



Thesis for the Degree of Master of Engineering

Self-Powered Food Assessment System Based on Deep Learning and RF Energy Harvesting

by

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by

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List of Abbreviations

NFC	Near Field Communication
RFID	Radio Frequency Identification
RFEH	Radio Frequency Energy Harvesting
CNN	Convolutional Neural Network
MLP	Multi-Layer Perceptron
TVOC	Total Volatile Organic Compound
UHF	Ultra High Frequency
DTV	Digital Television
LTE	Long Term Evolution
GSM	Global System for Mobile Communications
MOS	Metal Oxide Semiconductor
PCE	Power Conversion Efficiency
DC	Direct Current
DL	Deep Learning
DBN	Deep Belief Network
RBM	Restricted Boltzmann Machine
ReLU	Rectifier Linear Unit
SGD	Stochastic Gradient Descent

Acknowledgment

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Self-Powered Food Assessment System Based on Deep Learning and RF Energy Harvesting

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Abstract

In recent years, the demand for food monitoring system development is becoming extremely necessary because of the effects of food safety on human health. However, some conventional methods show several drawbacks such as complexity, high power consumption and expensive. Aiming towards a novel method for food monitoring, in this thesis, the authors proposed a self-power online food monitoring method based on far-field RF energy harvesting and machine learning techniques.

The system includes a smart sensor module and an energy harvester escalated inside a seal food container. The energy is harvested from radio frequency at ultra-high frequency band 915MHz transmitted by a 1W radio frequency identification (RFID) reader. To improve the RFEH performance and fit into a compact foot print, a Yagi type structure antenna with three elements was implemented as receiver antenna. Additionally, we presented a new approach for food scanning by observing the increasing gradually of air pressure inside the food package during storage through an air pressure sensor mounted on the designed module. With this approach, the sensor tag is capable of working at ultra-low power, less than 1mW while the other conventional method whose power consumption over 10mW. To verify the feasibility of the proposed solution, a set of demonstration was conducted to monitor the variation of packaged pork and fish in seven days under ambient and refrigerated storage conditions. To classify different states of food quality, a convolutional neural network (CNN) model was developed and trained on the food dataset which contains the collected data in the experiments. To investigate the capability of the proposed CNN model, several machine learning models

included MLP and SVM, are also studied. Their classification performance based on confusion matrix are identified and compared.



RF 에너지 하베스팅과 딥러닝 기반의 자가 동력 식품 평가 시스템

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Abstract

최근 몇 년 동안, 식품 안전이 인간의 건강에 미치는 영향 때문에 식품 감시 시스템 개발에 대한 수요가 극도로 요구되고 있다. 그러나 일부 기존 방법은 복잡성, 높은 전력 소비 및 고비용과 같은 몇 가지 단점을 보여준다. 본 논문에서 저자는 식품 모니터링을 위한 새로운 방법을 목표로 원거리 RF 에너지 수집 및 기계 학습 기법을 기반으로 한 자체 파워 온라인 식품 모니터링 방법을 제안했다.

이 시스템에는 스마트 센서 모듈과 씰 푸드 컨테이너 내부에 에스컬레이션된 에너지 수확기가 포함되어 있습니다. 에너지는 1W 무선 주파수 식별(RFID) 판독기에 의해 전송되는 915MHz 초고주파 대역에서 무선 주파수에서 수집됩니다. RFEH 성능을 향상시키고 소형 풋프린트에 맞추기 위해, 3개의 요소를 가진 야기형 구조 안테나가 수신기 안테나로 구현되었다. 또한, 우리는 식품 포장 내의 기압이 점차적으로 증가하는 것을 관찰함으로써 식품 스캔에 대한 새로운 접근방식을 제시했다. 이 접근법으로 센서 태그는 1mW 미만의 초저전력에서 작동할 수 있는 반면 전력 소비량이 10mW 이상인 다른 기존 방식에서는 사용할 수 있다. 제안된 솔루션의 타당성을 검증하기 위해, 주변 및 냉장 보관 조건에서 7일 이내에 포장된 돼지고기와 생선의 변화를 모니터링하기 위한 일련의 시연이 실시되었다. 식품 품질의 다른 상태를 분류하기 위해, 실험에서 수집된 데이터를 포함하는 식품 데이터 세트에 대해 CNN 모델이 개발되고 훈련되었다. 제안된 CNN 모델의 기능을 조사하기 위해 MLP 및 SVM을 포함한 여러 기계 학습 모델도 연구된다. 혼돈 행렬에 기초한 분류 성능을 확인하고 비교한다.



Chapter 1 : Introduction

1.1 Motivation

In recent decades, food safety is becoming the top concern of the community. Indeed, unsafe food poses a global health threat, endangering every people. According to statistics of the World Health Organization, an estimated 600 million, nearly 1/10 people in the world get sick after eating contaminated food and 420000 people die each year [1]. Unsafe food causes a vicious cycle of diarrhea and malnutrition, threatening the nutritional status of the most vulnerable, especially infants, young children, pregnant women and the elderly. One of the main causes of unsafe foodborne illnesses is the use of rancid foods and the expiration date. Consumers often rate food quality emotionally based on external factors such as appearance texture, colors, smell [2]-[4]. However, these methods are often not highly accurate in assessing the quality levels of the food as well as the best time to use the product. Therefore, it is very important to develop a food quality monitoring and classification system during storage to avoid problems arising from the use of rancid foods.

With the interest of the research community, many methods have been proposed to improve efficiency in food monitoring. Methods involved in the identification of dirty food chemical properties are highly accurate [5]-[7], but this approach requires a high cost, complex equipment and the ability to deploy in quantities have many difficulties. Meanwhile, with the advancement of the information technology industry, the development of IoT devices, electronic sensors have been able to collect the signs generated during food storage with high precision and transmit synchronously these data to the processing center for analysis and make an assessment with good reliability. Some systems developed in this approach are called the electronic nose [8]-[9]. However, these systems also have some disadvantages, most of which are usually powered by cables or batteries and therefore, often have cumbersome, complex designs and maintenance, especially battery sensors are extremely toxic because battery chemicals that arise during use can directly affect the food.

Therefore, the development of an electronic module sensor that does not use the battery will bring many benefits and efficiency. There are many methods of collecting energy to feed the electronic sensors, which can be mentioned as solar, vibration, thermal energy, radiofrequency. In particular, in recent years, RF reception technology is emerging as a promising method for self-powered systems with high applicability in IoT systems [10]. In this system, a fixed source emits RF waves, and the sensors capable of converting these waves into DC source and feeding the electronic components to function. In the application of food quality monitoring, many scientific works have announced the use of RF energy collection technology [11]-[14]. However, conventional RF energy harvesting systems have problems with the transmission distance from the source to the sensor because the energy that the sensor node receives will depend greatly on this distance. On the other hand, these studies are that they often focus on collecting the index of gas arising in the process of food damage caused by microorganisms. The biggest disadvantage of this method is that the power to the gas sensors is very large, usually over 10mW whereas the harvested energy from RF wave is at a level of microwatts [15]-[19]. Consequently, the energy required to operate the circuit needs to be collected for a very long time while the

consumption time is very fast, along with the reduced transmission distance between the sensor and the transmitter. Besides, gas type sensors with metal oxide gas sensing material need a warm-up time before they can go to normal operation, typically about 30 minutes [20]. This leads to the problem that the collected energy is mainly used for heating the gas sensor, while the energy used for the data collection will be greatly reduced.

Different from existing methods, in this study we proposed a new battery-less system for monitoring and evaluating food quality. To increase the collected energy as well as the transmission distance, we recommend using a printed Yagi three elements antenna as the receiver antenna. Also, to overcome the weaknesses in the conventional food monitoring method, we used an air pressure sensor to reduce the energy consumption of the entire circuit. Besides, to improve the accuracy of the food quality classification, in this project we developed a CNN network model that uses two inputs, temperature and air pressure to identify the good state, the warning state and the bad state of the food. This classification is based on several available studies. To compare the feasibility of the proposed CNN network model, we also apply some other machine learning algorithms such as SVM, MLP. The classification result is then compared based on the confusion matrix.

To achieve the desired goals with a battery-less system, this thesis employs the following strategies:

- (1) Survey existing RF energy harvesting techniques and their circuit topologies.
- (2) Design a printed Yagi antenna three elements for RF energy harvesting and wireless data communication.

- (3) Assess antenna performance in wireless communication and RF harvested energy.
- (4) Design and fabricate a compact smart sensor module that is able to work totally passively.
- (5) Deploy a set of experiment for food monitoring in different environment conditions.
- (6) Utilized deep learning models to accurately predict and classify the sensing output values, thereby supporting for food monitoring in an efficient manner.
- (7) Compare the classification performance of the proposed CNN model with other conventional machine learning algorithms.

