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Research article

Modeling of an Intelligent Cooking Gas Leakage Detection System Using Convolutional Neural Network

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ABSTRACT

This paper presents the modeling of an intelligent cooking gas leakage detection system using convolutional neural network (CNN). The study reviewed many relevant literatures which shows that cooking gas accident have remained a major cause of fire outbreak at home and has remained a major challenge over the years. This problem was addressed in this research using cooking gas data collection with FLIR GF346 gas camera and then trained with a convolutional neural network algorithm modeled using architectural diagram, self-defining equations and then implemented using Simulink. The result when tested showed high gas leakage detection accuracy of 99%.

Keywords: *Cooking Gas; Convolutional Neural Network (CNN); Leakage Detection System;*

Introduction

According to the World Bank Group (WBG, 2017) about 60% of the overall world population depends on natural gas and liquefied petroleum gas (LPG) for cooking. These LPG for long has been the main fuel choice for many urban and rural localities due to the clean energy, effective cooking, and lack of air pollution it offers when compared to the conventional cooking approaches using other fuels like kerosene, charcoals or firewood, etc.

Liquid petroleum gas (LPG) is a highly flammable mixture of hydrocarbon which is used as fuel in hospitals, industries, vehicles, etc., but in this study, the researcher is only interested in cooking gas, which is applicable in homes, hotels, etc., therefore, LPG serves as fuel in cooking equipment. LPG is a mixture of 48% propane, 50% butane, and 2% pentane. Natural gas is another widely employed fuel mainly used at home for cooking. Natural gas is a mixture of 93.5% methane, 4% ethane, 2% propane and 0.5% butane. Both gases burn to produce clean energy and are reliable for most of the cooking, baking, and a lot of domestic applications. These gas when purchased are stored in enclosed cylinders and supplied to the cooking burner via valves for domestic applications.

However, the lack of an intelligent system to detect gas leakages at home and for domestic purposes resulted in a fire outbreak which has led to environmental hazards, and loss of lives and properties. These gas leakages have been attributed but are not limited to poor maintenance of cylinder and gas burners, enlightened gas regulators, expired gas cylinders, loose gas burners, and loose gas pipes. Hence there is a need for an intelligent LPG detection system that identifies this gas leakage spontaneously and triggers necessary control measures.

Over time various traditional approaches have been proposed to help combat this challenge of gas leakage, using techniques such as gas detectors, heat sensors, smoke, and fire detector among others, however, they all have their advantages and disadvantages (Attia, Hussain, & Halah, 2016; Mahalingam, Naayagi, & Mastorakis, 2012). The conventional gas sensors commercially available in the market today for LPG detection lack intelligence, suffer issues of false alarm and are hence not reliable for real-time LPG detection. However, the use of gas detectors provides a better solution to gas leakage detection issues compared to other approaches aforementioned.

According to Shing, Steven, & Emerson, (2019), gas detectors are sensing elements that are designed to detect gas leakage, based on certain gas characteristics and then notify users for control measures. These sensors are classified into three which are ultrasonic-based, electrochemical, and infrared-based sensors. The ultrasonic sensor detects gas leakage based on the acoustic sound wave but most times suffers from false alarm and high cost, the electrochemical sensor detects gas based on chemical components of the gas and converts to current for identification but is affected by environmental factors such as heat and temperature. The infrared sensor operated based on the photonic properties of the gas and is not affected by environmental factors such as temperature, pressure, and oxygen but suffers from issues of prediction accuracy. However, the infrared sensors due to their ability to counter environmental factors like temperature, pressure, etc. have more potential for system reliability than the rest.

Infrared sensors (IRS) are sensing elements that detect LPG leakages based on the thermal properties of the gas and infrared technology. These IRS are camera that captures data of the gas, analyze the infrared properties of the gas and detect it as leakages. The limitation with the IRS sensor however is an issue of system reliability as the sensor only makes the decision based on the level of infrared and thermal properties identified within the environment (Mahalingam, Naayagi, & Mastorakis, 2012). Hence when the leaked gas levels do not satisfy the desired infrared and thermal property threshold, they are not signaled as leakages. This as a result has become a major challenge in the application of IRS for LPG detection and required urgent attention. This research proposes to address these challenges using the machine learning (ML) technique.

