

SPECTROSCOPIC SENSOR BASED IoT SYSTEMS FOR IDENTIFYING MILK ADULTERATION AND DETERMINING FOOD CONSTITUENTS

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ABSTRACT

Practicing food adulteration is now a very common activity by the food industry chain cycle, especially in milk is the dairy product which is a very basic and essential food ingredient used worldwide. So, there are huge volume of milk is consumed by the millions of people in daily basis hence people who are associated with this industry and meet the supply of this food chain, are uses some bad and unhealthy practices of adulterating milk with varieties of mixing toxic adulterant like urea, salicylate, dextrose, hydrogen peroxide, ammonium Sulphate etc. This, toxic contents are used as preservative to store milk for longer time and showing like a fresh one. Hence it is becoming very important us to identify the adulterated milks and the level of adulteration so that one can have the idea of level of adulterations of milk what they are consuming in daily basis. Now water become the most used adulterant in daily practice in all levels of milk industry. People associated with the milk industry and its product they used to practice the water adulteration in milk so, it is become a serious threat to out health especially to little infants. As majority portion of milk consumed by infants hence ensuring zero adulteration in food especially in milk is very essential. So, to address the problem we developed a spectroscopic sensor-based system which can identify the different levels of adulterated milk along with can determine different food contents. The developed system is consisting of AS7265x sensor module having three sensors AS72651, AS72652, AS72653 covering all three spectral ranges of light ultraviolet, visible and infrared. The spectral information or data is very unique for a particular milk sample with a fixed physical condition hence in the thesis work, author includes all standard possible different levels of adulterated milk samples along with different physical conditions. The different data sets are so unique that they represent the particular experimental outcome according to the experimented sample and setup. Author extending the same methodology of extracting the data from sample, biscuit has chosen to determine the different food content of biscuit. Author also, make the advancement of the projected system by incorporating the IoT application by using the WIFI module ESP8266 and ESP32 to send the data website called “ThingSpeak”. This advancement made the proposed system a complete system of collecting data from milk and other food sample from anywhere and can get the information about the quality of food. Hence this is become the great advantage for food industry by locating only one data collecting and analysing centre and communicate through WIFI. Author made different decisions using signal processing and machine learning techniques namely GPR and RRC. At the end in conclusion author discussed about the effectiveness of proposed system along with the future research scopes from the system.

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LIST OF ABBREVIATIONS

UV	Ultraviolet
LEDs	Light-emitting diode
EAP	Electroactive Polymer
IPMC	Ionic Polymer Metal Composite
WIFI	Wireless Fidelity
AI	Artificial Intelligence
LGA	Land Grid Array
VDD	Positive Supply Voltage
MLE	Maximum Likelihood Estimation
IR³C	Iteratively Reweighted Regularized Robust Coding
Nm	Nano meter
PC	Personal Computer
VIS	Visible
NIR	Near InfraRed
FWHM	Full Width at Half Maximum
UART	Universal Asynchronous Receiver-Transmitter
ADC	Analog To Digital Converter
SoC	System on a Chip
IDE	Integrated Development Environment
TCP	Transmission Control Protocol
IP	Internet Protocol
TTL	Transistor-Transistor Logic
VDD1	Positive Supply Voltage 1
VDD2	Positive Supply Voltage 2
USB	Universal Serial Bus
RESET	Resetting Initial State

ESP32	Espressif System's 32 bit microcontroller
BLE	Bluetooth Low Energy
ROM	Read only memory
SRAM	Static Random Access Memory
CPU	Central Processing Unit
DAC	Digital to Analog Converter
I2C	Inter-Integrated Circuit
CAN 2.0	Controller Area Network
SPI	Serial Peripheral Interface
I2S	Integrated Inter-IC Sound
PWM	Pulse Width Modulation
GPR	Gaussian process regression
RRC	Regularised Robust Coding
API	Application Programming Interface
QWIC	Qwiic Connector

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CHAPTER 1

INTRODUCTION

- **BACKGROUND**
- **RELATED RECENT WORKS**
- **MOTIVATION OF PRESENT WORK**
- **PROPOSED METHODOLOGY**
- **THESIS OUTLINE**
- **SUMMARY**

1.1 BACKGROUND

Food adulteration nowadays is very important and common problem to get extra immediate profit. As a result, we are consuming the harmful toxic content in milk and food. Adulteration is added in foods like milk can cause severe health problem specially in little one. Food adulteration involves adding water in milk, making it larger in volume, adding starch in curry powder, adding papaya seeds in black pepper, etc. As of 2023, the total domestic consumption volume of milk was over 207 million metric tons in India. This was an increase as compared to the previous year when the consumption volume was about 202 million metric tons. Statistic showed that India plays the best role in cow milk consumption. Cow milk contains nutrients such as lactose, fat, protein, minerals and vitamins in a significant proportion which serves the better human diet. Since the locals consume the milk and its byproducts in a daily basis, so detection of adulteration level in milk [2] is very important research area to ensure the health safety of the humans. In thesis we mainly focus on milk adulteration problem [2] to ensure the level of water mixing in milk sample. Spectroscopic based adulteration detection technique is adapted here to solve the above problem [2]. The qualitative and quantitative spectroscopic technique provides better and affordable solution to detect adulteration level in milk and get best sight of milk that is going to be consume. All the available spectroscopic methods for milk adulterant detection are based on laboratory-based with costly equipment. This laboratory-based detection takes a long time and is more expensive, which may not be afforded by a everyone. To overcome this problem, this research work involves the design and development of a low-cost, portable, multispectral, AI-based, non-destructive spectroscopic sensor system that can be used to detect the milk adulterant in instant real time. The designed sensor system uses the spectroscopic method with wavelength ranges from (410-940nm) which consists of three different bands ultraviolet (UV), visible, and infra-red (IR) spectrum to improve the accuracy of detection. Adulterant detection problem is formulated as a classification problem and solved by machine learning algorithms after taking the data from spectroscopic sensor system.

The spectroscopy system offers the measurement, production, and interpretation of spectra due to the interaction of electromagnetic radiation and matter. The analysis methods may differ with respect to molecules or atoms and the type of matter-radiation interaction, such as diffraction, absorption, and emission. The interaction with milk and other food particles with different wavelengths light coming from spectroscopic sensor system incident on milk and food sample will decide the level of adulteration involve in food sample (milk and biscuit). Based on emission or absorption of radiation in ultraviolet (UV), Visible, and infrared (IR).

The relationship between the concentration of absorption and absorbance of a substance whose chemical constituents are being measured, identified, by Beer lambert's law as [2],

$$A = \varepsilon \times CL \quad (1)$$

where, A represents absorbance, ε represents molar absorption coefficient, C is concentration of substances and L is path length (cm). Absorbance has no unit, it is the log ratio of beam powers. Molar extinction coefficient varies for each molecule and it is represented as a constant which has the unit of $\text{Lmol}^{-1} \text{cm}^{-1}$. The spectrometer uses a cuvette to measure the sample, which is 1 cm in width, L is the path length, assumed to be equal to 1 cm. The concentration C of the sample was expressed by mole/L.

The traditional spectroscopic methods are a bit expensive but our proposed system is cheaper and can detect level of adulteration in real time. There are many literatures works reported for adulteration of milk detection given in listed Table 1. Table 1 is formed to explore the possible wavelength of response for the milk adulteration and level of accuracy.

Table1.1: Possible wave length of light used for detection milk adulteration

Adulterant	Responsive wave-length (nm)	Method	Result achieved	Related work
Water	1200-1450	NIR	Accuracy 99%	R.de Souza, et al (2016)
Water	1450-2310	NIR	Accuracy 99%	Kasemsumran et al (2007)

These methods are carried out in controlled lab environmental setup but not in real time. But our proposed system will give the result is not in a controlled Lab environment with fixed temperature and fixed illumination condition but also give exact same accuracy result in any outdoor location which enables the detection of milk and other food condition in real time in any temperature and illumination condition. So, our proposed system is capable of on-field analysis which make the system more effective and appreciable in decision making in real time with instant result of considered milk sample in on-field. So, our research work is mainly focus on the following aspects:

- The proposed research work deals with designing and developing portable, cheaper, non-destructive, works in real time.
- Developing of multi-spectral sensor system is carried out to capture data from three different bands called UV, Visible (Vis), and NIR with six channels for each group in a total 18 channels to improve the detection accuracy.
- The spectroscopic system is independent of environmental constraints i.e. surrounding temperature and illumination condition where the data is taken for adulteration detection.
- Adulteration detection is formulated as classification problem and solved by applying different machine learning algorithms i.e. RRCL1, RRCL2, Gaussian regression for getting the different level of adulteration levels called 10% water milk sample, 20% water milk sample, 30% water milk sample, 50% water milk sample.
- The sensor system is enabling as an IoT device to transmit the on- field taken data to any other PC located in other location (so called central analysis lab) and do further analysis.

1.2 RELATED RECENT WORKS

As milk adulteration is become practice in every part of our country and in daily basis so we motivated to do a look upon the all recent and past research on solving milk adulteration problem. Here are some recent works which are trying to solve milk adulteration problem. In the paper [12], an ultrasonic transducer (transmitter) transmits an input signal of function generator to an ultrasonic signal having some frequency and intensity then this signal is transmitted through the milk sample. As the signal is passing through the milk sample so its frequency is decayed due to fluid interaction [13] and the second ultrasonic sensor transducer which is receiver convert the signal into electrical signal and send it to Electronic Storage Oscilloscope. Here two transducers were used which will increase the cost and dependency on sensor module and the coordination between them, making fix the room temperature is also a challenge and require a function generator, Electronic Storage Oscilloscope which are increasing the cost of project. Also, the prepared system is only suitable in a proper laboratory arrangements hence it was not compact and reliable to test in any outdoor location such as some store and local dairy etc, hence we are searching for more reliable, compact and low cost solution to solve the our problem of identifying the milk adulteration and determine the food constituents.

Another paper [14] works on same problem with the development of a new technique which check the amount of water added to milk based on near-infrared (NIR) spectroscopy, which is observing the absorption of electromagnetic radiation in NIR spectral region by the samples of the product that is milk. Molecular absorption bands in NIR region was used for analysis. In their work they develop an electronic system which control and detect the NIR radiation in the milk sample. LEDs where, used to generate electromagnetic radiation with three different wavelengths in NIR region and then transmit through milk sample and then collected by an InGaAs photodiode. The change in light intensity with change in medium was observed. Here for light detection and signal conditioning they prepared a circuit which is additional cost adding factor. Also, interference with external light is also threat to this system, used of spectroscopic technique is giving an idea of doing qualitative analysis of milk and food molecule sample so in work we explore all three regions of light to get better spectroscopic analysis of milk -water and food sample and trying to discard the any function generator or signal conditioning circuit.

Another paper [15] used the standard photolithography and lift-off technique [16] where the generated voltage is then fed to operational amplifier OP07CN and the milk sample is treated as the feedback resistance; change in voltage amplitude depending upon different samples depending on level of adulteration of milk, is used to calculate the impedance of the sample. Here as the electronic circuit consist of operational amplified so its parameters are may change with temperature and feedback path may make some discrepancy in getting output voltage also produced voltage level may corrupted due to effect of external electric field. Hence, we are searching for a reliable, robust and cost-effective solution which can be implemented outside of control environment of laboratory. In paper [17] the optical sensor was being used to determine milk adulteration but here they used only one wavelength of 900nm produced by LEDs and received by 9 LEDs (OPT101P) set up displaced by 20° each other forming a semi-circular arc, and by means of refraction of light the water and adulterants molecules was being tracking but the setup is no longer relevant as they are not considering fat content of milk but fat content of milk is changing the density of milk and hence changing the

refractive index of milk and optical sensor fail to get proper data as a result the technique is no longer relevant in discriminating buffalo milk and cow milk.

In paper [18] the author used the electroactive polymer (EAP) material ionic polymer metal composite (IPMC) as a taste sensor which producing output potential depending upon milk concentration as the additional water is added to pure milk which already have 87% of water the concentration of milk decreases hence giving the output potential much lower which is indicated by the clock wise and anticlockwise angle of deflection of IPMC tip. But the IPMC has the hysteresis which leads to give the non-uniform response and giving error. In another paper [19] author developed an electrical impedance sensor system which is measuring electrical impedance of milk samples but as this process is completely depending upon environment temperature as increasing in temperature increase the mobility of milk ions hence decreasing the impedance of milk sample, therefore require an extra temperature controller circuit and leading to work only in controlled laboratory condition.

In paper [20] author again using electrical impedance sensor for getting real time data of milk sample. Also, in paper [21] change of permittivity of medium that is milk with different adulterated milk samples are changing the capacitance value so the entire system also leads to temperature variation, effect of stray capacitors and fringing effects also giving only change of capacitor value i.e. the single value. In paper [22] multiple parameters of milk sample in terms of colour of milk is taken and then send the data to cloud for further data processing. System developed in [23] different gas sensors were used to classify different adulterated milk sample. In paper [24] spectroscopic sensor module AS7265x is used to classify different foods like milk, fruits, chilli powder, turmeric powder and it has the future scope as it is a non-destructive process, reliable, compact and low cost the further modification in data processing and a IoT application of it can make the system more acceptable nowadays. AI based classification will increase the system more versatile in finding the different food constituents without damaging the food itself.

In paper [25] the author detects the milk quality by Fourier transform infrared spectroscopy. FTIR spectra data is taken by Fourier transform Infrared Spectrometer and then then further data processing done as per paper [26].

Paper [27], [28] describing another method of IoT based solution to detect the milk adulteration.

1.3 MOTIVATION OF PRESENT WORK

Milk adulteration or the food adulteration is the very common in food industry and very threatening to lives especially lives of little ones as they are much more sensitive and exposed to the milk in daily basis. So, solving the milk adulteration problem [2] is very important in this context. There are many milk industries are practicing the milk adulteration to gain some extra profit and hence it gives lot of motivation to conduct work regarding this and solve as much we can to judge and do not compromise the quality of milk that we are going to consume. Now there are lot of works has been done regarding the predicting milk adulteration but they all need lot of resource and a dedicated sophisticated lab to conduct the experiment that is why we are opt to take up this problem to find a realistic, effective and an economical solution. Mixing variety of compounds with milk will change its property and benefits which we are

expecting to have after consume it, but in reality adulterated milk mixed with different compounds are not giving that expected benefits. Also, different compounds are mixed with milk are giving harmful effect in our health. Normally 100% pure milk is having 70 % to 80% water but people are mixing additional water with milk which decreasing drastically the consume benefit of milk. Also, different compounds such as hydrogen peroxide is adulterated in milk to activate enzymes and increase the life time without store it in cool place. It may cause different health issue such as irritation and redness. Ammonium Sulphate is mix with milk as it is rich with nitrogen component, sodium salicylate used to increase the lactation and as preservative to preserve the milk for long time. These all are very alarming as per as human health is concerned. In General, contains of milk depends upon the breed, type of animals, different types of feeding and stage of lactation. In general, in Indian milk 87 % of water is present, approximately 4.8% carbohydrate (basically lactose), 4% of total fat which having most complex fatty acids of edible fat along with triglycerides in a form of globules, Protein, and rest are Minerals and Vitamins in different forms. This are also varies with different company's milk and their different versions. Hence it is well known that pure milk itself having most of it i.e. 87% of water so addition water inclusion become very threatening and we are basically loosing its nutritional value therefore it is becoming very important to search for an effective solution to solve the milk adulteration and getting other constituents of milk especially total fat value and also getting constituents of other food like biscuit.

1.4. PROPOSED METHODOLOGY

In the presented thesis work we taken two kinds of problem namely identifying the adulteration level of milk sample and determining the food constituents of food like milk and biscuit. As discussed in earlier section of 1.2 food adulteration now become the daily practice in every part of world hence determining the food constituents along with food adulteration identification is demanding problem.

In this work we have used the spectroscopic data analysis along with AI based data processing technique [2]. The spectroscopic data of milk and biscuit sample is being taken by a multi-spectral sensor module AS7265x as paper [24]. As discussed in section 2.2 multispectral sensor system is having total three sensors AS72651, AS72652, AS72653; each having total 6 channels with 6 different wavelengths of light containing three different region of light namely visible range, near infrared and ultra violet. As per the paper [14] the spectroscopic analysis on milk sample is very effective but using only one wavelength in near infrared region by LEDs, so in work we advancing this methodology of spectroscopic analysis on milk by increasing the number of wavelengths of light and covering all three regions of light with different wavelength. Here we are investigating the nature of reflected rays of light that is signals from milk and food surface. Here we are using the embedded microcontroller Arduino UNO connected through QWIIC cable with multi spectral sensor AS7265x.

Total 18 channel data of different wavelength is collected from milk and biscuit sample by the spectral sensor. As the reflected light rays are being captured by sensor and stored so every channel should capture an unique floating value depending upon particular milk and biscuit sample.

Then collected data are taken in several standard predefined conditions as per section 3.3 to get variations in data for further processing. Generated data then feed to Gaussian process

regression as per section 4 and Regularised robust coding section 5. Two methods the data is sub divided in fixed ratios of training and testing data.

The proposed system is associated with ESP-32 WIFI module which is allowing the system to send data to a web server called “ThingSpeak” through WIFI. Which is allow the system to work as an IoT based application as papers [24, 26,27].

As the data of sensors are very robust, reliable as they are not changing with time and well distinct from each other so they are very suitable for feeding to AI based algorithms as per section 4 and 5.

1.5 THESIS OUTLINE

In chapter 2 of the presented thesis author describes the proposed spectroscopic sensor based multi spectral sensor system, where the different components, their interconnections, their working principle, used components advantages and overall system’s circuit diagram.

In chapter 3, author describes data collections from different milk and food samples along with the different physical parameters. Here both different levels of adulterated milk’s sample and biscuit samples are considered.

In chapter 4, author gives the information about machine learning technique called Gaussian process regression (GPR) and its application in the proposed problem of classification for decision making.

In chapter 5, regularised robust coding, its application and the its performance evaluation in identifying the different levels of milk sample are discussed by the author.

In chapter 6, Author ended up the thesis by conclusion and all possible future research scopes associated with the proposed system.

1.6 SUMMARY

So, food adulteration is a big problem and directly related to the health of any country and need to take it very seriously and act accordingly. In this thesis work author is introducing a spectroscopic sensor-based milk adulterated identifier system which can identify in percentage the level of adulterated milk and can determine the different food constituents of food like biscuit. Different levels of adulterated milk like 10%, 20%, 30% and 50% water-milk adulterated solution is tested by the proposed system which capable of transmit the data through wired as well as via WIFI mode.

CHAPTER 2

DESIGN OF MULTI SPECTRAL SENSOR SYSTEM FOR DETERMINATION OF LEVEL OF MILK ADULTERATION

- **INTRODUCTION TO DESIGN OF AI-ENABLED MULTISPECTRAL SENSOR SYSTEM FOR MILK ADULTERATION DETECTION**
- **MULTI SPECTRAL SENSOR**
- **ARDUINO ESP8266 WIFI DEVELOPMENT BOARD**
- **ESP-32 WIFI MODULE**
- **CIRCUIT DIAGRAM AND DEVELOPTED SET UP**
- **COMMUNICATION BETWEEN SENSOR AND WIFI MODULE**
- **SUMMARY**

2.1 INTRODUCTION TO DESIGN OF AI- ENABLED MULTISPECTRAL SENSOR SYSTEM FOR MILK ADULTERATION DETECTION

The prototype of designed AI-enabled sensor system is shown in figure 2.1. Which is consists of a triad spark fun spectroscopic system, Arduino blackboard (Arduino UNO inbuilt wireless module ESP8266), QWIIC cable, PC is used to collecting data and AI software module implementation.

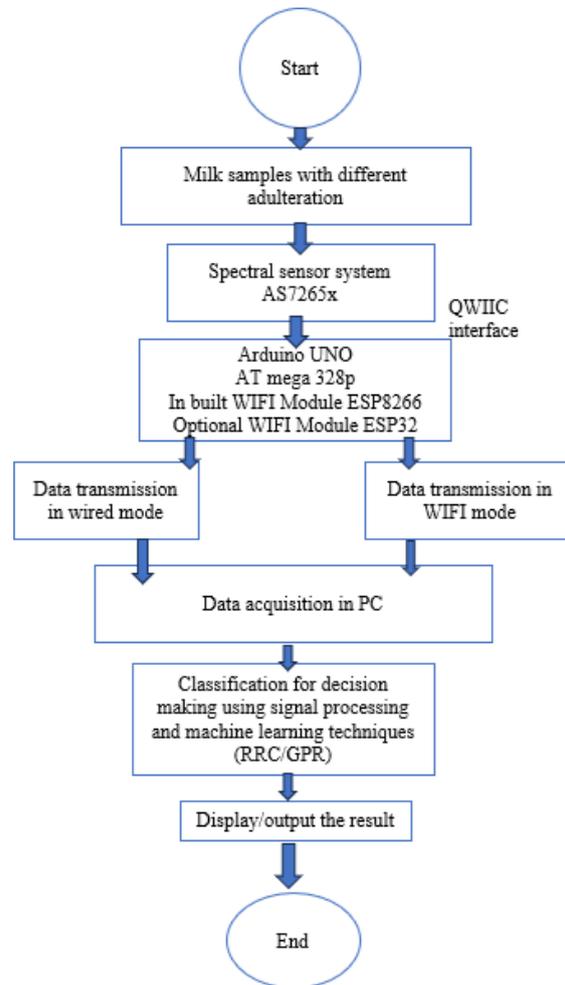


Figure 2.1: Flow chart of AI-enabled multispectral sensor system

Fig 2.1 shows the AI-enabled multispectral sensor system; the AS7265X sensor system is on chipboard consisting of 3 sensors AS72651, AS72652, and AS72653 having different spectral channels with different wavelength channels with a total of 18 channels connected with Arduino UNO blackboard which has inbuilt WIFI module ESP8266 through QWIIC cable interface which develop the spectral sensor. Collected data was then transmitted via WIFI to other PCs for analysis of data and predict the level of adulteration of milk and composition analysis of food (here biscuit). Data is collected in Excel sheet or text format and then pre-processed the data and sent to different AI Algorithms for solving the classification problem.

2.2 MULTISPECTRAL SENSOR

AS7265X smart 18 channel VIS to NIR spectral Id 3 – sensor chipset is the heart of the proposed system. The AS7265x chipset consists of three sensor devices AS72651 with master capability, AS72652 and AS72653. The multispectral sensors can be used for spectral identification in a range from visible to NIR. Every of the three sensor devices has 6 independent on-device optical filters whose spectral response is defined in a range from 410nm to 940nm with FWHM of 20nm. The AS72651, combined with the AS72652 (spectral response from 560nm to 940nm) and the AS72653 (spectral response from 410nm to 535nm) form an AS7265x 18-channel. The intensity of light is precisely measured up to 28.6nW/cm² with an accuracy of + –12%. It has a light source with LEDs of 405nm UV, 875nm IR, and white LED. This optical sensor is 3.3V compatible [40]. It communicates over I2C /serial interface via Qwiic cable by 115200 bps (bits per second) transfer rate. Table 2.1 gives the data of AS7265X chip set benefits and Features.

Table 2.1: Data of AS7265x chipset benefits and features [29]

Benefits	Features
Compact 18-channel spectrometry chipset solution	<ul style="list-style-type: none"> • 3 chipsets including the master device delivering 18 visible and NIR channels from 410nm to 940nm each with 20nm FWHM • UART or I2C slave digital Interface. • Visible filter set realized by silicon interface filters.
No additional signal conditioning is required	<ul style="list-style-type: none"> • 16-bit ADC with digital access. • Programmable LED drives. • 2.7V to 3.6 V with I2C interface.
Small, robust package, with in built aperture	<ul style="list-style-type: none"> • 20-pin LGA package 4.5mm×4.7mm×2.5mm-40⁰ C to 85⁰C temperature range suitable for Indian temperature variation in winter and summer in different part of country.

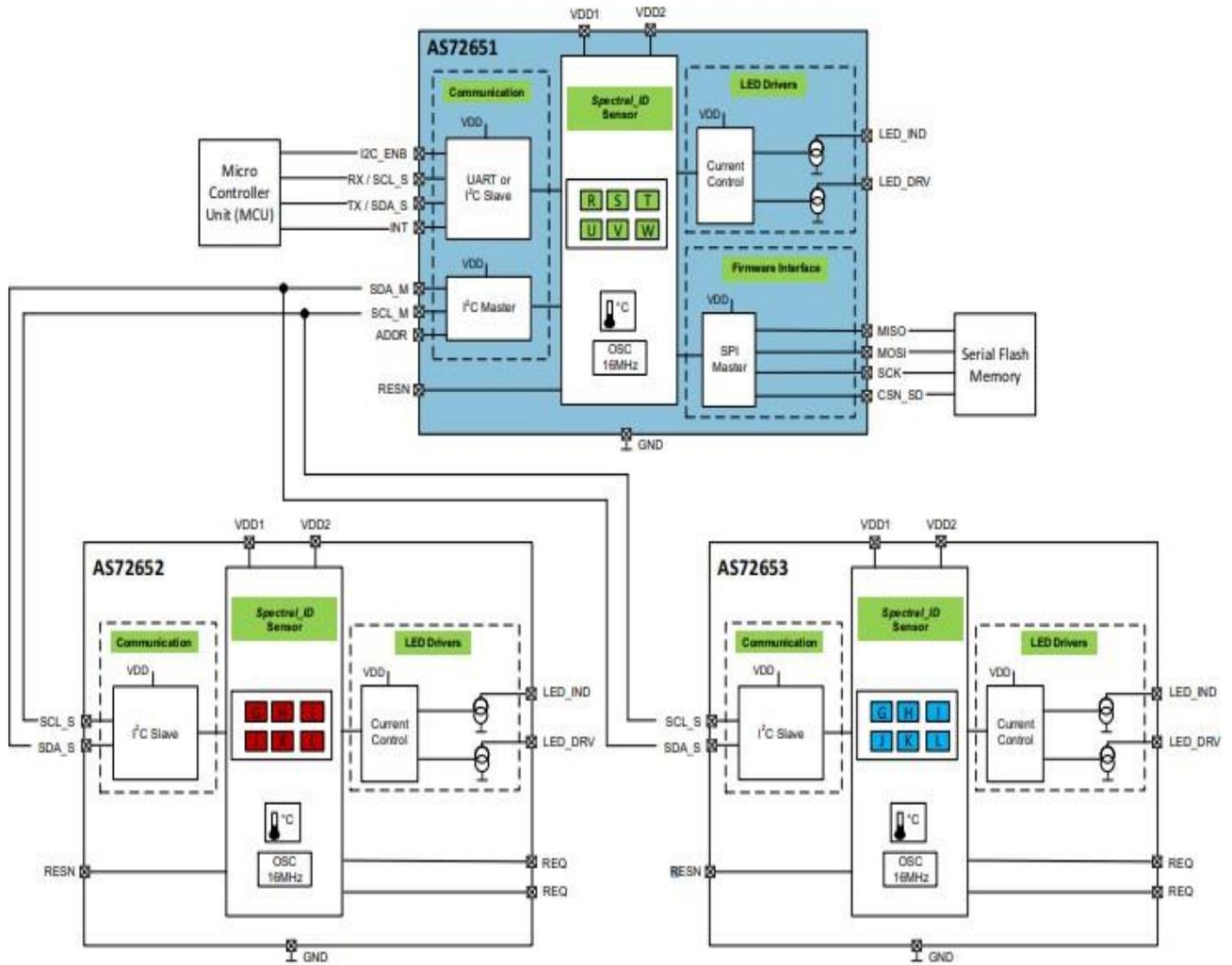


Figure 2.2: Block diagram of AS7265x sensor system [29]

Figure 2.2 shows the multi-spectral sensor chipset block diagram, which can be used for spectral identification in the range from Ultraviolet, visible to NIR (Near Infra-Red) region. This sensor system is placed at different vertical heights 1 inch and 2 inches above the milk sample surface for getting a variety of conditional data to achieve a robust system. The AS72651 provides the smart UART interface with the microcontroller Arduino Uno ATmega328p. The sensor system produces spectral data based on received reflected light of different wavelengths from milk and food samples. It has the flash memory to store the data with UART Communication with Arduino blackboard in proposed system. Each chip contains the Analog to Digital Converter (ADC) so that reflected lights are quantified in digital format. There are LED DRV pins on all AS7265X sensor systems. These pins are used to control external LED sources as needed in application to eliminate environmental good or bad illumination condition constraints. LED DRV can sink a programmable current of 12.5 mA, 25 mA, 50 mA or 100 mA. The control can be turned on or off based on I2C registers or AT commands, and it provides the AS7265x device with an electronic shutter.

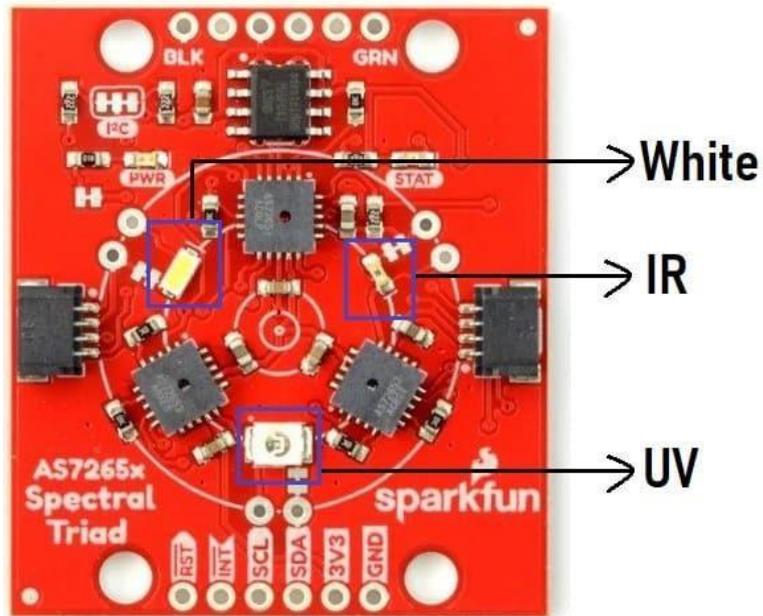


Figure 2.3: AS7265x sensor module by sparkfun [29]

The spectral sensor system has a total of 18 channels comprising 6 channels for each optical range. Figure 2.4 gives the sight of 18 channels' spectral responsivity.