1.2 Thesis contribution

As mentioned in the previous chapter, the main contribution of the thesis was the design a non-invasive battery-free food measuring system. During the design process, RF energy harvester and sensor module were selected to optimize the obtained energy and reduce significantly the energy consumption of the circuit. In addition, deep learning techniques have been applied to increase the efficiency of food quality classification based on obtained data from the sensors. We summarize the contributions of this study as below:

(a) A food monitoring solution is proposed that is non-invasive and no battery, overcoming the weaknesses of existing food monitoring systems.

- (b) Antenna plays a pivotal role in RF energy capture system. This study proposed and implemented a 3-elements printed Yagi-Uda antenna operating at UHF band of 915Mhz with low cost, compact design and optimum collected energy efficiency.
- (c) The ultra-low power consumption sensor selections were considered in designing the sensor module.
- (d) Propose a new approach for application of far-field RF energy harvesting in food monitoring based on the variation in air pressure inside the food package, which greatly reduced the power consumption of the circuit, along with making the designing and configuration process much simpler.
- (e) Deploy experiments with difference sort of food such as pork, chicken and fish to investigate the feasibility of the proposed system.
- (f) Build a Food dataset from the obtained sensor data, conduct preprocessing the data to train the machine learning models.
- (g) Develop and train a Convolutional Neural Network (CNN) model to evaluate food quality based on the Food dataset. The classification results achieved extremely high accuracy has proven the feasibility of the proposed model. This approach also opens up a new and effective direction for other studies that have other type of data obtained from food surveillance such as colors, TVOCs, images, etc.
- (h) Compare the classification accuracy between several machine leaning models to investigate the applicability of the proposed CNN model.

Chapter 2 : Background and Related Work

2.1 Energy Harvesting Technology

Energy harvesting is the process of gathering energy from the ambient environment and converting them into electrical energy and power for the electronic equipment and sensor networks. There are many sources of energy around the environment that can be collected, such as solar, wind, thermal, electromagnetic field. The amount of power which is collected and converted into electricity depends greatly on the supply sources. While sources such as solar and wind provide a quite large amount of energy, up to 100mW/cm² depending on environmental conditions, other sources give us a much smaller amount, less than $2\mu/cm^2$. However, each type of energy harvesting technique has its advantages and disadvantages. The comparison between different energy scavenging techniques based on criteria of energy density, possible output voltage, available time, advantages and disadvantages of each technique is discussed in Table 2-1.

°					
	Solar Energy	Thermal	Ambient	Piezoeleo	ctric Energy
	1 M	Energy	RF Energy	Vibration	Push Button
Power	100	60 μW/cm ²	0.0002~1	200	50 µJ/N
Density	mW/cm ²		µW/cm ²	$\mu W/cm^3$	-
Output	0.5V(single	-	3~4V	10~25V	100~10000V
voltage	Si cell)		(Open		
			circuit)		
Available	Day Time	Continuous	Continuous	Activity	Activity
Time	(4~8 Hrs)			dependent	dependent
Weight	5~10g	10~20g	2~3g	2~10g	1~2g
Pros	Large	Always	Antenna	Well	Well
	amount of	available	can be	developed	developed
	energy, well			_	tech, light

Table 2-1.	Available	Ambient	Energy	Sources	
------------	-----------	---------	--------	---------	--

	developed tech		integrated onto frame, widely available	tech, light weight	weigth, small volume
Cons	Need large	Need large	Distance	Need large	Highly
	area, Non-	area, low	dependent,	area,	variable
	continuous,	power,	depending	highly	output, low
	orientation	rigid &	available	variable	conversion
	issue	brittle	sources	output	efficiency

In recent years, energy harvesting techniques have been advanced in researches and applications due to their extraordinary benefits. There are four primary points of interest in these procedures as taking after:

- Not require maintenance and replacement which are the essence of the battery-powered sensor network, thereby reducing time-consuming and labor costs. Even the life cycle of an energy collector is infinite if the circle is well designed.
- Could be used as a backup power source for the dedicated power source when the main power is suddenly turned off, thereby maintaining the operation of electrical equipment.
- Flexibility is one of the great advantages of energy capture technology. The energy collection units can be integrated on IoT devices, guaranteeing that they can operate steadily for a long time.
- Researching energy harvesting technologies also promotes the development of low-energy electronic components, increasing energy efficiency in conventional electronic equipment.

An energy harvesting system can be designed according to figure 2-1. The main components of an energy harvesting application system are composed of an energy harvester and application module. The energy harvester is responsible for converting collected energy into electricity. The main components included in this module are rectifiers, energy storage block, and energy management block. The rectifier unit converts the alternating current energy to direct current, the choice of this circuit design depends on the desired output voltage level and the input energy of the receiver. The common storage block is a rechargeable battery or a supercapacitor. When the power level reaches a certain threshold, they will be used for the application module. The energy management unit is responsible for optimizing the use of obtained energy. Depending on the power level at the storage, this block is responsible for opening and closing the power source for the following applications. The application module includes sensors to collect data from the environment and a microcontroller to process the collected data and transmit that data to the processing server. The components selected for this module design must have extremely low energy consumption in order to optimize the total circuit power consumption due to the limitation in the amount of harvested energy.

HOLV

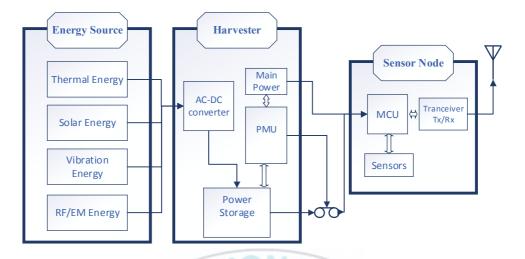


Figure 2-1 Block diagram of an energy harvesting system.

In this study, we focus on energy harvesting from radio waves due to their outstanding properties and suitability for food surveillance applications. We will go into this technology in the next section.

2.2 Radio frequency energy harvesting

The technique of obtaining energy from the electromagnetic field is the ability to gather RF energy from free space and change over them into electrical vitality. In later a long time, this innovation has gotten awesome intrigued by the research community due to its preferences. Whereas solar and wind energy sources are profoundly subordinate to natural conditions, RF energy can be collected continuously, many sources are plenteous within the encompassing environment and can be utilized in any area. Radiofrequency sources can be partitioned into two sorts of ambient sources and dedicated sources. Harvesting energy from an ambient source is intended to convert radio waves which is available in the surrounding environment into electrical energy. These radios are derived from DTV, LTE, GSM, UTSM stations, wi-fi transmitter, Bluetooth devices [20]-[42]. The received energy

level depends greatly on the source and the density of transmitting stations. Many studies are investigating the density of RF energy obtained from urban and suburban areas. The comparison of RF energy harvesting methods at different frequency bands is shown in Table 2-2.

Related	RF source	Sensitivity	RF-DC	Load	Range	Tx
work			Conversion			power
			Efficiency			
A.P	RFID	-8.7 dBm	30%	180 kΩ	4.3m	1W
Sample	Reader			resistor		
	(915 MHz)		ONLA			
D.Donno	RFID	-14 dBm	16%	3 kΩ	4.8m	3.2 W
	Reader	Nr	1	resistor		(EIRP)
	(866.5	-				
	MHz)					
A. Dolgov	Ambient	-15.2 dBm	60%	1 kΩ	50 m	-
	Cenllular			resistor	- \	
D.Masotti	Ambient	-	~18% (at -	50 Ω	- 1m	50 mW
	Urban		10 dBm)	resistor	0	
	Wireless					
	Signals:					
	GSM900,				/	
	and Wifi				14	
	(900 MHz					
	and 2.45	1				
	GHz)	0				
M.Pinuela	Ambient	-25 dBm	40%	100 μF	-	-
	Urban		(Overall)	capacitor		
	Wireless					
	Signals:					
	Digital-					
	TV,					
	GSM900,					
	GSM1800,					
	and 3G					
T. Ajmal	Low	-	~50%	1 k Ω	20 km	150 kW
	Frequency					
	Radio					

Table 2-2. The comparison of RF energy harvesting methods

R. J. Vyas	Ambient	- 14.6 dBm	15%	100 μF	6.3	48 kW
	Digital-TV	(Single		capacitor	km	
	(512~566	tone) -37				
	MHz)	dBm				
		(Multitone)				
R. Shigeta	Ambient	-20 dBm	30% (at -10	$50 \mathrm{k\Omega}$	6.3	380 kW
	Digital-TV		dBm)	resistor	km	(Tokyo)
	(540 MHz)					

Although the RF sources are exceptionally assorted, the energy gotten from questionable sources is exceptionally moo. The most elevated esteem is as it were around -15.2 dBm which is collected at BTS stations. Up to now, there has been no investigation to create conceivable applications from this vitality source. Another more eminent approach is the utilize of settled broadcast sources. A diagram of a dedicated source framework has appeared in Figure 2-2.

