Identifying Liquids through Radiometric Effect and Deep Networks

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ABSTRACT

In this report, we propose a lightweight liquid testing system for categorizing different liquids and detecting adulterants by analysis through signal passing through liquids. Because different liquids have very different chemistry compositions, the light transmitted and scattered through the liquids will usually produce noticeably spectral signatures. By passing light of different wavelength through different types of liquids, our framework is able to measure the attenuation in the signals created by light transmitting and scattering, and then do analysis on the measurement by training neural network models for characterizing and therefore achieving liquid detection for future liquid inputs. Our system has four important advantages: the system requires very few customized hardwares and hardwares being used are very affordable. Also, our system is highly generalized and can be possibly used for additional liquids with proper training.Moreover our system requires no direct contact to measure the signal attenuation.Lastly, our system provides an identification of these liquids with decent accuracy.

1. INTRODUCTION

Liquids play an important role in our daily intakes. Nowadays, we confront different health challenges induced by adulterated liquid foods or water contamination, for example, consuming contaminated water can cause chronicle deceases or infectious diseases. Therefore, the topic of ensuring the quality of human liquid intakes attracts the interests from both the general public and the research community[3]. The research community has recently experienced a surge of research on the topics of liquid sensing on ubiquitous applications. It includes contamination detection, adulterants detection in liquid foods, and liquid type identifications. Unlike traditional liquid sensing methods which can only be done in labs with expensive equipment, the latest researches focus on ubiquitous applications design, which makes it more accessible to general public.

Different liquids have very different chemical compositions, the light transmitted and scattered through the liquids will usually produce noticeably spectral signatures. We make use of this property and design lightweight, low-cost framework on liquid identification. This is achieved by passing Visible lights and Infrared lights of different wavelength through different types of liquids. Our framework is able to measure the attenuation in the signals created by the transmission and scattering of light. The measured data are then being used for neural network training. With the neural network model, we are able to capture the features of given liquids which can be used for future liquid identification. In sum, this paper makes the following contributions:

- We design and implement a lightweight, low-cost system for liquid identification.
- We elevate our system on experiments on a few different types of liquids.

2. RELATED WORK

The topic of ubiquitous liquid testing has recently received significant attentions. There are some proposals that try to infer electric permittivity of the liquid by using UWB radios, for example LiquID. In this section, we will review the following related methods in liquid identification: RF-EATS by Ha et al., LiquID by Dhekne et al., and Nutrilyzer by Rahman et al. in details.

2.1 RF-EATS

Ha et al. proposed a system for food and liquid sensing called RF-EATS in 2020[2]. This noninvasive and zero-calibration system functions in a closed container and with no requirement of contact with the liquid content. RF-EATS is based on off-the-shelf Radio Frequency Identifiers(RFID) which is cheap and widely accessible. The RF-EATS relies on a neural learning model which can efficiently learn Radio Frequency features on the content of a container, and remove the features introduced by extraneous environmental changes. The authors test the system in seven different applications. The result of the experiments show RF-EATS is able to achieve overall 83% classification accuracy in the seven application it tested. However, their transmission is a log antenna with significant size constraints.

2.2 Nutrilyzer

Nutrilyzer is a mobile photoacoustic sensing system published by Rahnab et al. in 2016[3]. The system consists of an array LEDs in ultraviolet, visible and near-infrared region. Since different liquids have different spectral signatures as being yielded by the chemistry composition of the liquids, Nutrilyzer system is able to detect the unique spectral signatures created by the transmitted and scattered lights of different wavelength passing through various liquid. Then the unique spectral signatures are processed by signal processing algorithms and machine learning algorithms, and spectral signatures being mapped to various liquids characteristics including nutrients and adulterants. The paper evaluates the effectiveness by developing two models: a model to predict milk protein concentration which can detect a few common milk adulterants, and a model to predict alcohol concentration in clear and colored alcohol.