According to Sharma (2020); Nwobodo (2020), ML is a set of algorithms that learn through data collection, and training and make accurate decisions. The algorithms range from support vector machine, K-nearest neighbor, Naïve Bayesian, and artificial neural network among others. Each of these algorithms has its area of specialty (i.e., area where they perform best) depending on the data type and is more efficient when these factors are considered. For instance, in solving pattern recognition problems, artificial neural network (ANN) has provided the best result so far compared to the other ML algorithms. ANN is a biologically inspired network of neurons that learn by adjusting its weight and bias function when data is fed to it. ANN are of many types which include the feed-forward, recurrent, convolutional, the multi perception among others (Mahalingam, Naayagi, & Mastorakis, 2012). However, for solving image-based pattern recognition problems like the case study, the convolutional neural network (CNN) is preferred. These CNN are classes of artificial neural networks called deep learning with the ability to learn patterns of image data and make the predicted decision. This technique is proposed in this research to train the data collected by the IRS and use it to detect leakages accurately. This system will also be incorporated with short message service and alarm to notify the users, and to take early control measures.

Literature Review

Attia, Hussain, & Halah (2016) presented research on the electronic design of liquefied petroleum gas leakage monitoring alarm and protection system based on discrete components. In the research, discrete electronic components were used to develop a gas leakage detection system and a buzzer was used as the monitoring alarm to notify the user of the gas leakage event. However, despite the success achieved in this research, the sensing element can be improved using artificial intelligence.

Jong (2019) presented a study of gas sensors based on conducting metal oxide. In the study, a new sensor was developed based on metal oxide conduction and then used to design a gas detection system. The limitation of the sensing element is the lack of adaptive intelligence as the gas identification ability is based on the number of metal oxides. The accuracy of 85% can be improved.

Kanaka, Aruna, & Gopi (2019) presented a study on IOT based LPG leakage sensing and alerting system. The research developed a GSM-based system for alert notification on LPG gas leakage. The design was done using electronic components and sensors and then implemented with Proteus. The limitation of the research is the high rate of false alarms.

Mahalingam, Naayagi, & Mastorakis (2012) presented research on the design and implementation of economic gas leakage detector. In the research, a hardware system was developed and presented for the detection and monitoring of gas leakage. The limitation of the system is the high cost and false alarms. Hence there is a need for an intelligent system that complements these challenges and provides reliable detection results.

Rhonnel & Israel (2019) presented research on LPG leakage detection using Arduino with SMS Alarm and Sound alarm. In the study, an Arduino controller was used to integrate alarm and SMS on the LPG gas detection system. The system when tested was good, but suffer issues of false alarm.

Mohammed, Somayeh, Roohalah, Sayed, & Alireza (2018) presented research on modeling the consequences of an explosion, fire, and gas leakages in domestic cylinders containing LPG. In the design, a four-stage model was used to characterize the danger poses by various gas cylinders considering the distance from the cooking source. The study recommended developing an emergency response plan is essential and will have an important role in limiting the harmful effects of the release of gas and hazardous substances.

Materials and Methods

The main materials used are power source, IR sensor (camera), deep learning tool, GSM module, buzzer, digital to analogue converter, liquid crystal display, transistors, resistors, capacitors, voltage regulators and circuit board. These materials are all discussed as they were employed to develop each method as discussed below;

Data Collection

The first step of the system development was to collect data of LPG leakages which was used to train the artificial intelligence system. Till date, there is no publicly available thermal image-based LPG gas dataset available; however, a standard dataset developed by Niklas (2015), using FLIR GF346 gas camera was collected. The camera was used to capture time series synchronized images of LPG gas leakages from cylinders and stored in video format as the dataset for the development of the proposed system.