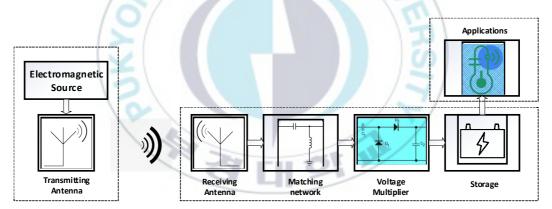


Figure 2-2 Block Diagram of a dedicated source RF energy harvesting system.

A reader acts as an RF transmitter, with a certain transmit power, ordinarily around 1 to 3 W. To get these RF waves, a recipient unit is outlined with an antenna working within the same frequency as the source. The RF waves after resonating with the receiving antenna will be changed over into DC energy and fed into the energy management units and applications. With its mobility and steady energy source, the fixed RF energy source has pulled in many pieces of research and high feasibility applications. Particular applications will be talked about within the next section. There are numerous commercial RF transmitter producers such as Power Cast RF gatherer, Impinj, or smartphones supporting NFC function.

In addition to the classification of the RF energy harvesting technique based on the source type, the operating frequency is also a key factor in distinguishing the different RFEH system. The frequency factor can be summarized as follows:

- Low Frequency (LF): 125 kHz 134 kHz
- High Frequency (HF): 13.56 MHz
- Ultra-High Frequency (UHF): 860 960
- Microwave: 2.45 GHz and 5.8 GHz

The selection of operating frequency greatly influences the transmission distance of energy and signal. It is possible to separate the magnetic field around the source into two sorts of the near-filed and far-field region. The near-filed RF energy harvesting can be distinguished by either magnetic resonance coupling or inductive coupling. Magnetic resonance is based on the exchange of energy between two resonant circles at the same frequency through a magnetic field association. Meanwhile, energy is transmitted within the inductive coupling system by magnetism through the two loops. The near field energy harvesting system is characterized by large concentrations of the collected energy. In any case, this energy source depends enormously on the transmission distance between the loops, so it could be constrained by the applicability of this technology in remote sensor systems and IoT gadgets. Near field technology is widely used in wireless charging devices for phones, tablets, wearable devices as well as many other applications. A typical near field system NFC is used as a common function in smartphones. A system using the NFC function to power a sense module is shown in Figure 2-3.

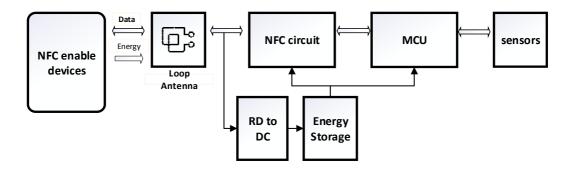


Figure 2-3 The block diagram of a conventional NFC energy harvesting system.

RF energy transmission is considered a far-field case in case the distance is over $\lambda/2\pi$, where λ is the working frequency of the RF source. This strategy permits energy to be exchanged over a long distance and an expansive range. In any case, the gathered energy with this method is very low. Recently, a far-field RF energy harvesting circuit has been optimized to extend the effectiveness of RF to DC vitality transformation. Other than, the appearance of ultra-low energy chips has made this innovation promising, particularly the internet of things systems or indoor applications. Table 2-3 compares the properties of the close and far-field advances.

Characteristics	Far field transfer	Resonant coupling	Inductive coupling
Field	Electromagnetic	Resonance	Magnetic method
Method	Antenna	Resonator	Coil
Efficiency	Low to high	High	High
Distance	Short to long	Medium	Short
Power	Low to high	High	High
Safety	EM	None	Magnetic
Regulation	Radio wave	Under discussion	Under discussion

Table 2-3. RF power transmission characteristics.

2.3 RFEH Applications

With its outstanding benefits, RF energy harvesting technology has proven its high applicability not only in the research field but also in daily practical applications. RFID is a prominent application of RF energy scavenging, especially in warehouse management, attendance systems, public transport systems. According to *IDTechEx*, the RFID market is worth \$ 11.9 billion in 2019 and is expected to reach \$ 13 billion by 2022. Focused products include tags, readers, and associated service software for label and tag systems, both passive and active RFID.

The retail sector accounts for the largest share of the RFID consumer market, with card supply exceeding 10 billion cards in 2019 and continuing a strong trend in the following years. The growth is mainly in products using UHF RFID technology (RAIN RFID). The payment card market also grew strongly with the number of cards providing up to 2.3 billion cards.

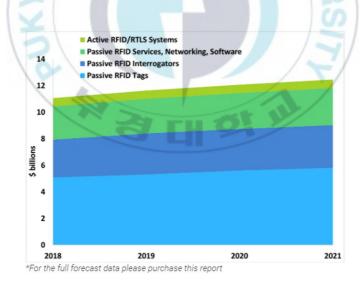


Figure 2-4. Total RFID market in US\$ billions (Source: IDTechEx)

For passive RFID tag systems, experts predict the growth in the coming years to focus on the areas which are mentioned in Table 2-4.

Passive UHF market data	Passive HF RFID market	Passive LF market data
segments 10 years	data segments 10 years	segments 10 years
forecast	forecast	forecast
 Retail apparel and footwear Retail-other Medical/health care Assets, logistics containers Air baggage Access 	 Contactless cards/fobs Smart tickets Books Medical Assets/tools Passports People NFC 	 Livestock and pets Access control Vehicle immobilizers Medical People Other
Control/ticketing	• Other	m
 Sensors and 		
Embedded (I2C)		10
People		0
• Other		

Table 2-4. Passive RFID market segment 10 years forecast

Traffic is one of the areas that benefit most from RFID applications. Modern wireless card systems have replaced the classic ticket checking system and bring many benefits to investors and service users. Although the initial installation investment costs are expensive, returns are much more effective in the long run. The transaction payments are completely by card, so customers do not need to bring the exact amount to be paid or the odd amount. The operator at the bus station also does not have to directly collect and pay tickets to avoid causing congestion on the bus. Data about operations, number of customers, and trips are accurately statistic and digitized, helping executives to manage their business well. One of the largest transport systems implementing RFID systems is the metro system in Seoul, South

Korea, which started in 1996. The RFID technology used in this project is MIFARE (inductive coupled, 10 cm, 13.56 MHz), one of the most popular systems in public transport. Electronic identity systems are also used in the agricultural industry to automate product supply chains, tracing the origin of animal and control disease and product quality. There are four types of transponders attached to animals: collar transponder, ear tags, injectible transponders, and bolus. RFID systems are considered state-of-the-art in this area, replacing the traditional barcode system, which is not fully automatic system and still requires manual control.

Healthcare is additionally a potential area where RFID systems could be deployed. Warehouse and drug administration systems can be attached with RFID labels to digitize management, minimizing misfortune during operation. Therapeutic offices can be prepared with a system of participation, get to control for staff and patients, which helps to control operations in sensitive areas in clinics. Not only for operation observing, but RF vitality collecting is also applied in clinical considers such as power supply for heart rate checking system []. In this study [], the authors developed a system that can be utilized to identify the movements of patients, particularly the elderly. They created a UHF RF receiver that can work up to a distance of 2.5 meters and works in real-time.

Recently, large numbers of studies have focused on applications of RF energy harvesting system [43]- [56]. Notably, the studies on measuring food quality use RF sensor tags that are completely passive. Some of these studies [13]-[14] using a 915 MHz system for non-invasive food surveillance. In this study, they developed a sensing system that could self-energize their operation by converting RF waves into DC power. The energy harvesting distance can be up to 4 m. The sensor mote is placed in the food storage box to measure the variation of volatile chemical

compounds (TVOCs) produced during the food quality modification. In addition, the temperature and humidity parameters are also collected. These data are then fed into the machine learning model for food quality classification and storage evaluation.



Chapter 3 : Theory of Energy Optimization

In this chapter, we will present optimal principles for harvesting and using the collected power. One of the most important factors in an efficient energy harvesting system is the receiver antenna. We will present the principle of directional antennas, namely the three-elements Yagi antenna, which are best suited for far-field dedicated energy scavenging applications. Besides, this chapter also gives the principle of using a pressure sensor as an index to monitor food quality. The application of this principle will optimize the energy consumption of the sensor module, while also simplifying the design compared to existing methods.

3.1 Far-Field RF Energy Harvesting with Directional Antenna

3.1.1 Fundamentals of RF transmission

Understanding the principle of RF wave transmission is vitally in the design of an RF energy harvesting system. The behavior of the RF waves varies depending on the frequency, transmission distance, and operating environment, which is discussed thoroughly in the study [58]. Depending on the intended utilization, the designer can select the parameters for the electromagnetic system to get the best results.

