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Design of smoke detection system using deep learning and sensor fusion with recursive feature elimination cross-validation

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ABSTRACT

The fire safety system is an important component that controls material and immaterial losses. Fire disasters are generally indicated by the appearance of excess smoke and changes in temperature, pressure, and changes in other parameters in the environment. Conventional smoke sensors are limited in reading parameter changes around their environment, making them less effective in early fire detection. This study aims to design a smoke detection system as an early fire detection system, using sensor fusion based on deep learning using the recursive feature elimination method with cross-validation (RFECV) using a random forest classifier used to select optimal parameters from public datasets as the basis for determining the sensor to be used. Based on the RFECV optimal feature, a deep learning algorithm was performed and obtained an accuracy of 0.99, a precision of 0.99, a recall of 1.00, and an F1 score of 0.99, with a latency time of 34.02 µs, which is 71.76% times faster than the original model.

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1. INTRODUCTION

The fire safety system is an essential component that plays a role in controlling the level of material sand immaterial losses. The World Health Organization (WHO) estimates at least 300,000 deaths due to accidents caused by burns, with 95% of these accidents originating from low- and middle-income countries [1]. Fires are dominated by residential and office areas, with the most significant cause of non-fatal fires caused by cooking activities, namely 45%, and the most significant cause of fatal fires caused by smoking activities, namely 16% [2].

Fire disasters are generally indicated by the appearance of excess smoke and changes in temperature in the environment. Smoke sensors that are commonly used have limitations on the level of sensitivity so that there is a minimum volume of smoke to be detected as a fire; ionization-based smoke sensors have limits on the amount of smoke detected so that they are less effective in early detection of smoldering fires, and on photoelectric-based smoke, sensors have limitations on the detection activation time and the type of smoke that passes through it [3]. Futhermore, smoke sensors often give false positives when detecting a fire, such as when cooking steam is cooking and dust when cleaning [4]. Due to this limitation, it is necessary to have a more accurate and precise sensosr for detecting the presence of smoke as a fire prevention measure.

Several studies have been conducted to overcome this problem, one of which is using convolutional neural network (CNN)-based image processing on embedded systems [5], however, the detection system approach through pixel color readings often gives false positives when there is excessive lighting or contrast in the pixel readings. Hence, this approach is not suitable for use in indoor areas. Multiple wireless sensors are also used in a fire detection system using barometric sensors, humidity sensors, and temperature sensors connected to a server as a monitoring system [6]. This research shows that applying multiple sensors can be used as an indicator in determining forest fires. Still, this approach does not utilize the sensor fusion concept, which is capable of detecting fires. Still, these sensors act independently as parameter readings which require operator supervision in determining the occurrence of a fire hazard in the forest, The use of a machine learning approach with the supporting vector machine (SVM) method and partial least square discriminant analysis (PLS-DA) using gas-based sensors such as metal oxide sensors, electrochemical sensors, temperature sensors, and humidity, shows increased accuracy in the use of machine learning based on sensor fusion and gas parameter correlation in fire detection systems, the use of a barometer to measure air pressure around the fire area as a fire extinguisher, and the use of particulate-matter sensors to detect fires in wild forests [7]–[10]. The use of parameters such as heat, smoke and flame are also used as decision-making parameters in the sprinkler and alerting process [11], [12], and android based application with global positioning systems is also used for wildfire reporting and monitoring system [13]. The diversity of sensor types used as parameter reading instruments in early fire prevention systems has led to increased complexity in system design and the selection process of sensor components.

This study addresses the challenges by developing an advanced early fire prevention system. It employs a data-driven approach, utilizing recursive feature elimination with cross-validation (RFECV) based on sensor fusion and machine learning within a computer modeling program. Key parameters, including temperature, humidity, total volatile organic compounds (TVOC), eCO2, H2, Ethanol, and air pressure, are optimized through parameter selection. This optimization enables efficient smoke-related predictions. The RFECV outcomes are refined via deep neural network retraining on a microcontroller. This step serves as a test to assess the efficacy and efficiency of the system as an early fire prevention mechanism. Through this methodology, the paper aims to mitigate these issues and contribute to enhancing fire safety systems using a combination of data-driven techniques and advanced hardware for more effective fire prediction and prevention.