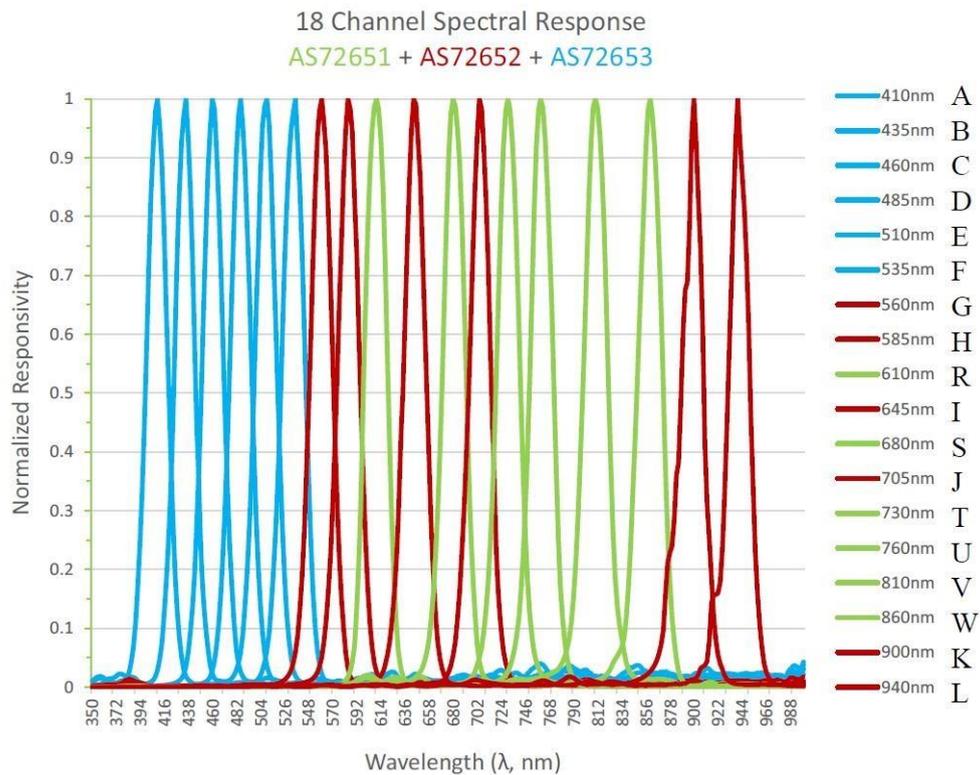


Figure 2.4: 18 channels spectral responsivity of sensor AS7265x [29]

Figure 2.4 shows the total responsivity of a spectral sensor system. Here total of 18 channels starting with channel A (410 nm) to channel L (940 nm). The spectral sensors send different light rays with definite wavelengths, depending on reflection from milk or food particles the respective channel data is coming and differentiates itself from the data coming from different adulterated milk samples.

Now figure 2.5 shows the spectral responsivity of AS72651 [29]

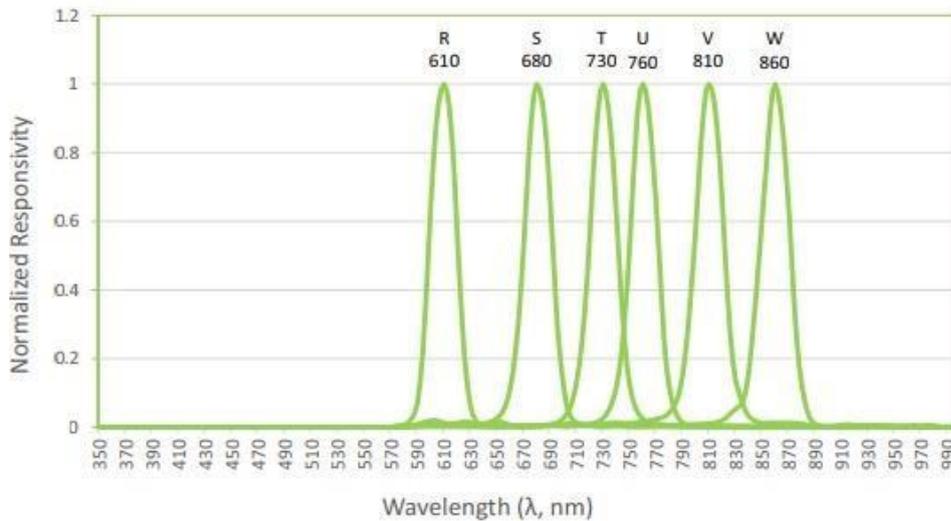


Figure 2.5: spectral responsivity of AS72651 [29]

Table 2.2: Wavelength of AS72651 with name of channel [29]

Symbol	Parameter	Channel (nm)
R	Channel R	610
S	Channel S	680
T	Channel T	730
U	Channel U	760
V	Channel V	810
W	Channel W	860

So AS72651 sensor is responsible for the data reflects back from milk or biscuit sample for the given wavelength in table.

Now figure2.6 shows the spectral responsivity of AS72652 under any condition

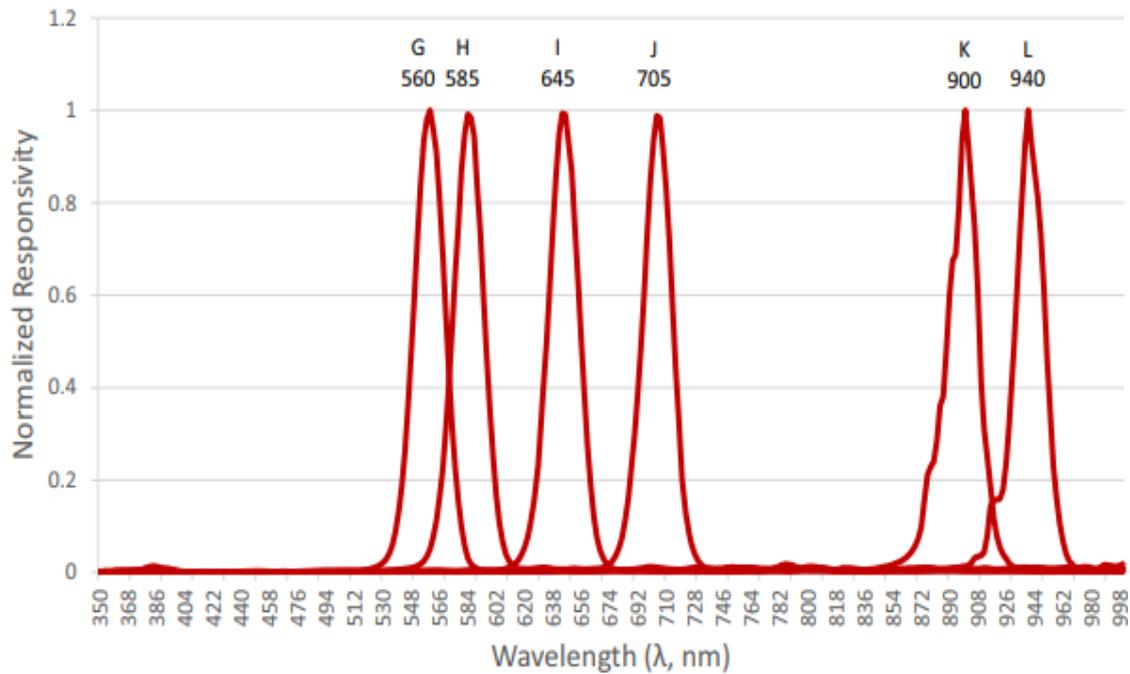


Figure2.6: The spectral responsivity of AS72652 under any condition [29]

Table 2.3 wavelength of AS72652 with name of channel [29]

Symbol	Parameter	Channel (nm)
G	Channel G	560
H	Channel H	585
I	Channel I	645
J	Channel J	705
K	Channel K	900
L	Channel L	940

So AS72652 sensor is responsible for the data reflected back from milk or biscuit sample for the given wavelength in table

Now AS72653 spectral having the spectral responsivity is as follows

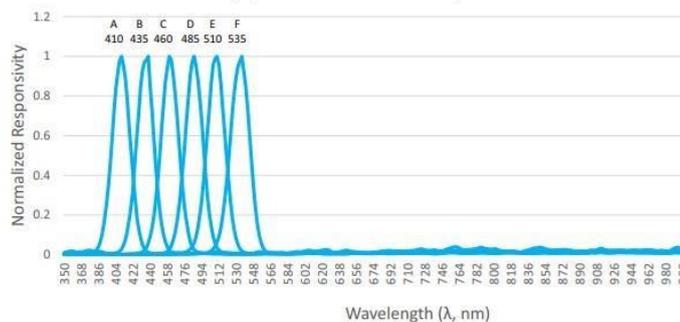


Figure 2.7: Spectral responsivity of sensor AS72653 under any condition [29]

And following table 2.4 shows the wavelength of AS72653 with name of channel

Table 2.4: Wavelength of AS72653 and its channel name [29]

Symbol	Parameter	Channel (nm)
A	Channel A	410
B	Channel B	435
C	Channel C	460
D	Channel D	485
E	Channel E	510
F	Channel F	535

So AS72653 sensor is responsible for the data reflected back from milk or biscuit sample for the given wavelength in table.

Following figure shows the diode Array of AS72651, AS72652 and AS72653 which is help us to clearly understand the different sensors operating in different light ranges that is green indicates visible range of light, red indicates near ultra violet and blue colour indicates ultra violet range of light spectrum.

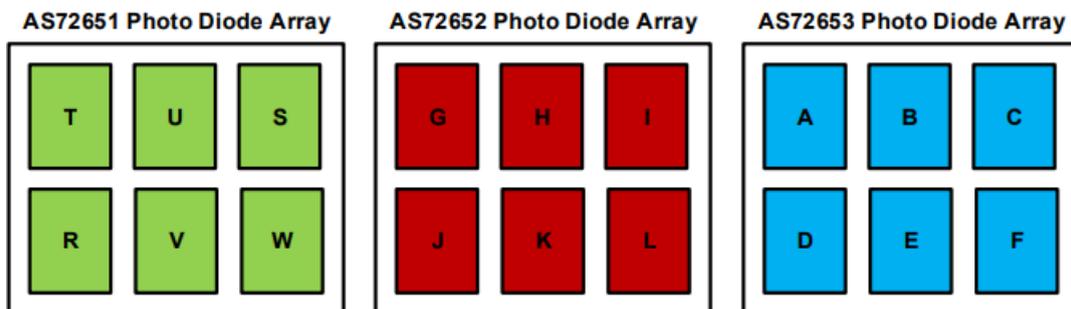


Figure 2.8: Different photo diode array of AS7265x sensor [29]

Following table 2.5 shows the electrical parameter of AS7265x

Table 2.5: Electrical parameter of AS7265x sensor [29]

Symbol	Parameter	Conditions	Min	Typ	Max	Unit
VDD1/VDD2	Operating supply voltage	UART interface	2.97	3.3	3.6	V
VDD1/VDD2	Operating supply voltage	I ² C interface	2.7	3.3	3.6	V
T _{amb}	operating temperature		-40	25	85	^o C
I _{VDD}	Operating current				5	mA

So, from the given table it is clear that, we can supply the sensor a 3.3 V operating voltage with 5 mA

Maximum supply current from microcontroller unit. And by this sensor we can test any milk or other food sample in any parts of our country so this sensor system is really compatible with our Indian temperature variation depending upon variation in location.

2.3 Arduino ESP8266 WIFI Development Board

We used for our project work for microcontroller unit is Arduino UNO R3 inbuilt WIFI module ESP8266 which is popularly called as UNO+ WIFI R3 AT mega 328P+Node MCUESP8266 CH340G Board Compatible for Arduino. This product is an Arduino Uno with integrated WIFI module ESP 8266. This board use the feature of ATmega328P with an ESP8266 WIFI module integrated. The ESP8266 WIFI module has SoC with integrated TCP/IP Protocol stack that is providing access to the any user's WIFI network (so that that device can act as access point for the data collection and process the data for further classification). The Arduino Uno WIFI is programmed by the Arduino Software (IDE).

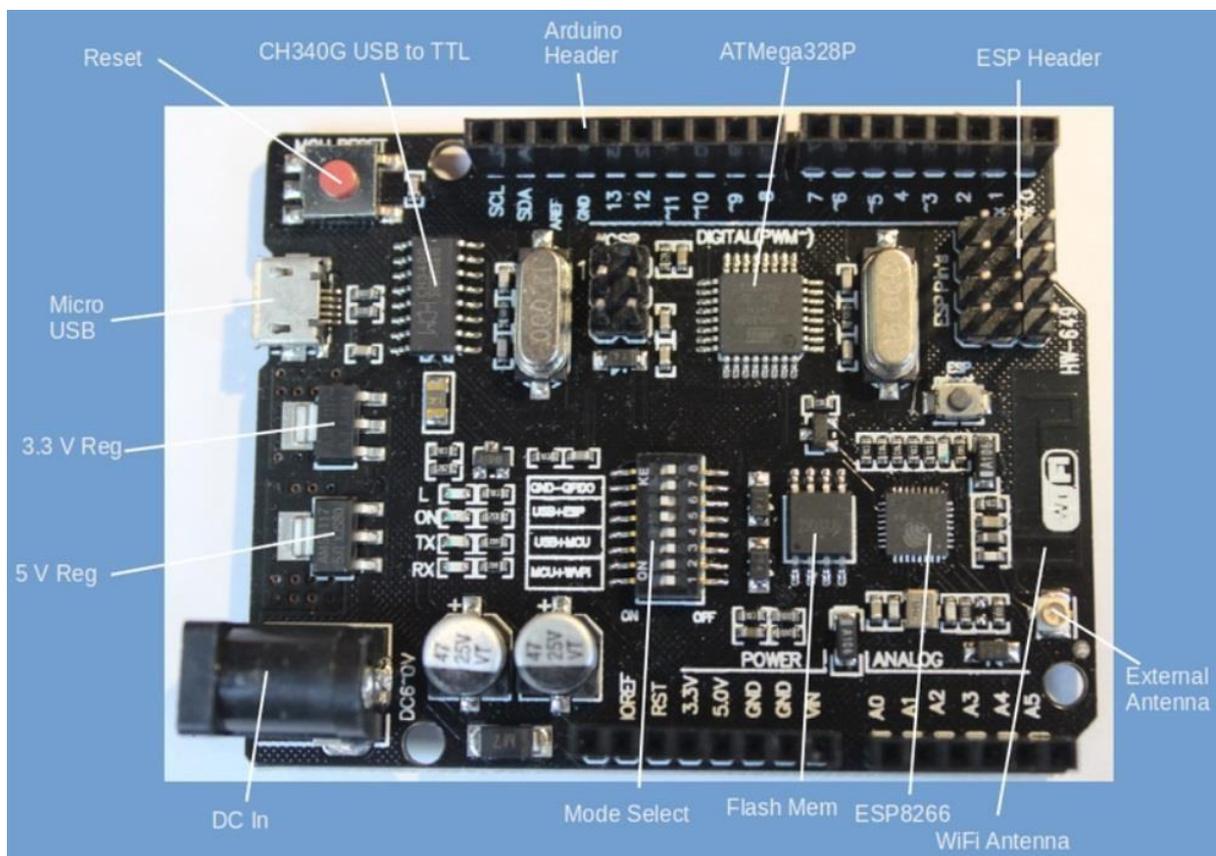


Figure 2.9: Arduino Uno development board [30]

The specification of the board is as follows:

- Model Number: UNO + WiFi-R3-AT328-ESP8266-32MB-CH340G
- Supply Voltage :6 to 9 V
- CPU: ATmega328
- WIFI: ESP8266
- USB: TTL converter: CH340G

- Header Pinout: Uno R3

2.3.a DESCRIPTION OF COMPONENTS ON THE BOARD

- The board includes a 5V and 3.3 V Voltage regulator to allow to supply 3.3 V supply operating voltage as VDD1/VDD2 to the sensor system.
- Instead of the large USB connector used on a standard Arduino, this board uses a micro-USB connector for serial communication and programming so that we connect it with PC and do the necessary programming.
- The board is having RESET button for resetting both ATmega328P and ESP8266 WIFI module.
- The header pin out is as like standard Arduino board. This allows any Arduino compatible shield to be connected to this development board.
- This board is having a small antenna for communication purpose with the provision of adding big size antenna for greater range requirement so that we can transmit sample data record to another PC located in other location.
- The communication establish between ATmega328P and WIFI module ESP8266 via serial lines and uses well known serial library.

2.3.b MODES OF ARDUINO WIFI MODULE BOARD

This Arduino WIFI Module board has total 4 modes which are very important to establish the given work and use it. this board having total 8 DIP switch to change and fix a Mode. This, modes are responsible for correctly operate the board and do the necessary work.

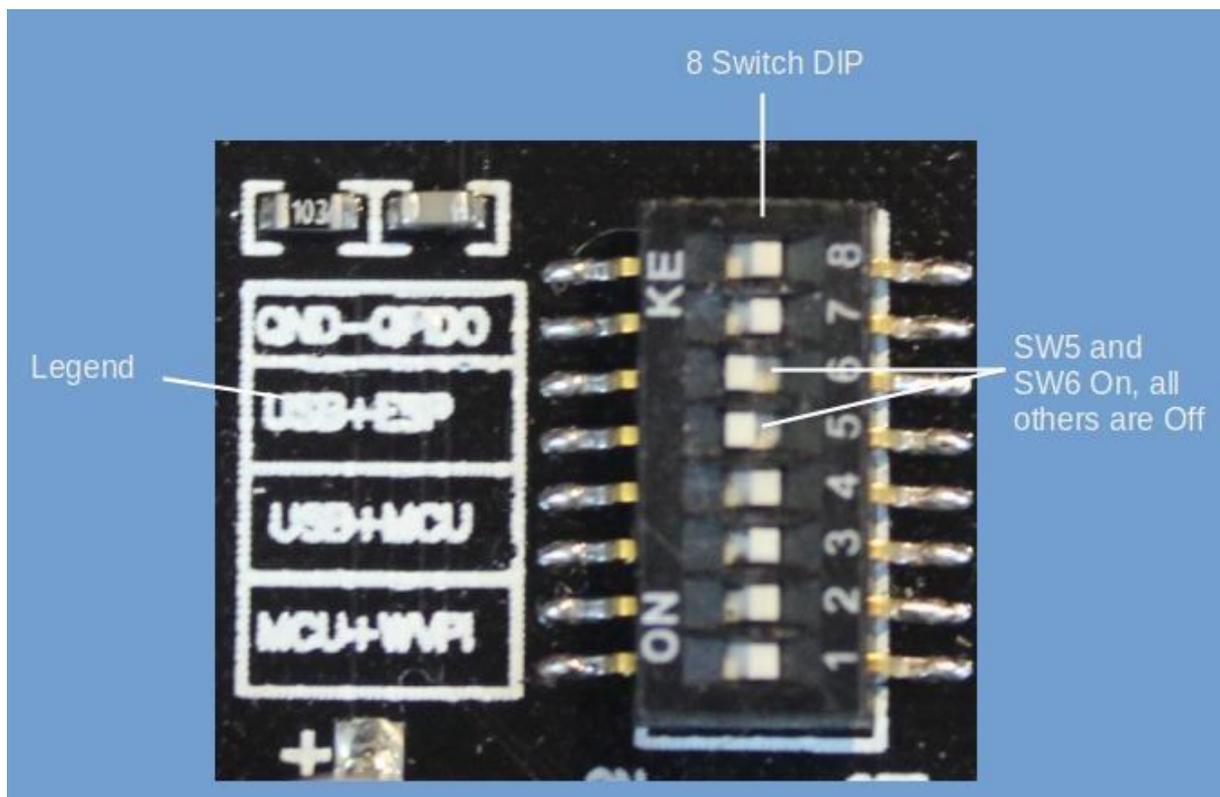


Figure 2.10: Mode selector of Arduino Uno board [30]

The given figure shows the total 8 DIP switches of Arduino WIFI board. Now given table 2.6 shows the different modes of this board of operation

Table 2.6: Different modes of Arduino Uno WIFI enabled board of operation [30]

Switch Status and mode selection	Name of Mode	Switch1	Switch2	Switch3	Switch4	Switch5	Switch6	Switch7	Switch8
CH340 Connected to ESP8266 to upload sketch	1	OFF	OFF	OFF	OFF	ON	ON	ON	No use
CH340 connected to ESP8266 to connect	2	OFF	OFF	OFF	OFF	ON	ON	OFF	No use
CH340 connected to ATmega328P to upload sketch	3	OFF	OFF	ON	ON	OFF	OFF	OFF	No use
ATmega328P connected with ESP8266 WIFI module	4	ON	ON	OFF	OFF	OFF	OFF	OFF	No use
All modules are independent	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	No use

So, for proper operation we need to select the appropriate mode for upload sketch and run the program on the board.

2.4. ESP32 WIFI MODULE

The ESP32 is a series of low-cost and low-power System on a Chip (SoC) microcontrollers developed that include WIFI and Bluetooth wireless capabilities and dual-core processor. Apart from WIFI connectivity, Bluetooth connectivity feature is also an additional as compared to ESP8266. The ESP32 consumes very little power compared with other microcontrollers, and it supports low-power mode states like deep sleep to save power so that during data collection mode from sensor module it consume least power.

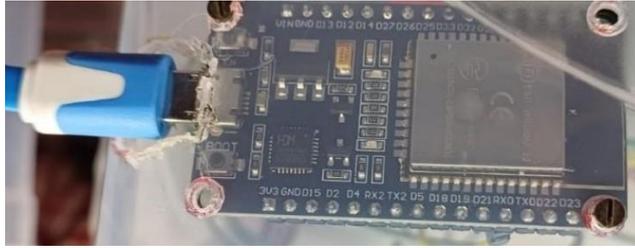


Figure 2.11: ESP32 module set in proposed setup

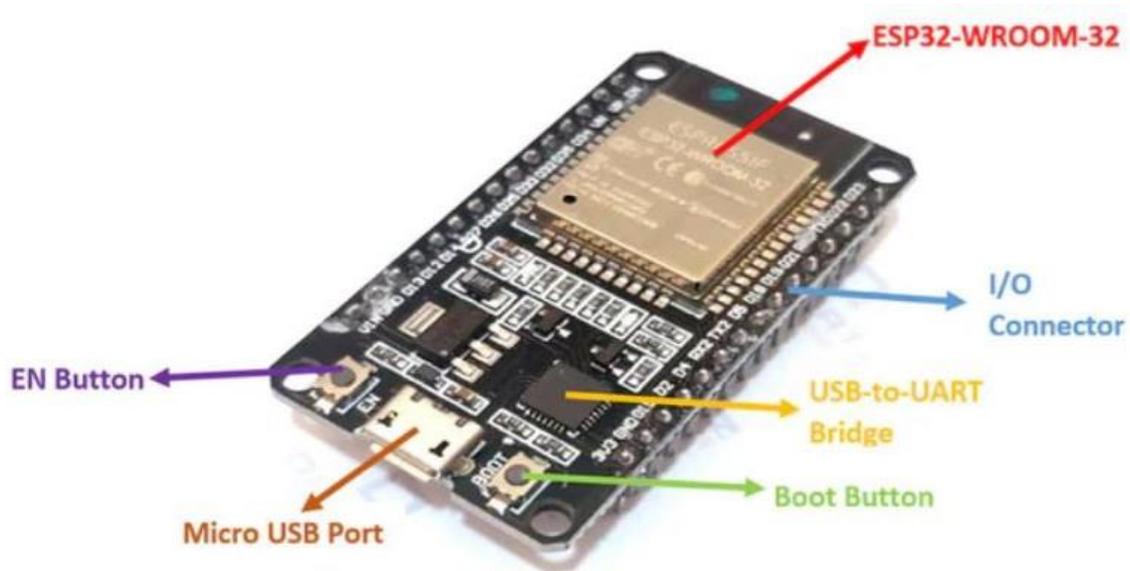


Figure: 2.12: ESP32 Module depicting different part of module [30]

2.4.a. SPECIFICATIONS OF ESP32 MODULE

ESP32 WIFI module is having following specifications so that we are incorporating it in project work:

Wireless connectivity WIFI: 150.0 Mbps data rate with HT40.

- **Bluetooth:** BLE (Bluetooth Low Energy) and Bluetooth Classic.
- **Processor:** Tensilica Xtensa Dual-Core 32-bit LX6 microprocessor, running at 160 or 240 MHz

Memory:

- **ROM:** 4.48 KB (for booting and core functions).
- **SRAM:** 520 KB (for data and instructions).
- **RTC fast SRAM:** 8 KB (for data storage and main CPU during RTC boot from the Deep Sleep mode).
- **eFuse:** 1 Kbit (in which 256 bits are used for system and MAC address and chip configuration) and remaining 768 bits are reserved for user's specific applications.
- **Embedded flash:** Flash connected internally via IO16, IO17, SD_CMD, SD_CLK, SD_DATA_0 and SD_DATA_1 on ESP32-D2WD and ESP32-PICO-D4.

As compared to ESP8266, ESP32 has more numbers of input output ports, wireless connectivity options and memory so we used it as additional WIFI module in project work. Following table shows the specifications of ESP32 module

Table 2.7: Specifications of ESP32 Module

Number of Core	2 (dual core)
Wi-Fi connectivity	2.4 GHz up to 150 Mbits/s
BLUETOOTH	BLE (Bluetooth Low Energy) and legacy Bluetooth
Architecture	32 bits
Clock frequency	Up to 240 MHz
RAM	512 KB
Peripherals	Capacitive touch, ADC (analog to digital converter), DAC (digital to analog converter), I2C (Inter-Integrated Circuit), UART (universal asynchronous receiver/transmitter), CAN 2.0 (Controller Area Network), SPI (Serial Peripheral Interface), I2S (Integrated Inter-IC Sound), RMII (Reduced Media-Independent Interface), PWM (pulse width modulation), and more.
Built-in LEDs	built-in blue LED connected to GPIO2; built-in red LED that shows the board is being powered just after connecting power supply.

USB to UART bridge	CP2102
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2.5 COMMUNICATION BETWEEN AS7265X SENSOR WITH ESP32

In the developed system we use UART (universal asynchronous receiver/transmitter) protocol which do not use clock so as called it asynchronous communication protocol between sensor module and WIFI module for establishing the serial communication. The serial port of Arduino UNO is getting the sensor data of AS7265x and by serial communication this sensor data is transmitted to ESP32 to send data to host website called “ThingSpeak”.

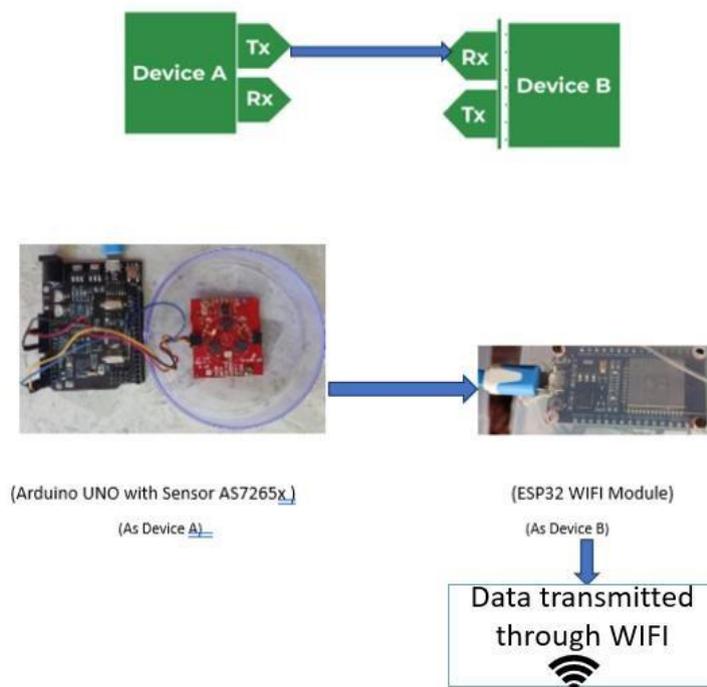


Figure 2.13 schematic diagram of communication between device A and D

Figure 2.14: Block diagram of communication between sensor and ESP32

2.6 CIRCUIT DIAGRAM AND DEVELOPED SETUP

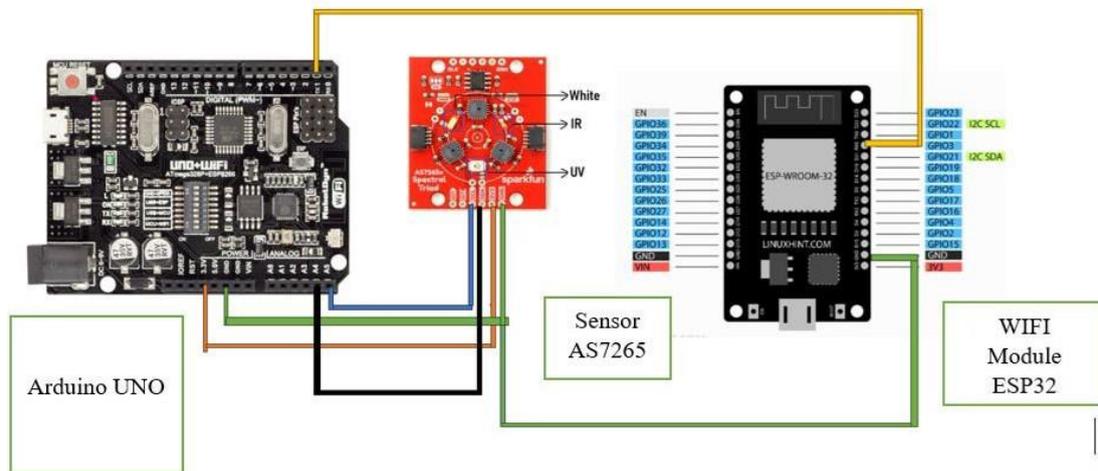


Figure: 2.15 Circuit diagram of developed system

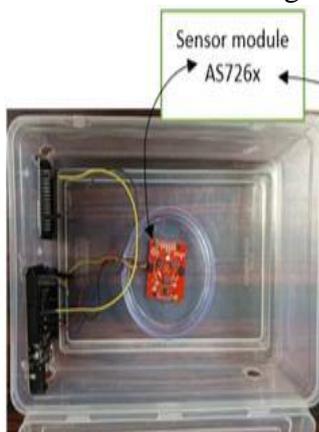


Figure 2.15: Back side view



Figure 2.16: Top view image



Figure 2.17: Front view of developed system

Steel container with food sample



Figure: 2.18: View of back side

2.7 SUMMARY

So, sensor-based milk adulteration identifying and food constituents determination system is made of a spectral system AS7265x which having three different sensor connected in Master - slave fashion with consisting total 18 different wavelength of light namely AS72651, AS72652, AS72653, covering the three regions of lights namely Ultraviolet, near infrared and visible. And a microcontroller Arduino UNO which is WIFI enabled and an WIFI module ESP32 for better performance, a QWIIC cable. So, the proposed system is compact as it does not consume much space, robust, and cost effective as this system is made under Rs 9000 and this system has huge potential in other food industry applications as future scope.