Training Dataset

The dataset collected has a sample size of 1008 thermal image of LPG leakage images with each image frame containing 24 by 24 pixels and a total resolution of 576 resolutions. The data samples are presented in figure 1;

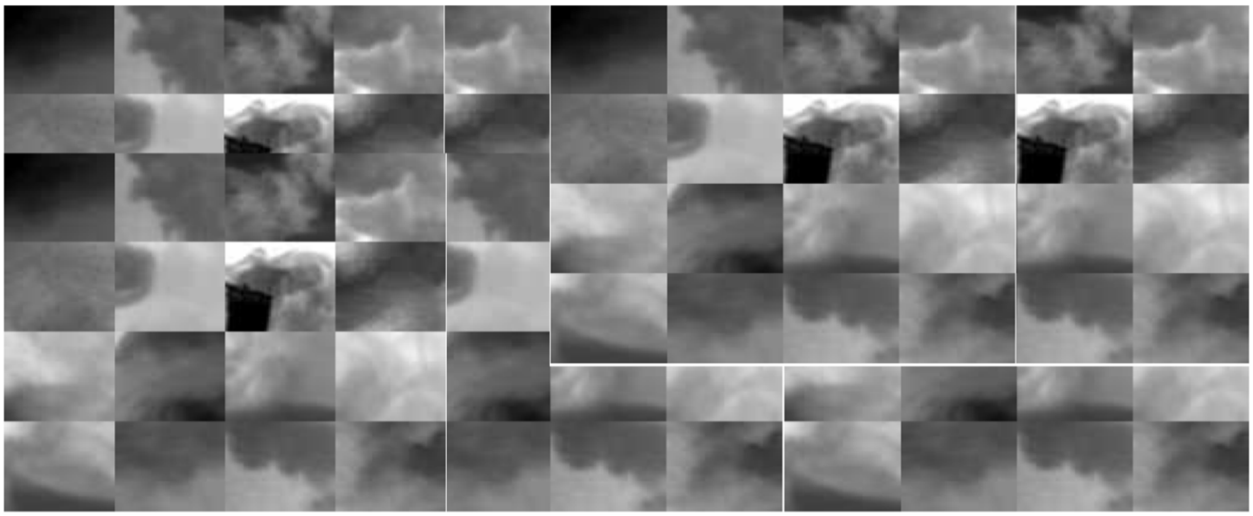

Figure 1: Samples of the Data Collected

Convolutional Neural Network (CNN)

This is an artificial intelligence technique which was used for the development of the proposed system. The CNN is a deep learning-based algorithm which has four major sections which are the input layer, the convolutional layer, fully connected layer and output layer. The input layer was used for the configuration of the input image data collected from the infrared sensor, the convolutional layer uses filter to scan and the pool the extracted features from each convolution a then the fully connected layer summed the extracted vectors and trained with neural network for detection of LPG leakage. The block diagram of the CNN is presented in figure 2;