2. METHOD

The smoke detection system is an instrument used to detect smoke in the surrounding area. In conventional sensors, the presence of smoke is only detected based on the input value of one sensor parameter, so the tool's reliability is often questioned because smoke detection sensors often make false alarms or false positives where the alarm sounds even though there is no smoke around it. On this basis, it is necessary to add input values to increase the predictive ability of the smoke detection system.

This study discusses the design and conceptualization of the system using sensor fusion to combine inputs from several sensors to obtain input values from pressure, particular matter, humidity, temperature, TVOC, eCO2, and H2 which has been tested and can be used on microcontroller systems such as ESP8266 [14], [15]. The input values of these parameters will be used to predict the smoke's presence. In making the design, several steps need to be carried out to ensure that the input data can be used to effectively predict the presence of smoke. Shown in Figure 1. The process stages are divided into data preprocessing, feature selection, and modeling after the model is obtained, the model performance is evaluated to determine performance based on performance metrics and predictive latency time, the design of the new system can be carried out by paying attention to several aspects.

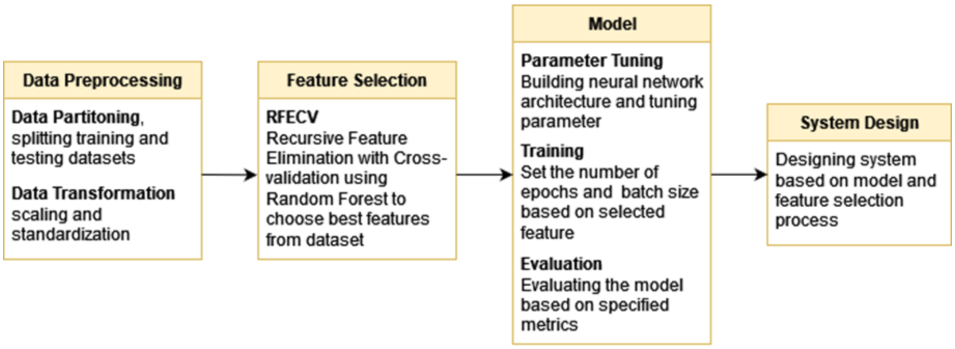


Figure 1. Data pipeline process

2.1. Dataset
The data used in this study uses secondary data from reading information from several sensors located on the Arduino Nicla Sense ME microcontroller architecture. BMP390, BME688, and SPG30 sensors are used to read humidity, temperature, air pressure, particulate matter, number of concentration particle and TVOC data. The data is sourced from public datasets [16] with the amount of data reaching 814,190 data with a sample rate of 1 Hz. Data was collected in indoor areas with high humidity, providing smoke from burning wood, coal, and gas grills.

2.2. RFECV
The features of the dataset have a lot of influence on computational time and computational size during the inference and training processes and the use of certain algorithms can speed up and improve the quality of the data used [17]. To speed up computational time and weight, it is necessary to eliminate redundant features that have little effect on the model. The method of eliminating this feature needs to pay attention to certain factors; this is intended so that the removed feature does not significantly influence the level of accuracy of the model created. The use of RFECV with the wrapper method has advantages over other methods; this is because the RFECV elimination process is based on a predictive model and does not depend on the dataset; the selection of this elimination is based on interactions between features so that the least significant features can be identified. The use of cross-validation is done to avoid the process of overfitting the model [18].

The RFECV procedure involves selecting a model as a reference for feature selection accuracy and subsequently selecting k-values to partition the dataset into k-segments. In this instance, the random forest classifier is adopted as the RFECV model. This choice is attributed to the classifier's adeptness in achieving high accuracy with constrained datasets, all while maintaining swift training times. Notably, this efficiency surpasses that of decision trees, support vector machines, and logistic regression classifiers [19].

2.3. Deep learning
The algorithm used in the prediction process is a deep learning algorithm; this is because deep learning algorithms have algorithms with the highest accuracy compared to other algorithms if the dataset is high [20]. Deep neural network is a machine learning subfield with characteristics like neural networks, often referred to as artificial neural networks. Deep neural network works by extracting features from a large amount of data by building a layered architecture between neuron nodes to form output neuron nodes that function as regression or classification as shown in Figure 2 [21].

