO_2	MG-811	PPM (Parts per Million)

In order to collect pertaining data, our experiments have been conducted during a couple of days. The sensors have been exposed to different conditions, sensing data from regular ambient condition to more extreme conditions with gas and fire. The aggregation node transmitted continuously and periodically data every 5 seconds. The sensors have been configured with their default parameter values that served as a baseline for comparisons with different conditions.

We also have tested the efficiency of our prototype, and implemented a notification service through emails and Line Messaging API for alerting pertaining persons.

Furthermore, the interaction with other systems such as smart aeration and smart gas systems was presented through the second edge node containing some actuators as output in case of incidence (e.g. Fans, LEDs).

IV. Results

A. Data acquisition

During data acquisition, we collected during 1.5 days 21,146 sample measures from the sensors. Each sample counts 7 values, i.e., one value by sensor. Every sample have been collected periodically every 5s. The data have been collected under usual and extreme conditions engendering risks.

Fig. 4 presents our experiment in regular conditions. All the sensed data was relatively stable over time. For instance, Temperature presents a typical day/night pattern with peak above 30°C as it is commonly the case in Japan in summer. This experiment is to serve as a comparison baseline to predict anomalous pattern during extreme conditions. The range values for regular conditions are presented in Table II.

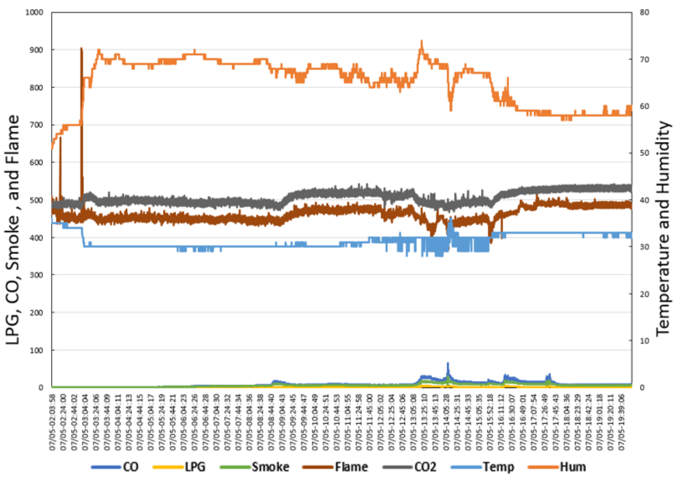


Fig.4. Measurments taken in usual conditions

The Figure 5 presents our experiment under extreme conditions (Fire). The experiment starts from regular conditions (no fire), and then at 23:58, we can observe a dramatic increase of CO, LPG, and smoke, along with a slight decrease of CO2 (38 PPM). In the meantime, Temperature increases progressively and reach up to 60°C. The temperature then stabilizes at 00:34 as it reaches the physical limit of the sensor. Conversely, Humidity increases first and reaches up to 85%, and then it decreases drastically up to 0% when Temperature was maximal. From now, the presence of flames has also been detected. At 00:34, Gas and Smoke become too low to be detected by sensors. Finally, from 00:48, the fire ended and all the metrics return to the regular ranges as observed in Fig. 4.

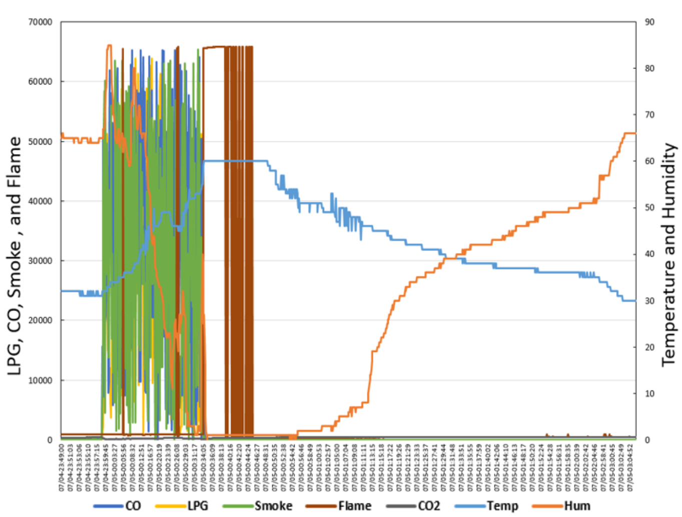


Fig.5. Measurments taken under extreme conditions

Table II provides a comparison between the range of values under normal and extreme conditions.