The transmitted energy from the transmitter to the receiver will be lost during the emission of RF signals in transmission space. In designing the energy harvesting system, factors impacting the transmission energy scattering incorporate the gain of the transmitting and receiving antennas, the operation frequency, and the distance from the transmitter to the receiver. The properties of the electromagnetic waves vary depending on the distance to the source, and these properties are categorized as close and far-fields as said within the previous chapter. More

particularly, the near field is considered to be a zone inside Fraunhofer's distance and the far-field is decided to be the exterior of this distance. The Fraunhofer's distance equation is characterized as takes after:

$$d_f = \frac{2D^2}{\lambda} \tag{1}$$

Where d_f is the Fraunhofer distance, D is the maximum size of transmitting antenna and λ is the operation wavelength. The distribution of near-field and far-field is described in the Figure 3-1.

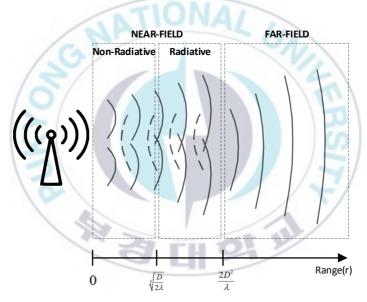


Figure 3-1 The distribution of near-field and far-field region in space

For a transmitter-receiver antenna system in the far-field free space, the amount of radiated energy which is harvested at the receiver antenna could be calculated by Friis's formula:

$$P_{R} = \frac{P_{T}G_{T}G_{R}\lambda^{2}}{\left(4\pi R\right)^{2}} \qquad (2)$$

Where P_R is the power at the receiving antenna, P_T is the transmitted power, G_T is the gain of transmitting antenna, G_R is the gain of the receiving antenna, λ is the operation wavelength, and R is the distance between transmitter and receiver. In case f is expressed in MHz, the distance R is in km and the gain G_T and G_R is measured in *dBi*, the free space power loss (FSPL) can be inferred as:

$$P_L(dB) = 20\log_{10}(f) + 20\log_{10}(R) + 32.44 - G_T - G_R$$
(3)

Through the FSPL formula, we can determine the loss of energy in the transmission line and the possible harvested power at the receiving antenna relatively. This formula does not consider other factors of transmission environment such as reflection waves and other attenuation, so it is possible that the lost energy is larger in practice. However, the determination of the obtained energy is also an important processing step for power management and sensor module designing.

3.1.2 The directional antenna in RF energy harvesting system

Gain, resonance frequency, and bandwidth are characteristic parameters of an antenna's performance. In an obstructive environment, the transmitting antenna is isotropic, the propagation in all direction is uniform. Therefore, the energy density at each point is inversely proportional to the square of the distance from that point to the RF wave generator. This relationship is described in the following formula:

$$S_{isotropic} = \frac{P_T}{4\pi R^2}$$
(4)

Where R is the distance from the source, S is power density at the distance R, and P_T is the transmitted power.

However, antennas are not always isotropic, they can be designed to radiate more energy in a direction than in the other depending on the application. The proportion between the greatest power density of an antennas at a given distance to the power density of an ideal omnidirectional or isotropic antenna at the same distance is called the gain (G) of the antenna. The gain value of an antenna can be expressed as:

$$G_{(\theta,\varphi)} = \frac{S_{(\theta,\varphi)}}{S_{isotropic}} = \frac{4\pi R^2 S_{(\theta,\varphi)}}{P_t}$$
(5)

In this way, the energy density at a separate R from transmitting antenna in common is given by:

$$S = \frac{P_T G_T}{4\pi R^2} \tag{6}$$

In the case of an isotropic antenna, the value $G_t = 0 dBi$. The above equation is additionally pertinent to receiving antennas in a transceiver system. Assume that the receiving antenna has an effective aperture given by A_{ER} , then the harvested energy at this antenna is calculated by:

$$P_{R} = \frac{P_{T}}{4\pi R^{2}} G_{T} A_{ER} = \frac{P_{T}}{4\pi R^{2}} G_{T} \frac{\lambda^{2}}{4\pi} G_{R}$$
(7)

This is known as the Friis's Transmission Formula as mentioned in the previous section. In RF transmission applications, if the position of the source and the receiver is unknown, then a low gain antenna is more useful since the RF generator can transmit in different directions and the receiver can collect the signals from multiple directions. On the other hand, in the RF transceiver applications where the transmitter and receiver position has been determined, increasing the gain of the transmitter and receiver antenna gives many benefits and improves the efficiency of the system. In an RF energy harvesting system with a dedicated transmitter, a high gain receiver antenna increases the harvested power and extends the transmission distance between the receiving node and the reader.

3.2 Theory of food monitoring based on air pressure variation

3.2.1 Food Deterioration Process

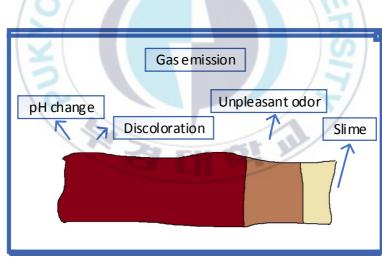


Figure 3-2 The illustration of the identifiable factors of the food preservation process The process of food deterioration is complex in which chemicals, microorganisms, and physical agents interact to make the food no longer safe for human health. The causes of food quality changing include the following main factors: • Biological: Undesirable biological factors such as bacteria, yeasts, molds decompose the storage food and make it unsuitable for consumption.

• Chemical: an enzyme or any chemical reaction can lead to changes in the chemical structure of a food and make it unfit for intake.

• Physical: External factors such as air, humidity, and temperature also affect the food and can destroy the quality of the food.

Due to these factors, during food preservation, several phenomena can occur inside the food storage package such as change of color, pH level variation, gas emission, mass change of meat. Figure 3.2 shows the identifiable derivative factors of the food preservation process, specifically the types of meat.

3.2.2 Conventional Food Monitoring Techniques

As discussed in the earlier, the development of a food monitoring system is essential to avoid consuming food spoilage. In recent years, many studies have been carried out to track variable factors in the process of preserving food, mainly focus on detecting gases and thereby classifying food quality levels. The reason is that during the food decomposition process, biological and chemical factors interact with each other to produce gas compounds such as CO2, Hydrogen Sulfide (H2S). So that detecting the appearance of these factors in the food storage duration is a reliable method for monitoring the freshness of food. The gas sensors used in these systems are designed based on the Metal Oxide Semiconductor (MOS) mechanism of action. These materials inside the sensor are heated to a certain temperature. Under the action of gas compounds in the air, these Metal Oxide Semiconductor materials will change their properties such as resistance and impedance. The sensors utilize this information to identify the presence of gases. However, this process requires a large amount of energy consumption, and the time it takes for the sensor to reach the required temperature normally is quite long. An example of the common gas sensor CCS811 requires about 30 minutes of warm-up before it can function normally. This downside has a significant impact on the performance of power-constrained applications such as energy harvesting, battery-less food monitoring systems.

3.2.3 Idea on Food Monitoring Based on Air Pressure Variation

To overcome the weaknesses of ordinary strategies, accomplish more prominent precision, and lower energy utilization, in this study we applied a methodology of monitoring the variation in air pressure inside the sealed food packages. This method is investigated in the works [57]. This pressure is expected to increase during the decay of food since gasses are produced in a consistent volume sealed container. The pressure calculation equation is shown below:



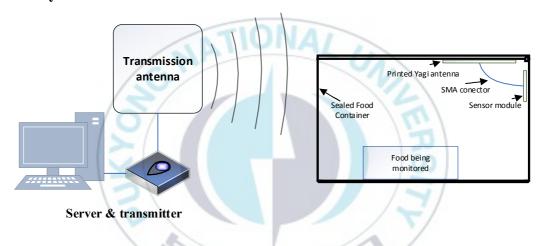
Where P, V, T are the air pressure, the volume of the package, and the absolute temperature, respectively. R is the ideal gas constant and n is the number of moles of gases. Due to the insignificant change in storage temperature, it is quite clear that the air pressure increases linearly with the increase in the gas. Unlike gas sensors, the energy consumption of air pressure sensors is extremely low, only about a few microwatts. Besides, many manufacturers now integrate air pressure sensors, temperature, and humidity on the same chip, thereby reducing the

complexity of system design and programming, and making reduce costs significantly. Based on these characteristics, it can be said that the method of measuring the air pressure in the food package is a suitable alternative for current gas systems.



Chapter 4 : System Design and Implementation

In this chapter, we will discuss in more depth the design of battery-free food monitoring systems. The main components of the system include a printed Yagi antenna to capture RF energy at 915 MHz and capacitance for backscatter communication, rectifier, and power management block, microcontroller unit, and sensor and sensor data communication module.



4.1 System Overview

The complete system firstly incorporates a food storage package that is utilized to hold foods for tracking quality such as pork, chicken, and fish. The self-powered sensor tag is attached beneath the top of the food package. The radiofrequency wave is radiated persistently by a transmitter placed at a certain distance from the food container. The information on air pressure, temperature, and humidity which is measured inside the food package are detected by a profoundly accurate integrated sensor chip. These data are at that point handled by the microcontroller and transmitted to the server through the backscatter protocol. Several machine

Figure 4-1 The overview of the intelligent battery-less food monitoring system.

learning models was developed utilizing pressure, temperature, and humidity information to classify and anticipate different states of the food.