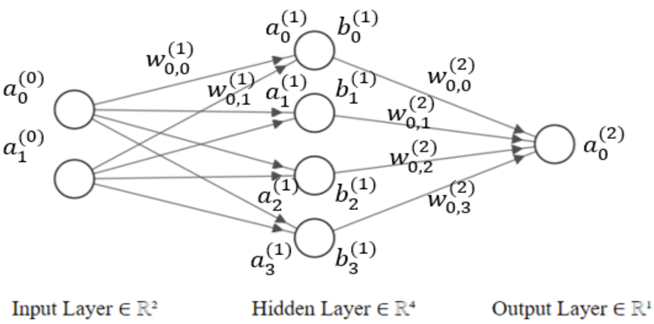


Figure 2. Deep neural network architecture

Forward propagation is a process of computing data from input data values in the initial neuron layer to producing output values in the final layer neurons which function to produce regression or classification results by adding the weight and bias values of each parameter in the deep neural network [22]. The value of the final output node is determined from the value of the neuron nodes in each layer. Each node is affected by the weight and bias values of the previous neuron node, which is then fed into the predetermined activation function [23], the equation of each neuron in each layer is represented in (1), with the value of (2) being the value of each parameter weight and bias that has been activated in (1).

$$z_j^L = \sum_{k=1}^{K} w_{j,k}^L a_k^{L-1} + b_j^L \quad (1)$$

$$a_j^{(L)} = \sigma\left(z_j^{(L)}\right) \quad (2)$$

L : Layer
k : Node input
K : Total node input
j : Node output
σ : Activation functions

The activation function is essential in the learning process in studying patterns and complex relationships from data to given labels. The activation function is tasked with obtaining the final value of the node obtained by entering the weight and bias values of the initial neuron node into the specified activation function. The rectified linear unit (ReLU) activation function is the most widely used activation function in the hidden layer because of its light computational ability and ability to overcome vanishing gradients [24]. The equation of the ReLU activation function is shown in (4), with the resulting range of activation values (3); this equation is used in the training process in the form of a derivation in (5).

$$\sigma(z_j^L) = \begin{cases} 0 & for\ z_j^L < 0 \\ z_j^L & for z_j^L \geq 0 \end{cases} \tag{3}$$

$$\sigma(z_j^L) = max(0, z_j^L) \tag{4}$$

$$\sigma'(z_j^L) = \frac{\delta\sigma(z_j^L)}{\delta z_j^L} = u(z_j^L) \tag{5}$$

In binary classification, the activation function is used to map the value of the input node into two output values [25]. These two output values are divided by applying a threshold of 0.5 at the output node shown in (6). The initial calculation and declaration of the derivation of the final activation function are carried out using the chain rule to speed up computation time in the optimization process, as shown in (7).

$$\sigma(z_j^L) = \frac{1}{1+e^{-z_j^L}} \tag{6}$$

$$\frac{\delta\sigma(z_j^L)}{\delta z_j^L} = \frac{\delta}{\delta z_j^L}\left(\frac{1}{1+e^{-z_j^L}}\right) = \left(\frac{1}{1+e^{-z_j^L}}\right)\left(1 - \frac{1}{1+e^{-z_j^L}}\right) \tag{7}$$

The training process of the deep neural network is called the deep learning process; this process calculates the error between the output values of the final layer neurons to the actual output values of the data; this learning process is called backward propagation [26]. Backward propagation is evaluated by changing all parameter neurons' weight and bias values based on the error values obtained between the final layer output neuron values and the actual data values. The error value is obtained from the predetermined cost function; Logistic binary cross entropy is used to measure the error value in the binary classification prediction because of its ability to provide a penalty in optimizing the error value. Logistic binary cross entropy provides a penalty against errors better than mean square error provides a penalty against errors in the optimization process.