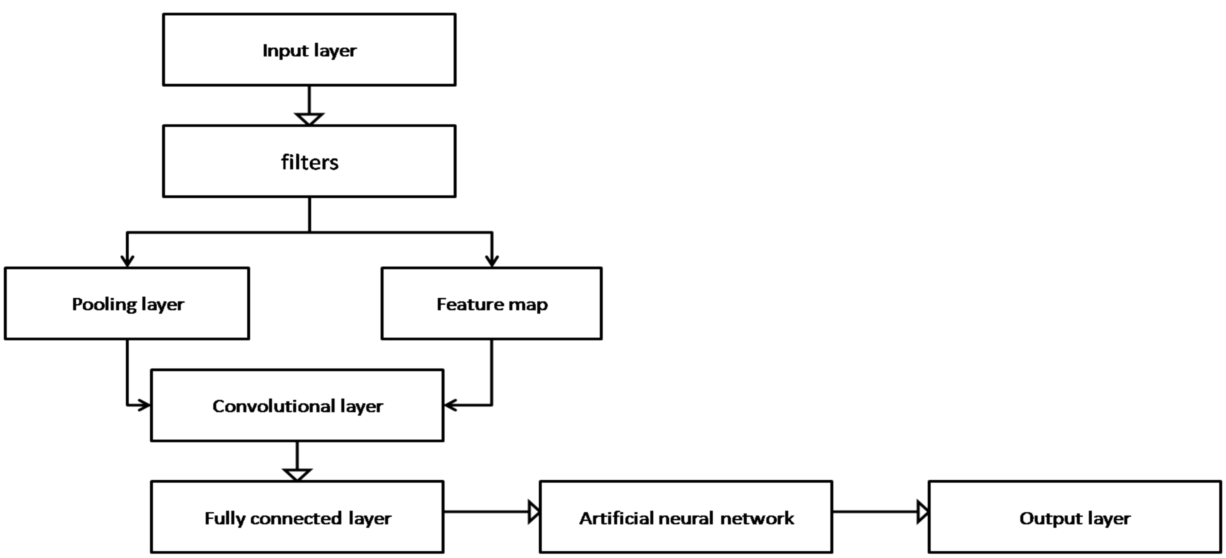

Figure 2: The Block Diagram of CNN

Training
Training is the process of learning the data collected with from the convolutional layer with the artificial neural network in the fully connected layer. The training process involves the use of training algorithm to adjust the weight of the neurons to learn the patterns of the convoluted features and generate a reference model for classification.

Classification
This is the process of comparing time series data of LPG captured by the infrared sensor with the reference model generated by the convolutional neural network to make decision of LPG is detected in the environment.