CHAPTER 3

DATA COLLECTION FROM DIFFERENT MILK SAMPLES BY MULTI SPECTRAL SENSOR SYSTEM

- **INTRODUCTION TO DATA COLLECTION FROM DIFFERENT MILK SAMPLES.**
- **SAMPLE PREPARATION**
- **DIFFERENT EXPERIMENTAL SET UP AND ENVIRONMENT CONDITIONS FOR COLLECTING DATA**
- **COLLETING DATA FORM LOCAL DAIRY COW MILK SAMPLE**
- **COLLETING DATA FORM AMUL TAAZA COW MILK SAMPLE**
- **COLLETING DATA FORM RED COW MILK SAMPLE**
- **COLLETING DATA FORM BHAGIRATHI COW MILK SAMPLE**
- **COLLETING DATA FORM SUPERT COW MILK SAMPLE**
- **COLLETING DATA FORM METRO COW MILK SAMPLE**
- **COLLECTING DATA FROM OTHER FOOD SAMPLE LIKE BISCUIT**
- **SENDING DATA TO “THINGSPEAK” WEBSERVER**
- **SUMMARY**

3.1 INTRODUCTION TO DATA COLLECTION FROM DIFFERENT COW MILK SAMPLE

Taking data from different cow milk sample is done by developed multi spectral sensor system consisting of AS7265X sensor which capable of taking readings from different milk samples through three different spectral sensor consisting visible region, ultra violet region and near infrared region. Here, the data is collected in different environmental condition with different physical condition mentioned later section in this chapter. Here triad sensor system consisting of six channels dedicated to a fixed wavelength in each region of light so total 18 channels are present, so that for a particular instance at a time all 18 channels are giving the data that is reflected value from milk surface. For collecting data we experimented in various illumination condition they are bad illumination condition, moderated illumination condition and good illumination condition. Different vertical distances can give different value of reflection of different wavelength light rays. For taking data and storing we used Arduino uno with inbuilt WIFI module ESP8266. At first, we need to prepare sample from the selected milk sample. In this project work we need more numbers of data to perfectly predict the adulteration level in unknown cow milk sample. So, we try to get as many samples can we bring in this task, finally we got total six cow milk samples they are namely local dairy cow milk, Amul Taaza cow milk, red cow milk, super T cow milk, metro cow milk, Bhagirathi cow milk all this are used to prepare total five different levels of adulterated milk sample. This are producing data and train gaussian regression model and robust regression model to solve classification problem.

3.2 SAMPLE PREPARATION

For collection the data from cow milk sample first we need to prepare the sample. For sample preparation we need a fixed volume of milk and water so that our sample volume is well understood and it is become easy for maintaining sample volume for all future references. So first we fixed our total volume of milk or mixture of milk and water will be 100ml. 100ml total volume is giving us the relaxation to calculate percentage addition of water into the pure milk sample and make it different level of adulterated milk in all future experiments. So, we take a total 10 ml container which has the mark of 2.5ml, 5ml and 10ml.



Figure 3.1: Measuring container and 100% pure milk sample

So now as we make our total volume of milk and water sample is 100ml so now we can take 10ml every time and create 10%, 20% ,30% and 50% milk and water solution for future examination. For experimental usage we prepare total five different level of adulterated milk they are 100 % pure milk that is pure 100ml milk with no added water, 10ml water is mixed

with 90ml of pure cow milk which is called 10% water milk solution, next is 20 ml water is mixed with 80ml pure cow milk making total volume of solution is 100 ml and called as 20% water milk solution, then we added 30 ml water with 70 ml pure cow milk making 30% water milk sample, next we prepare our last sample as 50 ml of water is mixed with 50 ml of pure milk making 50% water milk sample. All this samples are made under normal room temperature with 32⁰ C to 38⁰ C and the water is used here is having 40ppm to 70ppm of TDS which is normal tap water.

3.3 DIFFERENT EXPERIMENTAL SET UP AND ENVIRONMENT CONDITIONS FOR COLLECTING DATA

For the experimental need we vary the illumination condition of Jadavpur university measurement lab. Here we first done our experiment under good illumination condition along with blinking in built LED of sensor module which created reflected values from milk surface by the sensor module with a very high magnitude. Next time we take measurement under moderate lighting condition without blinking the inbuilt LED of sensor module. And after that we took measurement under low lighting that is we call bad illumination condition. Under the low or bad illumination condition the data are having very low magnitude with almost zero value for most of the channels of sensor module so we made a decision on ideal environment to real life and industrial application point of view in conclusion part of this chapter. As we are getting almost zero for most of the channels so we restrict ourselves to take data under good illumination condition and moderate level of illumination condition where we put off inbuilt LED of sensor and having all lights on in the measurement lab. For the next experimental references we take two condition from environmental illumination condition one is good illumination and other one is bad illumination condition. We also vary the vertical distance in between sensor module and milk surface. We restrict ourselves in two different vertical distance one is 1inch vertical distance and other one is 2inch vertical distance as we see there is no such big variation in readings under different vertical distances under fixed illumination condition. So, we have total eight different conditions under which we perform our experiment and under all this condition we perform experiment with taking each version of sample that is for 10% water milk solution, 20% water milk solution and so on. For experiment we used two different container one is steel container and other is glass container. So, we are having following conditions under the experimental setup.

Table 3.1: Different conditions for collecting data

Number of conditions	Conditions
1	Good illumination condition with 1inch vertical distance with glass container
2	Good illumination condition with 1inch vertical distance with steel container
3	Good illumination condition with 2inch vertical distance with glass container

4	Good illumination condition with 2inch vertical distance with steel container
5	Bad illumination condition with 1inch vertical distance with glass container
6	Bad illumination condition with 1inch vertical distance with steel container
7	Bad illumination condition with 2inch vertical distance with glass container
8	Bad illumination condition with 2inch vertical distance with steel container

Under each condition we perform the experiment taking each adulterated sample of milk.

3.4 COLLECTING DATA FORM LOCAL DAIRY COW MILK SAMPLE

First, we took local dairy cow milk for collecting the data. Here as per article 3.2 we have prepared milk sample of 100ml.

3.4.a DATA COLLECTION FROM PURE MILK SAMPLE

As we discussed as per 3.3, we have fixed total 8 variable conditions to do the experiment now we start our experiment by collecting the data from pure local dairy cow milk sample. As per the circuit diagram we set all the hardware, then we perform the required software setup and collecting the data. Data is consisting of total 18 rows and we take the data from sample for 1 minutes hence we got total 60 samples for each 18 rows as the data were collected after 1 seconds. So, the data become a size of 60x18. Here the values corresponding to each channel is a float value and distinct, each channel pausing an identical and fixed float value for a particular sample. As here we take pure milk sample so the values are fixed for this sample for each channel. Here we took data for each condition mentioned in 3.3.

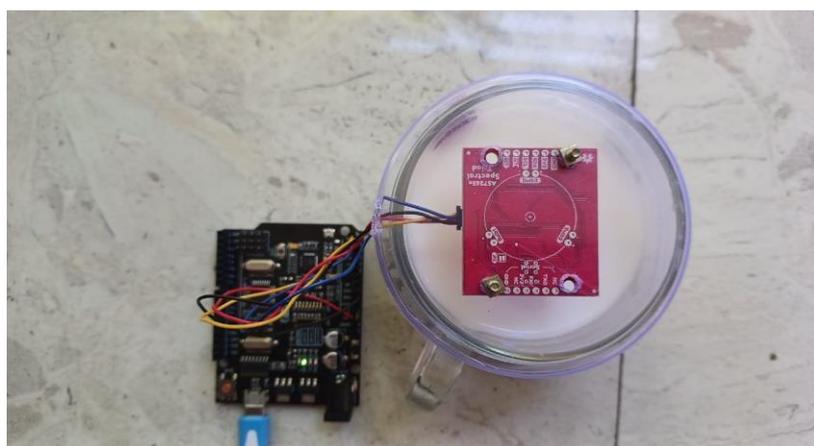


Figure:3.2: Data collecting of local 100% pure cow milk in glass container



Figure.3.3 Data collecting of 100% pure cow milk taking steel container

CONDITION 1

Channel variation for sample of 100% pure milk sample under condition 1 as per section 3.3 i.e. good illumination condition taking glass container with 1 inch distance between sensor module and surface of milk sample

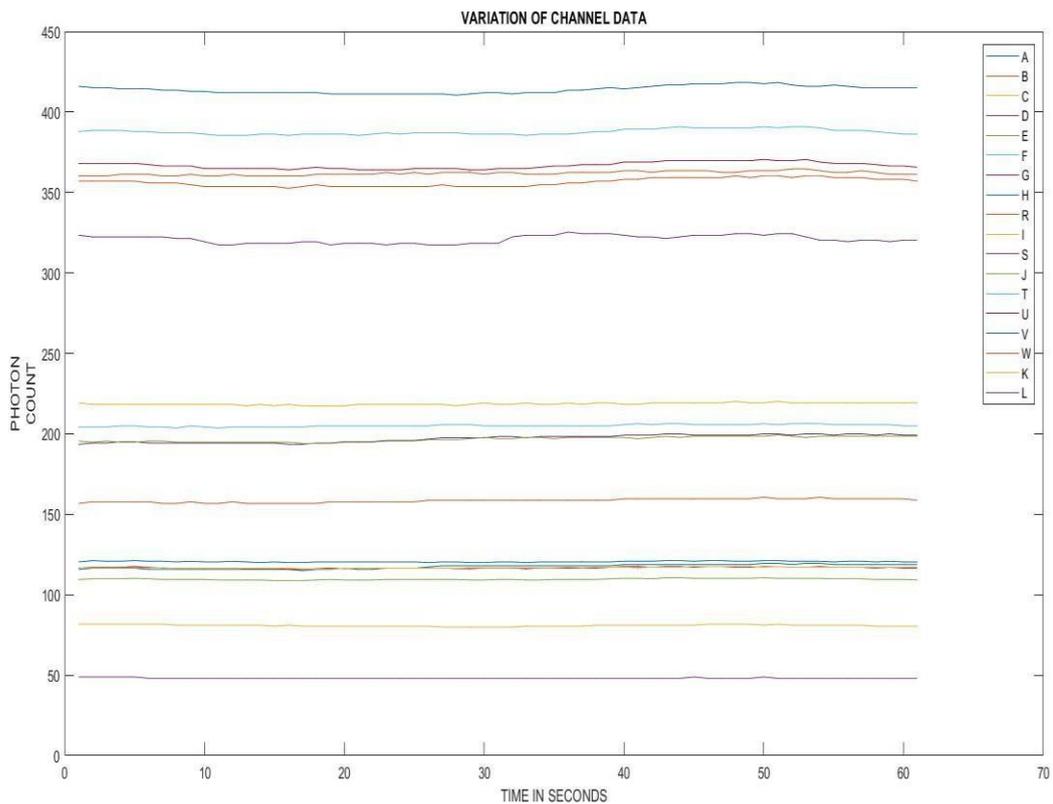


Figure 3.4: All 18channel response for 100% pure local cow milk

Figure 3.4 shows the different channel variation under condition 1 as per section 3.3, here we are observing the pattern of channels data variation and we can clearly observe that each individual channels having distinct and differ from each other. No such overlapping among the data is observed hence this data is very suitable for post analysis of data with AI based

algorithm GPR (Gaussian process regression) and robust regression. For solving the classification problem feeding this data is very ideal situation. Now we are trying to see individual channel variation under condition 1 as per section 3.3.

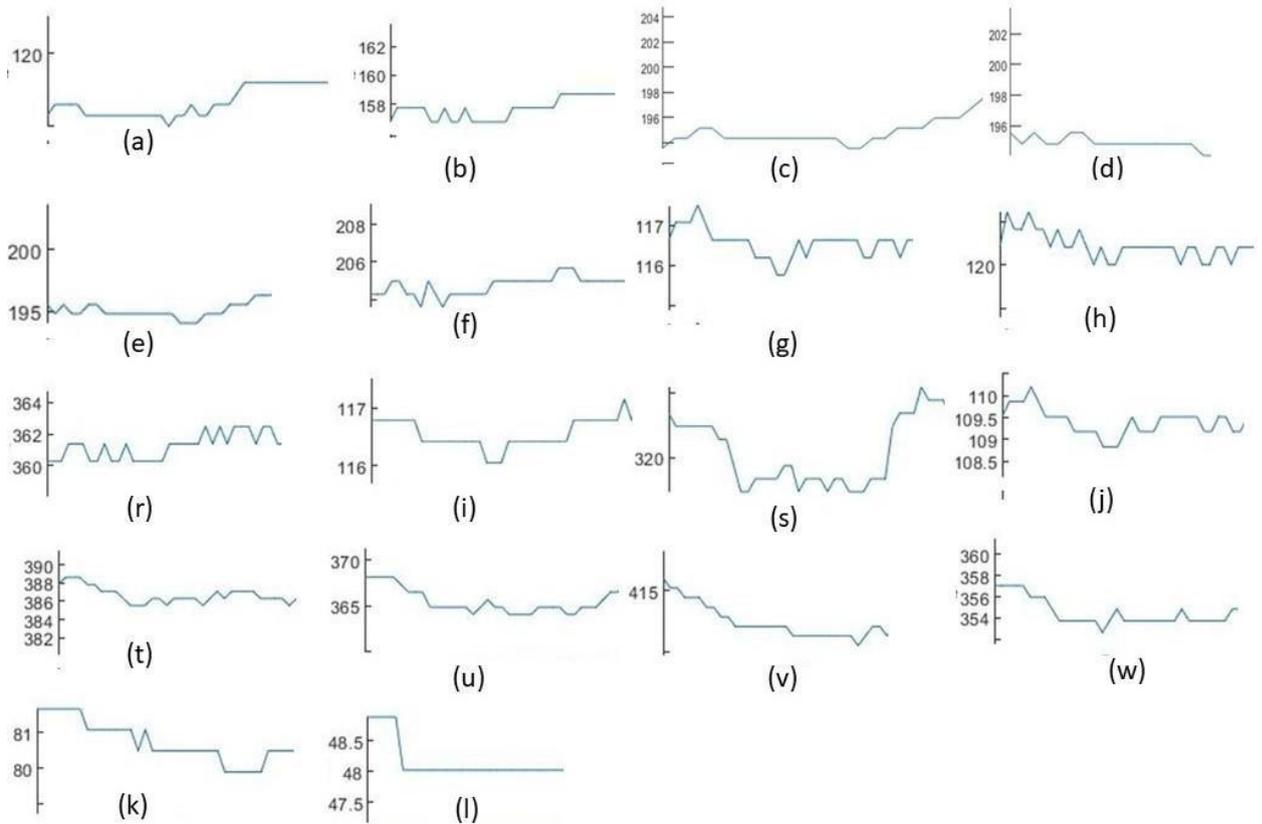


Figure 3.5 :Variation of all channels for pure 100% local cow milk as (a) Channel A, (b) Channel B, (c) Channel C, (d)Channel D, (e) Channel E, (f) Channel F, (g) Channel G, (h) Channel H, (r) Channel R, (i) Channel I, (s) Channel S, (j) Channel J, (t) Channel T, (u) Channel U, (v) Channel V , (w) Channel W, (k) Channel K , (l) Channel L

Figure 3.5 shows the variations of data for each channel it is clearly visible that all channels having distinct and almost fixed value. Value corresponding to each channel almost fixed, for an example channel A is having value of around 120.00, channel T having the value of in between 388 to 390 hence the value is fixed and pausing the same value for every advancement of time, therefore it is confirmed that this distinct values for each individual channels are signature for pure local cow milk sample. And we take it as reference for future data collection from different adulterated milk samples.

CONDITION 2

Now for condition 2 as per section 3.3 we collected data from local cow milk with 100% purity sample, following figure 3.4 shows the variation of channel values.

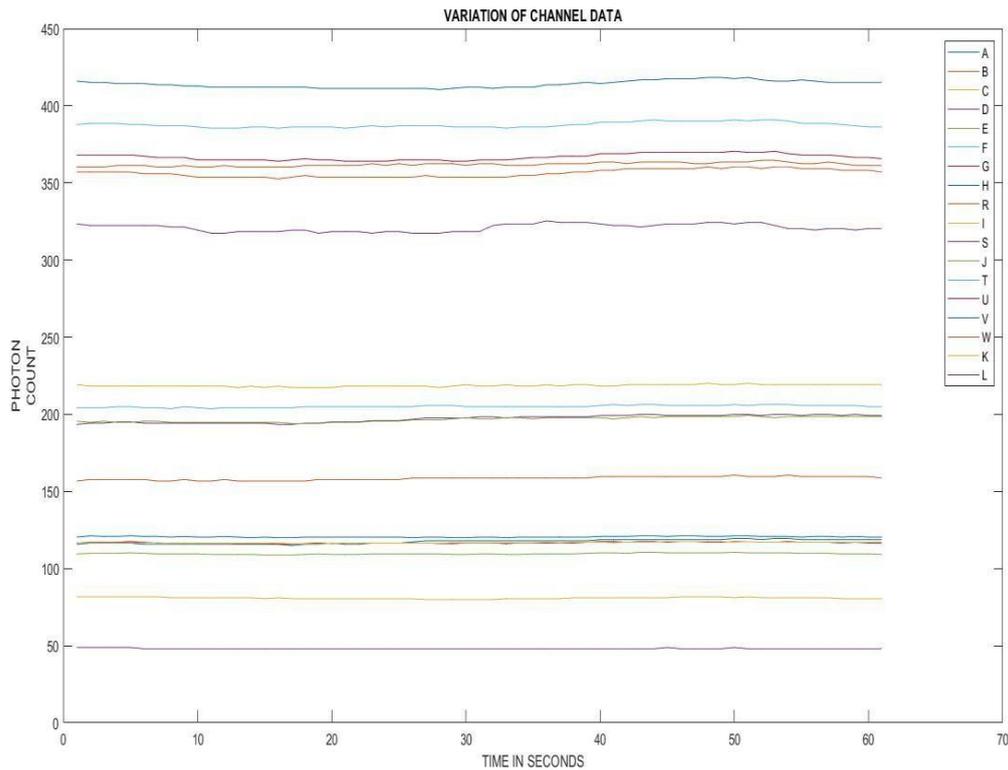


Figure 3.6: All channels response under condition 2 of 100% pure local cow milk

Figure 3.6 shows exactly same variation of sensor channels data as for condition 1 where all parameters are same except instead of using glass as a container here, we changed it to steel container. There is no variation of data for that sample, hence the choice of container is independent of current experiments.

CONDITION 3

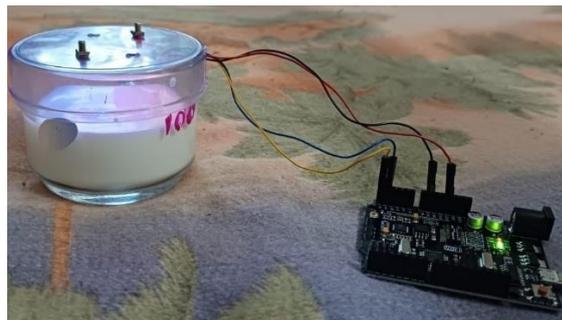


Figure3.7: Data collection from 100% pure local cow milk

Now again for the same pure local cow milk sample data is collected under the condition 3 as per section 3.3. Following figure 3.8 shows the variation of channel here also the channel data are almost same with previous data set as the vertical distance is doubled here from 1 inch to 2 inch hence magnitude may change but the relative variation among the channel data is same here as we observe in previous conditions.

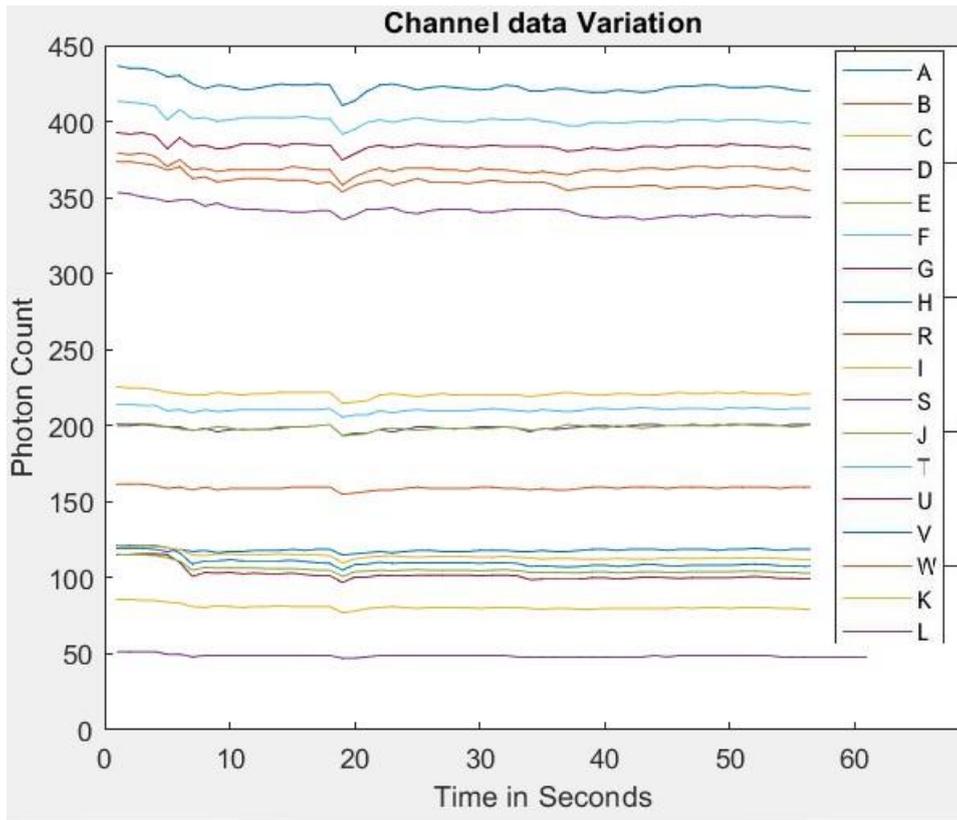


Figure 3.8: All channels response of 100% pure local cow milk under condition 3

The wave pattern of all channels having similar and almost pauses the fixed magnitude like a dc signal. Following figure 3.9 and figure 3.10 shows the individual channel data from channel A to Channel L.

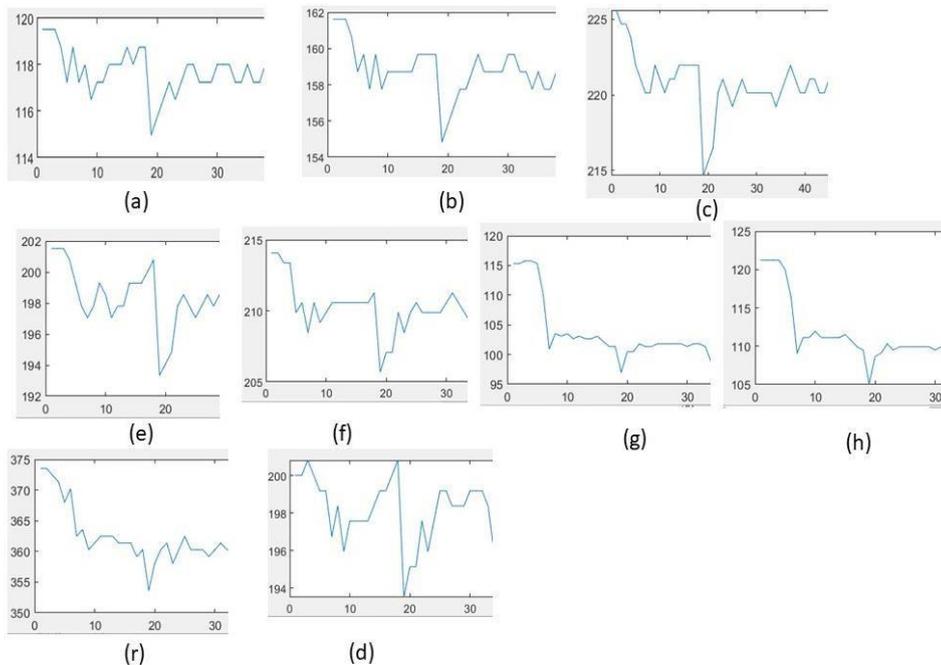


Figure 3.9: Channel A to Channel R response under condition 3 of local 100% pure cow milk (a) Channel A, (b) Channel B, (c) Channel C, (d) Channel D, (e) Channel E, (f) Channel F, (g) Channel G, (h) Channel H, (r) Channel R

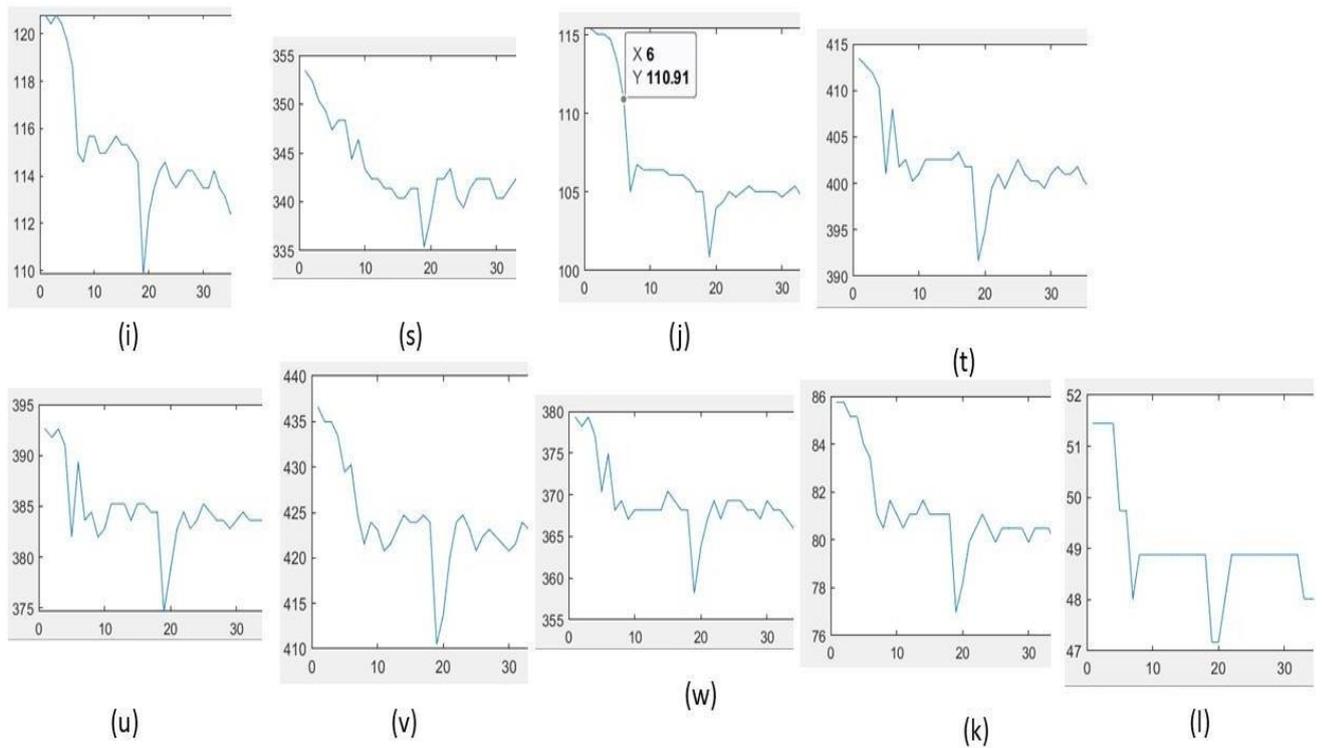


Figure 3.10: Channel I to Channel L response under condition 3 of local 100% pure cow milk as (i) Channel I, (s) Channel S, (j) Channel J, (t) Channel T, (u) Channel U, (v) Channel V, (w) Channel W, (k) Channel K, (l) Channel L

Here not only magnitude the pattern of data is also same under this condition as previous condition so the variation of vertical distance is also independent with the experiment.

CONDITION 4

Under the condition 4 as section 3.3 where steel container is being used, the data is collected and following figure 3.11 shows the pattern of data of sensor data. As shown in figure 3.11 the result is exactly same where glass container was used so the sensor data does not depend on steel or glass container.

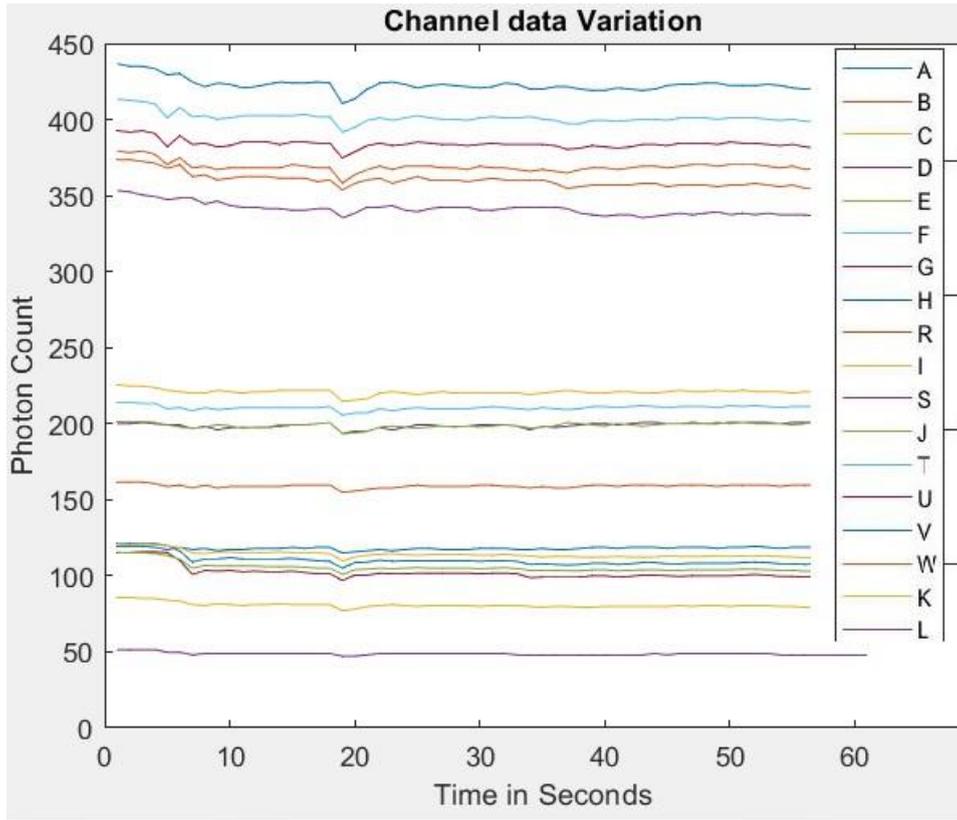


Figure 3.11: All channel Response of 100% pure local cow milk under condition 4

CONDITION 5

Here low illumination condition is created under the condition 5 as per section 3.3. Following figure 3.12 shows the channel data variation with time . It is clearly observable that not only magnitude of channel signal pattern also changes drastically under low illumination situation. But up to first 40 seconds all channels signal is having pattern but differ in magnitude but after 40 seconds the signals are getting stable and having almost stable and fixed pattern but signal data of channel here gets mix up so the data is not suitable to feed the AI based algorithms to solve the classification problem. So, this is the limitation, under the low lighting condition sensor cannot collect data properly so we cannot predict the level of adulteration of milk and food constituents.