$$C_{BCE}(a_j^L, C) = C\ log(1 + e^{-a_j^L}) + (1 - C)\ log(1 + e^{a_j^L}) \tag{8}$$

$$\frac{\delta}{\delta a_j^L} C_{BCE}(a_j^L, C) = -C\left(1 - \frac{e^{a_j^L}}{1+e^{a_j^L}}\right) + (1 - C)\frac{e^{a_j^L}}{1+e^{a_j^L}} = \frac{e^{a_j^L}}{1+e^{a_j^L}} - C \tag{9}$$

C_{BCE} : Cost function logistic binary cross entropy
C : Label class

The enhancement of error calculation precision for predicted-versus-actual data values, as derived from (9), involves adjusting weight and bias parameters across iterations. This adjustment aims to attain a global minimum [27]. Within the backward propagation process, stochastic gradient descent is employed. This technique modifies input data into diverse batches during each iteration. This approach serves two purposes, which is diminishing the computation time essential for training and conserving memory allocation [28].

Stochastic gradient descent computes the error by evaluating the partial derivative of the loss function expressed in (8) for every data point within the data batch, as expressed in (9). The optimization process involves adjusting the weight values for each neuron in each layer through (10), while the bias values are updated via (11). This weight and bias adjustment occurs using (12) and (13), wherein a predefined learning rate is incorporated. This iterative procedure strives for a global minimum, where minimal error is attained, repeating these steps across each iteration.

$$\frac{\delta C_{BCE}(a_j^L,C)}{\delta w_{j,k}^L} = \frac{\delta C_{BCE}(a_j^L,C)}{\delta a_j^L}\frac{\delta a_j^L}{\delta z_j^L}\frac{\delta z_j^L}{\delta w_{j,k}^L} \tag{10}$$

$$\frac{\delta C_{BCE}(a_j^L,C)}{\delta b_j^L} = \frac{\delta C_{BCE}(a_j^L,C)}{\delta a_j^L}\frac{\delta a_j^L}{\delta z_j^L}\frac{\delta z_j^L}{\delta b_j^L} \tag{11}$$

$$w_{(j,k)_{i+1}}^L = w_{(j,k)_i}^L - \alpha\frac{\delta C_{BCE}(a_j^L,C)}{\delta w_{j,k}^L} \tag{12}$$

$$b_{j_{i+1}}^L = b_{j_i}^L - \alpha\frac{\delta C_{BCE}(a_j^L,C)}{\delta b_j^L} \tag{13}$$

α : Learning Rate
i : Iteration

2.4. Performance evaluation

The methods used to evaluate the model's performance are precision, recall, accuracy, and F1. These four evaluation metrics are the most commonly used to evaluate model performance [29], the value of these four metrics is obtained from a comparison between the predicted value and the ground truth value. A true positive (TP) value is obtained if the predicted value has the same value as the ground truth positive value, a false positive (FP) is obtained if the model predicts a different value from the ground truth on positive ground truth, true negative (TN) is obtained if the model can predict Negative labels such as ground truth and false negative (FN) are obtained if the model predicts a different value from the ground truth on negative ground truth.

$$precission = \frac{TP}{TP+FP} \tag{14}$$

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{15}$$

$$recall = \frac{TP}{TP+FN} \tag{16}$$

$$F1 = \frac{2\times precission\times recall}{precission+recall} \tag{17}$$

3. RESULTS AND DISCUSSION

Pre-processing begins with splitting the dataset into training data (80%) and test data (20%) randomly from a dataset of 62,630 rows with 15 features with 939,450 data. The process of eliminating features that are not important is done to reduce the overfitting process of redundant features and the resulting elimination of two features. The resulting dataset is 814,190, with 651,352 training data and 50,104 test data. The data transformation process is carried out by scaling the data by converting the data into z-score form to maintain the scale of the data.

3.1. Feature selection

The selection of the ranking of the features is made using a random forest based on the gini impurity value of each feature, the results are obtained as represented using the errorbar graph in Figure 3. The mean decrease value is obtained from the average impurity value for each feature of all trees in the forest and the error value represents the variation of each gini impurity in each feature of all the trees in the forest. These data show that pressure, TVOC, and humidity have an important role in determining the amount of smoke produced in the fire detection. The presence of TVOC has an important role in detecting the presence of fire because it is based on readings of contents such as benzene, formaldehyde, and toluene in the air. This is strengthened by data from Vilčeková *et al.* [30], which shows that smoke presence is strongly influences by TVOC, PM2.5, and PM10 factors. The use of humidity sensors, barometric pressure sensors, and temperature sensors in fire detection systems has been used by several authors. It proves the correlation between the presence of fire and these parameters [6], [31].