2.3 LiquID

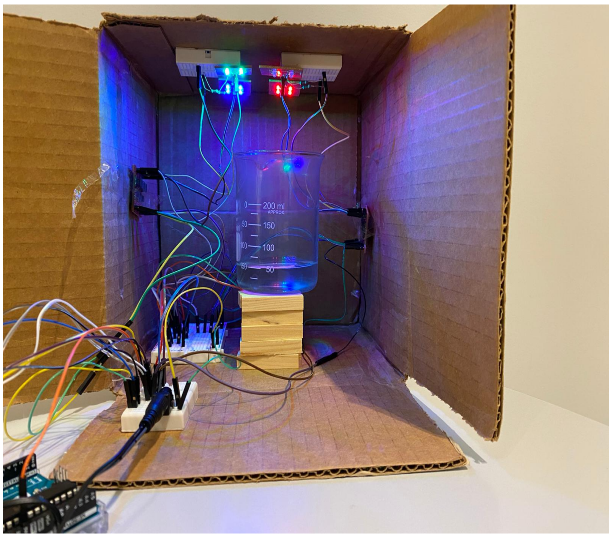
Dhekne et al. present a liquid testing method called LiquID in 2018[1]. LiquID incorporates radio signal by using two cheap off-the-self ultra-wideband(UWB) radios. It sparkles a UWB signal from one side of a fluid compartment and gets the sign on the opposite side and the time of travel of the signal is then measured. This combines with the phase and RSSI of the signal received allows the authors to model the permittivity of the liquid, which lead to identification of the liquid. The system, while being able to provide sub-second latency solution, has several limitations: the RF attenuation and phase are comparably sensitive to liquid depth, the measurement has to be carefully calibrated. And therefore, it might be subject to large error. In this case, median relative error is 9% inϵ' and 11.9% inϵ'' for permittivity estimates for 33 liquids using LiquID. Also, the system might get confusion liquids with close permittivities (VNA's 5% error range) like mineral water and diet pepsi. Lastly, the choices of containers for the system to work on are limited.

3. SYSTEM DESIGN

In this section we will go through our approach towards this problem and present a brief overview of our solution.

3.1 Hardware

We design our system by utilizing the following hardware:



1. One 200ml Beaker
2. One 12",12",15" cardboard box
3. 4 breadboards
4. One Ardino UNO Pinout
5. Adafruit SI1145 (UV index / IR / Visible Sensor)
6. 4 IR LED of 850-950 nm wavelength, 4 red LEDs of 700-740 nm wavelength, 4 green LEDs of 530-550 nm wavelength, and 4 blue LEDs with 485-500 nm wavelength.
7. Multiple Wood blocks
8. Multiple 20cm-jumpers
9. One 12V Power Adapter
10. 2 LED Drivers (PicoBuck)
11. 1kΩ resistors

The above hardware was used to construct the project setup. The overall assembly of the system was organized in a cardboard box with the breadboards attached to the sides and top of the board. Two panels of LED were powered by one of the LED drivers, whereas the other two panels of LED were powered by the second LED driver. This configuration was adopted due to the requirement of sufficient source of light for detection at the sensor. These LED panels were connected through a 1kΩ resistor in series. The LED panels were placed on the top of the board, as shown in above figure.

The Adafruit sensor uses serial communication to provide the readings for the signals. It is a multipurpose sensor, which can give Visible light measurement, in addition to Infrared signal strength. It also has the ability to provide a UV index based on the Visible light and IR signal strength. This sensor was placed at the bottom of the board on a pair of wooden blocks, with the beaker placed on top of it through the help of some additional blocks. This ensured two pathways to the sensor: line of sight signal and multi-path/diffracted signal. It also served to block light being reflected from the sides of the cardboard box.

For this initial set of experimentation, the LED were powered on in a sequential manner, and for each of the LED panels, all the values for Visible, IR and UV were recorded. This gave us a 3 feature data-set for each of the LED panels. Due to memory constraint of the Ardunio Uno, a batch size of 100 values for each of the LED panels was chosen. In this manner, a total of 10000 samples were collected from all of the 9 different sample sets. The data was collected in python module through serial communication of Arduino with python.