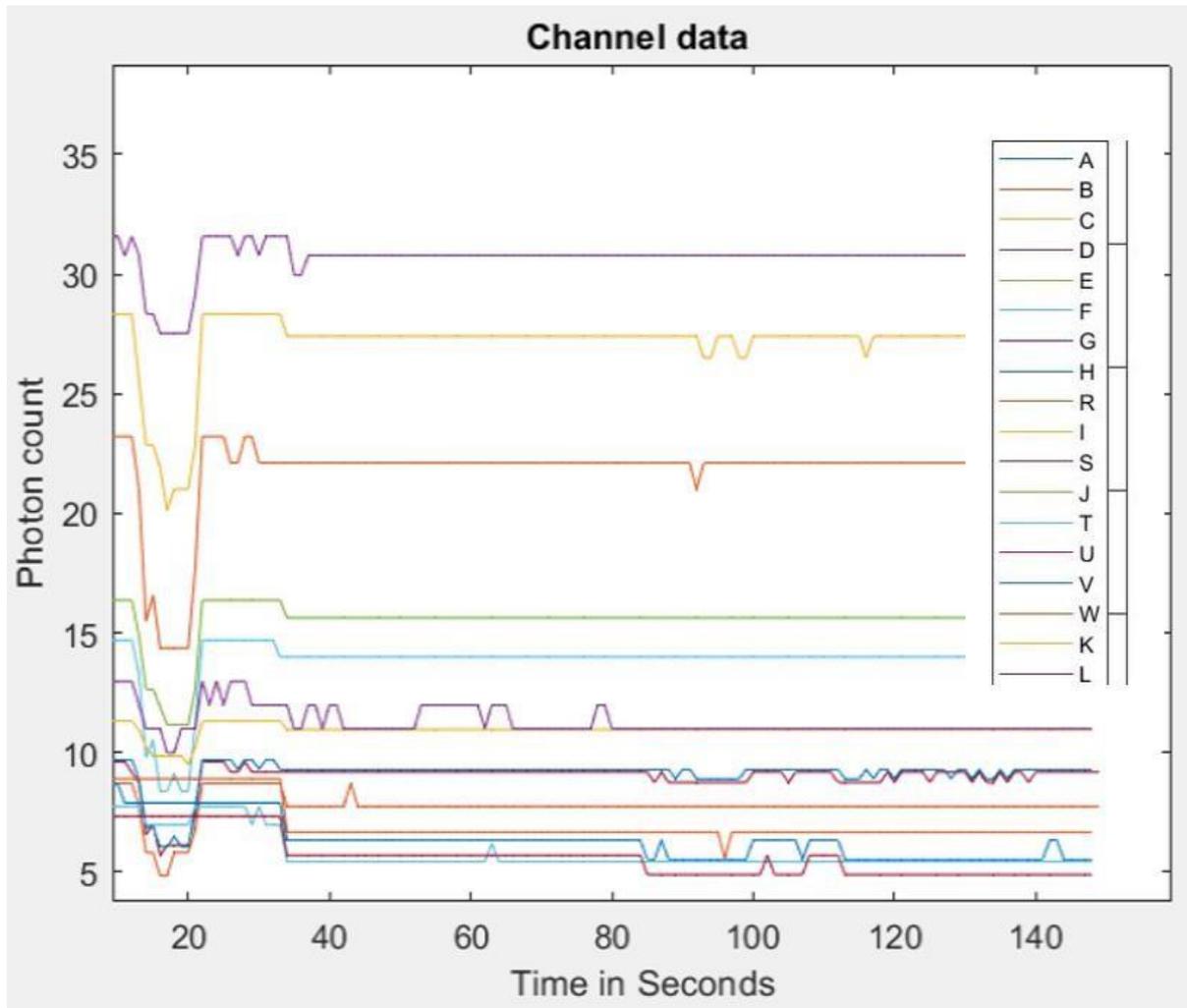


Figure 3.12: All channel response of 100% pure cow milk under condition 5

CONDITION 6

As per section 3.3 we experimented the pure local cow milk sample under low illumination condition with steel container and 1inch vertical distance between milk surface and sensor. Here also the same result came as under condition 5 as here author only changes the container of milk but as we know from our previous discussion container does not play any role here so get exact same wave pattern of channel data as following Figure 3.13

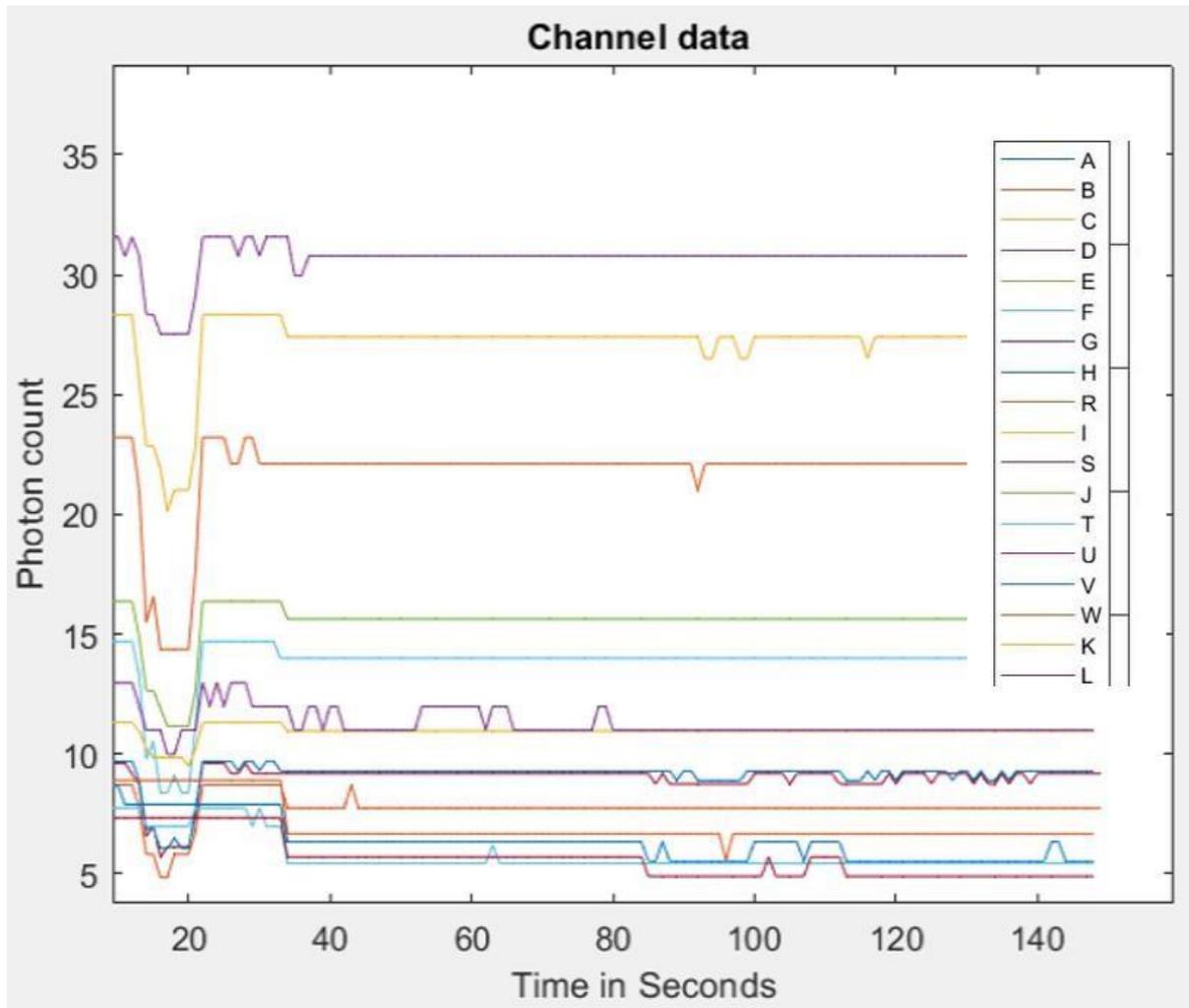


Figure 3.13: All channel response of 100% pure local cow milk under condition 6

Condition 7 and 8 are also showing the same result as under condition 5 and 6 as vertical distance between sensor module and food surface does not change the pattern of signal of channels so under low illumination condition both are showing exactly same result so no such further analysis is required.

So, from the above discussion, it is clear that to feed the sensor data for post processing one must be sure about the environmental illumination condition, bright and clear environment is suitable for the experiment otherwise one must ON the inbuilt LED of sensor module to get good illumination condition.

3.4.b DATA COLLECTION FROM 10% WATER LOCAL COW MILK SAMPLE CONDITION 1

As per the section 3.3 under good illumination condition the data is taken from 10% water milk sample where out of total 100ml of solution 10ml is tap water having TDS of 43 PPM (Parts per Million) is mixed with 90 ml pure local cow milk. Following figure 3.15 shows the pattern of data collected from sensor under this situation.



Figure3.14: TDS meter

Figure 3.14 shows the tap water TSD that is 43 PPM (Parts per Million) and TDS meter for measuring TDS of water in PPM (Parts per Million). Tap water having TDS of 43 PPM is being used for all future experiments.

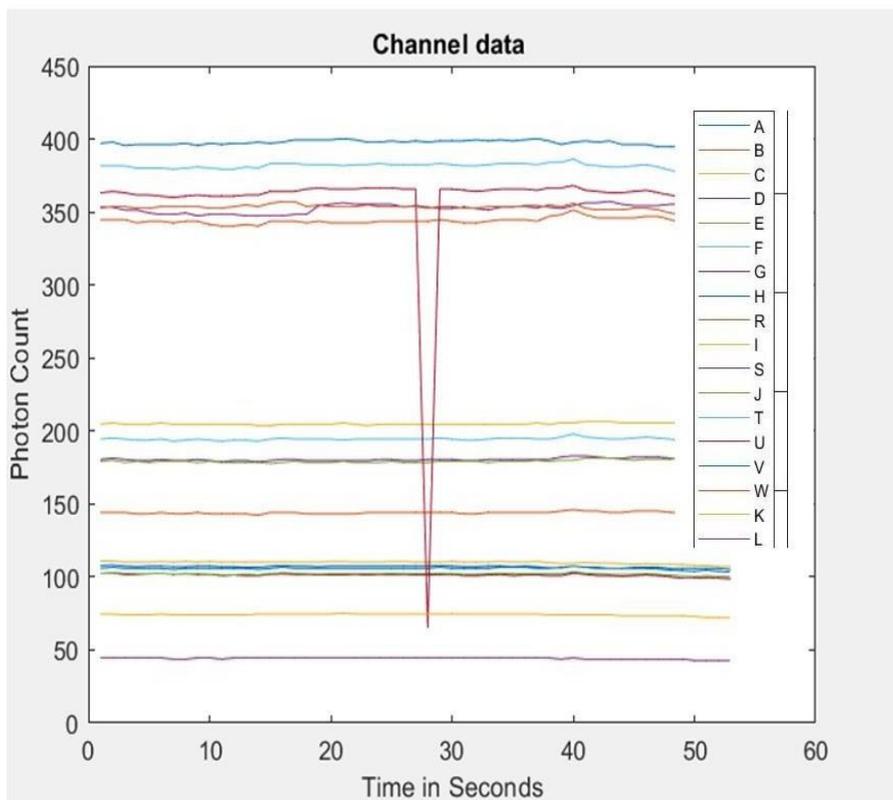


Figure 3.15: All channel response of 10% water milk solution of local cow milk under condition1

Data pattern changes from the 100 % pure local cow milk sample as compared to figure 3.4, this figure 3.15 the wave pattern is absolutely different hence sensor module recognises the changes in the channel signal pattern hence can predict the 10% water milk solution.

CONDITION 2

Under condition 2 as per section 3.3 data is being collected from 10% water mixed local cow milk sample and the following figure 3.16 depicts the variations of channel data

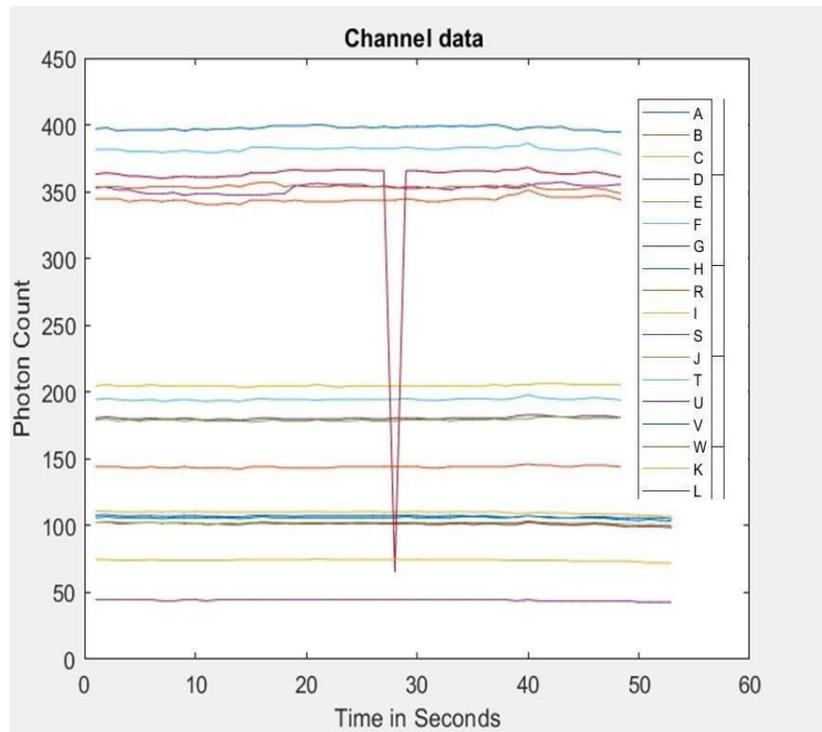


Figure 3.16: All channel response of 10% water milk solution of local cow milk under condition 2

Here also in figure 3.16 shows the same result as in case with glass container as condition 1 therefore material of container is independent of the experimental outcome.

Similarly, all conditions as per section 3.3 we have taken the data and as outcome we got that under the good illumination condition the channel signal variation is well noticeable and well recognized but the result are now as good in low illumination condition or say in dark background condition.

3.4.c DATA COLLECTION FROM 20% WATER LOCAL COW MILK SAMPLE

Under the same conditions as per section 3.3 the data are collected for 20ml water of TDS 43 PPM is mixed with 80 ml of pure local cow milk and outcomes are depicted in figure 3.17

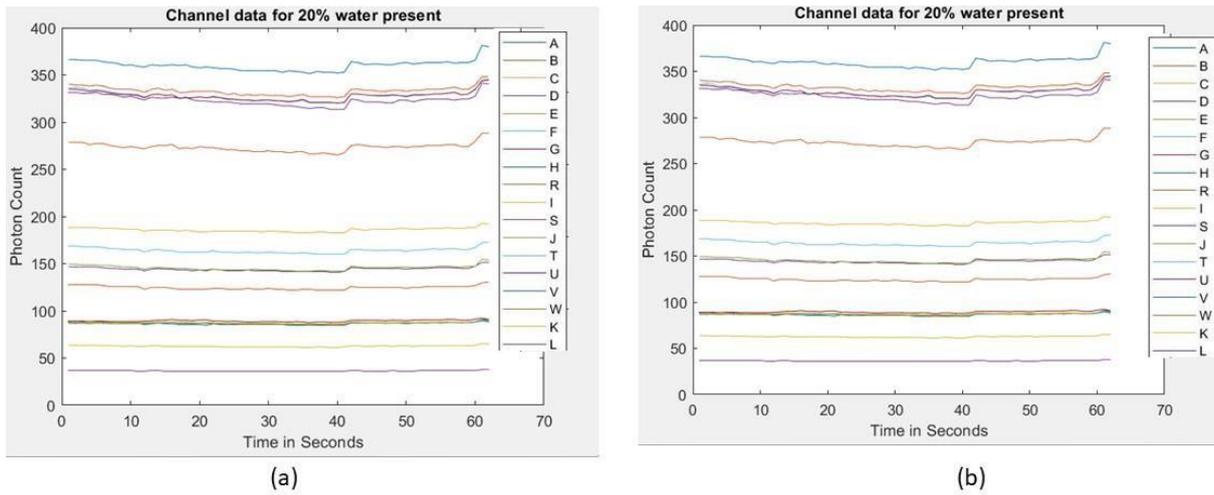


Figure 3.17: All channel response of 20% water milk solution of local cow milk under condition1 as (a) channel data with glass container, (b)channel data for steel container

Figure 3.17 shows the outcome from sensor module under condition 1 and 2 as per section 3.3 for 20% water local cow milk solution. Accordingly, all data is being taken for all 8 conditions as per section 3.3.

3.4.d DATA COLLECTION FROM 30% WATER LOCAL COW MILK SAMPLE

30ml of tap water with TDS 43 PPM is mixed with 70 ml of pure local cow milk solution is prepared and accordingly as per section 3.3 for all condition data is taken now the following figure 3.18 shows the variation of data under condition one in section 3.3.

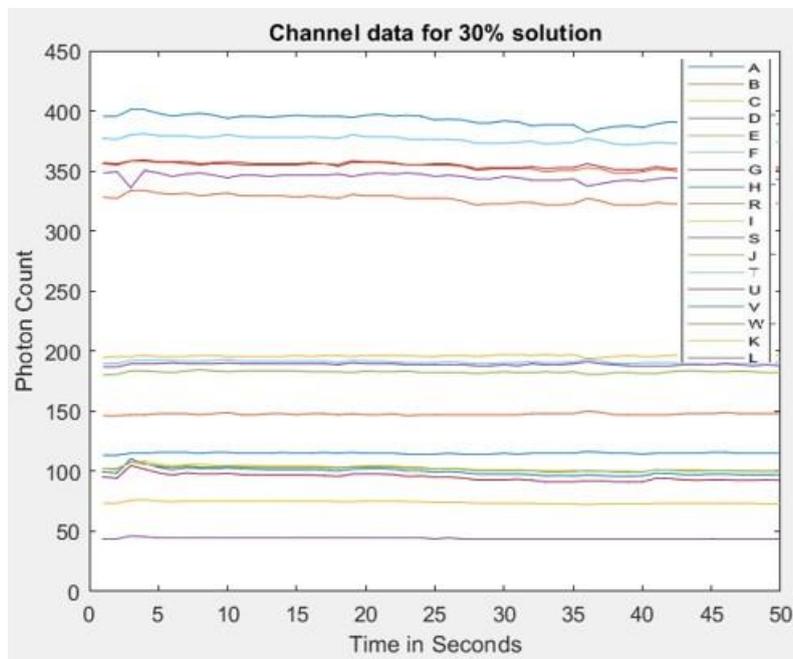


Figure 3.18: All channel response of 30% water milk solution of local cow milk in good illumination condition

3.4.e DATA COLLECTION FROM 50% WATER LOCAL COW MILK SAMPLE

50ml of tap water with TDS 43 PPM is mixed with 50 ml of pure local cow milk solution is prepared and accordingly as per section 3.3 for all condition data is taken now the following figure 3.19 shows the variation of data under condition one in section 3.3.

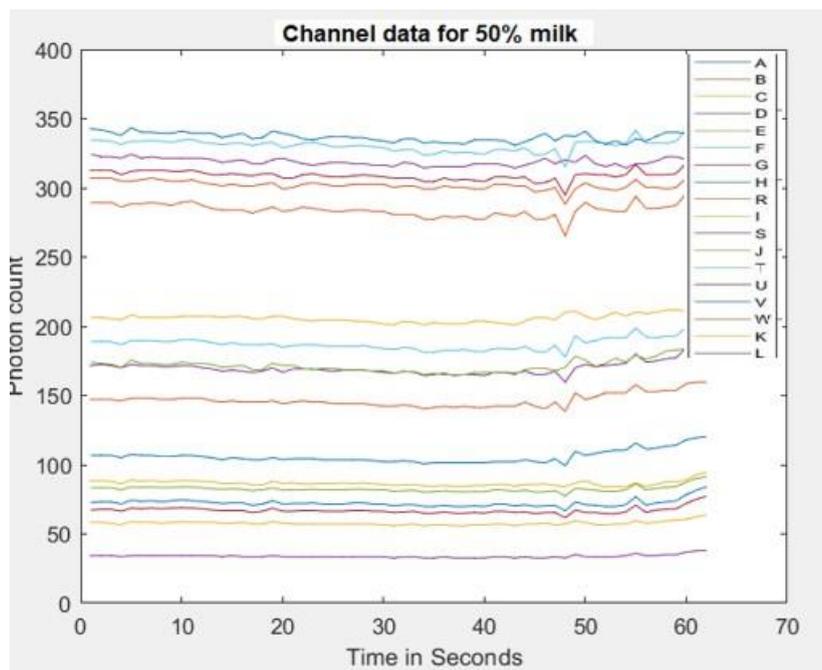


Figure 3.19 All channel response of 50% water milk solution of local cow milk

From the depicted figure 3.19 it is clearly noticeable that for 50% adulterated milk the channel data changes its variation after 50 seconds and they the gap between the channels are increases, so a perfect pattern is formed so that we can classify the different adulterated milk.

3.4.f CHANNEL VARIATION FOR PURE LOCAL COW MILK SAMPLE FOR DIFFERENT ADULTERTED MILK SAMPLE

Figure 3.20, 3.21, 3.22 and 3.23 are depicted the variation for individual channel signal. The channel variation here is considered under condition 1 as per section 3.3 where good illumination condition along with glass container and 1inch vertical distance is considered. Under one fixed set up and physical condition data of channels are compared in figure 3.20 to figure 3.23. Here, we are observing that irrespective of channels and magnitude of signal, the respective variation is fixed which is desirable to predict other milk sample under given set up condition so the following figures are just given to observe the variation of channel data.

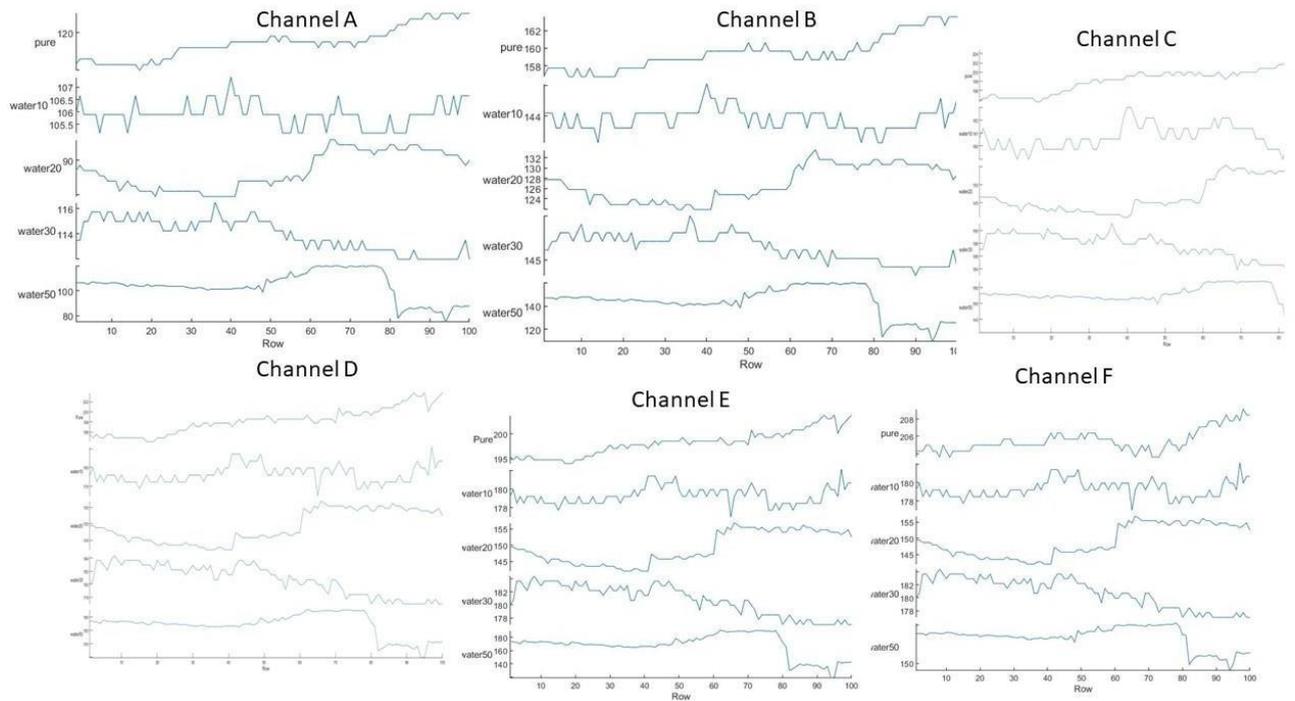


Figure 3.20: Individual channel responses comparison from channel A to channel F for local cow milk

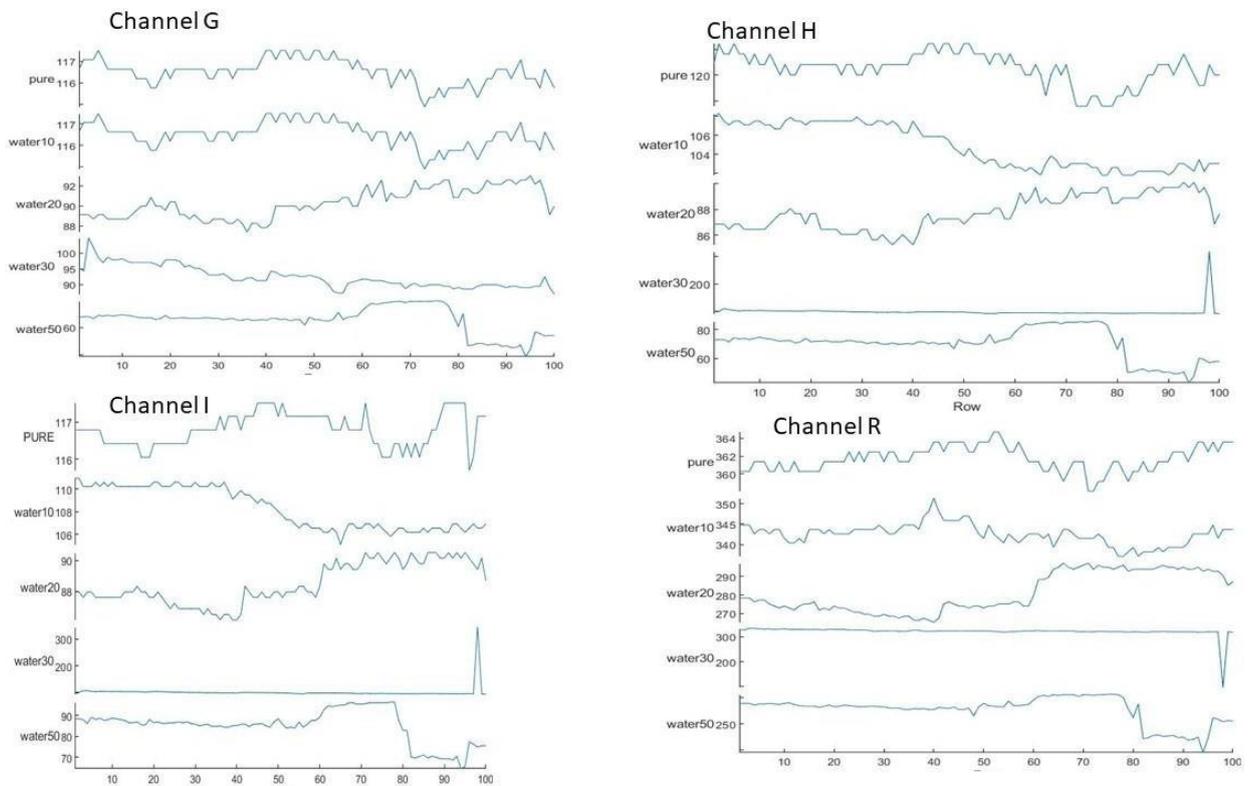


Figure 3.21: Individual channel responses comparison from channel G to channel R for local cow milk

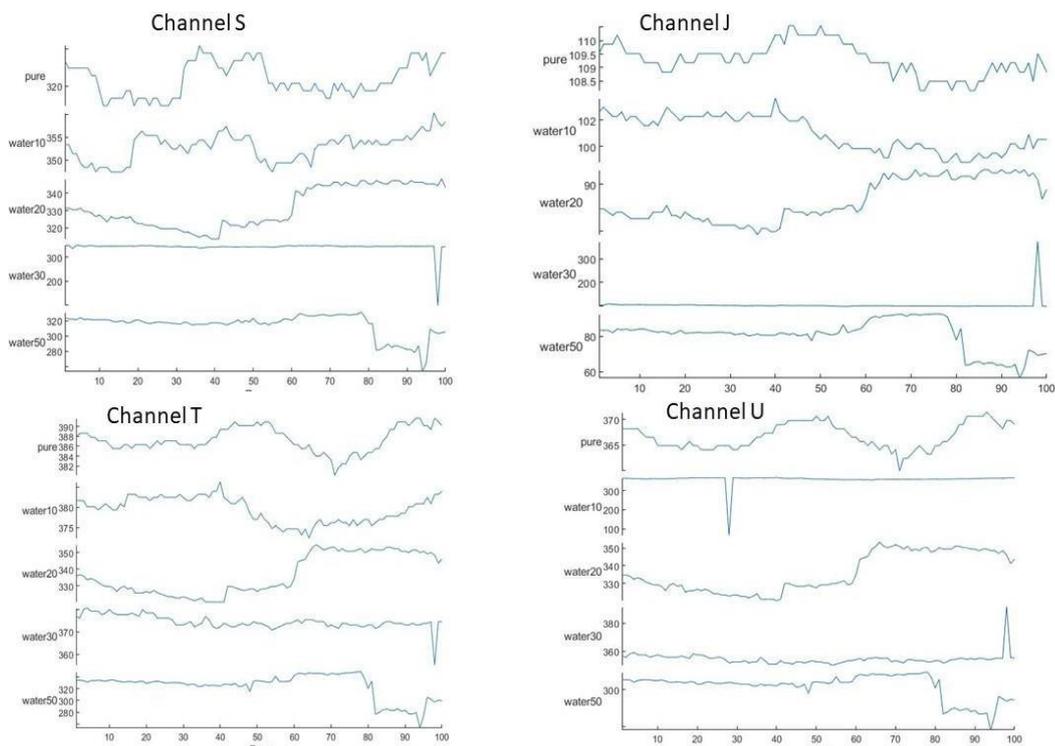


Figure 3.22: Individual channel responses comparison from channel S to channel U for local cow milk

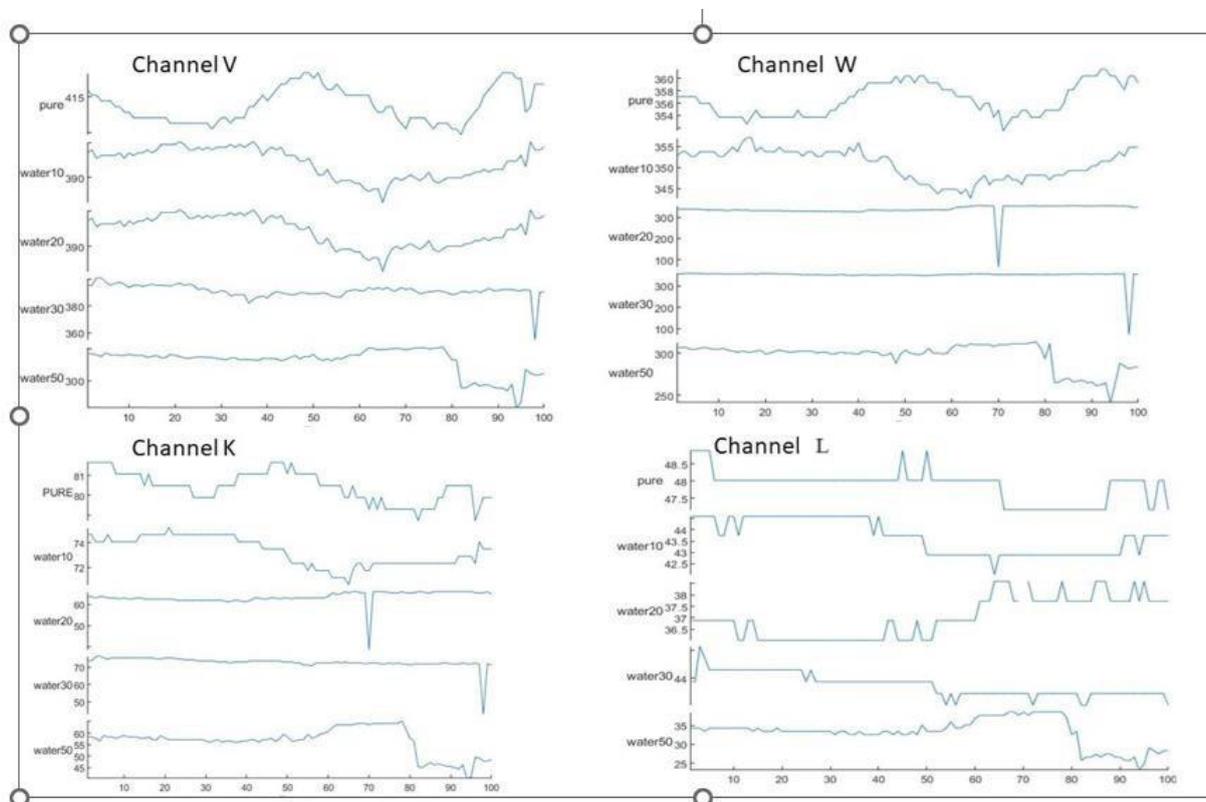


Figure 3.23: Individual channel responses comparison from channel V to Channel L for local cow milk

3.5 COLLECTING DATA FROM AMUL TAAZA COW MILK SAMPLE

Now, we took Amul Taaza cow milk for collecting the data. Here as per article 3.2 we have prepared milk sample of 100ml.