The cross-validation process is carried out by selecting a value of k = 10 with the Random Forest Classifier as the model, and the optimal number of features reaches 7 features, with feature data Humidity, TVOC, H2, Ethanol, Pressure, PM1.0 and NC0.5. And the data that were eliminated were temperature, PM2.5, NC1.0, eCO2, and NC2.5 data. There is a difference between the important feature results and those obtained using simple random forest feature selection and recursive feature selection with RFECV. The difference is due to the difference in the method used. The RFECV method selects important features based on the relationship between features on prediction accuracy. In contrast, the random forest selects essential features based on the gini impurity value of each feature.

The outcomes derived from RFECV illustrate fluctuations in accuracy values for each employed feature selection during training. Throughout the training process, accuracy remains relatively consistent, with a value of 0.99, as depicted in Figure 4. However, adopting a single feature leads to a decline in accuracy, registering at 0.94. On the other hand, utilizing two features counteracts this drop and increases accuracy by 0.98, which matches that of using a single feature. For heightened accuracy, the training procedure employs the number of features identified through RFECV, totaling seven features.

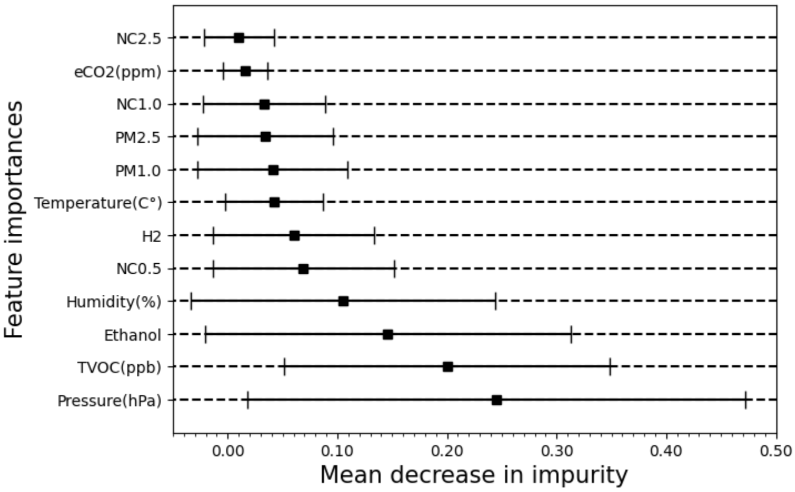


Figure 3. Mean decrease in impurity of dataset

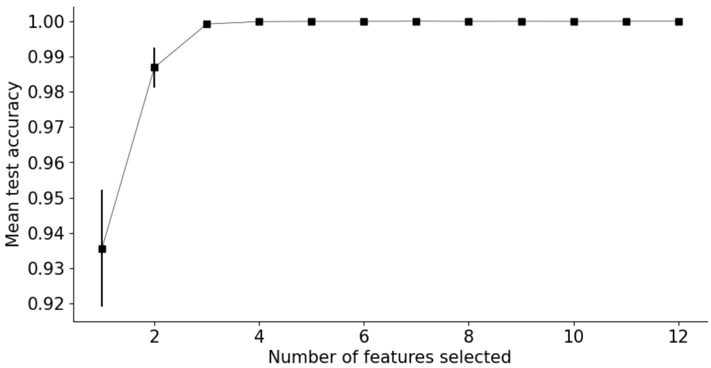


Figure 4. RFECV mean test accuracy toward feature eliminaions

3.2. Design system

The design of the system is shown in Figure 5 refers to the features that have been selected using RFECV; the feature is humidity (%). TVOC (ppb), ethanol, air pressure, PM1.0 and NC0.5. Selection of the main computing system using the ESP32 microcontroller as the main control and as a deep learning prediction processing device; the use of ESP32 as a microcontroller is due to its inference time in predicting 10,000 deep learning operations within 1599µs [32]. The choice of the BMP388 sensor is due to its accuracy