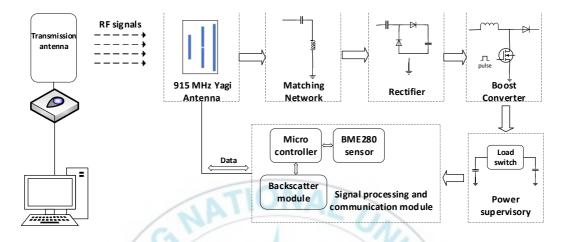


Figure 4-2 The proposed architecture of RF energy harvesting system for food monitoring.

4.2 Printed Yagi-Uda Three Elements Design

The antenna is the first component and plays a vital role in the energy capture system. Since the density of RF energy propagating through the free space is extremely low, the design of a highly efficient antenna will significantly increase the received RF energy. In this study, we have developed a Printed Yagi-Uda Three element, a directional antenna, because of its simplicity in design, easy matching, compact size, and low cost. Notice that the Yagi antenna is a type of directional antenna so that it is suitable for applications where transmitter and receiver positions are determined. The operating frequency of the antenna is chosen at 915 MHz ISM band. The antenna's design shape is shown in Figure 4-2.

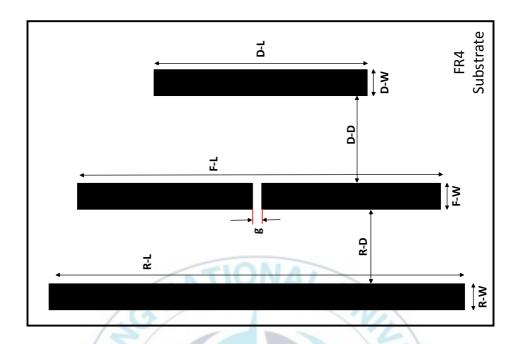


Figure 4-3 The proposed printed Yagi-Uda Three Elements Antenna.

Yagi-Uda antenna is widely used as a high gain antenna. Typically, this antenna system consists of a driven dipole antenna along with several other components, including reflectors and directors. Gain and emission characteristics depend on the number of elements used. Yagi-Uda antenna with its compact features, low cost, and easy design, has been selected in many applications [59]-[62]. In the food monitoring application, we focused on designing a printed Yagi-Uda antenna operating at 915 MHz ISM frequency. A plate of FR4 substrate material ($\varepsilon = 4.4$) with a thickness of 1.6 mm was selected as the surface for the antenna printed circuit. The material used as antenna elements is copper. The antenna is designed with a dipole element responsible for creating electromagnetic oscillation with an optimal size of 12.2 cm, a width of 5 mm. A copper bar acts as a reflective element, placed in the opposite of the radiated direction of the antenna. The reflectors should be longer than the driven dipole, and they should be optimized to enhance the front-

to-back ratio. The third element added to the antenna design is the director. More directors can be added to enhance gain as well as directivity, a gain of 20 dBi can be achieved with this antenna design. However, there is a trade-off between the gain of the antenna gain and its size. The number of directors and the size of the antenna will increase significantly along with gain increasing. In the food quality measurement, the size of the sensor module placed in the food storage packages is indispensable. The designed module must have a compact design and suitable for the size of the container. For that reason, only one director element is considered in adding to the antenna structure. The size of the directional rod must be smaller than the emitting rod and be in the same direction as the emitting direction of the antenna. HFSS software is utilized to simulate and optimize the antenna dimensions to achieve the best gain coefficient. Dimensions are detailed in the selection in Table 4.1

Parameter	(mm)
D-L	80
F-L	122
R-L	146
D-D	32
R-D	44
D-W	5
F-W	5
R-W	5
g	4

Table 4-1 The optimized parameters of the proposed antenna

4.3 Rectifier and Power management design

The harvested RF energy is transmitted through an RF rectifier and a voltage multiplier circuit. Here, the RF waves are converted into a direct voltage which can be used for most common electronic components. This strategy has also been applied to many energy harvesting systems.

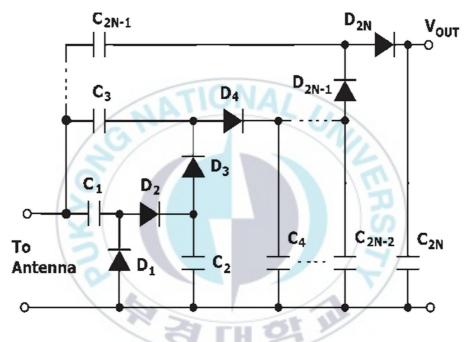


Figure 4-4 A multi-stage rectifier using Schottky diodes.

Many rectifier topologies have been studied for many years, including Greinacher, Dickson models. These studies both show that the output voltage increases with the number of multiplier circuits. However, the power is dissipated according to the number of rectifier stages because the voltage drops across the rectifier elements, thereby reducing the circuit's performance. After much consideration, a singlelayer Dickson rectifier based on the Schottky diode was selected for our rectenna design. Figure 4-3 shows the schematic of a multi-stage rectifier using capacitors and Schottky diodes. Avago's HSMS-285x diode families have been considered suitable for design by some of their outstanding advantages as below:

- Compact design, footprint is SOT-23.
- Low activation voltage 150 mV.
- Suitable for applications with input power level greater than -20 dBm and frequencies below 4.0 GHz.

The required operating voltage for most common sensor microcontrollers is 1.8 to 3.7 V depending on the particular type. However, the output voltage after the rectenna in energy harvesting architecture only achieves a level of approximately 1 V. Therefore, to generate enough voltage to supply the application, a boost circuit is used to raise the output voltage. out. In this study, we use a nano-power buckboost converter (BQ25570, Texas Instruments, USA). The performance of this chip is demonstrated in two main phases: cold start phase, when the circuit can extract energy from the low input DC power, and boost charging phase when the converter performs an MPPT configuration (maximum power point tracking) sampling network to optimize the transmitted energy. The output voltage, V_{harv} is stored in a supercapacitor for utilization.

4.4 Sensor module design

The sensor module consists of three main components: a low-energy MCU, a backscatter communication chip, and a low-energy pressure sensor with high sensitivity. More detailed energy consumption is mentioned in Table 4-2.

Name	Component Type	Voltage Supply	Average Current
		Range	Consumption
MSP430FR5969	Microcontroller	1.8V-3.6V	$\sim 40 \mu W$
SL900A	Backscatter chip	1.8V-3.6V	~187 µW
BME280	Temperature,	1.8V-3.6V	$\sim 10 \mu W$
	Humidity, Pressure		
	sensor		
Total			237 µW

Table 4-2 Average energy consumption of sensor module

The MSP430FR5969 ultra-low-power microcontroller (Texas Instruments, USA) is selected to process sensor data and control module operations. The MSP430596x family is designed with an embedded 16-bit RISC architecture with a 16 MHz clock and can operate in a voltage range from 1.8 V to 3.6 V. The operation of the chip is divided into four modes to optimize usage as below:

- Active mode: Approximately $100 \mu A / MHz$
- Standby (LPM3 with VLO): $0.4 \mu A$ (Typical)
- Rea-Time Clock (LPM3.5): $0.25 \mu A$ (Typical)
- Shutdown (LPM4.5): $0.02 \mu A$ (Typical)

Besides, this chip series also supports a lot of popular protocols such as SPI, I2C, UART, IrDA and therefore can be combined with many other sensor types. Because of its low power consumption, this series of chips are designed specifically for applications in sensor energy harvesting architecture, wearable devices, and data collection (Data Logging).

To measure the temperature, humidity, and air pressure inside the food container, we choose the BME280 sensor (BOSCH, Germany). This line of the sensor has been designed with extremely low power consumption with average current consumption in sleep mode is only about $0.1 \,\mu A$, in normal mode, it is about 3.6 μA for getting 1Hz frequency data. The operation range for pressure ranges from 200 to $1100 \,hPa$ and temperature range from -40 to $85 \,^{\circ}C$, suitable for the pressure measured inside the food test with an average pressure of about $1020 \,hPa$. This sensor has a very small package dimension of $2.5 \times 2.5 \times 0.93 \,mm^3$, which greatly reduces the overall design circuit size.

The wireless data communication unit sends data to the UHF (AMS, AG, Austria) utilizing the SL900A tag chip. The SL900A is an EPCglobal Class 3 sensory tag chip optimized for battery-assisted smart labels with sensor functionality. The chip is perfect for applications utilizing lean and adaptable batteries but can too be powered from the electromagnetic waves from an RFID reader; that is, it can be operated entirely passive. The chip features a wholly integrated temperature sensor with a temperature range $-29^{\circ}C$ to $58^{\circ}C$. The operation frequency is within the run of 860 to 960 MHz. Because of its preferences, the SL900A is suited for the applications such as dynamic shelf-life applications, RFID to SPI interface, observing, and tracking environment conditions.