Figure 3.24: Image of Amul Taaza milk with Nutritional Information

Figure 3.4 showing the Nutritional Information about Amul Taaza milk of 500ml pasteurised homogenised toned milk. From the table of nutritional information we got the total fat content of 3.0g (9%) per 100ml which we will use for calibration purpose to find total fat in unknown milk.

3.5.a DATA COLLECTION FROM PURE AMUL TAAZA MILK SAMPLE

Under the conditions as per section 3.3 all 8 conditions are explored as in case of local cow milk.



Figure 3.25: collecting data under low light of Amul Taaza



Figure 3.26: collecting data under good illumination condition of Amul Taaza

Figure 3.25 is showing the data collection under low light or illumination condition and Figure 3.26 depicts the data collecting under good illumination condition. From pure milk sample we

collect the data for four different conditions for good illumination condition as per section 3.3. They are as follows (a) good illumination condition with glass container keeping one inch vertical gap between sample surface and sensor module, (b) good illumination condition with steel container keeping one inch distance between sample surface and sensor module, (c) good illumination condition with glass container keeping two inch distance between sample surface and sensor module and (d) good illumination condition with steel container keeping 2 inch distance between sample surface and sensor module.

Following figure 3.27 showing the result under above conditions

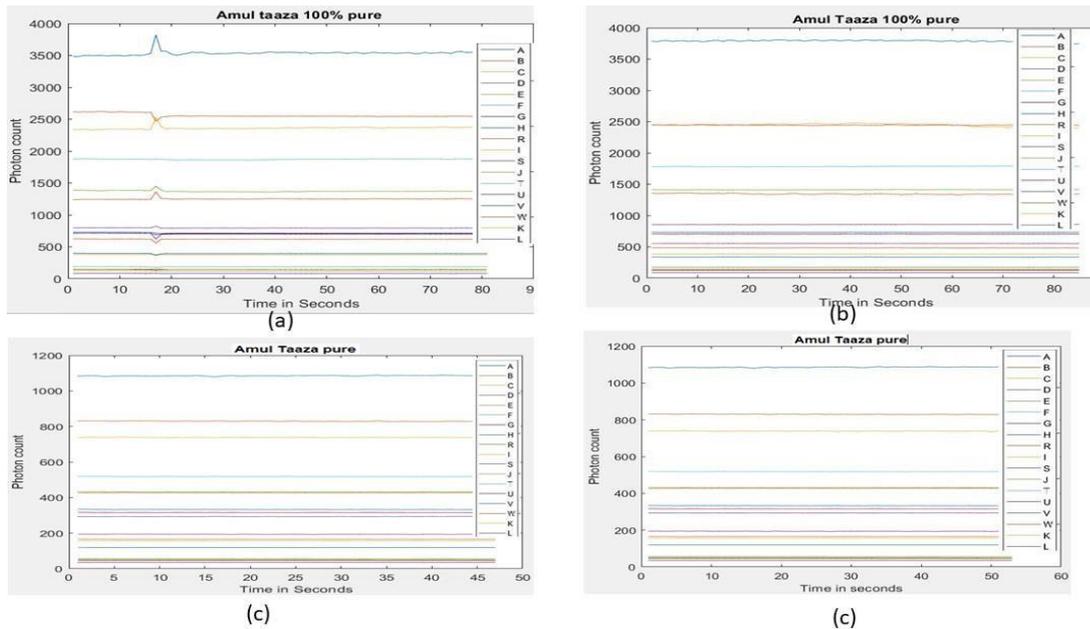


Figure 3.27: All channel response of Aul Taaza milk sample under good illumination with different container

Figure 3.27 shows that although the magnitude for may vary but their pattern is same for all above condition so under good illumination condition any container with any vertical distance is allowed to take reading for classify the milk sample based on level of adulteration.

Now for bad illumination condition we have total 4 conditions as per section 3.3, following figure 3.28 shows the all 18channel data in one go to visualize and identify the changes in graph. Here not only the magnitude of channel signal but the pattern of waveform also changes specially in case of bad illumination with glass container. Also, waveforms are overlapped each other in several portion of graph so to identify the unknown sample is not possible in case of bad illumination condition.

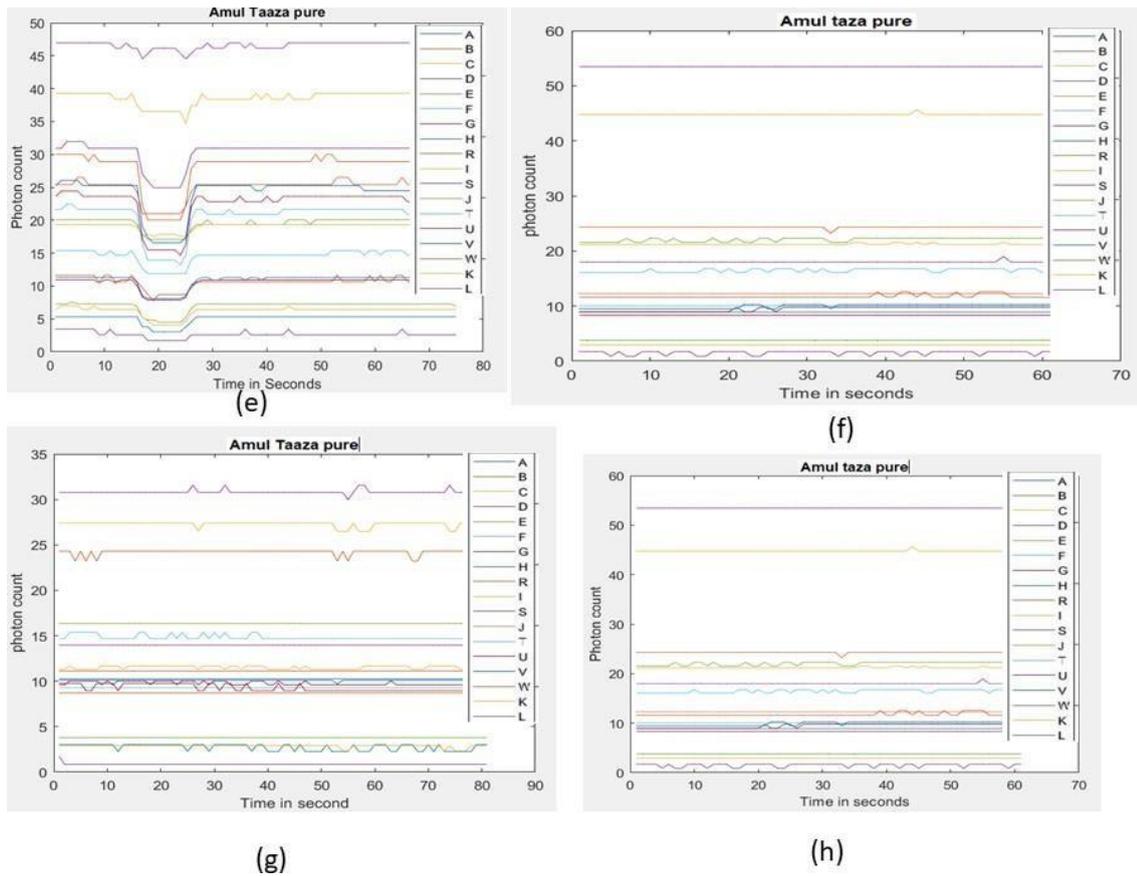


Figure 3.28: All channel response of Amul Taaza 100% pure milk sample under poor illumination with different containers as (e)Amul Taaza 100% pure in bad illumination condition with glass container keeping 1 inch vertical gap between milk surface and sensor, (f) Amul Taaza 100% pure in bad illumination condition with steel container keeping 1 inch vertical gap between milk surface and sensor, (g) Amul Taaza 100% pure in bad illumination condition with glass container keeping 2 inch vertical gap between milk surface and sensor, (h) Amul Taaza 100% pure in bad illumination condition with steel container keeping 2 inch vertical gap between milk surface and sensor.

3.5.b DATA COLLECTION FROM 10% AMUL TAAZA MILK SAMPLE

As per section 3.2 sample is formed of 10% water milk sample i.e. 10ml of water is mixed with 90ml of pure Amul Taaza milk and total 100 ml of solution. Following figure 3.29 depicts the channel data variation for good illumination condition as per section 3.3.

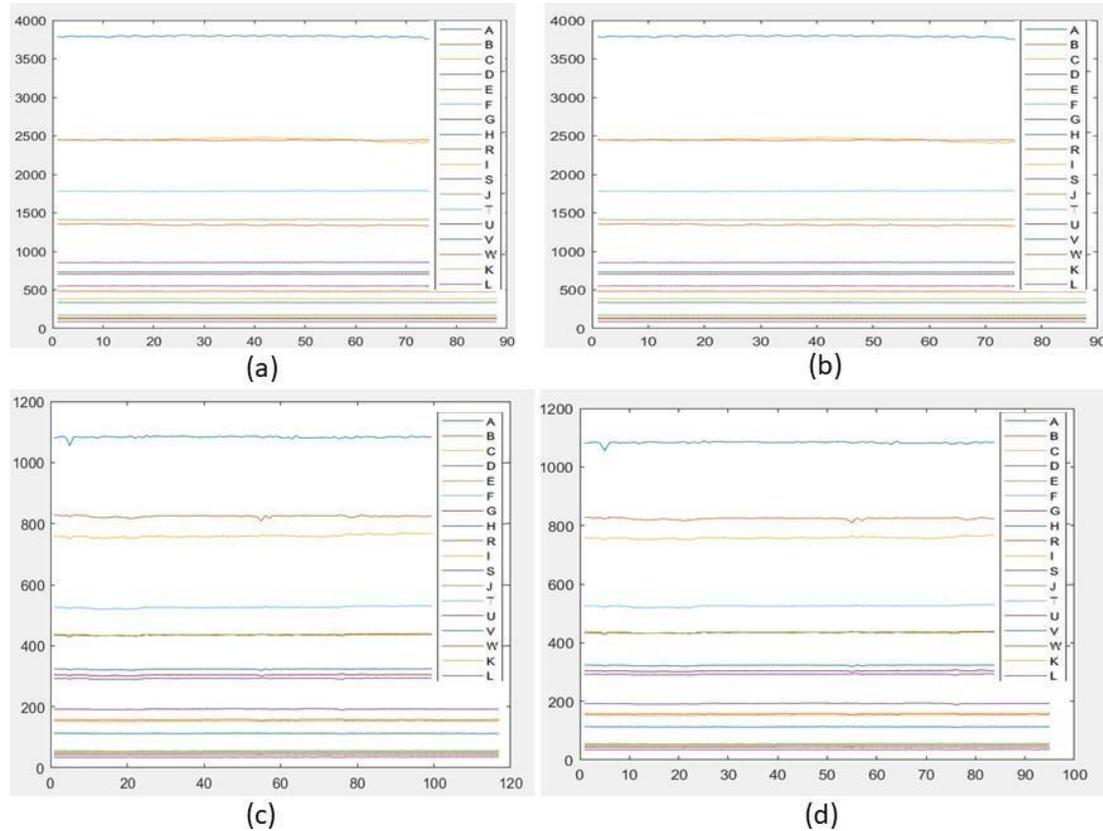


Figure 3.29: All channel response of Amul Taaza milk sample under good illumination with different container and vertical distance between sensor module and milk surface as (a) 10% water milk sample in good illumination condition with glass container keeping 1 inch vertical distance between sensor module and surface of milk sample, (b) 10% water milk sample in good illumination condition with Steel container keeping 1 inch vertical distance between sensor module and surface of milk sample, (c) 10% water milk sample in good illumination condition with glass container keeping 2 inch vertical distance between sensor module and surface of milk sample, (d) 10% water milk sample in good illumination condition with steel container keeping 2 inch vertical distance between sensor module and surface of milk sample

As the data are collected under good illumination condition so irrespective of container material all sample data is useful to classify the milk sample.

Now for the bad illumination condition the data are collected the following figure 3.30 is depicting the variation of channel signal. Here again the same pattern is observed where the signal magnitude along with the overlapping is came. Here one can observe that the variation of channel signal is changing mainly in glass container. In steel container the magnitude of signals are quite high in low illumination condition but equally not suited to for feeding classification problem solving by AI based algorithm.

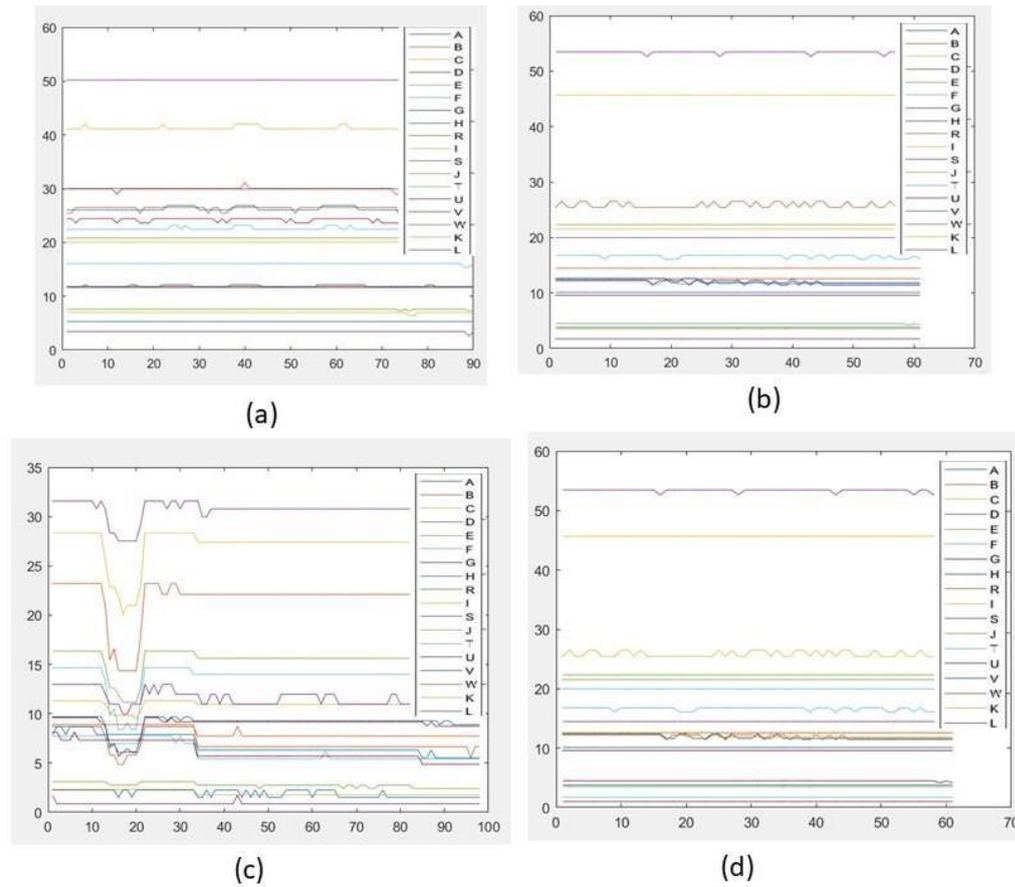


Figure 3.30: Response of 10% Amul Taaza milk in bad illumination condition as (a) under bad illumination condition 10% water milk solution in glass container with 1 inch gap between milk surface and sensor module, (b) under bad illumination condition 10% water milk solution in steel container with 1 inch gap between milk surface and sensor module, (c) under bad illumination condition 10% water milk solution in glass container with 2inch gap between milk surface and sensor module, (d) under bad illumination condition 10% water milk solution in steel container with 2 inch gap between milk surface and sensor module.

3.5.c DATA COLLECTION FROM 20% AMUL TAAZA MILK SAMPLE

As per section 3.2, 20% water milk sample is produced where 20ml of tap water is mixed with 80 ml of pure milk. As we got the experimental data in good and bad illumination condition in previous cases here also, we perform experiment for fist in good illumination condition and in bad illumination condition with different physical parameter as section 3.3.

Now for good illumination condition the figure 3.31 depicted the variation of channel data as follows

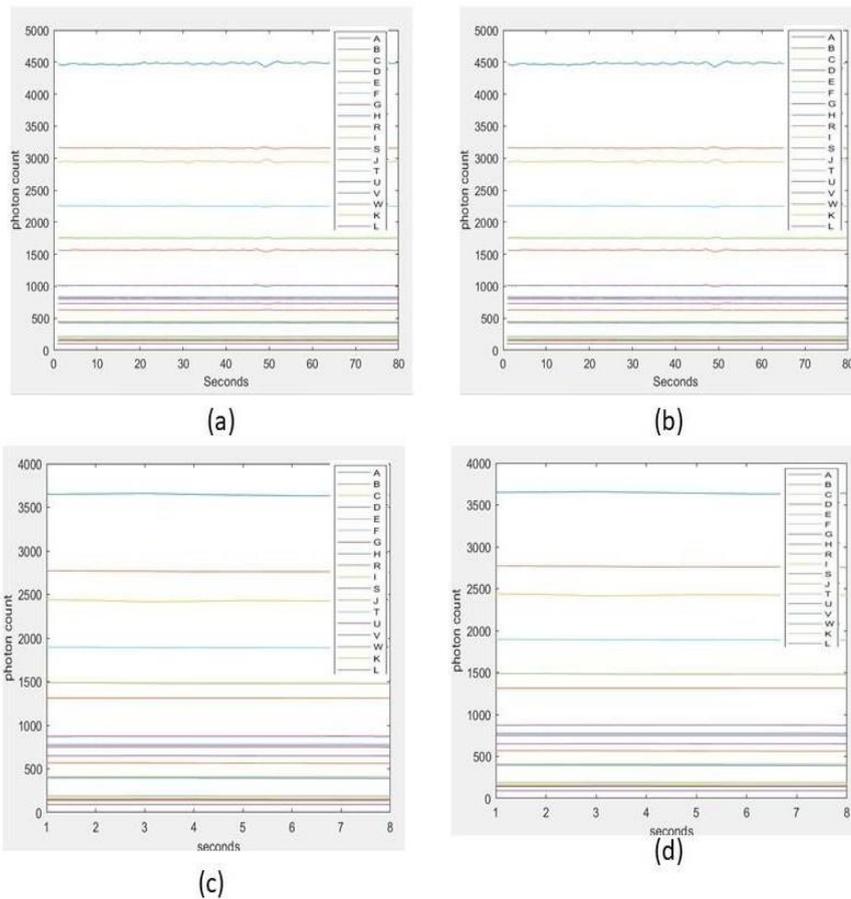


Figure 3.31: 20% Amul Taaza under low illumination condition as (a) under good illumination condition 20% water milk solution in glass container with 1inch gap between sensor and milk sample, (b) under good illumination condition 20% water milk solution in steel container with 1inch gap between sensor and milk sample, (c) under good illumination condition 20% water milk solution in glass container with 2inch gap between sensor and milk sample, (d) under good illumination condition 20% water milk solution in steel container with 2inch gap between sensor and milk sample.

Now for bad illumination condition figure 3.32 showing the channel data as follows. Here as usual low in magnitude and overlapping waveform is generated which has poor performance for classify the different adulterated milk.

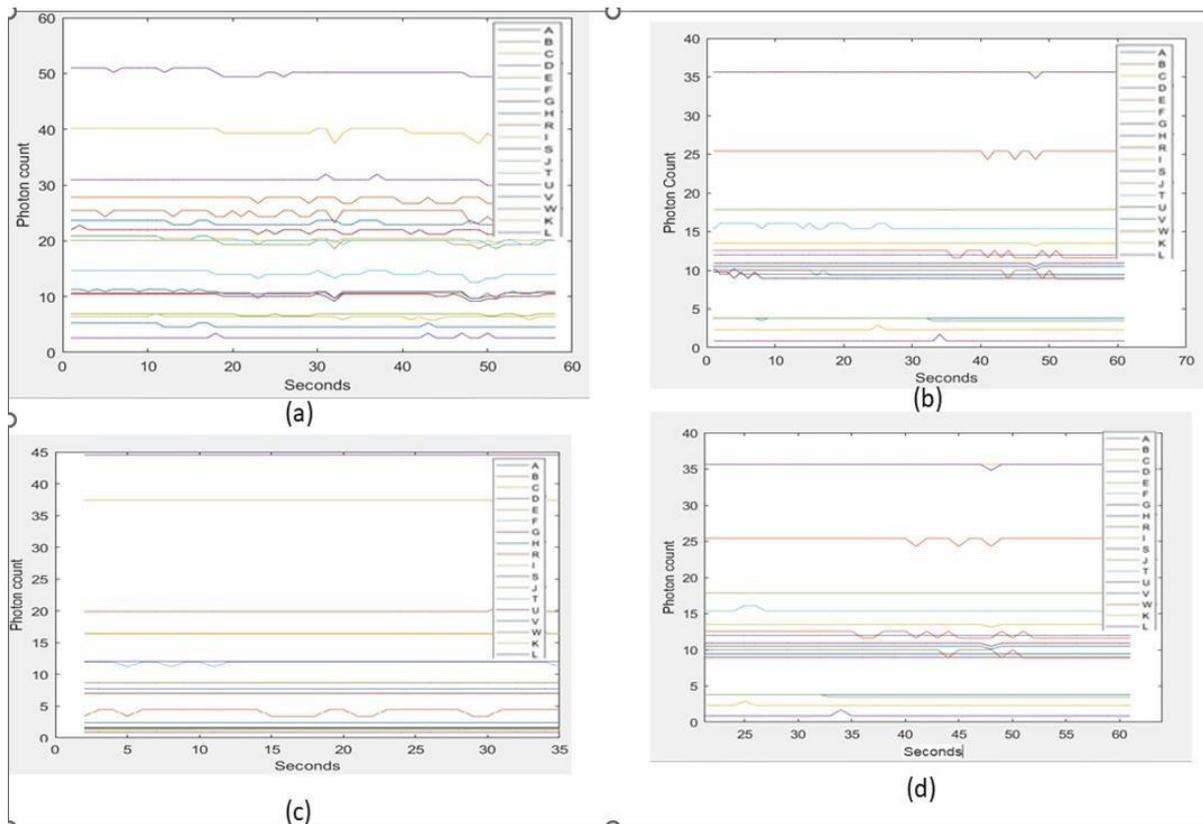


Figure 3.32: 20% Amul Taaza under low illumination as (a) Under bad illumination condition 20% water milk solution in glass container with 1inch gap between sensor and milk sample, (b) Under bad illumination condition 20% water milk solution in steel container with 1inch gap between sensor and milk sample, (c) Under bad illumination condition 20% water milk solution in glass container with 2inch gap between sensor and milk sample, (d) Under bad illumination condition 20% water milk solution in steel container with 2 inch gap between sensor and milk sample.

3.5.d DATA COLLECTION FROM 30% AMUL TAAZA MILK SAMPLE

As per section 3.2 sample is prepared using 30 ml of tap water mixed with 70ml of pure Amul Taaza milk and we got 30% water milk solution.

As per section 3.3 under different conditions data is collected now figure 3.33(a) shows the channel data variation under good illumination condition. As expected all channel data is having high magnitude with proper distinct and apart from each other, hence ideal for post processing. And Figure 3.33(b) shows the variation of channel data under low light or low illumination condition.

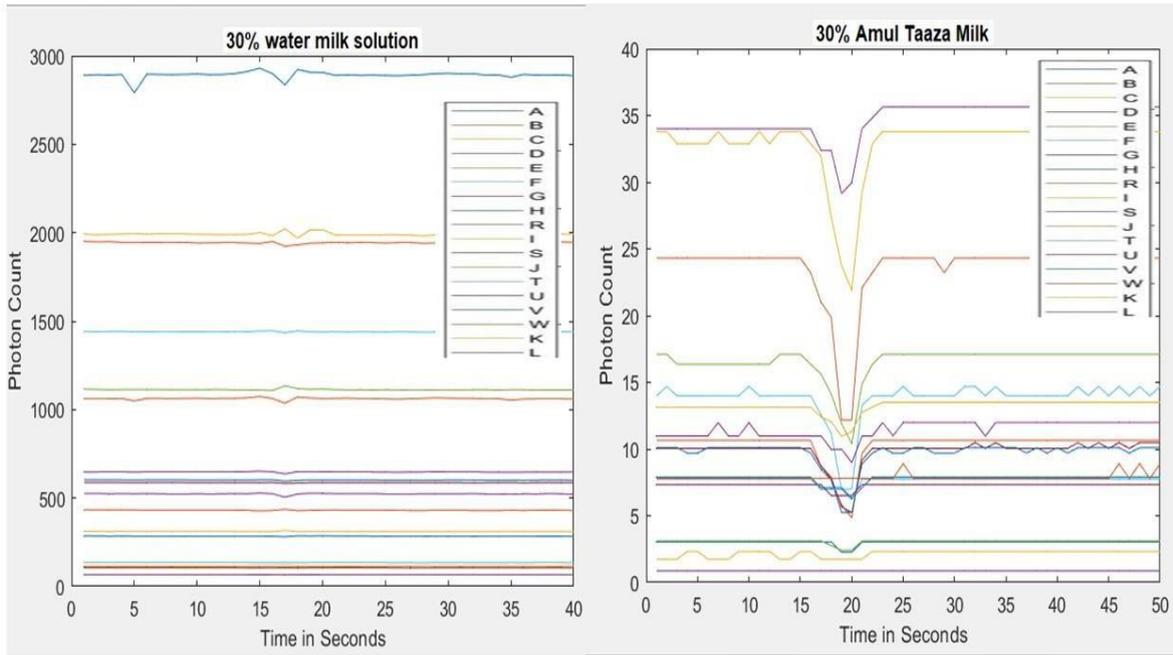


Figure 3.33(a)

Figure 3.33(b)

3.5.e DATA COLLECTION FROM 50% AMUL TAAZA MILK SAMPLE

As per section 3.2 sample is prepared using 50 ml of tap water mixed with 50ml of pure Amul Taaza milk and we got 50% water milk solution.

As per section 3.3 under different conditions data is collected now figure 3.34(a) shows the channel data variation under good illumination condition. As expected all channel data is having high magnitude with proper distinct and apart from each other, hence ideal for post processing. And Figure 3.34(b) shows the variation of channel data under low light or low illumination condition.

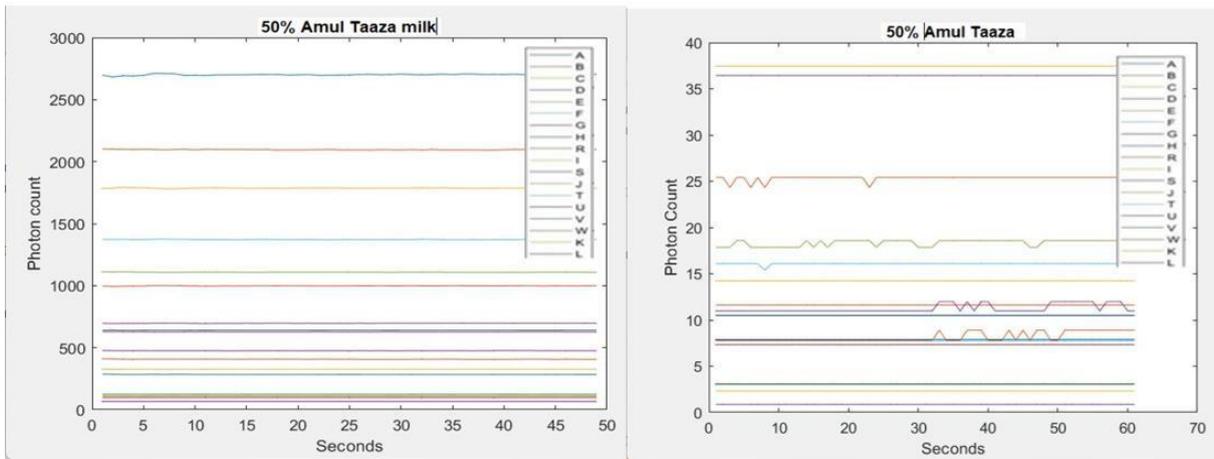


Figure 3.34(a)

Figure 3.34(b)

Figure 3.34: 50% Amul Taaza milk all channel response as (a) channel data under good illumination and (b) channel data under bad illumination

3.6 DATA COLLECTION FROM RED COW AND RED COW REGULAR COW MILK SAMPLE



Figure 3.35(a)

Figure 3.35(b)



Figure 3.35(c)

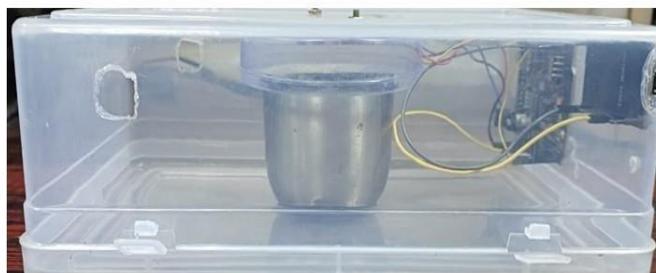


Figure 3.35(d)

Figure 3.35: Red cow milk with its nutritional elements as (a) Red cow creamy delight with its ingredients showing total fat content is 4.6 g (13.7%) per 100ml and (b) Red cow regular with total fat content 1.55g (4.6%) per 100 ml, also (c) data collecting in glass container with good illumination condition and (d) data is collected under low light or bad illumination condition.