in measuring pressure 300-1000hPa with an R2 value of 0.999 [33], SPS30 was chosen because it has an R2 of 0.98 on PM2.5 measurements and 0.98 on PM1.0 in indoor areas [34]. Humidity and temperature sensors using SHT31 have a more extensive range of humidity and more minor uncertainties than other sensors, such as DHT11 and DHT22 [35], and has higher accuracy and reading range for humidity and temperature parameters than BME688 describe in datasheet. The use of SGP41 as a sensor for measuring ethanol gas is used because of the accuracy and flexibility of the sensor in detecting volatile organic compound (VOC) gases. SGP41 has a wide range of VOC gases, one of which is acetone, acetonitrile, benzene, diethyl ether, ethanol, hexane, isopropanol, methanol, and toluene where these gases are an indication of a gas leak that can spread to a fire. SGP41 can measure these gases with a fast step response time, low concentrations, and varied gas distances than the BME688 [36]. The sensors are selected based on the needs, accuracy, and range of the type of parameter measurement being detected.

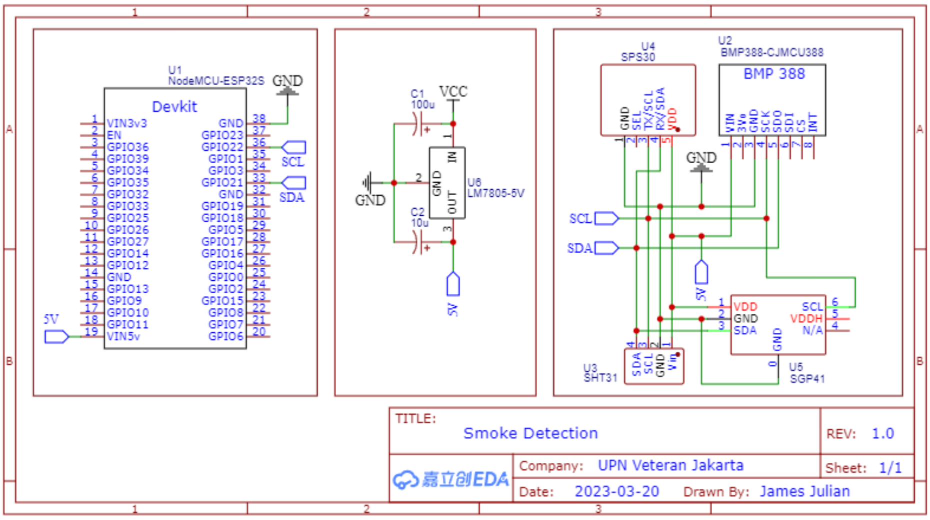


Figure 5. Schematic circuit of deep learning-based smoke detector

3.3. Training

The architectural model consists of 3 layers, one input layer, one hidden layer, and one input layer. The input layer consists of 12 neurons, each representing the input value of each parameter in the dataset, which is then continued to the hidden layer after calculating each weight and bias with a linear activation function. After the calculations for each node have been carried out, then proceed to the hidden layer using the ReLU activation function, which consists of 16 nodes, then a similar analysis is carried out to the output layer with the number of nodes 1 to state whether smoke is detected or not, the sigmoid function activation is used in binary classification with the logistic binary cross entropy function as a cost function with stochastic gradient descent as parameter optimization in the backpropagation process. The parameters of the architecture of each layer are shown in Table 1.