System Flow Chart

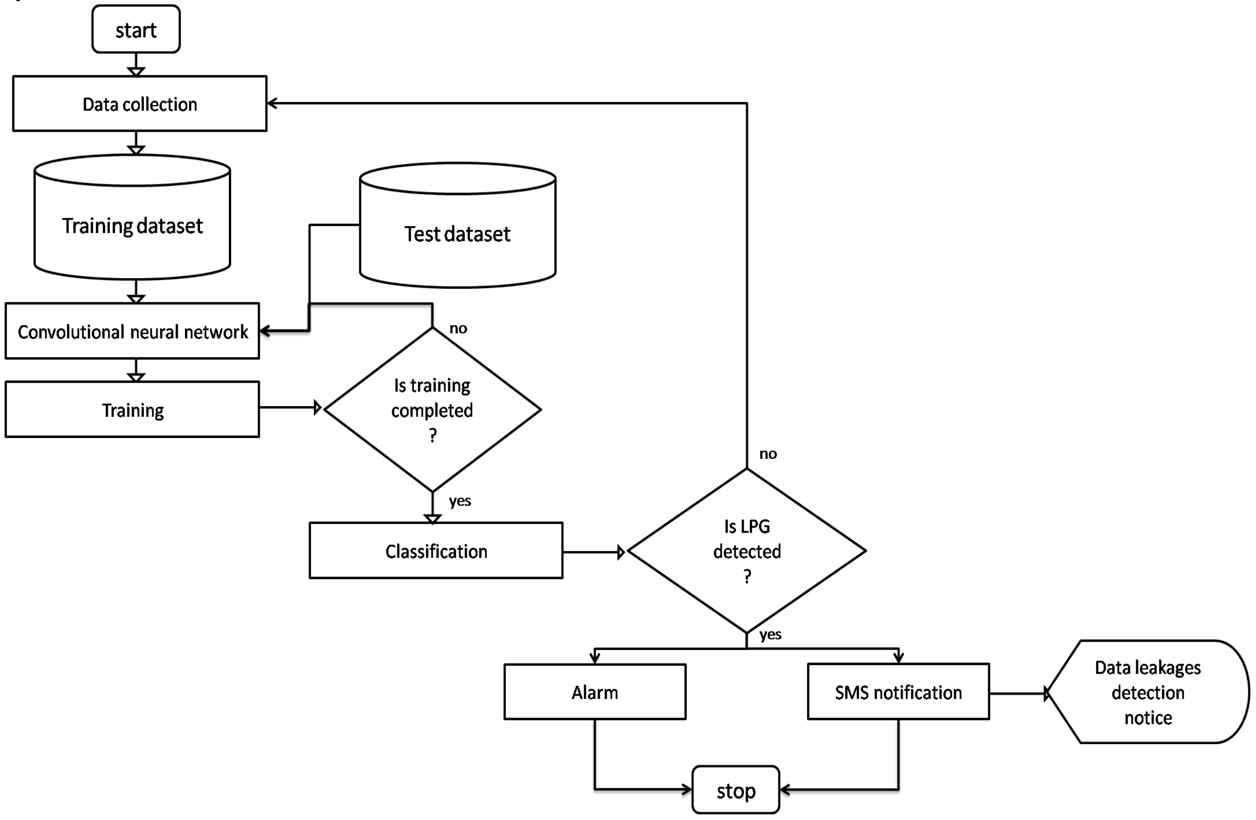

Figure 3: System Flow Chart

The logical flow chart was used to presented the interconnection between each method used for the development of the new system. The figure shows how the training dataset was used to train a convolutional neural network algorithm and used the reference model generated for classification of LPG gas. The classification result shows that when gas is detected then alarm and SMS are activated for control measures, else the process continuous to monitor for LPG leakages.

Modelling of the CNN
This section presented the development of the CNN algorithm proposed for the real time LPG detection system. The modelling was done using mathematical based self-defining equations, algorithms and universal modelling diagram. The CNN was designed using one input layer, three convolutional layers, pooling layer, filters, one fully connected layer and the output layer as shown in the figure 4;