The circuit diagrams of the above hardware as per below:

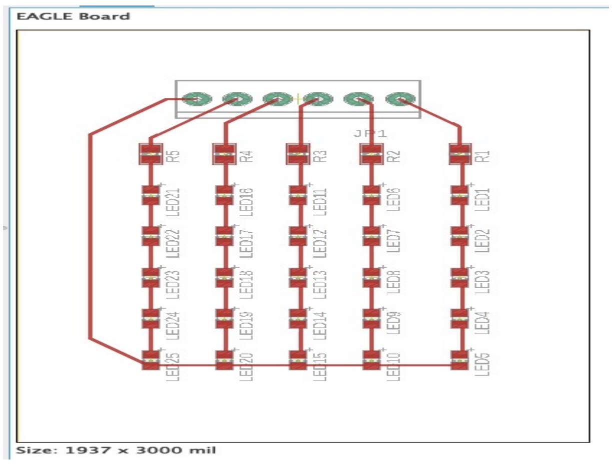


Figure 1: Initial attempt of PCB design

3.2 Learning Algorithm: Neural Network

We design our neural network in the following way:
We design the neural network with three linear layers. The first layer has 512 units, the second layer has 128 units and the third layer has 64 units. We use batch-normalization, activation functions, and dropout(p=0.4) layers after each of the network layers. After an intensive number of experiments with activation functions including ReLU, PReLU, RReLU etc, the function yielding the best accuracy was LeakyReLU. The batch size we use for our model is 1200, the steps are 1000, and learning rate is 0.001. The optimizer used for the learning was Adam optimizer.

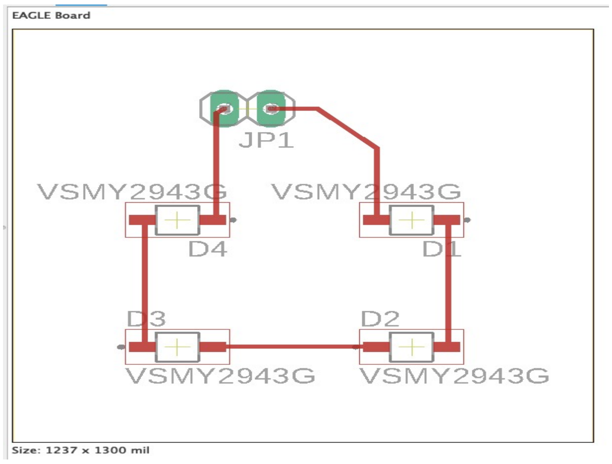


Figure 2: Final Infrared LED PCB Board

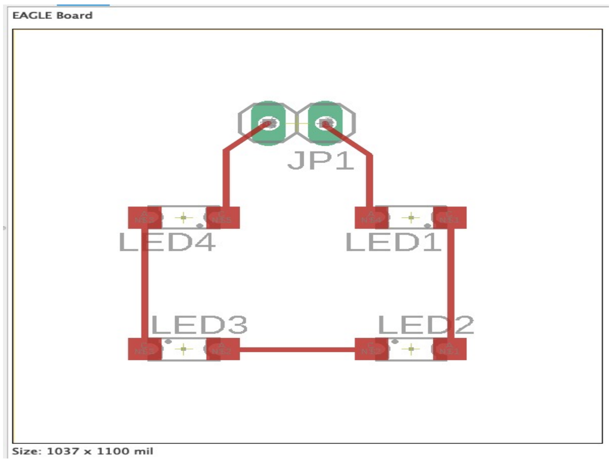


Figure 3: Final RGB LED PCB Board

All of these values were finalized after an extensive set of experimentation with batch size ranging from 400 to 2500, learning rate ranging from 0.1 to 0.0001, and the epochs ranging from 50 to 2000.

4. EXPERIMENT

We use the following types of liquid as our testing subject: Water, Soda, Milk, Olive Oil, Alcohol, Coffee. With these subjects, we create the following combination:

1. Water
2. Soda (Pepsi: Blacker shade)
3. Milk
4. Olive oil
5. Alcohol

6. Coffee (Light mix)
7. Water+Tablet
8. Water+Tablet+Alcohol
9. Water+Olive Oil

The data from all of these materials was first concatenated into a single DataFrame. This enabled the ease of processing of this data for our model related tasks. The materials were converted into 9 distinct categories, ranging from 0 to 8. The data was thoroughly shuffled for the purpose of generalization. Additionally, weighted loss was taken over all the categories: i.e. all categories were weighed down in the Cross-Entropy loss function by the max occurring class. Though our data-sets were fairly balanced, this step provided some improvement in overall accuracy.