TABLE II. THE RANGE OF VALUES UNDER REGULAR AND EXTREME CONDITIONS

Parameters	Ranges in Regular conditions	Min/Max values in Extreme conditions	Tendency in Extreme conditions
Temperature	25-35 C^0	60 °C $^{(*)}$	Increase
Humidity	60-70 %	0 %	Decrease
LPG	0-30 PPM	63,898 PPM	Increase
CO	0-50 PPM	65,280 PPM	Increase
Smoke	0-100 PPM	65,395 PPM	Increase
Flame	400-500	65,835	Increase
CO_2	400-500 PPM	38 PPM	Decrease

$^{(*)}$Maximal value allowed by DHT-11 sensor

B. Machine Learning Classification

We obtained from previous experiments a data set measuring environment under regular or extreme conditions. We therefore aim at correlating these data in order to detect specific pattern. This will help inferring abnormal pattern in the data and predict disasters such as fire or gas leakage. To this end, we will rely on Machine Learning methods and applied different algorithms to our data set.

Supervised learning method will be used to build a model from the training data. Our data set will be labelled and when similar condition occurs again, one can set the level of risks and prevent disaster. We then will classify our data set according to four level risks: (0) no risk, (1) moderate risk, (2) risk, and (3) high risk). We then separate our Data set into two parts: 80% for training and the remaining 20% for validation. In order to obtain better accuracy score, we also used a 10-fold cross validation. In this case, the training dataset is divided again into 10 equal parts: nine for training and one for testing.

It is important to compare the performance of multiple different machine learning algorithms consistently. In this study, 6 classification algorithms have been evaluated with our Data Set: Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Gaussian Naive Bayes (NB), and Support Vector Machines (SVM).

Fig.6 gives a box and whisker plot showing the spread of the accuracy scores across each cross validation fold for each algorithm. We can observe from these results that CART has the largest estimated score for our data set with more than 99.93% of accuracy. Which means that CART is worthy of further study on our problem. It indicates also that KNN with 99.71% of accuracy can be a good candidate for our study comparing to the rest of algorithms

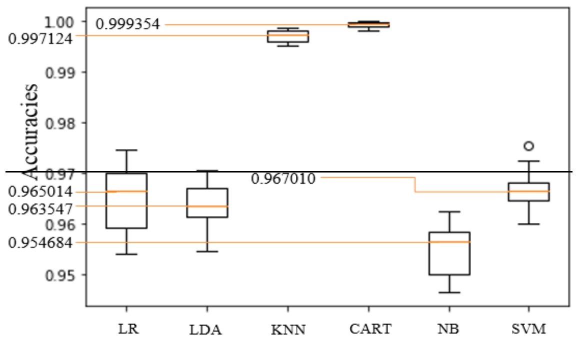


Fig.6. The different algorithms score comparison.

C. Discussion

Sensors can measure wrong information or miss collecting the information due to the extreme conditions or data losses. For instance, when sensors are exposed to high temperature or flame. These loss of information can be critical for the accuracy of our system. We then provide an analysis to minimize the impact of false values.

As a first solution, one can delete entries from our dataset corresponding to any missing or wrong values (sample with missing values). Figure 7 presents the accuracy of evaluated algorithms with the initial data set and the data set whose missing values have been deleted. Deleting missing data helps indeed increasing the accuracy score. However, there is a risk to remove too many samples and therefore losing valuable information that our classifier needs to differentiate between classes of risks and can lead to a non-reliable analysis. Thus, as another solution, the mean imputation technique can be used to estimate the values of each missing data. The mean values are computed in the training data set and missing data is replaced by this computed mean value. As shown in Fig.7, the accuracy score is improved compared with initial data set and the entire data set is maintained, which means that our classifier still has sufficient amount of data to learn classify our data set.

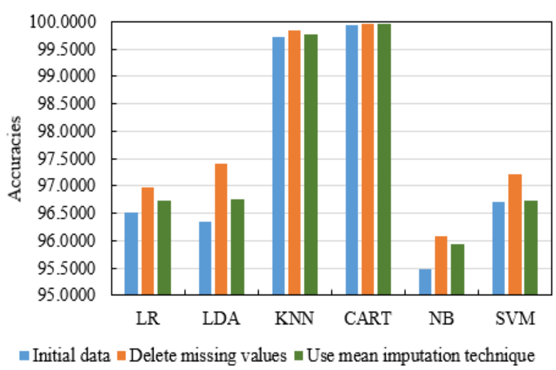


Fig.7. Handling the missing values.