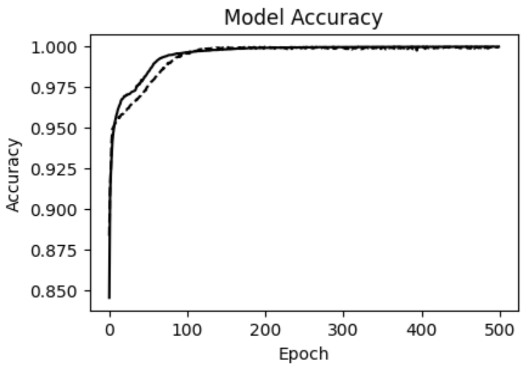
Table 1. Architecture summary

Layer Type	Node	Parameter
Dense	12	156
Dense	16	208
Dense	1	17
Total Parameters		381

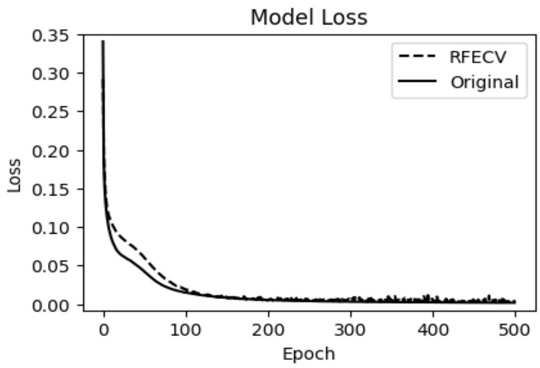
The training process is carried out with 500 iterations. The results obtained from the training accuracy and loss graphs are shown in Figure 6(a) by comparing the training process carried out using 12 features and training carried out using seven features that have been obtained in the feature selection process using RFECV. It was found that the two features have relatively the same accuracy, namely 0.99. The training process using

RFECV achieves faster optimization than the training process using 12 features; this is because the fewer features used, the fewer parameters are actively involved, so the optimization process in RFECV training is higher than the original using 12 features. Moreover, the loss graph as shown in Figure 6(b) RFECV has a smaller error value at the initial iteration stage than the original; this is because in the backward propagation process the number of parameters affects the complexity of the model, so the smaller the number of features given, the lower the level of complexity of the model [37].

The trained model is converted into a Tensor Flow Lite (TFLite) model, where the weight, activation, and bias are quantized to reduce memory size and computation time. The model from TFLite was then converted into the C++ model to be tested on the ESP32 microcontroller using standardized test data. Data testing is done by testing 1,000 samples of test data a thousand times to find out the performance of the converted model using (14)-(17) and the latency time of each prediction before and after the RFECV process is carried out.



(a)



(b)

Figure 6. Deep learning training result over iteration; (a) accuracy over 500 iteration and (b) loss over 500 iteration

The outcomes of the performance assessment are shown in Table 2. The performance results from training the initial model with 12 features and the RFECV-selected seven features exhibit comparably similar outcomes. Notably, the RFECV process showcases an average latency time that is notably faster, approximately 71.76% quicker than the original model. This translates to a latency time of 34.02 µs for the RFECV process, featuring a standard deviation 0.013. The original model exhibits a latency time of 47.41 µs with a standard deviation of 0.015.

Table 2. Performance evaluation model on ESP32

Model	TP	FP	TN	FN	Accuracy	Precission	Recall	F1-score	Latency (*µ*s)
Original	716	2	281	1	1.00	1.00	1.00	1.00	47.41
RFECV	717	10	273	0	0.99	0.99	1.00	0.99	34.02

4. CONCLUSION

Through the research and literature studies that have been carried out as shown in section 3, it is known that this deep learning algorithm-based smoke detection system has an accuracy of 0.99 with a latency time of prediction of 34.02 µs, 71.76% faster than prediction performance using 12 parameters before the RFECV process which is has been tested on ESP32 microcontroller. This proves that using RFECV can increase the effectiveness of predictions without significantly decreasing accuracy. The selection of sensors in the design process based on the RFECV process results in the elimination of 5 features from 12 original features in the dataset; the features used in the training process are moisture, TVOC, pressure, H2, ethanol, PM10, and NC0.5. Based on the results of the selection of the sensor based on the RFECV result parameters, the sensors are SHT31 to read humidity values, SGP41 to read ethanol, SPS30 to read the PM1.0 and NC0.5, and BMP388 to read air pressure; ESP32 microcontroller chosen as a central processing system to predict whereabouts as soon as possible based on sensor readings. In the future, it is necessary to carry out experimental research to prove the accuracy of the predictions from the model and prove the accuracy of the system design that has been made as a validation step.

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