MCU Based Edge Computing Platform for Liquid Level Measurement

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Abstract

An edge computing system based on micro control unit (MCU) for liquid level measurement is proposed in this paper. The system includes a solenoid electromagnet for bottle hit and a microphone to capture sound waves. The signals are converted from time domain to frequency domain by Fast Fourier Transform (FFT), employing an artificial intelligence (AI) model to predict the water level. Artificial Neural Network (ANN) model is applied for classification on the MCU. When optimizing hyperparameters, the accuracy of each parameter combinations should be considered. Ensure the model size suits the limited MCU memory and computing capabilities. The experimental results can be up to 99% accurate under multiple tests.

Keywords: Artificial Neural Network, Hyperparameters, Edge Computing, Audio Process

1. Introduction

As artificial intelligence (AI) is more popular, there are many applications to be proposed no matter for the consumer or industrial market. Moreover, it is crucial to tackle the emerging challenges associated with edge computing [1], a topic of great significance and current prominence. The utilization of endpoints for model computation has attracted considerable attention, given its potential to reduce network latency and lower costs [2], [3]. Furthermore, the exploration of alternative AI models for measurement becomes pivotal in situations where sensor availability is constrained or cost prohibitive. When a container, such as bottle, experiences physical impact, it produces distinct tones depending on the liquid's varying levels inside, owing to vibration frequencies. Determining the water level through sound analysis, as presented in [4], relies on specific vessel geometries. However, employing an AI model or sound-based water level measurement becomes a viable option. Furthermore, given the limited resources of the endpoint platform, careful consideration of AI model selection and hyperparameter optimization for edge computing is crucial. Artificial neural networks (ANN) model, is simple yet effective for classification tasks, represent a viable candidate for this study [5], [6]. Moreover, Bayesian optimization emerges as a popular method for efficient hyperparameter optimization, offering convenient and efficient.

A micro control unit (MCU) based edge computing system for liquid level measurement is proposed in this paper, and all calculation and control including data acquisition are performed by a consumer MCU, Artery AT32F415 [7]. The proposed AI model utilizes one-dimensional sound information for classification, resulting in reduced memory requirements. During the training stage, the proposed system offers a data sampling function, where the gathered information is transmitted to a personal computer (PC). The hyperparameters optimization and model training processes are conducted on the PC. Once completed, the trained model will be installed onto the MCU, enabling edge computing for measurement tasks performed by this MCU.

2. Methodology

2.1. SYSTEM STRUCTURE

The proposed system structure is shown in Fig. 1. Two micro switches are used to trigger procedure, which includes knocking, sampling, and edge computing. Moreover, these two switches also could make sure that the hitting situation, such as position and distance. MCU is the center of the system, and controls the full procedure, as mentioned previously, which also provide the edge computing. The UART (Universal Asynchronous Receiver/Transmitter) protocol is adopted for communication with PC, the sound sampling is sent to PC for training from MCU.

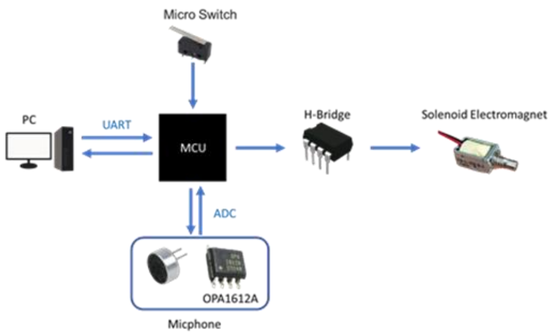

Fig. 1 The system diagram

A capacitive microphone is applied to convert sound to voltage, which amplitude is amplified and offset is shift by operational amplifier (OPA) [8] circuit for the input range of the Analog to Digital Converter (ADC), which is a built peripheral function of MCU. The knock component, a solenoid electromagnet, is driven by H-Bridge [9] to eject and attract.

2.2. *DATA ANALYSIS AND REPROPCESSING*

Before algorithm development, the data analysis is necessary. As mentioned previously, the converted sampling data are sent to PC for analysis and training via UART. The audio voltage is sampled at 10k Hz, and the number of sampling points is 2048 per trigger. The time domain waveforms of the different water levels are shown in Fig. 2 and there is not any saturation and truncation, it means that the sampling rate and length are suitable for this application. To develop the algorithm, the Fourier transform converts waveform data in the time domain into the frequency domain as shown in Fig. 3. Note, the frequency of the first spike, which decreases with increasing water volume, this phenomenon is consistent with the sound heard. Frequency information only from 83Hz to 1464.8Hz is adopted to identify water level. Furthermore, the frequency domain differences between different water levels are obvious, and the classification function could be performed by the artificial neural networks (ANN) model, which is simple and efficient for categorization. Compared to most other AI models, ANN requires less memory and calculation resource, in other words, it is suitable to be adopted into the simple edge-computing platform, MCU. So, Fourier transform (FFT) is selected for pre-processing, and ANN is applied to classify the water level.