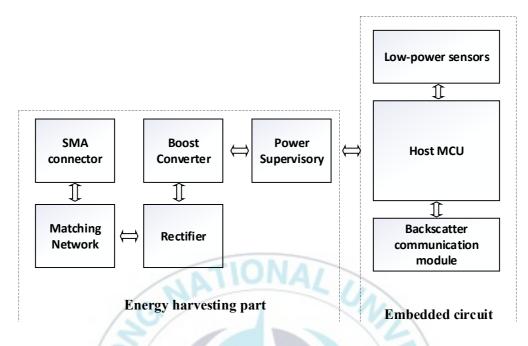


Figure 4-5 The block diagram of the sensor module.

The sensor block diagram is shown in figure 4-3. The rectifier unit, power management, and sensor module are integrated on two-layers FR4 substrates. The dimension of the entire circuit is approximately 3x4 cm. The Altium Designer software is utilized to design the sensor tag.

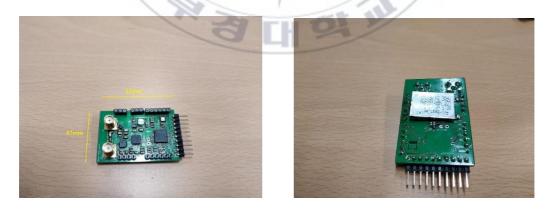


Figure 4-6 Top layer (left) and bottom layer (right) of the designed sensor tag.

4.5 Food Monitoring Experiments Setup

To evaluate the feasibility of the proposed system, we conducted a food quality monitoring experiment using the proposed system. Two experimental conditions have been set to measure the freshness of food: refrigerator temperature condition, and daily temperature condition, respectively. The three types of meat used for the experiment were pork, chicken, and fish, each weighing 200g, which was continuously monitored for 7 days. During food preservation, the total volatile organic compounds are released from the measured object, thereby increasing the air pressure inside the sealed container. The food containers are sealed with silicon so that no gas can escape during experiments.

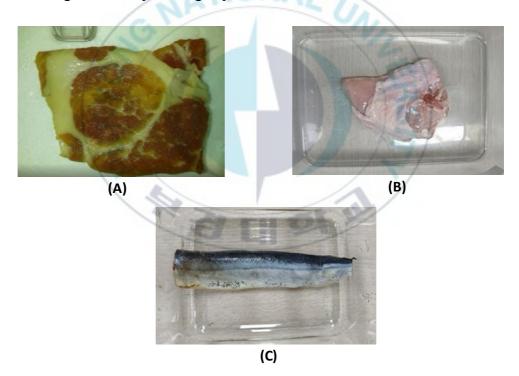


Figure 4-7 Meat samples for experiment setup: (A) Pork (B) Chicken (C) Fish.

Due to rapid meat quality changes, the sensor block is programmed to retrieve data every 2 minutes. A 1W reader is used as an RF generator. The transmitter's distance to the sensor module is adjusted to 2 meters to ensure stable sensor operation. Figure 4-4 describes the food monitoring system in ambient temperature condition.



Figure 4-8 Food monitoring experiment at ambient temperature.

ot

Chapter 5 : Experimental Result of Battery-less Sensing System

5.1 The Harvested Power Evaluation

As mentioned in the section 4.2, we have developed and optimized the design of a printed Yagi-Uda three elements antenna. Experimental results with the network analyzer showed that the printed Yagi-Uda antenna which is added a reflector and a director element achieved -26.8 dB in the return loss value of the antenna, agreeing well with the simulated result of 29 dBm. This is an improvement over if only using a single dipole antenna, which is performed -23 dBm. Figure 5.1 shows the performance evaluation of the antenna in simulation and practical.

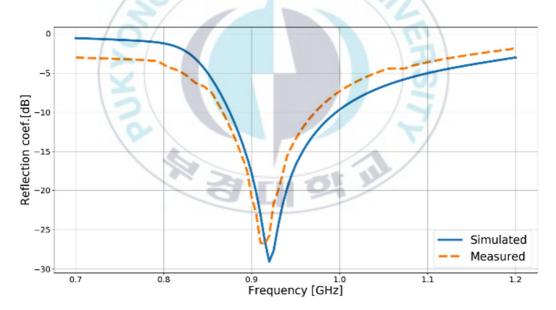


Figure 5-1 Reflection coefficients of the printed Yagi-Uda three elements in simulation and practical.

The simulation results show that the gain of the antenna designed according to the

optimal parameters achieves the gain of 6.54dBi. A dipole antenna which has the same dimension as the radiation element on the Yagi-Uda antenna is also investigated. The results show that the Yagi-Uda antenna outperforms the dipole antenna in terms of gain. The simulation has experimented on HFSS software, figure 5-2 and 5-3 shows the 3D radiation pattern of the Yagi-Uda antenna and the dipole antenna.

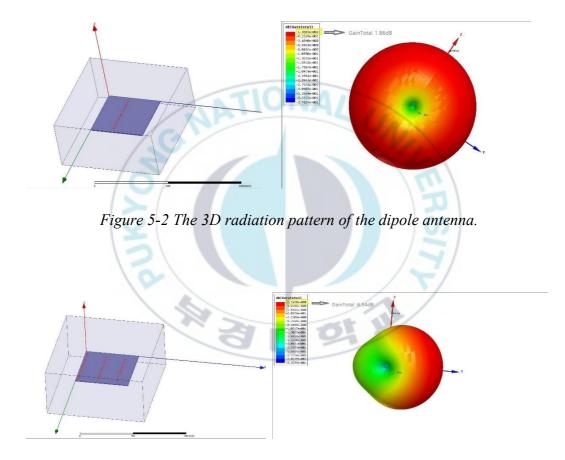


Figure 5-3 The 3D radiation pattern of the proposed Yagi-Uda antenna.

In addition to the antenna performance evaluation discussed in the previous section, the RF-to-DC conversion efficiency (PCE) was investigated. The efficiency is defined as the ratio of the rectifier output power to the input RF energy P_{in} . The formula for efficiency is determined as follows:

$$PCE = \frac{P_{dc}}{P_{in}} \times 100\%$$
(9)

To determine the quantities in this equation, we set up an experiment to measure the input power and the DC power. The received antenna is first connected to a spectrum analyzer (N9320, Keysight Technologies, USA) to harvest the RF waves emitted from the 1W transmitter at a specific distance d. The spectrum analyzer observes the RF input power P_{in} . To determine the P_{dc} , we used a voltmeter to measure the rectify output voltage of the sensor module placed at the same distance d.

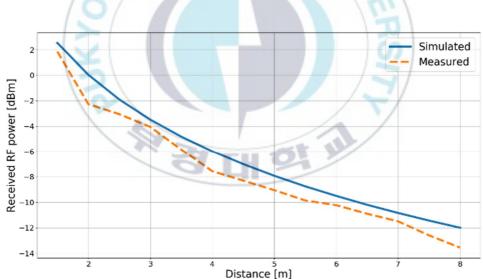
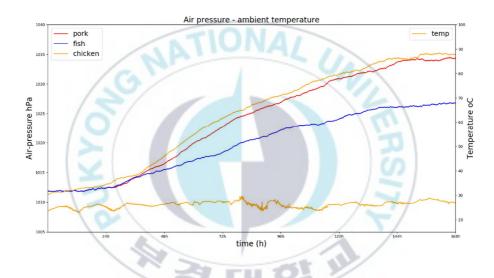


Figure 5-4 The simulated and measured received RF power as a function of transmission distance.

Figure 5-4 shows the simulation curve and the actual line of the harvested RF

energy. The simulation results are observed by using the advanced design system software. The measured distance varies from 1 to 8 meters. At a distance of 6 m, the harvested RF power reach to -10.9 dBm. At this level, the rectifying voltage was obtained at 380 mV, which is high enough for the BQ25570 to launch its functions. In other words, the designed module can operate from a distance of 6 meters from the transmitter.



5.2 Food Monitoring at different storage environments

Figure 5-5 Experimental result with pork, chicken, and fish at room temperature.

As mentioned in section 4.5, we have conducted experiments with various foods such as pork, fish, and chicken in turn. In each experiment, 200gram of each food was placed in a 2-litters sealed box with silicon as shown in figure 5.3. The energy harvesting sensor is attached inside the box to monitor the changes in the process of food degradation. The transmitter emits the RF waves for sensor operation. When the data is collected, this information is sent back to the server through the popular backscatter protocol in RFID communication. Temperature and air pressure data were read every 2 minutes under normal temperature, at refrigerator temperature for 7 consecutive days. Figure 5-5 depicts the variable air temperature and pressure inside a food container under room temperature ambient conditions. The temperature changes by day and night cycle and fluctuates around $24 \,^{\circ}C$. Experimental results showed that during the first 24 hours the air pressure inside the food box was quite stable around $1012 \, hPa$. Note that the test is in a location where the outdoor air pressure is $1011 \, hPa$. During the period from day 2 to day 5, atmospheric pressure increased significantly for all three pork, chicken, and fish foods. During days 6 and 7, the pressure increases slowly and is almost unchanged. The pressure is highest in the case of chicken, with a peak of $1034 \, hPa$.