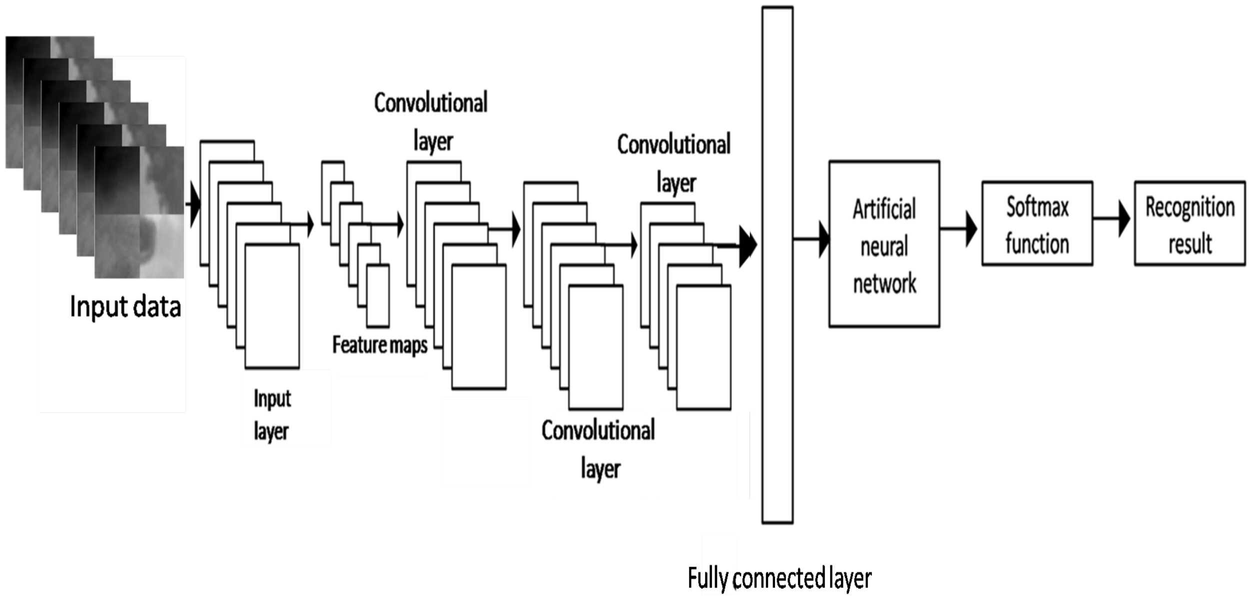

Figure 4: The CNN Block Diagram

Modelling of the CNN Layers

The input layer dimension the LPG data collected using the model in equation 1

D = h x w x c Equation 1

Where D is the dimensioned data, h is the pixel height, w is the pixel weight and c are the colour channel. For the dimensioned image (D) to be feed to the convolutional layer, the filter model in equation 2 was used.

F = (f_w x f_h x d) Equation 2

Where f_w is the filter weight, f_h is the filter height and d is colour dimension. This filter was used to scan the D in equation 1 and the extracted features are presented in equation 3;

$F_o = \left[\frac{F_i + 2p - k}{s}\right] + 1$ Equation 3

Where Fo is the output features, F_i is the input features, p is the convolutional padding, s is the strides size, k is the convolutional kernels size. During these feature extraction process, rectified linear unit (ReLU) was used to introduce nonlinearity in the features to transform all negative values into null. These feature maps in equation 3 was pooled using the average pooling technique in (Nishtha, 2019) to for the convolutional model in equation 4;

$C_O = ((w * h) + 1) *nf)$ Equation 4

Where the total pixels in the convolutional layer is given as (C_o), w is filter weight (w), filter height (h), number of filters (nf) and filter bias term (1). The model in equation 4 presented the total pixels values in the first convolutional layer only; however, to generate pixels for other convolutional layer, the number of previous pixels was added (np) and presented as;

$C_O = ((w * h \ *np) + 1) *nf)$ Equation 5

This model was used to sum up all the feature maps extracted per convolutional process in an array of matrix. The activation size is determined using the relationship between the number of image pixels and the depth as shown below;

$A_s = (w * h * d)$ Equation 6

In this model of equation 6, the parameters of w, h and d are defined based on each convolutional layer specifications.

Fully Connected Layer

This section of the CNN flattened the convolutional image in equation 5 and then feed to a neural network for training to learn the image features for LPG detection. The training was enabled using back propagation algorithm in figure 9, and was monitored for accuracy to ensure that no overshoot performance using the loss function model in equation 7;

L = $\sum_{i=l}^{K}(P_i - D_i)^2$ Equation 7

Where L is the los function, k is the number of observations, P is prediction and D is the training target. The model presented the loss between P and D, where K is the number of classes in the LPG data set, I is the output loss which is scalar.

Table 1: Deep Learning Settings

Parameters	**Values**
Epoch	15
Epoch between display	1
Maximum time to train in sec	Infinity
Maximum validation failure	5
Frequency of iteration	50
Momentum factor	0.75
Learning rate	0.01
Minimum performance gradient	1e-6
Resolution	576
Weight of neurons	1728
Image size	24 by 24
Number of Channel	3

Output Layer for Detection Result

This is the final layer of the network which produces the desired output of the training process. This layer is designed using a SoftMax activation function which transforms the learned feature vectors into probability distributions consisting of various probabilities proportional to the various exponential of the LPG input data. The model of the SoftMax function is presented below in equation 8.

$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$ Equation 8

Where σ is the softmax function; e^{z_i} is the standard exponential function for input vectors from the ANN output, k is the number of classes of the multiset classifiers; e^{z_j} is the standard exponential function for output vector, $\vec{z}$ is the input vector.