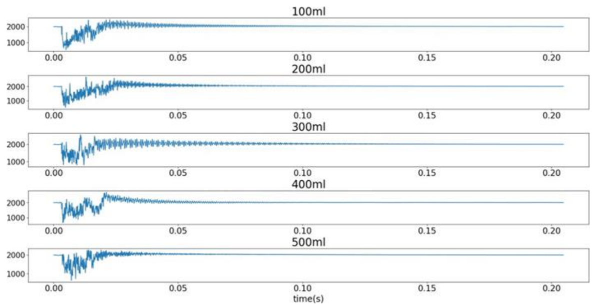

Fig. 2 Audio signals at different water level

In order to prevent the data from being affected by abnormal waveforms and to enhance the features, the system adopts Min-Max Normalization for each data. The Normalization finds the maximum and minimum values of the sound frequency, and then converts the maximum value is set to 1, and the minimum value is adjusted to 0. Finally, all audio data are scaled to the range between 0 and 1. The calculation formula is as (1) :

$$X_{nom} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Here, X is the original data, Xmin and $Xmax$ are the minimum and maximum value of the frequency domain data, and X_nom indicates the normalized data in frequency domain. The waveforms after data pre-processing are shown in the Fig. 3.

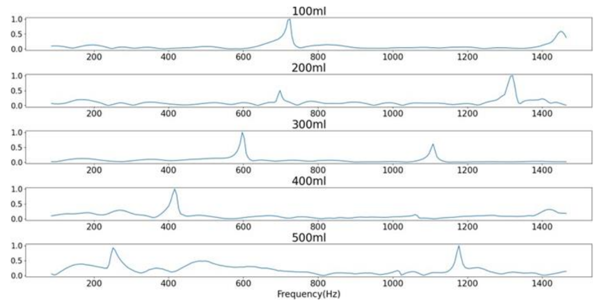

Fig. 3 Audio signals at different water level

2.3. *HYPERPARAMETER OPTIMIZATION*

Hyperparameter [10] is an important issue in deep learning algorithm as it determines the size and accuracy of AI model by selecting the number of hidden layers, the number of nodes and activation function in each layer. Typically, the hyperparameter combination that achieve the highest accuracy will be chosen to be implemented in the MCU. However, in this system, the implementation of edge computing is also a crucial consideration. Therefore, while ensuring the accuracy requirements are met, it is necessary to select a parameter combination that is suitable for the resource constraints.

Bayesian optimization [11] is a modelling method based on surrogate function that is used to optimizing the hyperparameter in the proposed system. It employs Gaussian process to model and updates the acquisition function based on the model's results, continually exploring the uncertain regions. As the number of searching increases, the surrogate function will be closer to the distribution of real function. Table 1 displays the results by hyperparameter search, sorted by the model size, number of hidden layers, number of nodes in each layer, and the corresponding model size and the accuracy rate Considering the memory limitation of the MCU, the first model which satisfies the accuracy requirements while also relatively small memory requirements is selected as the training parameters for this system.

Table 1. HYPERPARAMETER BY BAYESIAN OPTIMIZATION RESULTS

Hidden Layer(s)	Node 1	Node 2	Node 3	Node 4	Size (kB)	acc
2	5	5	0	0	49.75	0.99
2	5	7	0	0	49.77	0.98
2	5	16	0	0	50.75	0.99
3	5	8	8	0	57.53	0.99
4	32	32	5	8	172.50	0.99
4	32	32	5	16	174.50	0.80

After confirming the hyperparameters, the collected data and hyperparameters are utilized to train the AI model. The MCU code includes a knocking driver, ADC sampling, and pre-processing functions. Subsequently, the execution program is installed on the MCU. The execution time of the program, as shown in Table 2 is only 0.71 seconds for the entire process, including data sampling, pre-processing, and prediction, as illustrated in Fig. 4. Regarding MCU memory usage, the proposed system requires only 125.8 KB of read-only memory (ROM) and 28.8 KB of random-access memory (RAM). This system can be implemented in most of the memory management systems available in the market.

Table 2. PROGRAM EXECUTION TIME

	Sampling	Pre-processing	Prediction	All
Time(s)	0.20	0.22	0.014	0.71

```
arm-none-eabi-size --format=berkeley "Water_AI.elf"
   text    data     bss     dec     hex filename
 128568     244   29520  158332   26a7c Water_AI.elf
Finished building: Water_AI.siz
```

Fig. 4 Memory usage at MCU

3. Results and Discussion

The edge-computing platform proposed in this paper, which is include MCU, microphone, and solenoid electromagnet is shown in Fig. 5. In the picture, the micro switches on both sides of the solenoid valve ensure that the former can knock the middle of the bottle correctly

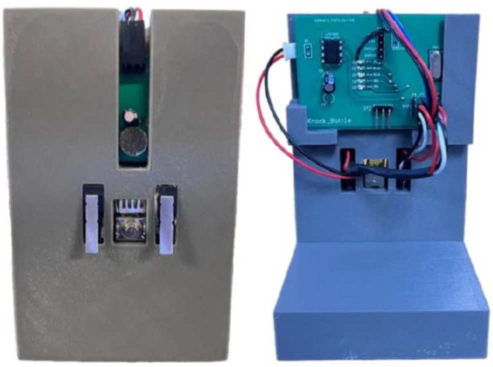

Fig. 5 Edge-computing platform

After installing the model into the MCU, the liquid level can be predicted. The performance of the AI model is often assessed using the confusion matrix, which categorizes predicted results into four classes: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). These metrics are used to calculate various performance indicators, including accuracy as defined in formula (5), true positive rate (TPR), false positive rate (FPR), true negative rate (TNR), and false negative rate (FNR).