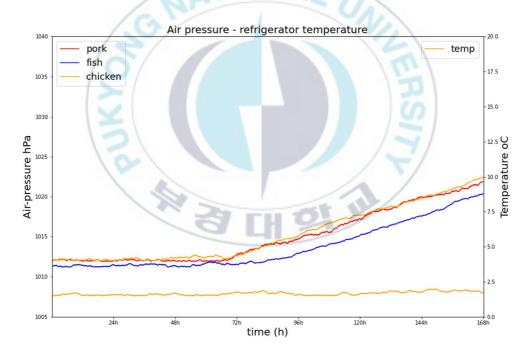


Figure 5-6 Experiment result with pork, chicken, and fish at refrigerator temperature.

Chapter 6 : Deep Learning for Food Monitoring Data

During recent years, Deep Learning (DL) has become somewhat of a buzzword in the research community. One of the reasons is these models' extraordinary results in the simulation of human-like decisions, such as solving classification and prediction problems. Areas that have significantly benefited from deep learning technology advances are mainly computer vision and natural language processing. This chapter will present a deep learning model based on the CNN network architecture to classify the quality of food during storage. We built a dataset, including the measured food data, to train the proposed model. A few classical machine learning models were also trained to compare the accuracy and evaluate the CNN network model performance.

6.1 Overview of Deep Learning Models

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the brain's structure and artificial neural networks. A machine learning process with a Deep Learning network goes through two primary stages: training and inferring. During phase training, deep learning networks extract features from large amounts of data while also relying on defined data labels to optimize network parameters. During the inferring phase, the trained deep learning model uses the optimized parameters to predict, categorize the new data. There are a few differences between the traditional machine learning algorithms and the deep learning model. The DL model requires extensive training data set to optimize the model parameters, while traditional machine learning models only require a small amount of data. DL is almost like an end-to-end machine learning model that means feature extraction is performed in the network while traditional models require the

user to correctly perform this step. However, DL also has some disadvantages, such as high-performance hardware requirements, long training times, and decisions made by the DL network that are often not transparent. Many DL models have been developed to perform specific tasks in critical areas such as computer vision, natural language processing, and recommendation systems. Some of the most popular models of DL can be mentioned as CNN, RNN, DBNs. We will look at these models in general.

6.1.1 Convolutional neural network (CNN)

CNN is the most prominent architect in DL techniques. This model is widely used in computer vision problems. The input data is passed through convolutional, pooling, fully connected main classes; through these classes, the data features are extracted and fed into classifiers or regression depending on the specific tasks. The overall architecture of a CNN network is shown in Figure 6-1.

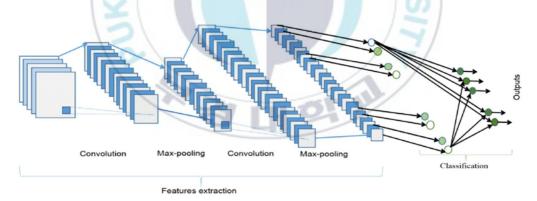


Figure 6-1 The overall architecture of Convolutional Neural Network (CNN). Some most popular CNN architecture are GoogLeNet[63], VGGNet[64], ResNet[65], Mask R-CNN[66].

6.1.2 Recurrent Neural Network (RNN)

Recurrent Neural Network is designed for the application of sequence data such as speech, language, sensor signals, data fluctuations over time. The core idea of RNN is to use not only the current input data but also the data that appeared before it to predict the value chain following it. As a result, the network can find the relationship between continuous data components and make more effective predictions. The basic architecture is shown in Figure 6-2.

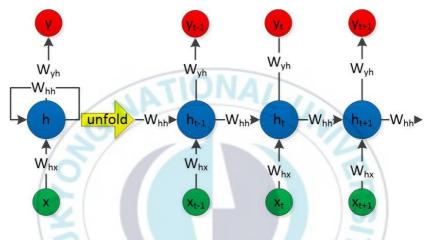


Figure 6-2 A basic architecture of Recurrent Neural Network.

The most famous RNN type model is Long Short-Term Memory (LSTM) which is widely used in natural language processing and translation tasks.

6.1.3 The deep belief networks (DBNs)

Deep Belief Networks are designed for unsupervised learning problems, in the cases of multidimensional datasets. The main components of a basic DBN are restricted Boltzmann machines (RBMs) classes and Feedforward network classes. This is one of the networks with the most reliable architecture with high accuracy and computational efficiency. The main applications of the DBN network can include areas such as: predicting human emotions, predicting economic trends,

predicting time series data, energy. Figure 6-3 shows the overall architeture of the Deep Belief Network.

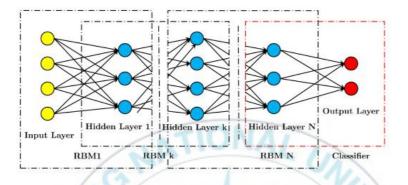


Figure 6-3 The overall architecture of Deep Belief Network.

6.2 The proposed CNN model for food dataset

Classification of food quality based on air pressure has been mentioned in the study [57]. In that paper, the author monitored the change in colors of the food during storage with the naked eye and, based on that, to determine the threshold air pressure levels inside the food box corresponding to meat states. However, eyes' visual monitoring methods are often not highly accurate and easily ignored when food changes to different states. Therefore, we need to develop a more efficient classifier to confirm this air pressure method's feasibility. A machine learning approach to classifying foods based on TVOCs 1-dimensional dataset was proposed in the study [13] and demonstrated its effectiveness with up to 98%

accuracy. This section proposes a CNN model to classify food quality based on temperature and air pressure data measured during storage.

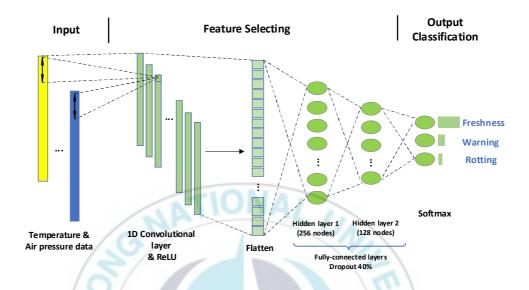


Figure 6-4 The architecture of the proposed CNN model for food quality classification. Figure 6-4 shows the model's architecture with three main layers: an input layer, N hidden layers, and an output layer. The input layer is designed with a size of 2x1 due to two one-dimension data, temperature, and pressure. The convolutional class is constructed with 64 filters, and the kernel size is 2. The activation function used is the rectifier linear (ReLU). The Convolution class is followed by two fully connected hidden layers. The first and second hidden layers have network node numbers 256 and 128, respectively. The dropping-out rate of convolution layers is adjusted to 40% for preventing the overfitting phenomenon. The output of the network consists of 3 nodes corresponding to 3 classes. The Softmax function is used as a classification function. This function takes the input of an N-dimensional vector of the real number and converts it exponentially into a vector with the same dimensionality of real numbers in the range (0,1). The standard Softmax function is shown below:

$$f_i(x) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$
(10)

Cross-entropy is chosen as the loss function at the output of the network. For a multi-class classification problem, the overall loss value of the model is calculated by the sum of the individual losses calculated through the identification of each object class, calculated by the following formula:

$$L = -\sum_{c=1}^{M} y_{x,c} \log(f_{x,c})$$
(11)

Finally, we choose stochastic gradient descent (SGD) as the optimization for the model. The training and predicting results will be discussed in detail in the next section.

6.3 Food Quality Classification

The input data must be labeled in a supervised machine learning model before it is fed to the training model. We will first describe how to perform data preprocessing and labeling. There is no global standard for the evaluation of food quality because different foods will experience different degradation. According to several studies [67][68] and the U.S Food and Drug (FDA) recommendations for food storage [1], some meats such as pork, chicken, and fish are of safe quality when stored within 3-5 days under $5^{\circ}C$. At room temperature, the deterioration of quality occurs more rapidly, and the safe time to use the food reduces. In the study [69], the authors

studied pork's time-varying states and proposed three different meat states. To examine the validity of this proposal, we experimented with examining pork changes over time. A camera system is designed to track pork's appearance for seven days under average room temperature.

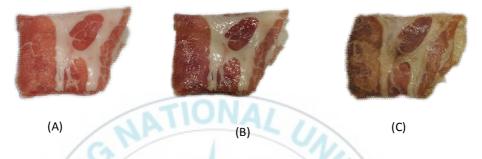


Figure 6.5 The food deterioration process after 7 days presented by colors: (A) Freshness Pork (B) Warning Pork, and (C) Rotting Pork.