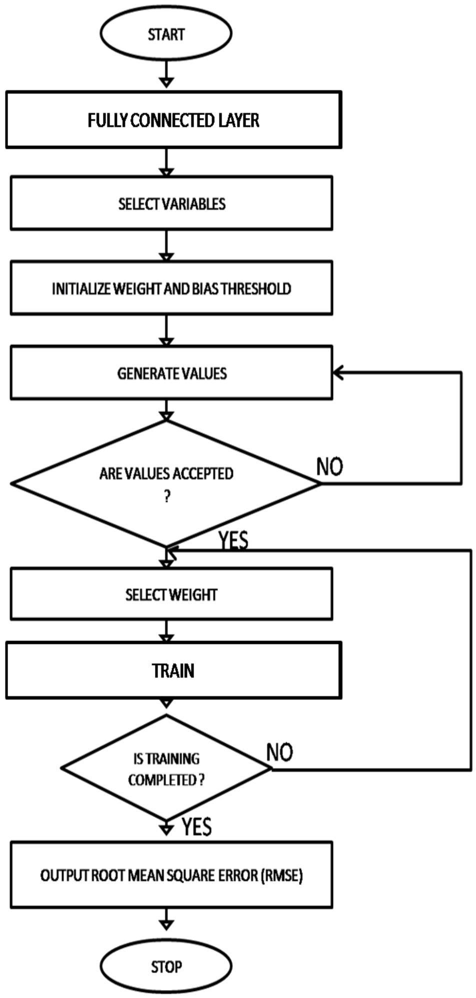

Figure 5: The Back Propagation Algorithm

Implementation

The system was implemented using deep learning toolbox, neural network toolbox and Simulink. This toolbox was achieved using the models developed which shows how the data captured by the sensor was feed to the CNN through the input layer which dimensioned the image as modelled in equation 1 and then used filter model in equation 2 to extracted feature maps clusters in equation 3 and form a convolutional matrix as presented in the model in equation 4. This process continues until the fully connected layer where the final convoluted feature vectors matrix as presented in equation 5 are flattened and then trained with artificial neural network algorithm in figure 5 to get the output result based on the SoftMax function in equation 8. The result is evaluated using loss function in equation 7 to check the validation of the training performance.

Results and Discussions

This section presented the performance of the training algorithm using the deep learning toolbox in Simulink. This was achieved by feeding the training dataset into the algorithm developed and then trained with the set out parameters in table 1. The result is presented in figure 6;