In this paper, a multicategory model is proposed as the basis of analysis. Fig. 6 illustrates the index calculation for the '100ml' category when there are five output categories. If the predicted result matches the true label ('100ml'), it is labeled as C_1,1 (TP). Here, the symbol C represents a case, and C_(i,j) denotes the case in the i-th row and j-th column of a confusion matrix. Therefore, C_1,1 represents the case in the 1st row (true label: '100ml') and 1st column (predicted label: '100ml') of a confusion matrix. TPR represents the probability that a positive sample is correctly identified as positive, while FPR is the probability that a negative sample is incorrectly classified as positive. TNR is the probability that an actual negative sample is correctly identified as negative, and FNR is the probability that a positive sample is incorrectly identified as negative. A complete list of formulas is provided in the following sections (2) to (6).

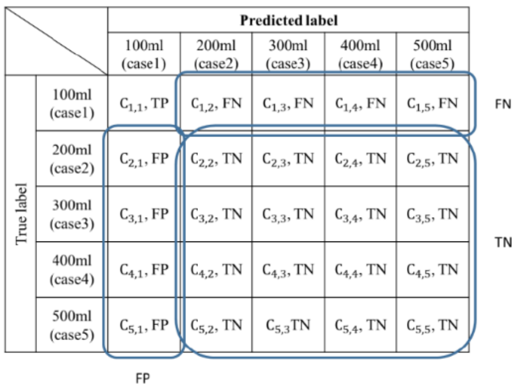

Fig. 6 Categories of Confusion matrix

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{2}$$

$$\text{TPR} = \frac{TP}{TP + FN} = \frac{C_{100,100}}{C_{100,100} + \sum_{k=200}^{500} C_{100,k}} \tag{3}$$

$$\text{FPR} = \frac{FP}{FP + TN} = \frac{\sum_{k=200}^{500} C_{k,100}}{\sum_{k=200}^{500} C_{k,100} + \sum_{i=200}^{500}\left(\sum_{j=200}^{500} C_{i,j}\right)} \tag{4}$$

$$\text{TNR} = \frac{TN}{FP + TN} = \frac{\sum_{i=200}^{500}\left(\sum_{j=200}^{500} C_{i,j}\right)}{\sum_{k=200}^{500} C_{k,100} + \sum_{i=200}^{500}\left(\sum_{j=200}^{500} C_{i,j}\right)} \tag{5}$$

$$\text{FNR} = \frac{FN}{TP + FN} = \frac{\sum_{k=200}^{500} C_{100,k}}{C_{100,100} + \sum_{k=200}^{500} C_{100,k}} \tag{6}$$

The Fig. 7 confusion matrix summarizes the actual and predicted classifications of online testing, and the confidence values of each liquid level are in line with expectations. As a result, 95% accuracy when calculating the true negative value of each water level, and 99% accuracy rate when calculating the full water levels.

The results of this study can be used to verify the feasibility of the proposed system as well as the discussed artificial intelligence model.

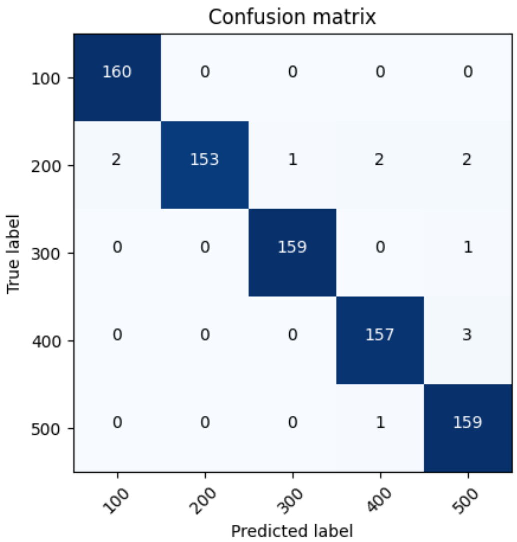

Fig. 7 Confusion matrix of the model

4. Conclusion

The paper proposes a MCU-based edge computing platform for liquid level measurement. This includes not only a knocking block, an audio signal preprocessing circuit, and MCU. but contains a detailed explanation of the development process, such as the optimization of hyperparameters, conversion of the model and installation for MCU. The utilization of glass bottles in the experiment led to more pronounced variations in the energy of the knocking sound. The experimental results can be up to 99% accurate under multiple tests. Experimental results indicate that the system is feasible and measurement accuracy is acceptable.

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