From previous evaluations, CART algorithm is the most accurate for our data set. Then, we evaluate the accuracy of the CART algorithm more precisely. Confusion matrix is a way to present in a table different predictions and test results and contrasts them with real-world values. It outlines the true positive with regards to predicted level of risks. In Fig.8, the confusion matrix shows that there is a limited number of false positive in the evaluation except the 4 errors (True Label 1 – Predicted Label 0 and Predicted label 2). This means for our results that they are inaccurately classified and can be source of wrong prediction of risk.

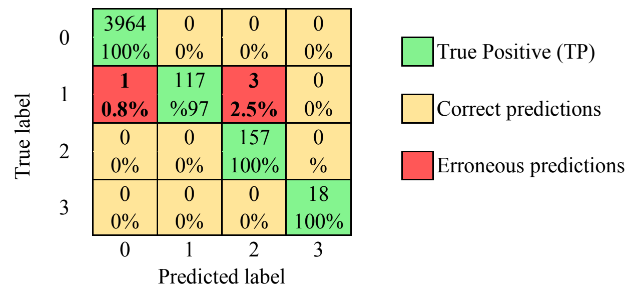


Fig.8. The confusion matrix of the model.

The classification report given in the following table (Table III) provides more details of each class by precision, recall, f1-score and support showing excellent results.

TABLE III. THE CLASSIFICATION REPORT

Risk	Precision	Recall	f1-score	Support
0	1.00	1.00	1.00	3964
1	1.00	0.97	0.98	121
2	0.98	1.00	0.99	157
3	1.00	1.00	1.00	18
Avg. / Total	1.00	1.00	1.00	4260

V. RELATED WORK

Some efforts have been conducted in terms of detecting and preventing smoke and fire in smart-home environment. In particular, Chen et al. [1] have presented a fire sensor system based on the simultaneous detection of CO, CO_2, and smoke concentrations. Islam et al. [2] proposed an application for automating standalone smoke alarms for remote notifications. This decreases the time delay between a fire incidence and the notification to relevant persons or emergency services. Ayyubi et al. [3] proposed an enhanced design of a wireless control system for smoke and fire detection with alarming provision and messages notification systems. A home based fire monitoring and warning system for home owners primarily has also been implemented [16]. Tao et al. [17] proposed a smoke detection based on deep convolutional neural networks from visual scenes. In [18], an adaptive threshold deep learning method for fire and smoke detection was proposed, in which authors has proposed a novel method for fire and smoke detection using video images. Solorzano et al. [19] proposed a fire detection using a gas sensor array with sensor fusion algorithms. A fuzzy logic approach for event detection using wireless sensor network was proposed by [20]. Similarly, [21-23] have also used the same logic to combine data coming from many sensors for getting the probability for fire occurrences. Finally, Yan-Hua et al. [24] adopted the back propagation neural network algorithm of multi-sensor data fusion approach for fire alarm.

Our work differs from previous ones as we are proposing an effective implementation of a preventive system for gas leakage and fire incidences in smart home environment which is natively including an improved monitoring and warning system comparing to [1-3] and [16]. Then, instead of focusing on visual scenes to detect smoke and fire, we are looking in our study for detecting these incidences in earlier stages as an assertive method using other data inputs such as gas and temperature which are not considered in [17] and [18]. Furthermore, comparing to [19-24] we are using additional sensors for obtaining more precise condition and from many vantage points. Finally, although we are involving machine learning methods for combining the multi-sensed data similarly to these studies, this work presents the particularity of treating the missing values for reducing the false alerts and improving the prediction performance.

VI. Conclusion

In this paper, we have contributed in the way of integrating gas leakage and fire systems within smart home environment in order to enhance safety using low-cost and less-energy consumption devices through M2M standard communication protocols. We proposed an effective dataflow system for gathering useful information to a central point in M2M home network. We deployed our system prototype with sensors and perform experiments under different conditions. From our data set, we applied a supervised machine learning process on several algorithms for observing events which are not conform to the expected pattern, and predicting the level of risks of danger. Our system is also able to send a notification to alert relevant persons and proceed accordingly.

In future, we will collect more additional data and apply other machine learning algorithms to improve the accurate of the model to reduce the false positive. We have also the trend toward real-time analysis using cloud services.

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