5. EVALUATION

After we perform the described experiment, we evaluate the performance of the model by calculating accuracy, precision, recall, and f1-score.

	precision	recall	f1-score	support
Water	0.96	0.97	0.97	363
Soda	0.63	0.67	0.65	364
Milk	1.00	1.00	1.00	376
Olive oil	0.81	0.83	0.82	380
Alcohol	0.73	0.75	0.74	373
Coffee	0.66	0.56	0.60	379
Water_Tablet	0.49	0.55	0.52	379
Water_Olive Oil	0.68	0.63	0.66	371
Water_Tablet_Alcohol	0.52	0.51	0.51	390
accuracy			0.72	3375
macro avg	0.72	0.72	0.72	3375
weighted avg	0.72	0.72	0.72	3375

Figure 4: Evaluation of materials

From Fig.4 we can observe that our setup was able to achieve an accuracy of 72% for all types of liquids combined. This is a significant performance considering the DIY setup of the project, as well as a fairly simple featurization scheme. In the following, we present the heatmap for the confusion matirx.

As seen in the Fig.5, our model is able to perform significantly well on differentiating between these liquids. Some performance loss in identification is for those materials that demonstrate a similar spectral response to the transmitted signals. However, our model is still able to generalize well given that our feature-set was simple: i.e. all LED panels turned ON

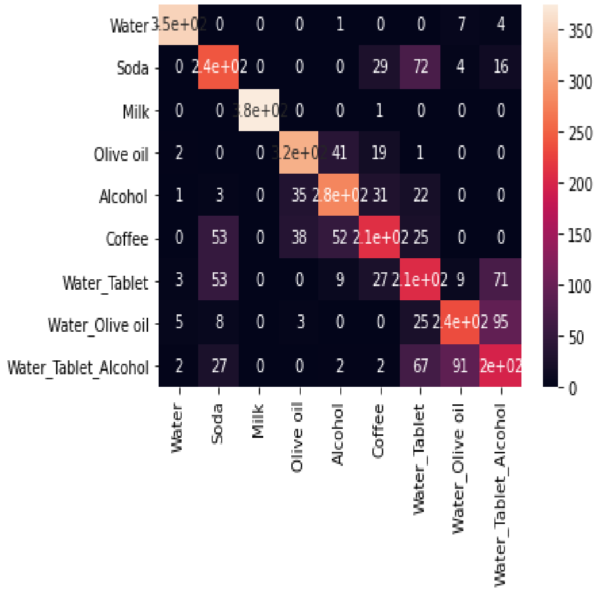


Figure 5: Confusion Matrix

sequentially. Another aspect to be noted here is that the adulteration tested here is mostly a combination of two or more of the original liquids in our data-set. This provides our learning model with a more challenged problem of identifying the liquids and then differentiating between the same liquids used as adulteration.

The coffee to soda and soda to coffee misclassification arises from the color of the soda and a light mixture of coffee being used. Another incidence of soda being classified as water_tablet is due to the spectral response of the adulterated water being similar to soda. Lastly, the adulterated material of water_tablet_alcohol is misclassified into a number of other liquid types because of it being a combination of different materials, and also because of the color response it produces as a result.
We also provide the classification martial counts of training data and testing data, as shown in Fig.6 and Fig.7. This shows the respective size of our data-sets for training and testing. The examples are evenly distributed amongst both the sets.