3.6.a DATA COLLECTION FROM 100% PURE RED COW CREAMY DELIGHT AND RED COW REGULAR MILK SAMPLE

Now as per section 3.3, experiments were conducted and following figure 3.36(a) showing the channel data variation under good illumination condition and figure 3.36(b) showing the data of channels under low illumination condition. Here also as expected at good illumination condition the channel data's magnitude and their separation is well defined but in case of low light situation the magnitude is low and channel data are overlapping.

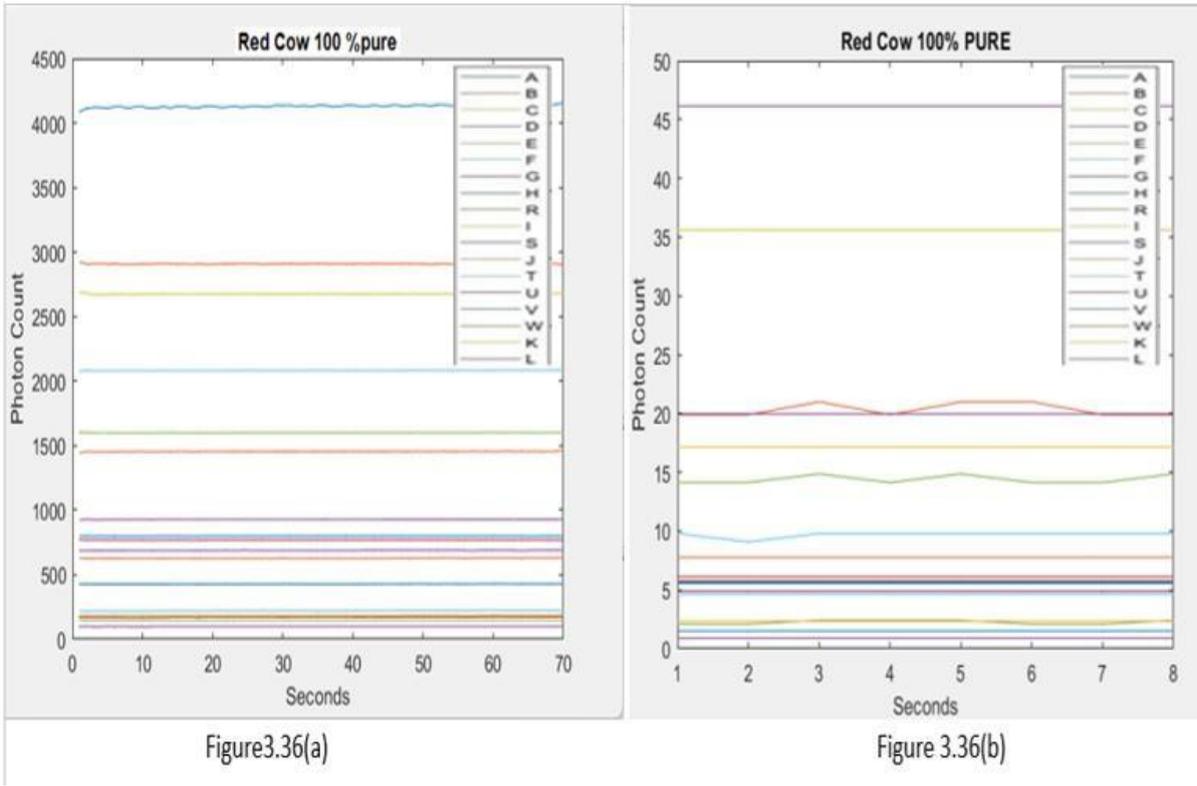


Figure 3.36: All channel response of red cow milk as (a) Under good illumination condition in glass container with 1 inch gap between sensor module and milk surface, 3.36(b) Under bad illumination condition in glass container with 1 inch gap between sensor module and milk surface.

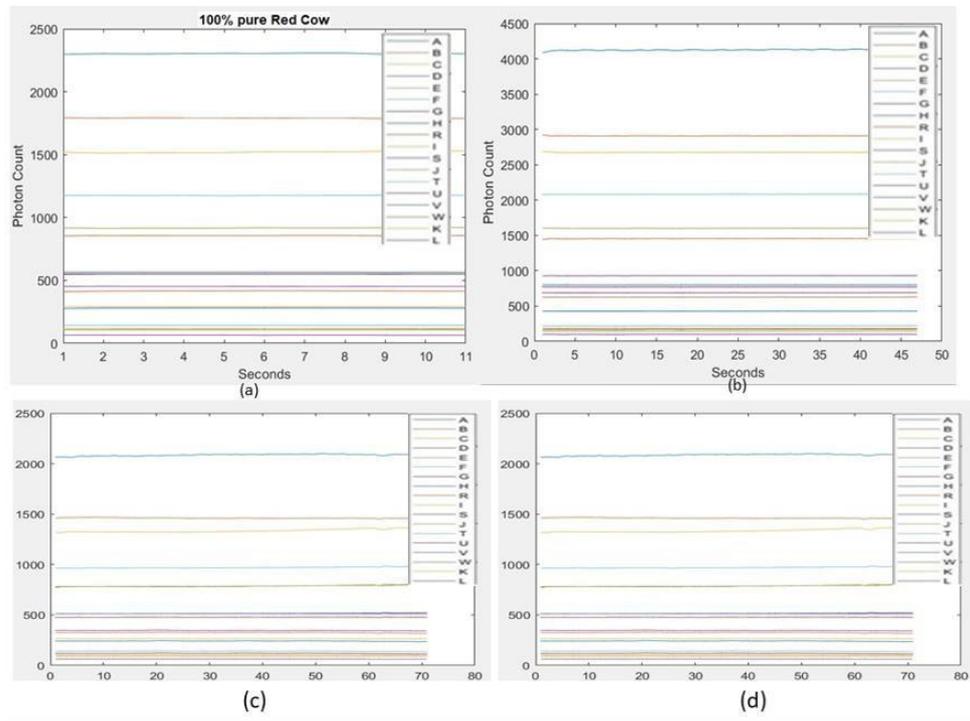


Figure3.37: All channel response of 100% red cow milk

Figure 3.37 (a) showing the channel variation under good illumination condition with glass container having 1 inch gap between sensor and milk surface, Figure 3.37 (b) showing the channel variation under good illumination condition with steel container having 1 inch gap between sensor and milk surface, Figure 3.37 (c) showing the channel variation under good illumination condition with glass container having 2 inch gap between sensor and milk surface and Figure 3.37 (d) showing the channel variation under good illumination condition with steel container having 2 inch gap between sensor and milk surface.

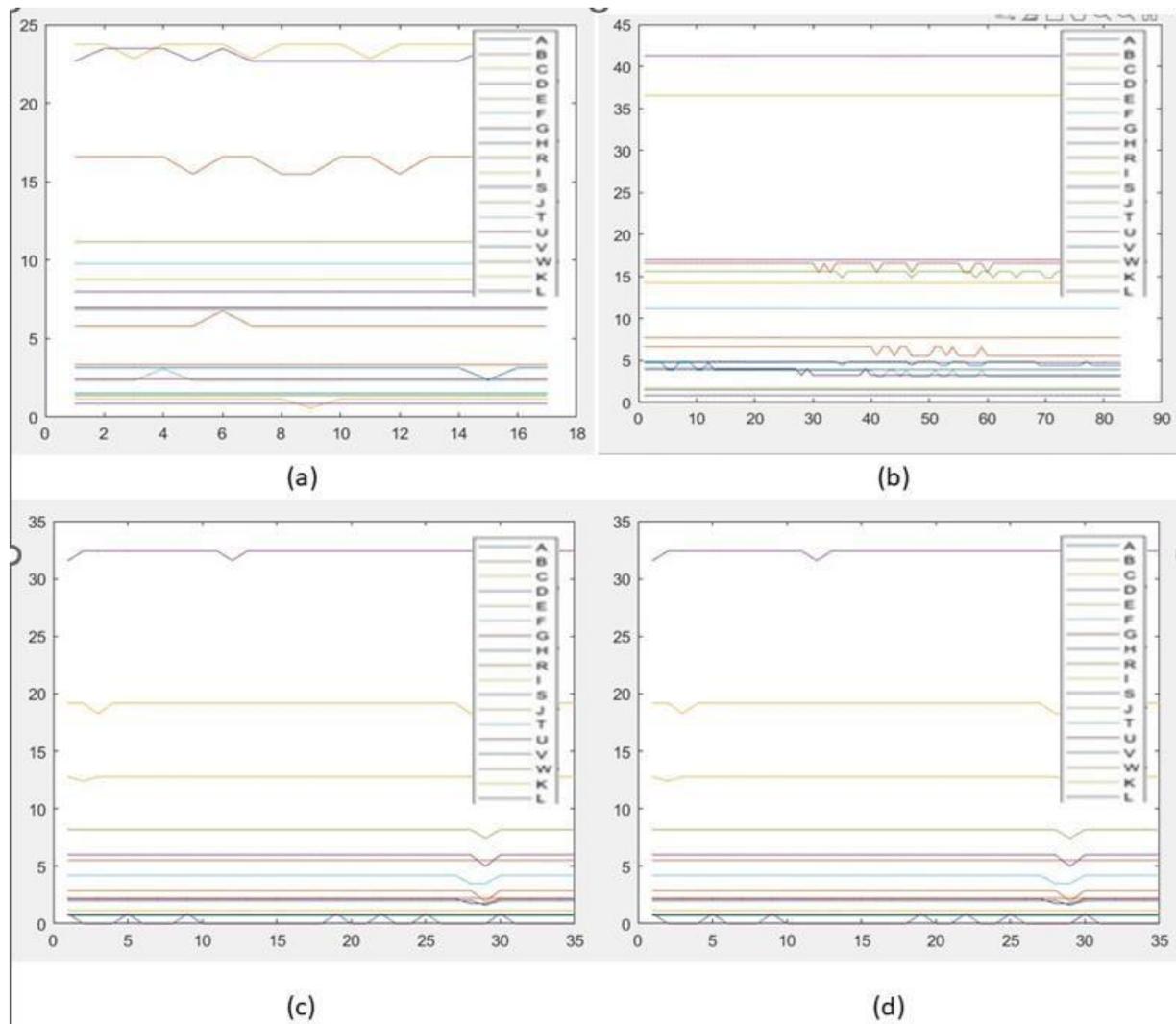


Figure 3.38: All channel response of 100% pure red cow as (a) under good illumination condition glass container with 1 inch separation, (b) under good illumination condition steel container with 1 inch separation, (c) under good illumination condition glass container with 2 inch separation, (d) under good illumination condition steel container with 2 inch separation

3.6.b DATA COLLECTION FROM 10% WATER RED COW CREAMY DELIGHT AND RED COW REGULAR MILK SAMPLE

As per section 3.2 sample is formed of 10% water milk sample i.e. 10ml of water is mixed with 90ml of pure Red Cow milk and total 100 ml of solution. Following figure 3.39 depicts the channel data variation for good illumination condition as per section 3.3.

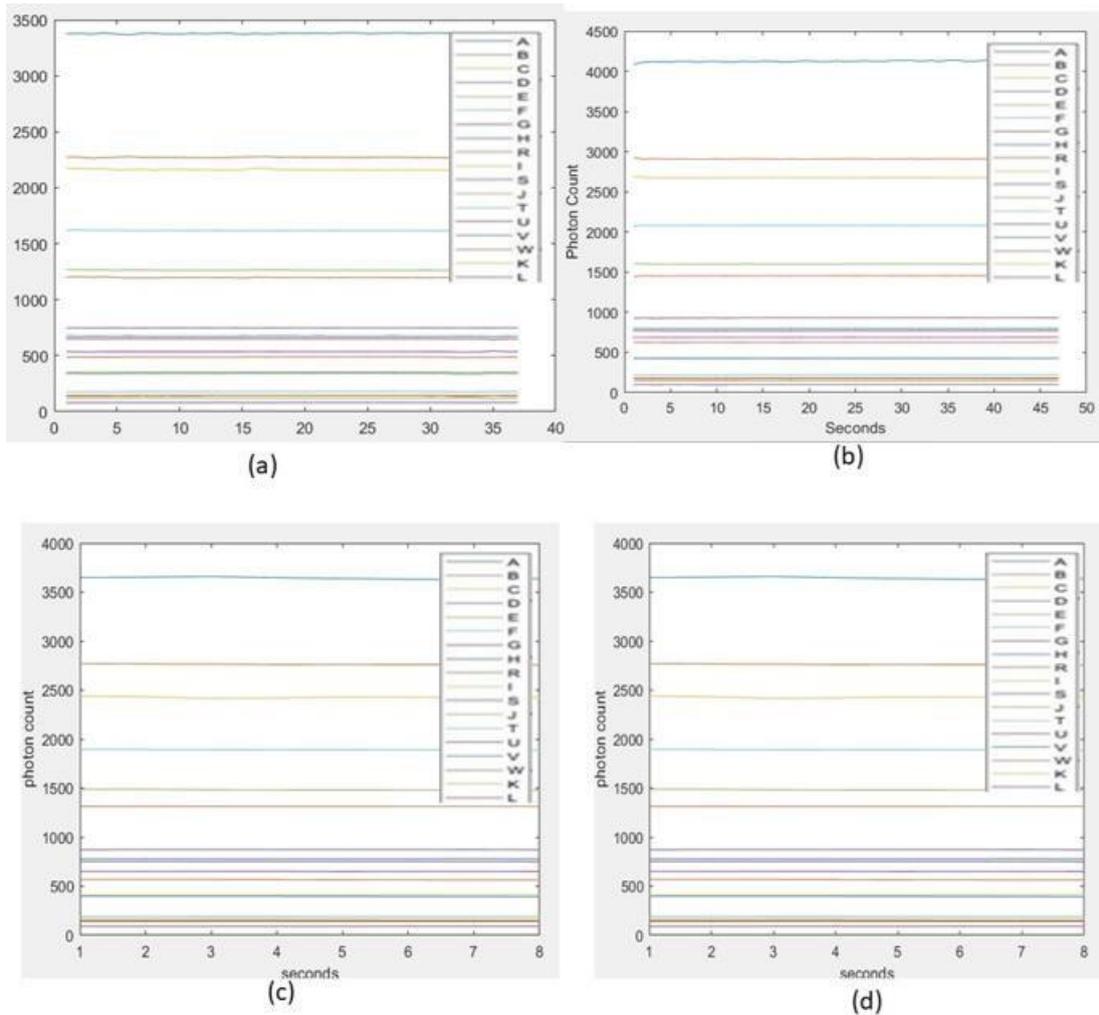


Figure 3.39: All channel response of 10% red cow milk as (a) under good illumination condition glass container with 1 inch separation, (b) under good illumination condition steel container with 1 inch separation, (c) under good illumination condition glass container with 2 inch separation, (d) under good illumination condition steel container with 2 inch separation.

3.6.c DATA COLLECTION FROM 20% WATER RED COW CREAMY DELIGHT AND RED COW REGULAR MILK SAMPLE

As per section 3.2 sample is formed of 20% water milk sample i.e. 20ml of water is mixed with 80ml of pure Red Cow milk and total 100 ml of solution. Following figure 3.40 depicts the channel data variation for good illumination condition as per section 3.3.

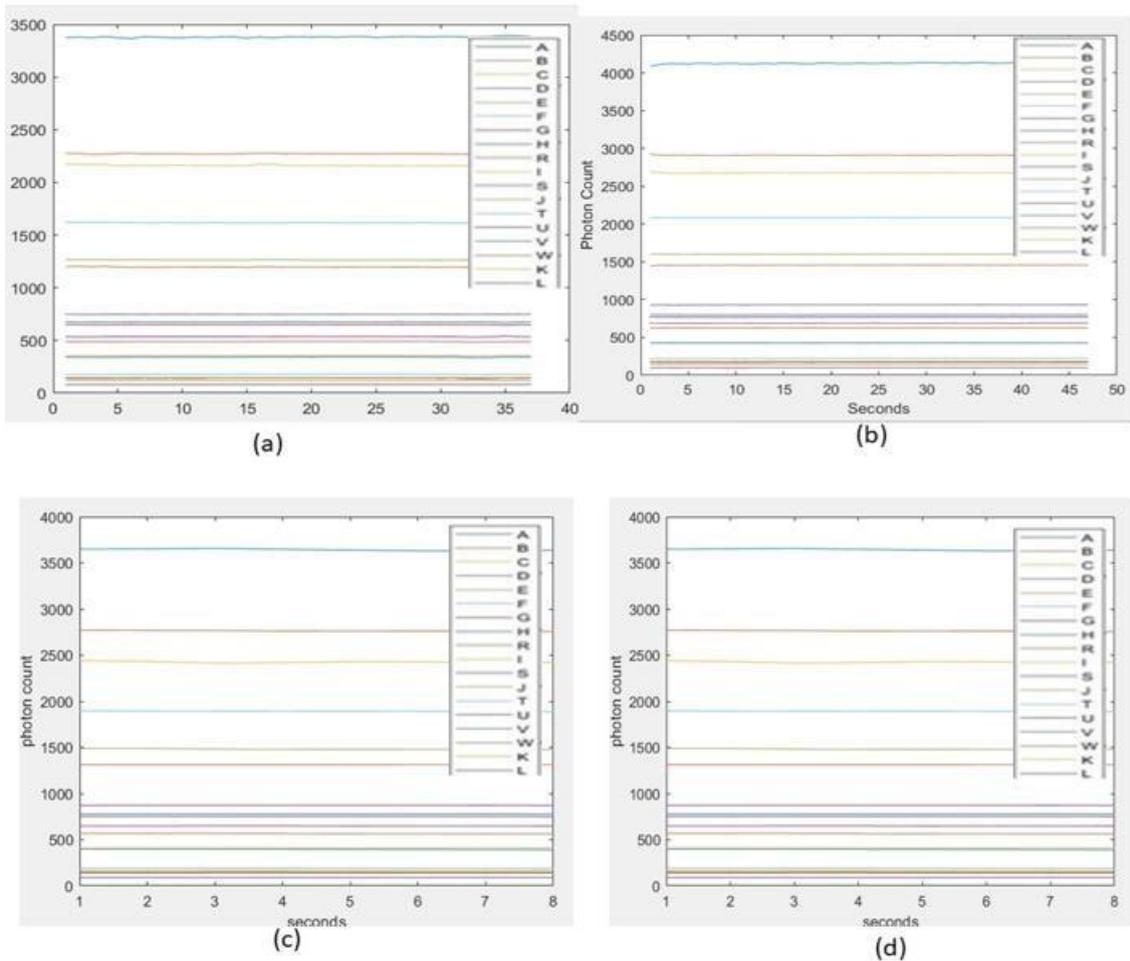


Figure 3.40: All channel response of 20% red cow milk

Figure 3.40(a) under good illumination condition glass container with 1 inch separation Figure 3.40(b) under good illumination condition steel container with 1 inch separation, Figure 3.40(c) under good illumination condition glass container with 2 inch separation, Figure 3.40(d) under good illumination condition steel container with 2 inch separation.

And figure 3.41 shows all 18 channel data under low illumination condition as follows

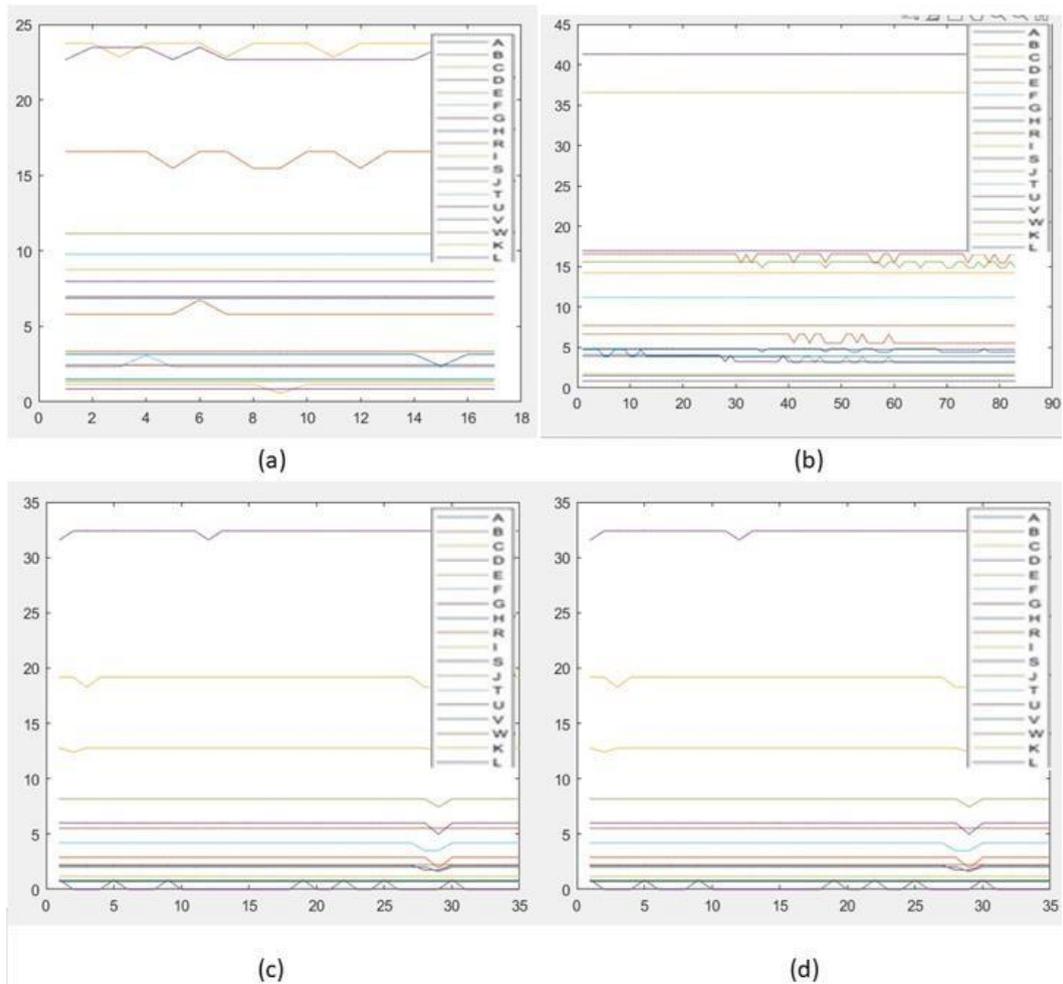


Figure 3.41: All channel response under poor illumination of 20% red cow milk

Figure 3.41(a) under poor illumination condition glass container with 1 inch separation Figure 3.41(b) under poor illumination condition steel container with 1 inch separation, Figure 3.41(c) under poor illumination condition glass container with 2inch separation, Figure 3.41(d) under poor illumination condition steel container with 2inch separation.

3.6.d DATA COLLECTION FROM 30% WATER RED COW CREAMY DELIGHT AND RED COW REGULAR MILK SAMPLE

As per section 3.2 sample is formed of 30% water milk sample i.e. 30ml of water is mixed with 70ml of pure Red Cow milk and total 100 ml of solution. Following figure 3.42 depicts the channel data variation for good illumination condition as per section 3.3.

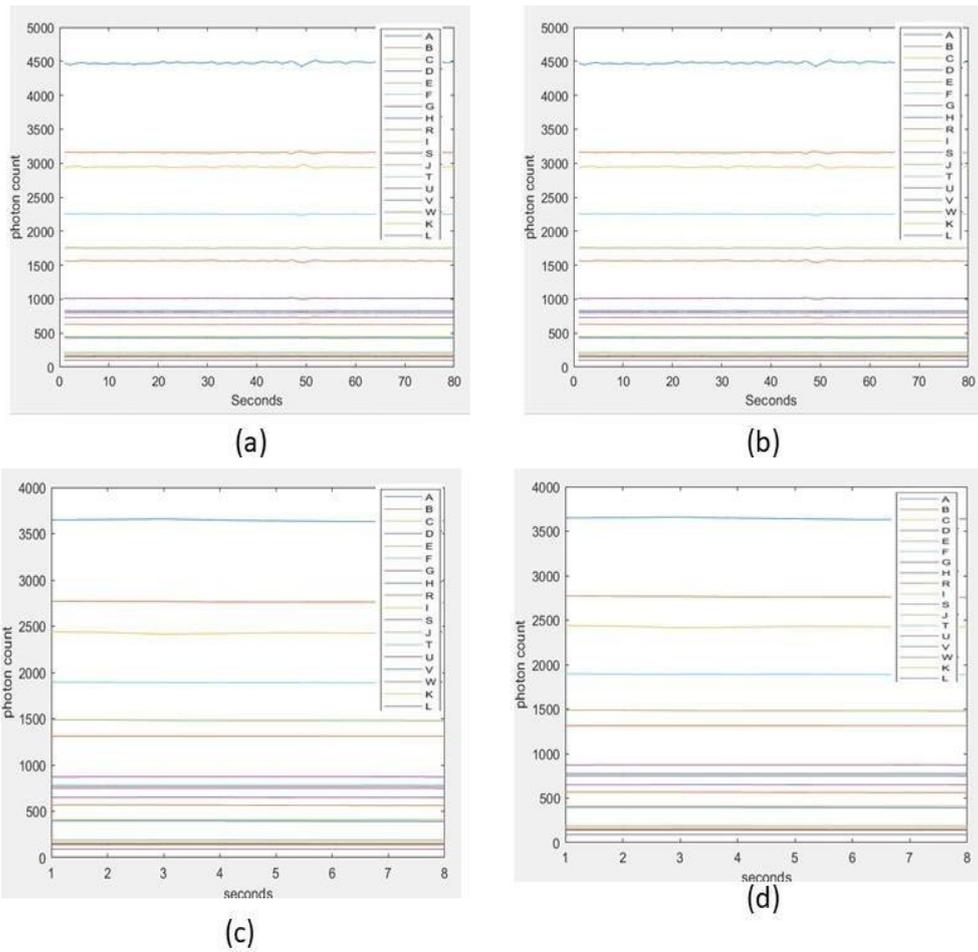


Figure 3.42: All channel response of 30% red cow milk as (a) under good illumination condition glass container with 1 inch separation, (b) under good illumination condition steel container with 1 inch separation, (c) under good illumination condition glass container with 2inch separation, (d) under good illumination condition steel container with 2inch separation.

And figure 3.43 shows all 18channel data under low illumination condition as follows

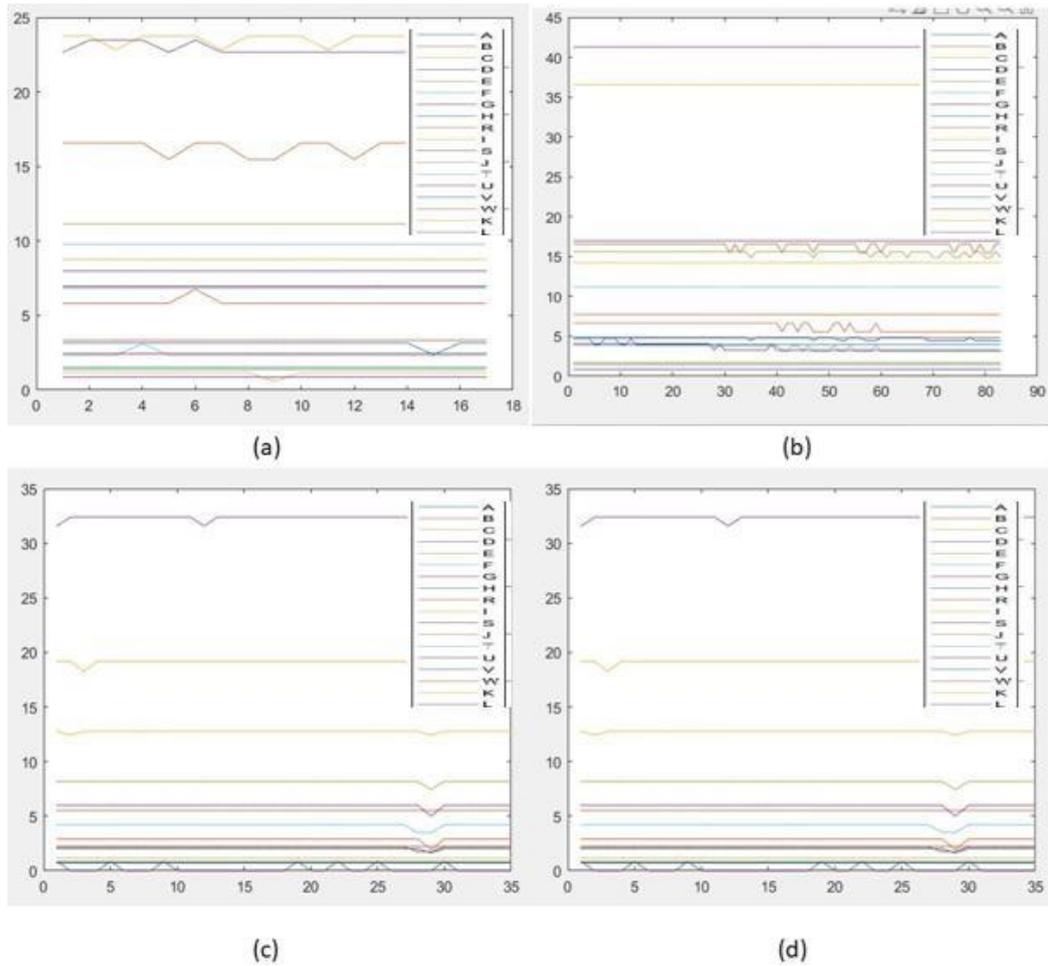


Figure 3.43: All channel response of 30% red cow milk under bad illumination as (a) under poor illumination condition glass container with 1 inch separation, (b) under poor illumination condition steel container with 1 inch separation, (c) under poor illumination condition glass container with 2inch separation, under poor illumination condition steel container with 2inch separation.