With the investigation results, we propose to label three states of food quality concerning the storage time as listed in Table 6-1.

States	Number of samples					
	Training		Testing			
	Pork	Fish	Chicken	Pork	Fish	Chicken
Freshness	719	719	619	72	72	62
Warning	1280	1280	1179	128	128	118
Rotting	3041	3040	2842	304	304	284

Table 6-1. Number of training and testing samples

Notably, training and validation loss gradually decreased and approximated after nearly 150 epochs. However, after that, the validation loss increased while the training loss decreased slightly. This is understandable because the model was overfitting after a long period of training. The early stopping technique has been used to select the best training results. Overfitting was not evident during training on chicken and fish datasets. Finally, we choose the model trained after 150 epochs for the best training weights.

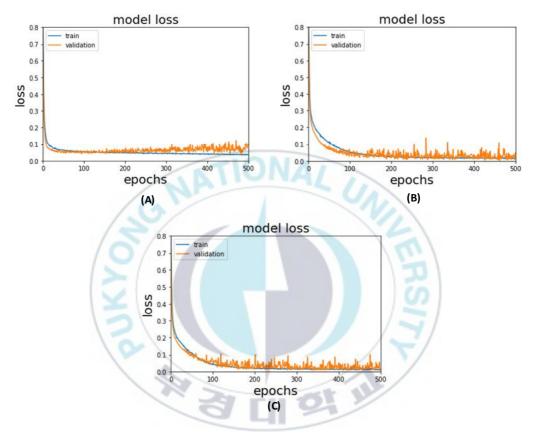


Figure 6-6 Classification Performance in terms of training loss and validation loss graph: (A) Pork (B) Fish, and (C) Chicken.

The overall accuracy of these models is presented by a confusion matrix, which is commonly used to evaluate classifiers' performance. The confusion is a twodimensional matrix, one is the actual labels of the object, and the other is the labels predicted by the model. Figure 6-7 shows the three proposed classifiers' confusion matrix corresponding to the three data sets for pork, chicken, and fish.

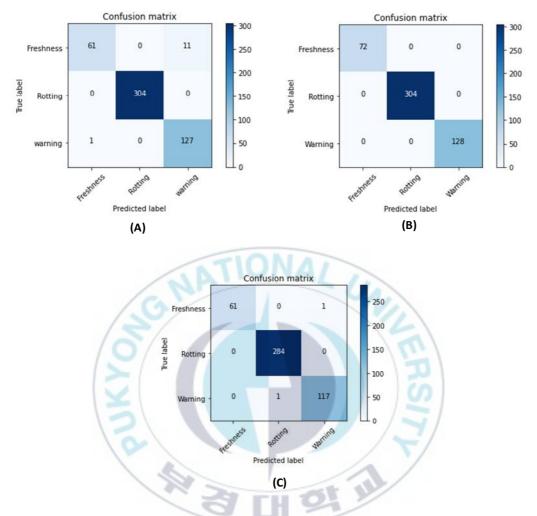


Figure 6-7 The confusion matrix of the proposed network: prediction results on (A) Pork (B) Chicken (C) Fish datasets.

The confusion matrix gives us much information to evaluate model performance through precision, recall, and F1-Score calculations. The results are summarized in Table 6-2. Table 6-2 and the confusion matrix show that the predicted pattern between the freshness-warning and warning-rotting are relatively easy to be confused. This is predictable since these are the food quality transitions and the pressure and temperature values at these points are quite similar.

		Pork			
	Precision	Recall	F1-score	Support	
Freshness	0.98	0.85	0.91	72	
Rotting	0.92	0.99	0.95	304	
Warning	1.00	1.00	1.00	128	
Avg/Total	0.97	0.95	0.95	504	
		Fish			
	Precision	Recall	F1-score	Support	
Freshness	1.00	1.00	1.00	72	
Rotting	1.00	1.00	1.00	304	
Warning	1.00	1.00	1.00	128	
Avg/Total	1.00	1.00	1.00	504	
	IAI	Chicken			
/	Precision	Recall	F1-score	Support	
Freshness	1.00	0.98	0.99	62	
Rotting	0.99	1.00	0.99 28		
Warning	0.99	0.99	0.99	99 118	
Avg/Total	0.99	0.99	0.99	684	

Table 6-2 The classification results of the proposed CNN model.

To demonstrate the model's feasibility, we investigate two more machine learning models, SVM and MLP. The SVM model is a classical algorithm that is commonly used in classification problems. For the food dataset, we designed the SVM with two air pressure and temperature inputs. The three-class classification problem is solved by using a one-vs-one strategy with three binary SVM classifiers.

Model	Accuracy(%)			
	Pork	Fish	Chicken	
MLP	98.61	99.36	99.54	
CNN	98.21	97.89	99.49	
SVM	97.60	96.23	96.55	
LSTM	99.21	99.53	99.4	

Table 6-3 Comparison of the results of different models.

Before CNN showed its remarkable results, MLP networks were considered stateof-the-art in the realm of machine learning. In the MLP network model, layers are built by being fully connected, so it consumes memory resources when training, and the number of parameters increases very quickly depending on the complexity of the network. This is also the reason that when training with this model, overfitting happens quickly. The results of the model comparison are shown in Table 6-3. All models are designed and trained based on the TensorFlow frameworks and the python programming language.



Chapter 7 : Conclusion

In this project, a battery-free food quality measuring system based on long-field RF reception technology was developed. A directional antenna is designed to increase the harvested energy performance due to these antennas' suitability for the dedicated source application. We chose the Yagi-Uda three elements antenna due to its advantages such as simple design, low cost, high gain, easy matching, and tunning. Thanks to the proposed system's high efficiency, the battery-free sensor module can operate at distances up to 6m. This result is a significant improvement over similar systems previously studied, which typically have a maximum distance of about 4m. Besides, we also focus on improving the energy consumption of the application block. Air pressure and temperature sensor have been used to monitor food quality, replacing traditional studies based primarily on gas sensors. Accordingly, the test results indicate that the air pressure inside the sealed food storage box increases with time, and the meat's quality deteriorates. The sensor block's total energy consumption and the microcontroller are only about $300 \,\mu W$, while the conventional gas sensors consume about $10 \,mW$.

One major contribution of this study is applying Deep Learning techniques in classifying food quality based on air pressure and temperature data obtained from a batteryless sensor system. Specifically, we have developed a CNN network model that uses two 1-D features inputs to predict different food states. Results obtained from the CNN model after optimizing the parameters reached 98%. Although this is not the highest result when training with existing datasets, the convolution layers in the CNN network can extract meaningful information, including absolute values of the data and their variation. Simultaneously, when there are new data inputs in addition to temperature and pressure, it is easy to upgrade the CNN network model.

The number of parameters increased is not too large as the MLP network, limiting the overfitting phenomenon and saving the training system's resources.

Finally, through this study, the feasibility of the food quality monitoring sensor system based on RF harvested energy technology and air pressure has been investigated. Other applications can be developed based on this technology, such as in the biomedical, agricultural, and cosmetic fields. Rectenna topologies based on CMOS technology and flexible materials can be extensively studied to reduce the circuit's size. To analyze the data, the CNN network model can be applied to extract meaningful information. Besides air temperature and pressure, Other data from food quality changes such as color, pH, and gas can be collected to expand the Deep Learning network model's input, thereby increasing the food monitoring system's reliability.



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List of Publications

- Huu-Dung Do and Wan–Young Chung, "A Deep Learning Approach for Food Quality Classification Based on RF Energy Harvesting and Mask-RCNN", Conference of Korean Institute of Convergence Signal Processing, August, 2020.
- Huu-Dung Do and Wan-Young Chung, "A Long-Range and Self-Powered Intelligent Food Monitoring System Based on Far-Field Energy Harvesting and Pressure Measurement", 237th ECS Meeting with the 18th International Meeting on Chemical Sensors, May, 2020.
- Huu-Dung Do, Thanh-Binh Nguyen, Nguyen Mai Hoang Long, and Wan-Young Chung, "High-efficient Self-powered Food Monitoring System Based on RF Energy Scavenging", 2020 International Symposium on Advanced Engineering, February, 2020.
- Huu-Dung Do and Wan–Young Chung, "Accurate Food Quality Estimation Using Long Short-Term Memory Neural Networks and RF Energy Scavenging", Conference of Korean Institute of Convergence Signal Processing, December, 2020.

<u>Awards</u>

 Best Excellent Paper Award, Huu-Dung Do and Wan–Young Chung, "Accurate Food Quality Estimation Using Long Short-Term Memory Neural Networks and RF Energy Scavenging", Conference of Korean Institute of Convergence Signal Processing, December, 2020.