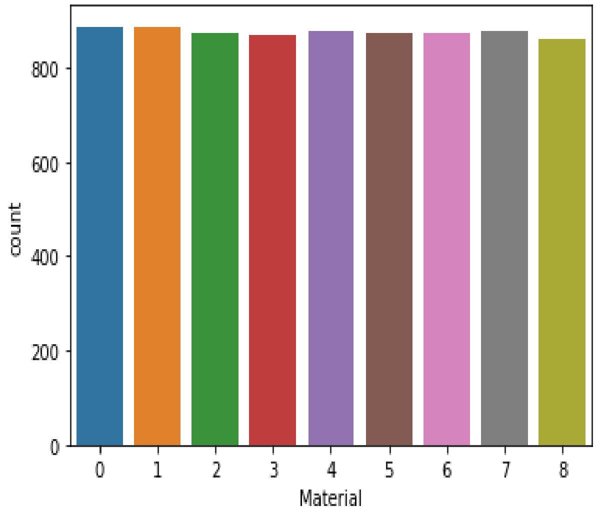


Figure 6: Classification Material Counts of training data (0: Water, 1: Soda, 2: Milk, 3: Olive oil, 4: Alcohol, 5: Coffee, 6: Water & Tablet, 7: Water & Olive oil, 8: Water & Tablet & Alcohol)

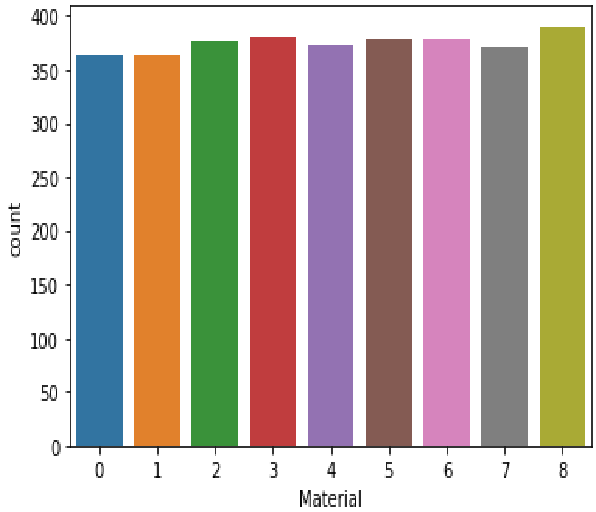


Figure 7: Classification Material Counts of testing data (0: Water, 1: Soda, 2: Milk, 3: Olive oil, 4: Alcohol, 5: Coffee, 6: Water & Tablet, 7: Water & Olive oil, 8: Water & Tablet & Alcohol)

6. CONCLUSION

With our model's accuracy being 72% overall, we believe that these results are a significant progress towards building a low-cost solution for the task of liquid categorization and adulteration detection. Our model was effectively able to perform identification of a variety of liquids, and adulteration. Additionally, the cost associated with the our system was comparatively far less than similar works in the field. Lastly, the time and skill requirement for constructing such a setup are lower.

7. LIMITATIONS AND FUTURE WORK

Based on the results of an extensive round of experimentation, we consider the following as our future directions: Due to the time and scope limitations for this report, we are only able to use four different types of LEDs. We want to incorporate more types of LEDs with different wavelength than we currently have. We expect that with more types of LEDs, we are able to get a more feature-rich set of data-points which can train the neural network even further and possibly achieve better results.

Another possible modification can be changing the way of LEDs flashing. Currently, we are following a sequential firing order of LEDs from a single wavelength panel and then passing them through the liquid. For future work, instead of sequential order, the system can take multiple wavelength LEDs turned on at the same time. This may help to provide additional features for neural network training.

Also, we want to expand our neural network to train on a combinatorial set of features. Since we have 3 values of Visible light, IR, and UV being computed for each LED panel, we can create a customized combination of these values for all liquids. This will create a rich feature set, without the effort of collecting more varied data. We can also have different classification models.

Furthermore, we only use 1 sensor for reception in the setup, and it could lead to less precise capturing of the signals. In order for the measurements to be more refined and accurate, we think more sensors would be useful. The other thing that could be done is to modify the placement schemes, such that the sensors or LED panels can be aligned to reduce possible errors.

8. APPENDIX

Shared Folder:
https://drive.google.com/drive/folders/1L$_w$ $-$
$VXnDBri1L2PkkPWiOflDzxKRMunA?usp$ $=$
$sharing$

9. REFERENCES

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[3] Rahman, T., Adams, A. T., Schein, P., Jain, A., Erickson, D., and Choudhury, T. Nutrilyzer: A mobile system for characterizing liquid food with photoacoustic effect. In *Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems CD-ROM* (New York, NY, USA, 2016), SenSys '16, Association for Computing Machinery, p. 123–136.