3.6.e DATA COLLECTION FROM 50% WATER RED COW CREAMY DELIGHT AND RED COW REGULAR MILK SAMPLE

As per section 3.2 sample is prepared using 50 ml of tap water mixed with 50ml of pure Red Cow milk and we got 50% water milk solution.

As per section 3.3 under different conditions data is collected now figure 3.44(a) shows the channel data variation under good illumination with glass container condition. As expected, all channel data is having high magnitude with proper distinct and apart from each other, hence ideal for post processing. And Figure 3.44(b) shows the variation of channel data under good illumination taking steel container.

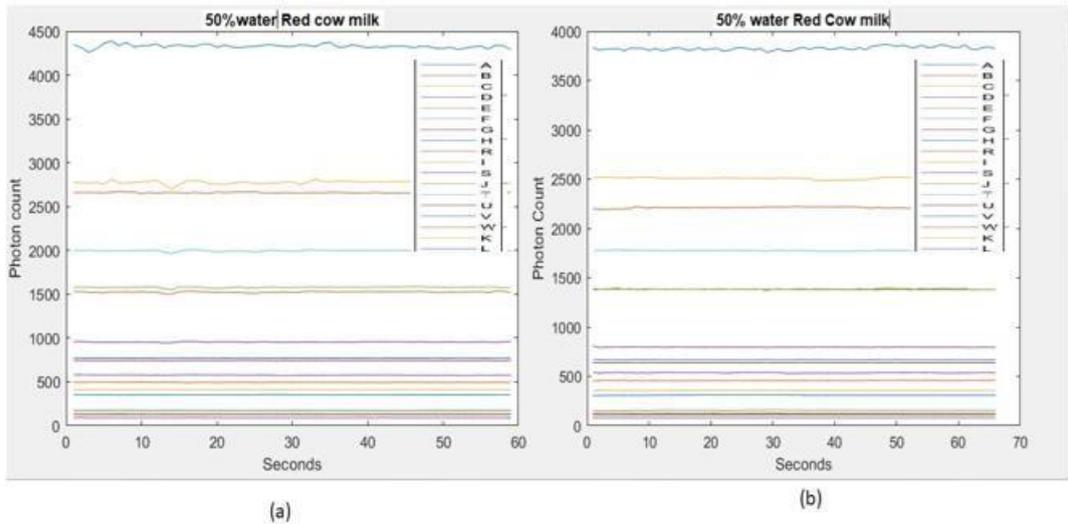


Figure 3.44: All channel response of 50% red cow milk under good illumination as (a) channel data variation under good illumination with glass container condition, (b) under good illumination taking steel container.

Figure 3.45 shows the variation of channel under low illumination condition

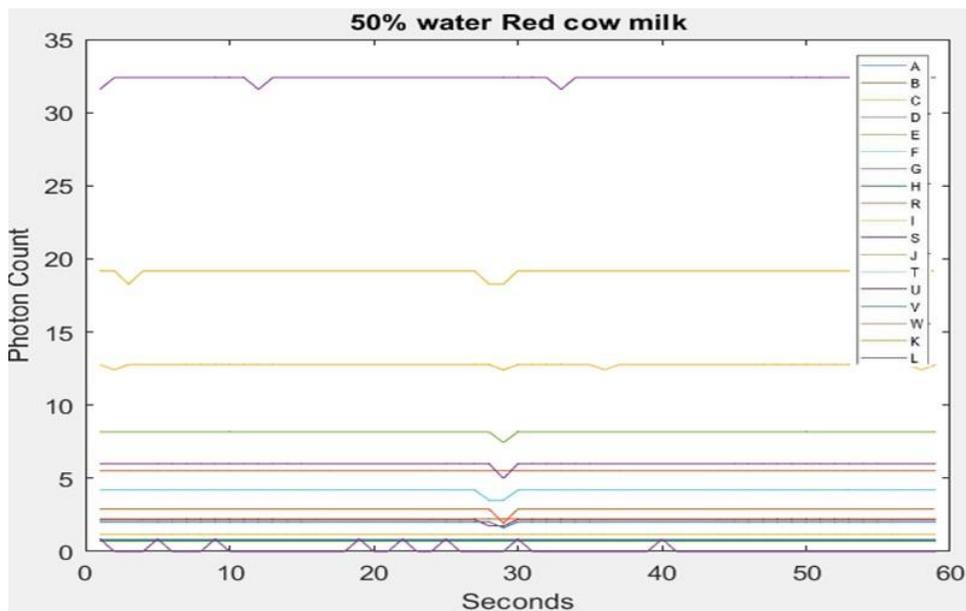


Figure 3.45: Variation channel response of 50% water red cow milk under low illumination
 Here in figure 3.45 also the channel data are mixing or overlapping and we got same outcome as previous cases.

3.7 DATA COLLECTION FROM BHAGIRATHI MILK SAMPLE



Figure 3.46: Bhagirathi milk with its contents

Figure 3.46 shows the Bhagirathi milk sample’s contents and we took total fat of 1.6g per 100g of milk sample. We consider this value to train the AI based algorithm to determine total fat content of unknown milk sample.

3.7.a DATA COLLECTION FROM 100% PURE BHAGIRATHI MILK SAMPLE

As per section 3.2, one can prepare the 100ml of pure milk sample and following figure 3.47(a) shows the all channel variation under good illumination and figure 3.47(b) shows all 18 channel variation under low illumination condition.

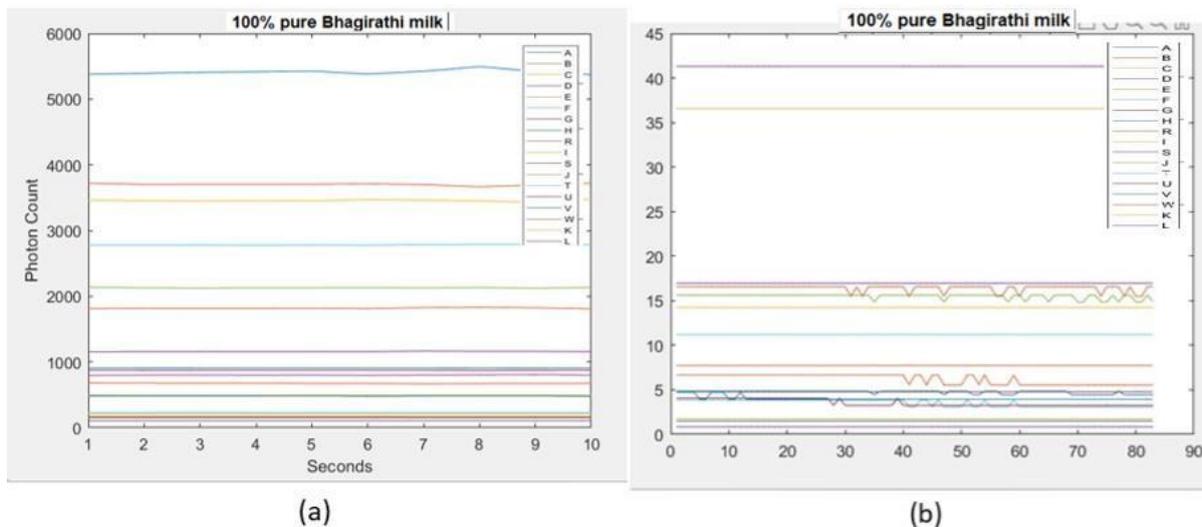


Figure 3.47: All 18channel response of Bhagirathi milk sample under good and bad illumination as (a) good illumination and (b) bad illumination

3.7.b DATA COLLECTION FROM 10% WATER MILK SOLUTION OF BHAGIRATHI MILK SAMPLE

As per section 3.2 sample is prepared and total 10ml water mixed with 90ml of Bhagitarhi milk sample and under good illumination condition we got the outcome which is depicted in figure 3.48 (a) and in figure 3.48(b).

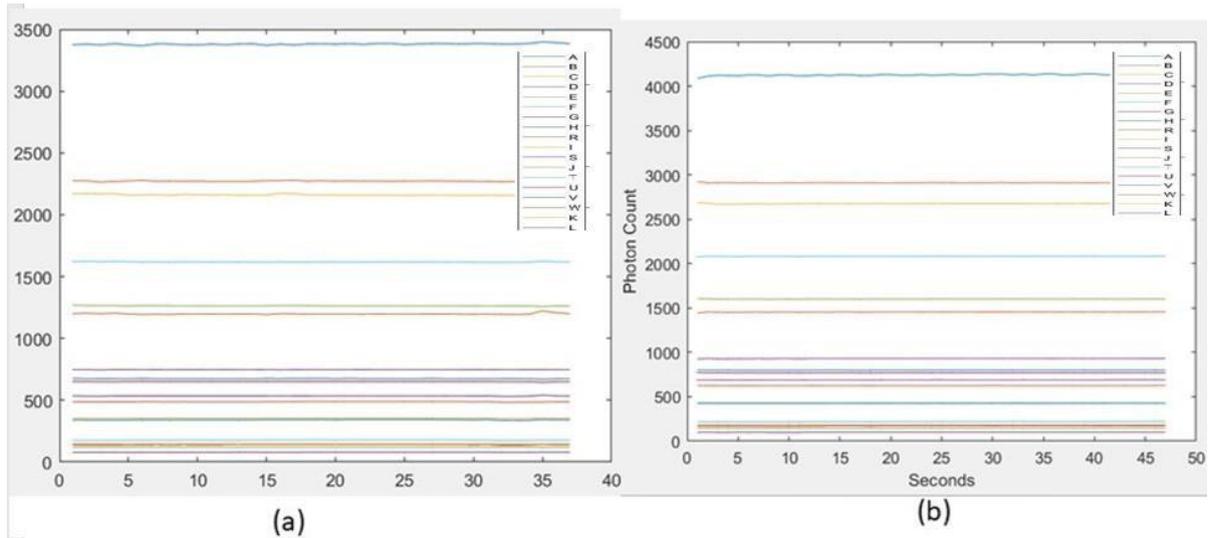


Figure 3.48: All channel response of 10% Bhagirathi milk sample under good illumination condition as (a) with glass container and (b) with steel container

3.7.c DATA COLLECTION FROM 20% WATER MILK SOLUTION OF BHAGIRATHI MILK SAMPLE

As per section 3.2 we mix 20ml of tap water with 80 ml of pure Bhagirathi milk to make 20% water milk solution and figure 3.48(a) and 3.48(b) shows the all 18 channels data variation under good and low illumination condition

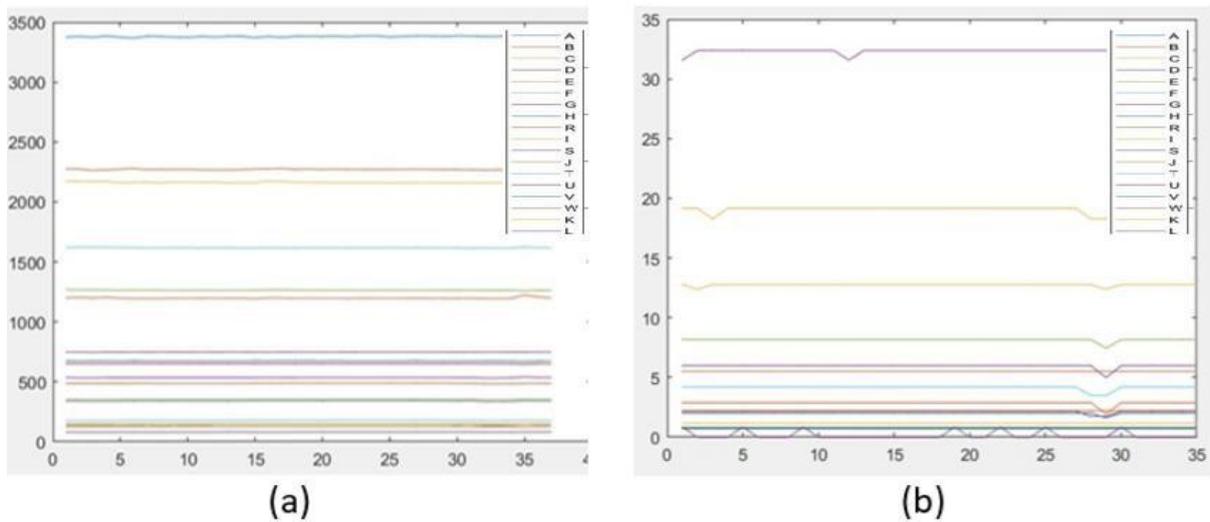


Figure 3.48: All channel response of 20% water Bhagirathi milk solution sample under good and bad illumination as (a) good illumination with glass container keeping 1 inch gap and (b) bad illumination with glass container keeping 1 inch gap

3.7.d DATA COLLECTION FROM 30% WATER MILK SOLUTION OF BHAGIRATHI MILK SAMPLE

As per section 3.2 the sample is prepared and figure 3.49(a) and figure 3.49(b) shows the all 18 channel data under good illumination and low illumination condition as follows

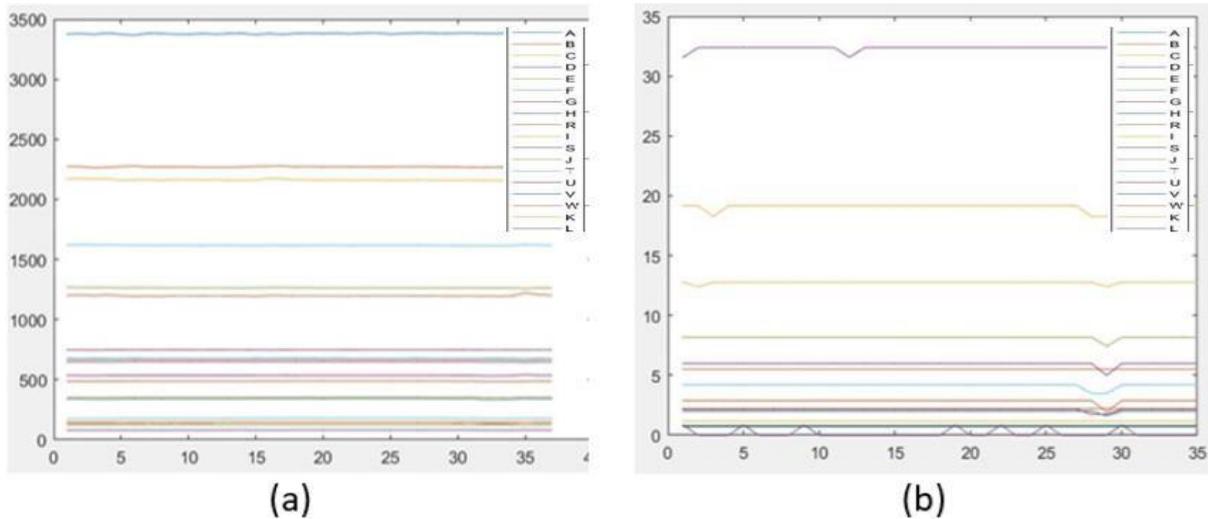


Figure 3.49: All channel response of 30% adulterated Bhagitarhi milk sample as (a) under good illumination and (b) under bad illumination with glass container keeping 1 inch gap

3.7.e DATA COLLECTION FROM 50% WATER MILK SOLUTION OF BHAGIRATHI MILK SAMPLE

As per section 3.2 we mix 50ml of pure Bhagirathi cow milk with 50ml of tap water having TDS of 43 PPM to make 50% water milk sample and figure 3.50(a) and 3.50(b) is showing the variation of all channel data under good and bad light condition as follows

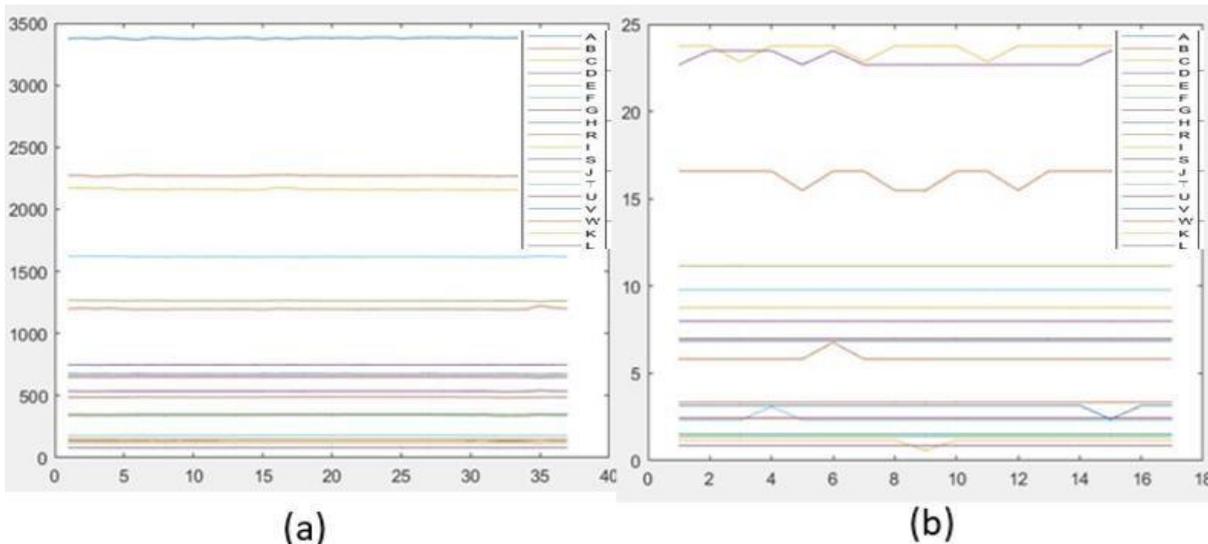


Figure 3.50: All channel response of 50% Bhagirathi milk under good and bad illumination as (a) under good illumination with glass container keeping 2inch gap and (b) under bad illumination with steel container keeping 1 inch gap

3.8 DATA COLLECTION FROM SUPERT MILK SAMPLE



Figure 3.51: Picture of SuperT milk with its content table

As per section 3.2 sample is prepared and as per section 3.3 all conditions are explored.

3.8.a DATA COLLECTION FROM PURE MILK SAMPLE

As per section 3.2, 100ml of pure superT milk is taken to perform experiment. Following figure 3.52 shows the variation of channel data under good and bad illumination condition.

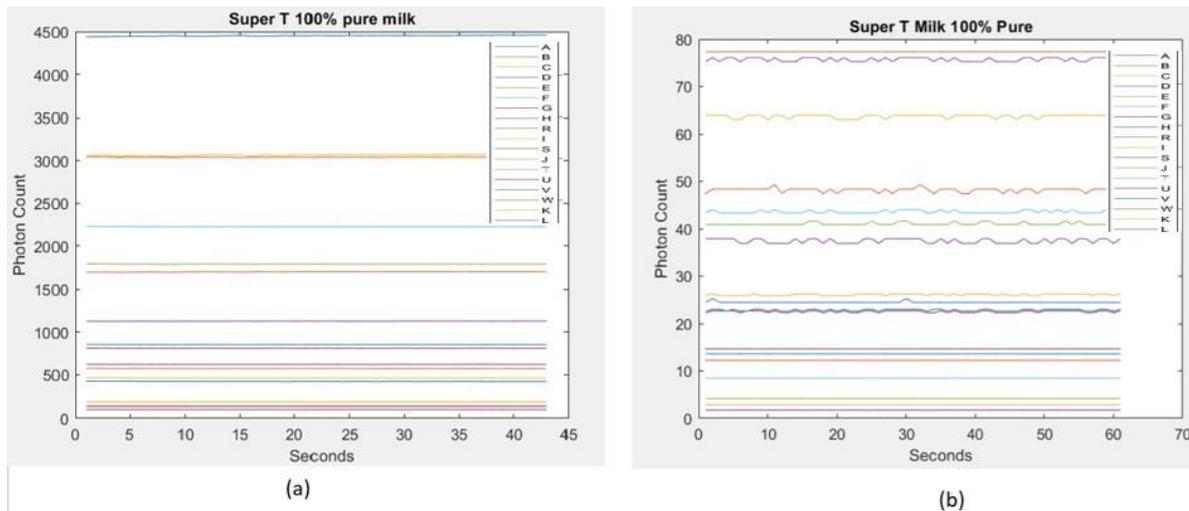


Figure 3.52: Response of SuperT milk under good and bad illumination condition

Figure 3.52(a) showing the response under good illumination condition and figure 3.52(b) shows the variation of data under low illumination condition. Both cases the milk sample was taken in glass container and keeping vertical gap of 1 inch.

3.8.b DATA COLLECTION FROM 10% WATER MILK SOLUTION

As per section 3.2, 10 ml of tap water is mixed with 90 ml of pure superT milk and the 10% water milk sample was made and the following figure 3.53 is showing the outcome under good and poor illumination condition.

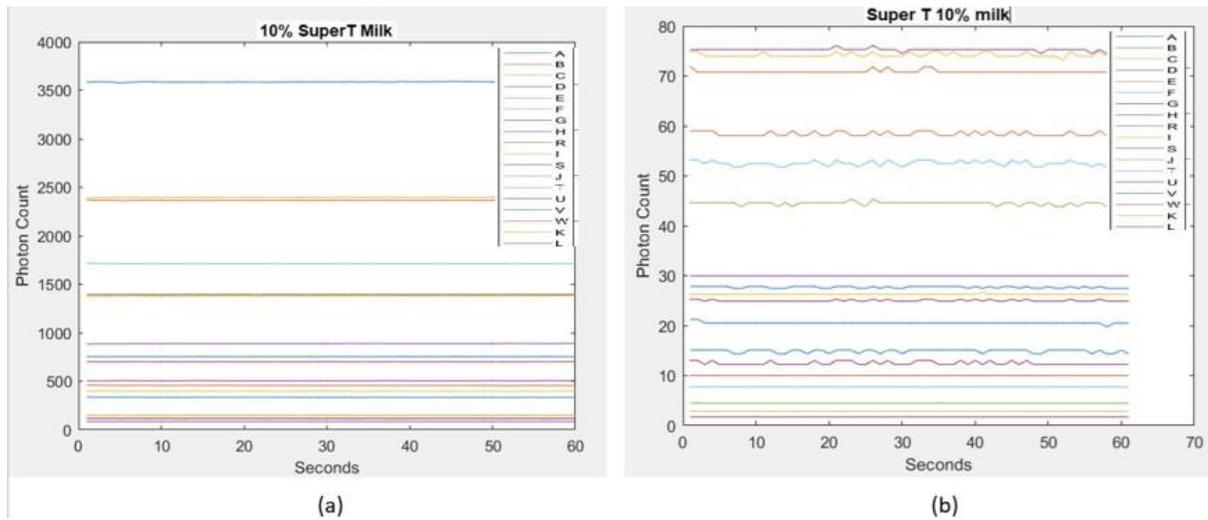


Figure 3.53: Response of all channel of SuperT milk sample under good and illumination conditions

Figure 3.53(a) shows 10% water milk sample spectroscopic response of all 18 channels response under good illumination condition. And figure 3.53(b) showing the channel data of 10% water milk solution under poor illumination condition.

3.8.c DATA COLLECTION FROM 20% WATER MILK SOLUTION

As per section 3.2, 20 ml of tap water is mixed with 80 ml of pure superT milk and the 20% water milk sample was made and the following figure 3.54 is showing the outcome under good illumination condition.

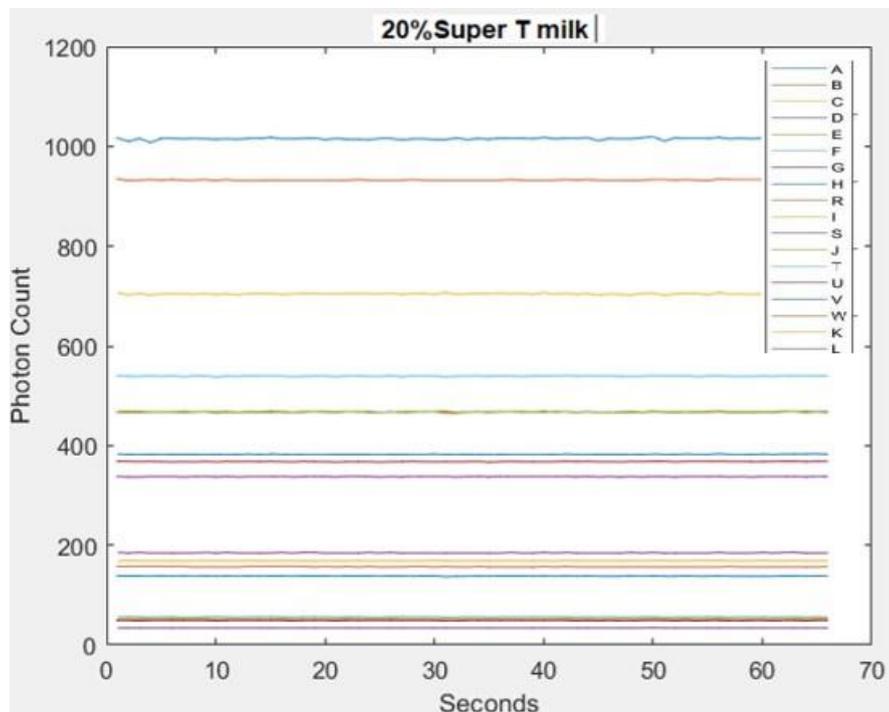


Figure3.54: Response of all channel of 20% solution of Super T milk sample under good illumination condition.

As shown in figure 3.54, under good illumination condition all channel's data are well separated and having high magnitude.

3.8.d DATA COLLECTION FROM 30% WATER MILK SOLUTION

As per section 3.2, 30 ml of tap water is mixed with 70 ml of pure superT milk and the 30% water milk sample was made and the following figure 3.55 is showing the outcome under good and bad illumination condition.

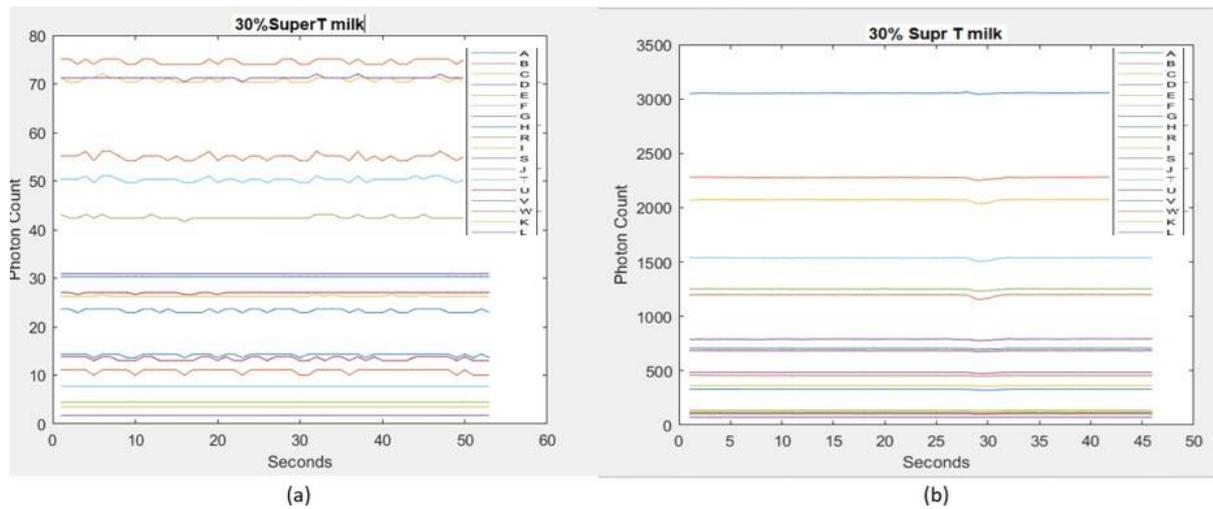


Figure 3.55: Channel response for 30% water SuperTmilk sample under good and bad illumination condition (a)under good illumination and (b) under bad illumination

In figure 3.55(a) shows the channel response under bad illumination condition, we can see here also that all channel data are distinct and well separated but having low magnitude as compared to channel response under good illumination condition which is depicted in figure 3.55(b).

3.8.e DATA COLLECTION FROM 50% WATER MILK SOLUTION

As per section 3.2, 50 ml of tap water is mixed with 50 ml of pure superT milk and the 50% water milk sample was made and the following figure 3.56 is showing the outcome under good and bad illumination condition.

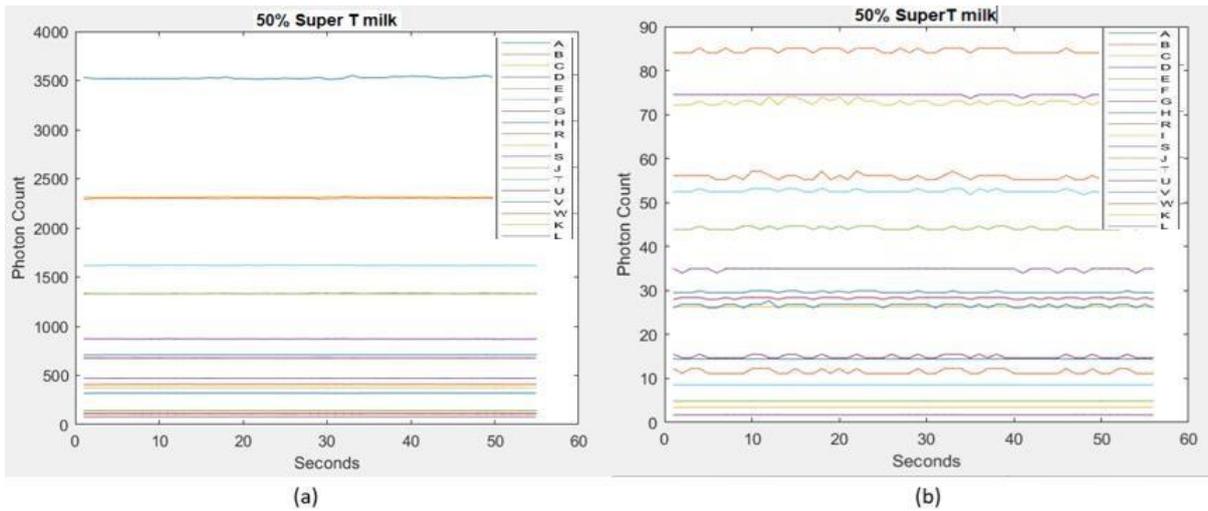


Figure 3.56: Response of 50% water SuperT milk solution under good and bad illumination condition as (a) and (b)

Here figure 3.5(a) shows the channel responses under good illumination condition and in figure 3.56 (b) shows the channel response under bad illumination condition. Both responses are well separated and distinct.

3.9 DATA COLLECTION FROM METRO MILK SAMPLE



Figure 3.57: Picture of Metro milk with its constituent table

As per section 3.2 sample is prepared and as per section 3.3 all conditions are explored.

3.9.a DATA COLLECTION FROM PURE MILK SAMPLE

As per section 3.2, 100ml of pure metro milk is taken to perform experiment. Following figure 3.58 shows the variation of channel data under good and bad illumination condition.