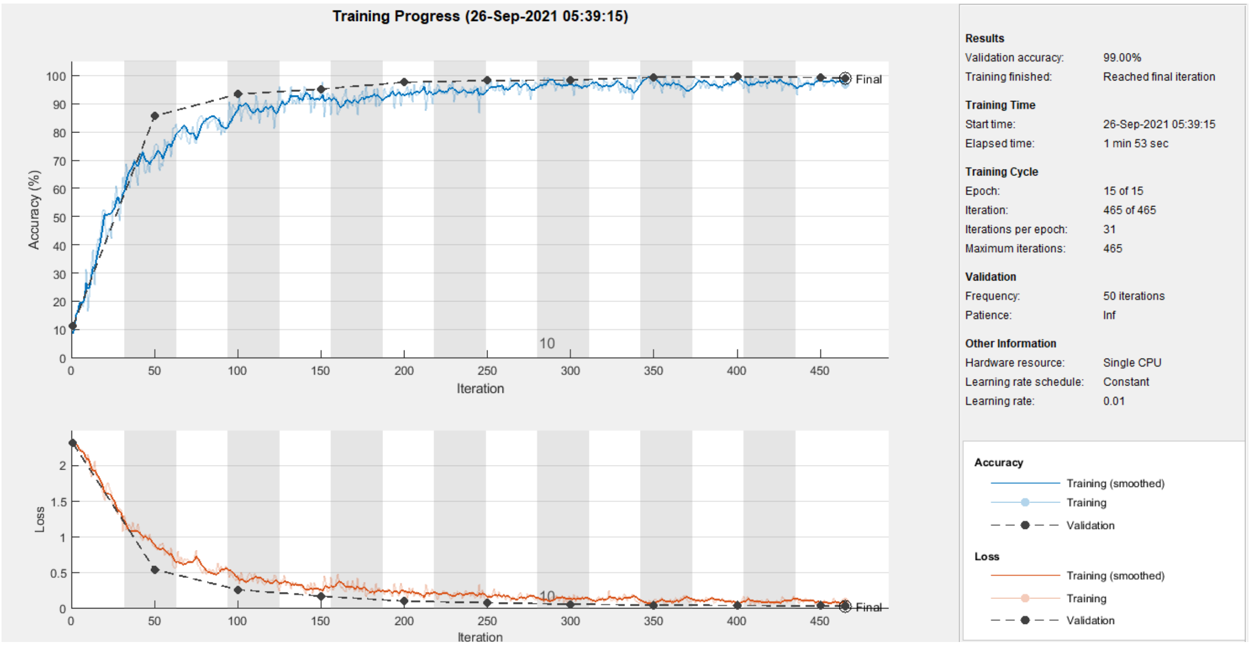

Figure 6: Training of the CNN

The result figure 6 presented the training performance of the deep learning algorithm developed for the classification of fire. The essence of this result is to determine how well the algorithm was able to learn the patterns of the gas data and used for classification of leakages. The training performance was measured using the loss function model in equation 7 which was able to check the prediction error rate of the algorithm developed. The result is analyzed as shown in the table 2; showing how the loss and accuracy varies as the algorithm learns the data at a steady learning rate of 0.001

Table 2: CNN Training Performance

Epoch	Iteration	Loss (Mu)	Accuracy (%)
1	1	2.5042	16.464
2	50	0.5000	86.771
3	100	0.2431	94.229
4	150	0.2269	97.498
5	200	0.1731	97.773
6	250	0.1488	97.989
7	300	0.1017	98.003
8	350	0.0593	98.575
9	400	0.0537	98.911
10	450	0.0302	99.000

The table 2 presented the learning performance of the CNN how it was able to learn the features of the gas data iteratively. The result showed that at the beginning of the training process, the algorithm increasing learn the patterns of the data with poor accuracy and high loss rate, but as the epoch increases the learning accuracy improved to a very accurate percentage and acceptable loss function which is 99% and 0.0302Mu.

To validate this result, the ten-fold validation technique was used which re-trained the algorithm in ten-fold and the result achieved is presented in table 3;

Table 3: Validation Performance

Iteration	Loss	Accuracy (%)
1	0.0302	99.00
2	0.0210	99.103
3	0.0543	98.982
4	0.0529	98.981
5	0.0231	99.073
6	0.1013	97.997
7	0.0507	98.903
8	0.0193	99.051
9	0.0107	99.011
10	0.0302	99.000
Average	0.0394	98.910

From the result collected after the validation in table 3, it was observed that that the average accuracy of the algorithm developed is 98.95% and the loss function is 0.0394Mu. The implication of this result showed that the gas leakage detection accurate is very reliable, good and can be used to detect gas at high precision, while the aim of the loss function is to achieve an equal or approximate loss value of zero. The result showed that the loss achieve here is approximately zero, which indicates that the margin for error in the new algorithm developed is minimal.

Contribution to Knowledge

I. A light weight convolutional neural network model was developed for intelligent detection of cooking gas leakages
II. A cooking gas leakage detection system with accuracy of 98.95% was developed
III. An easy to use, cheap and reliable cooking gas detection system with tolerable error margin of 0.0394Mu was developed

Conclusion

This research presented successfully a new lightweight convolutional neural network-based system for the detection of cook gas leakages at indoor environment. The system was developed to help address the problems of cooking gas leakage which have resulted to lots of accidents and hazards at homes. The study developed the new system using the latest artificial intelligence technique which has proved over the year to be the best in solving image-based classification problem and then test the performance with the result showing high accuracy and acceptable loss value which implied reliability.

Recommendation

Having completed this research successfully, the author recommends further studies to reduce the training time. This can be achieved using parallel toolbox

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