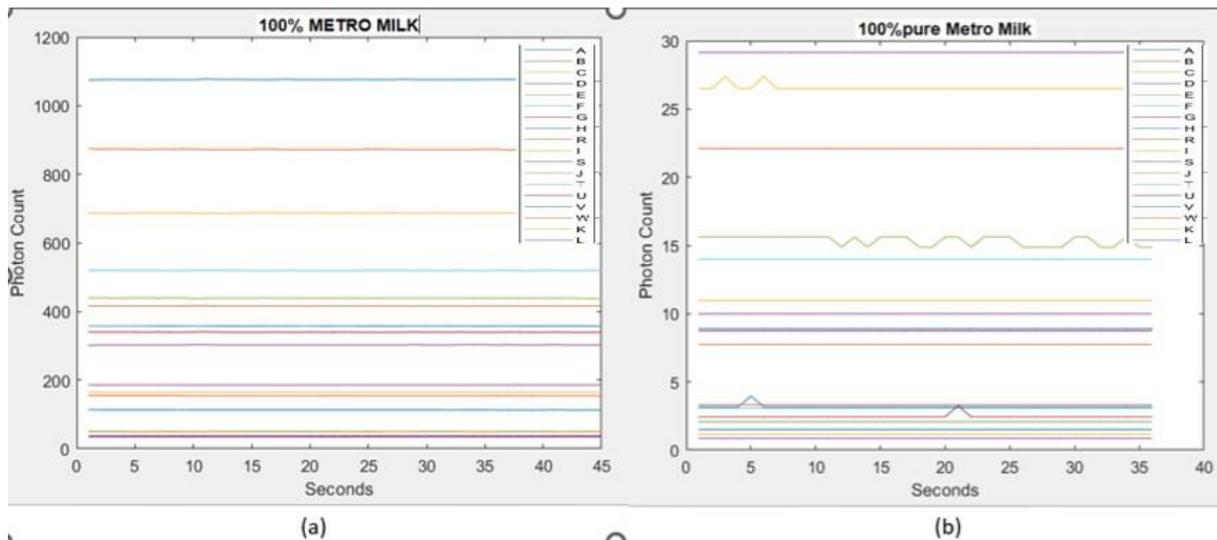


Figure 3.58: Response of channels for 100% pure metro cow milk under good and bad illumination condition as (a) and (b)

Figure 3.58(a) showing the response under good illumination condition and figure 3.58(b) shows the variation of data under low illumination condition. Both cases the milk sample was taken in glass container and keeping vertical gap of 1 inch.

3.9.b DATA COLLECTION FROM 10% WATER MILK SOLUTION

As per section 3.2, 10 ml of tap water is mixed with 90 ml of pure metro milk and the 10% water milk sample was made and the following figure 3.59 is showing the outcome under good illumination condition.

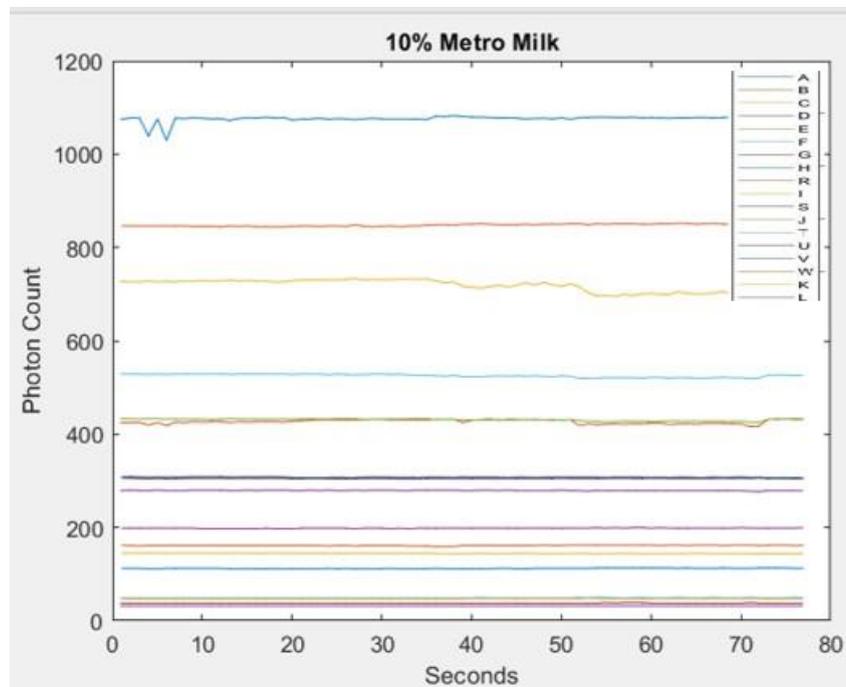


Figure 3.59: Response of 10% metro milk water sample under good illumination condition.

3.9.c DATA COLLECTION FROM 20% WATER MILK SOLUTION

As per section 3.2, 20 ml of tap water is mixed with 80 ml of pure Metro milk and the 20% water milk sample was made and the following figure 3.60 is showing the outcome under good illumination and bad illumination condition.

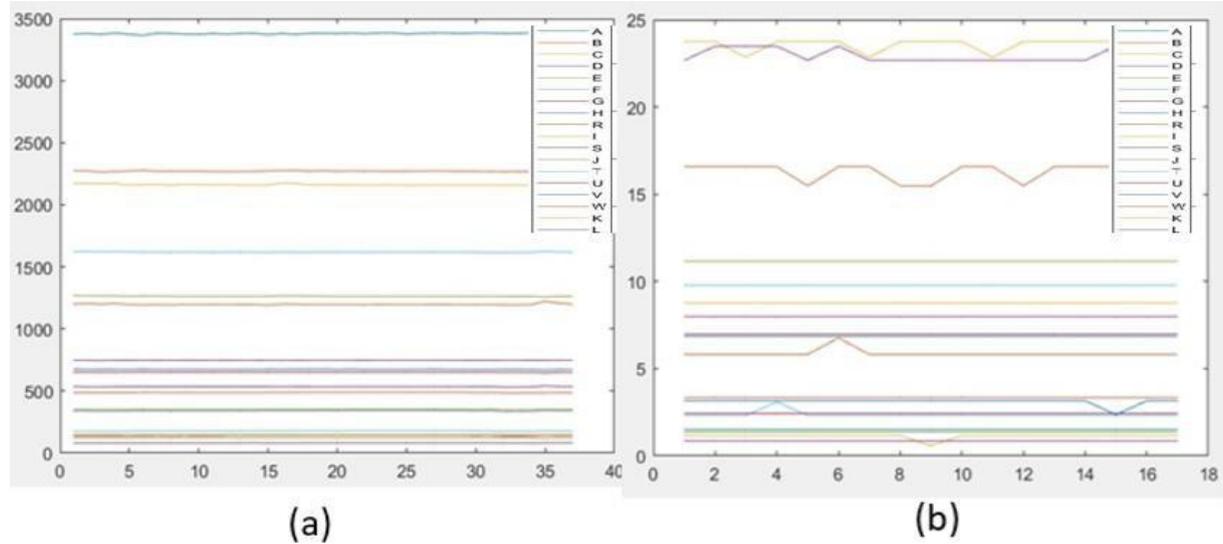


Figure 3.60: Response of 20% water milk sample of metro milk under as good and bad illumination conditions as (a) and (b)

Figure 3.60(a) showing the response under good illumination condition and figure 3.60(b) shows the variation of data under low illumination condition. Both cases the milk sample was taken in glass container and keeping vertical gap of 1 inch.

3.9.d DATA COLLECTION FROM 30% WATER MILK SOLUTION

As per section 3.2, 30 ml of tap water is mixed with 70 ml of pure Metro milk and the 30% water milk sample was made and the following figure 3.61 is showing the outcome under good and bad illumination condition.

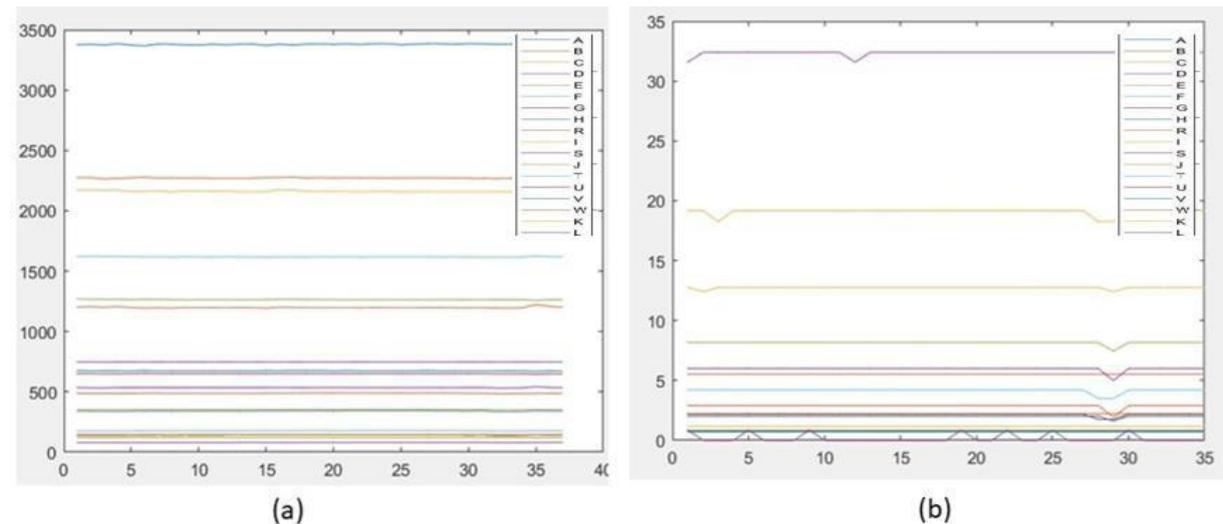


Figure 3.61: Response of 30% water milk solution of Metro milk sample under good and bad illumination condition as (a) and (b)

In figure 3.61(a) shows the channel response under bad illumination condition, we can see here also that all channel data are distinct and well separated but having low magnitude as compared to channel response under good illumination condition which is depicted in figure 3.61(b).

3.9.e DATA COLLECTION FROM 50% WATER MILK SOLUTION

As per section 3.2, 50 ml of tap water is mixed with 50 ml of pure metro milk and the 50% water milk sample was made and the following figure 3.62 is showing the outcome under good illumination condition.

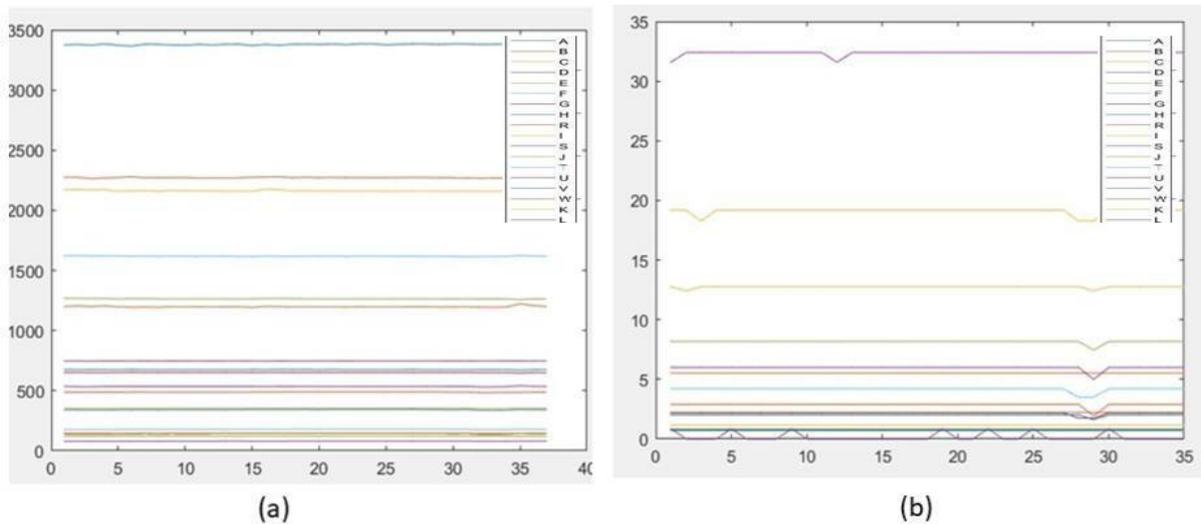


Figure 3.62: Response of 50% water Metro milk solution under good and bad illumination condition as (a) and (b)

Here figure 3.62(a) shows the channel responses under good illumination condition and in figure 3.62(b) shows the channel response under bad illumination condition. Responses for good illumination condition is well distinct and separated.

3.10 DATA COLLECTION FROM OTHER FOOD LIKE BISCUIT SAMPLE

Now we are taking spectroscopic data from other food samples like biscuit so that the we can get an additional reach and application of proposed sensor system on other foods to determine the food content information about an unknown food sample.

3.10.a DATA COLLECTION FROM BRITANNIA NUTRI CHOICE BISCUIT SAMPLE



Figure 3.63: Britannia nutri choice as (a) commercial pack of Britannia nutri choice with all nutritional information, (b) crashed biscuit in glass container

Figure 3.63(a) shows the Britannia nutri choice with its nutritional information where we total fat content is 12 g per 100g and added sugar content is 19.5g per 100 g etc. This, values are taken as reference to train the AI based algorithm and determine the all the constituents for an unknown sample of biscuit. And figure 3.63(b) shows the sample of biscuit taken in glass container keeping fixed 1inch gap between sample and sensor as discussed earlier in section 3.3.

Following figure 3.64 shows the all 18 channels outcome for this sample under good illumination condition

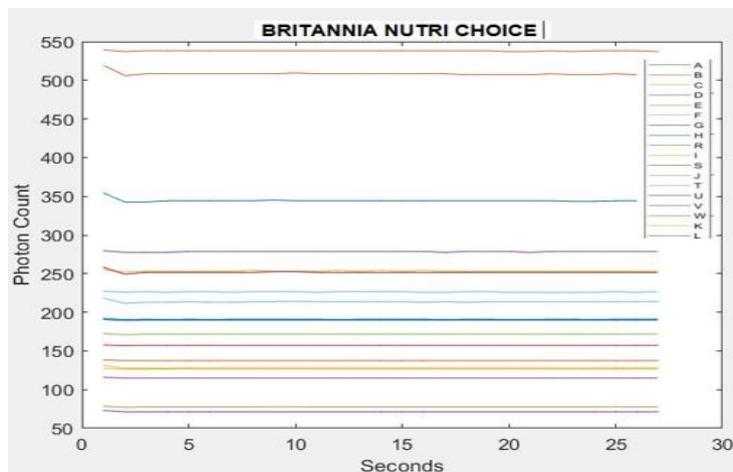


Figure 3.64: Response of all 18 channels under good illumination of ‘Britannia nutri choice’

Figure 3.64 also showing under good illumination condition using glass as a container and keeping 1 inch apart the sensor from biscuit sample we got the all 18 channels data, all channels’s data are well stable and apart from each other so this data set is ideal to solve classification problem by AI based algorithm Gaussian Process Regression and Robust Regression in the next chapters 4 and 5.

3.10.b DATA COLLECTION FROM LOCAL BISCUIT SAMPLE CALLED “MORNING TIME MILK COOKIES BAKERY BISCUIT”



Figure 3.65: local biscuit as (a) the local biscuit sample called “Morning Time” and(b) the crushed sample of biscuit sample in glass container.

Under good illumination condition all 18 channels spectroscopic data are depicted in figure 3.66.

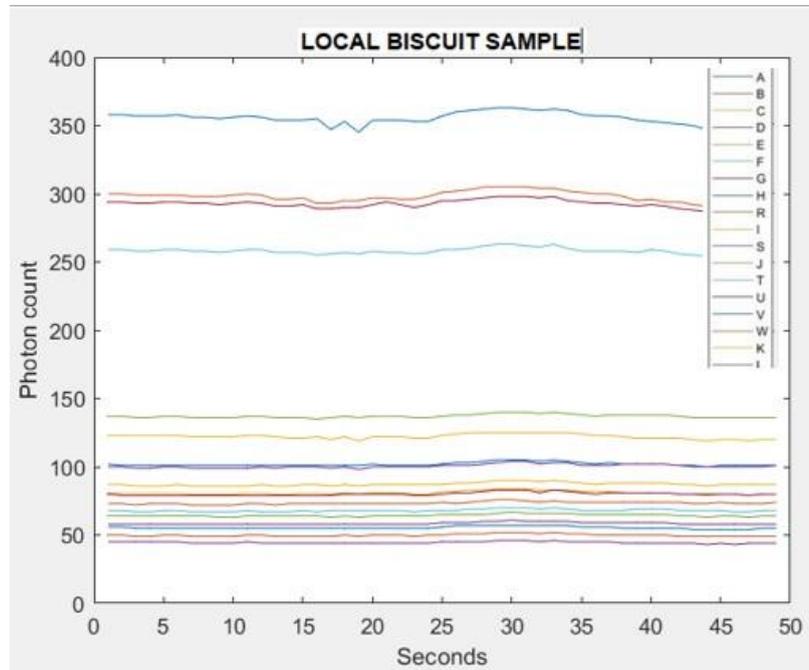


Figure 3.66: Channel response of local biscuit under good illumination condition

As compared to Britannia biscuit the local biscuit sample has low magnitude spectroscopic data under same physical condition that is good illumination and taking glass container with 1 inch gap between sample and biscuit. But the local biscuit sensor data also well stable and well apart from each other .

3.11 SENDING DATA TO “THINGSPEAK” WEBSERVER

As an IoT application we send the sensor data of different food samples to the ‘ThingSpeak’ webserver so that one can get the spectroscopic data of any milk or food sample in any time and any where. By the ESP 32 WiFi module we send the data to ‘ThingSpeak’ webserver by having only the API key of channel in ‘ThingSpeak’ and setting the fields to the corresponding channel of AS7265x sensor. ThingSpeak is an IoT analytics platform service that give us opportunity to aggregate, visualize and analyze live data coming from sensor module at real time. So this feature gives the huge opportunity to food industry to localize an data processing center any part of the world and get the data of food such as milk or biscuit and check the quality of food without going to the actual site or different part of country. Also it reduces the monitoring time of food sample in regular basis.

Here is the figure 3.67 shows the interface of ‘ThingSpeak’ website taking data of milk sample of channel A to Channel D.

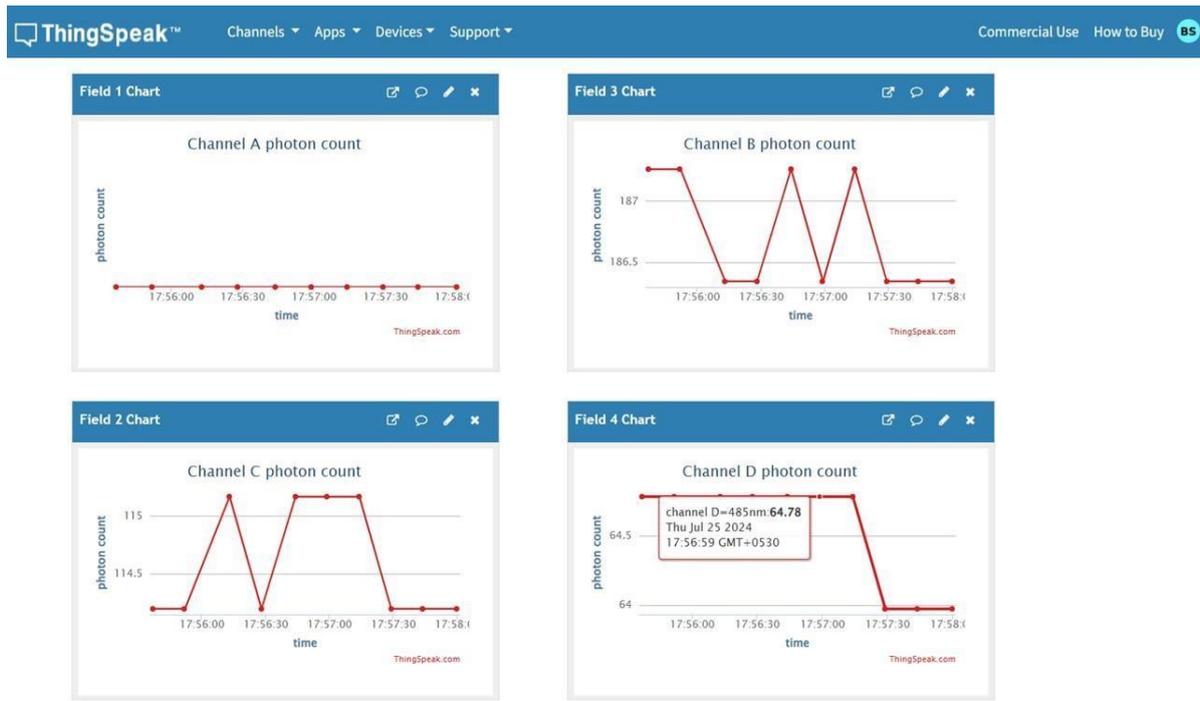


Figure 3.67: Spectroscopic response visualizing on 'ThingSpeak' website

Figure 3.67 shows the real time spectroscopic data of milk sample with real time with very high precision, let say for channel B is showing value in the range of in between 188.00 to 185.00 to so a small chages also determined by this portal in real time when the data is being collected i.e. Jul 25, 2024 17:56:59 GMT+0530.

3.12 SUMMARY

From the above discussion we can conclude that the spectroscopic sensor AS7262x is able to take all 18 channels data from any food sample whether it is milk or solid i.e. biscuit. The respective channels of sensor is able to collect at any distance from food sample, hence the quality analysis of any food is carried out using the sensor data. Collected data are very unique for a specific object that is food sample and hence is useful in identifying the adulteration level of milk or determine the food constituents. But under the good illumination condition the response of sensor is optimum and have high magnitude in stable mode and well separated as compared to sensor response in low illumination condition.

So we recommend, one should take measurement at good illumination condition. The great thing about the pattern of data is they are distinct for every different samples and stable. Practically for a fixed condition (basically in good illumination) on a fixed sample the data is fixed and stable not changing with time, one single data for a particular channel is repeating itself as time passes. So practically one can take the data just for a minute and examine the sample.

Here we also make changes in container material in between glass and steel, but there is not much difference in pattern of data set for a fixed sample. But in glass container we got higher magnitude spectroscopic data of channels whereas in steel container same pattern is captured but with little low magnitude. But the shape of waveforms are exactly same in case of both glass and steel container. So practically one can take any bowl in between glass or steel container.

There is no difference in signal pattern in one inch or two inch gap between sensor and food sample, so one can choose any vertical gap between sample and sensor.

CHAPTER 4

GAUSSIAN PROCESS REGRESSION (GPR) FOR SOLVING MILK ADULTERATION PROBLEM AND DETERMINATION OF FOOD CONSTITUENTS

- **INTRODUCTION**
- **GAUSSIAN PROCESS REGRESSION (GPR)**
- **PROPOSED METHODOLOGY**
- **EXPERIMENTAL RESULTS**
- **SUMMARY**

4.1 INTRODUCTION

The milk adulteration problem is considered as a non-linear regression problem where the prediction model is prepared to get a unique output in terms of adulteration level trained by the input data set comprises with 18 different values corresponding 18 different channels which is collected by AS7265x sensor which has the total 18 different channels with different wavelengths in nm. Here the learned model is used to predict the output in terms of adulteration level in percentage and in subsequent problem output is predicting the level of fat content in the given sample of milk. Another problem formulated unlike milk adulteration [2] is prediction the sugar content in given biscuit sample, here prediction model is trained by input dataset having total 18 different variables along with sugar content data of known biscuit sample. So the output in both the cases is nonlinear function of input data set.

In this chapter, the author proposes to employ Gaussian process regression (GPR) [10,11] to solve the formulated nonlinear regression problem, where the objective is to predict the milk adulteration level and amount of fat content in milk and amount of sugar content in given biscuit sample for a certain query input training data set.

Gaussian processes (GPs) [3] are extensively used by the statistics, machine learning, and signal processing communities for solving various identification, multi-class classification, and nonlinear regression problems, subjected to real-life noisy data. The GP, demonstrated to be a robust Bayesian nonparametric method for finding solutions of such problems, enables to realize a probabilistic prediction within a sophisticated and elegant inference framework while holding magnificent resilience to over-fitting that frequently takes place in machine learning.

Here the input data is almost fixed for a particular milk and biscuit sample only depending upon the environmental illumination. Input data i.e. data collected from 18 different channels are having the fixed value corresponding to a sample with fixed hardware adjustment as discussed in this chapter.

4.2 GAUSSIAN PROCESS REGRESSION

The objective of non-linear regression is to get a unknown function $g : \mathbb{R}^n \rightarrow \mathbb{R}$ from an arbitrary data set $\mathbf{D} = \{\mathbf{z}_j, w_j\}_{j=1}^u$, where for the n-dimensional input vector $\mathbf{z}_j \in \mathbb{R}^n$, the observation $w_j \in \mathbb{R}$ a scalar value can be considered as related to the underlying function value $g(\mathbf{z}_j)$ through the gaussian noise model [4] :

$$w_j = g(\mathbf{z}_j) + \varphi_j \text{ with } \varphi_j \sim \mathcal{N}(0, h^2(\mathbf{z}_j)) \quad (4.1)$$

where φ_j , termed as the observation error (or measurement noise), is commonly assumed to be independently and normally distributed with a mean of 0 and a variance of $h^2(\mathbf{z}_j)$ [4].

For ease of notation, the true function value and the noise standard deviation are indicated here by $g_j = g(\mathbf{z}_j)$ and $h_j = h(\mathbf{z}_j)$ respectively. Also, the sets of inputs, outputs, true function values and noise standard deviations are populated into $\mathbf{Z} = [z_1, \dots, z_u]^T$, $\mathbf{w} = [w_1, \dots, w_u]^T$, $\mathbf{g} = [g_1, \dots, g_u]^T$, and $\mathbf{h} = [h_1, \dots, h_u]^T$, respectively. The Gaussian process (GP) with which a nonparametric Bayesian modeling for an unknown function is performed, delineates a distribution of the function values $g(\mathbf{z})$ on the given input space \mathbf{z} by its mean function $\mu(\mathbf{z})$ and covariance function $c(\mathbf{z}, \mathbf{z}')$. For the finite set of inputs, z_1, \dots, z_u , the corresponding function values, $g(z_1), \dots, g(z_u)$, are then fully specified by a multivariate Gaussian distribution [10] as follows :

$$\begin{bmatrix} \mathbf{g}(\mathbf{z}_1) \\ \vdots \\ \mathbf{g}(\mathbf{z}_u) \end{bmatrix} \sim \mathcal{N}(\boldsymbol{\mu}, \mathbf{C}) \quad (4.2)$$

Where,

$$\boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}(\mathbf{z}_1) \\ \vdots \\ \boldsymbol{\mu}(\mathbf{z}_u) \end{bmatrix} \text{ and } \mathbf{C} = \begin{bmatrix} c(\mathbf{z}_1, \mathbf{z}_1) & \cdots & c(\mathbf{z}_1, \mathbf{z}_u) \\ \vdots & \ddots & \vdots \\ c(\mathbf{z}_u, \mathbf{z}_1) & \cdots & c(\mathbf{z}_u, \mathbf{z}_u) \end{bmatrix} \quad (4.3)$$

A usual assumption is to place a GP with $\boldsymbol{\mu} = \mathbf{0}$ prior over the function value, especially when no preceding information about the form of $g(\mathbf{z})$ is available. This is given as [4]

$$p(\mathbf{g}|\mathbf{Z}) \sim \mathcal{N}(\mathbf{0}, \mathbf{C}) \quad (4.4)$$

The covariance (kernel) function $c(\mathbf{z}_k, \mathbf{z}_l)$ is considered as a design parameter which delineates correlations between the function values g_k and g_l corresponding to any two given inputs \mathbf{z}_k and \mathbf{z}_l . A popular choice among the various available covariance functions is the *squared exponential* (SE) function. The infinitely differentiable SE kernel is expressed as [4]

$$c(\mathbf{z}_k, \mathbf{z}_l) = \alpha_g^2 \exp \left[-\frac{\|\mathbf{z}_k - \mathbf{z}_l\|^2}{2\gamma^2} \right] \quad (4.5)$$

Where, $\|\cdot\|$ is indicating the Euclidean distance between \mathbf{z}_k and \mathbf{z}_l , α^2 is the prior variance of the signal amplitude, and γ is the characteristic length-scale. The SE kernel is parameterized by $\boldsymbol{\phi}_g = \{\alpha_g, \gamma\}$.

Now, the joint distribution for the observed output \mathbf{w} and the function value g_{test} at a test input \mathbf{z}_{test} is given as [4]

$$\begin{bmatrix} \mathbf{w} \\ g_{\text{test}} \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mathbf{0} \\ 0 \end{bmatrix}, \begin{bmatrix} \mathbf{C} + \mathbf{V} & \mathbf{C}_{\text{test}} \\ \mathbf{C}_{\text{test}}^T & c(\mathbf{z}_{\text{test}}, \mathbf{z}_{\text{test}}) \end{bmatrix} \right) \quad (4.6)$$

where \mathbf{V} denotes the diagonal matrix of noise variances whose entries are: $[\mathbf{V}]_{jj} = h^2(\mathbf{z}_j)$ and $\mathbf{C}_{\text{test}} = [c(\mathbf{z}_{\text{test}}, \mathbf{z}_1) \ c(\mathbf{z}_{\text{test}}, \mathbf{z}_2) \ \cdots \ c(\mathbf{z}_{\text{test}}, \mathbf{z}_u)]^T$. Based on the conditional identity of a multivariate Gaussian distribution, the posterior distribution of the function value g_{test} at the test input \mathbf{z}_{test} is computed as [4]

$$p(g_{\text{test}}|\mathbf{z}_{\text{test}}, \boldsymbol{\phi}_g, \mathbf{h}, \mathcal{D}) \sim \mathcal{N} \left(\mathbf{C}_{\text{test}}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{w}, c(\mathbf{z}_{\text{test}}, \mathbf{z}_{\text{test}}) - \mathbf{C}_{\text{test}}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{C}_{\text{test}} \right)$$

(4.7)

Then one can obtain the posterior distribution over the test output w_{test} simply by summing up the noise variance h_{test}^2 at test input \mathbf{z}_{test} with the posterior variance of \mathbf{g}_{test} as [4]

$$p(w_{\text{test}} | \mathbf{z}_{\text{test}}, \boldsymbol{\phi}_g, \mathbf{h}, h_{\text{test}}, \mathcal{D}) \sim \mathcal{N} \left(\mathbf{C}_{\text{test}}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{w}, c(\mathbf{z}_{\text{test}}, \mathbf{z}_{\text{test}}) - \mathbf{C}_{\text{test}}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{C}_{\text{test}} + h_{\text{test}}^2 \right) \quad (4.8)$$

This conditional distribution presents the statistical property of the predicted test output \mathbf{g}_{test} , where the best estimate is generally selected as its conditional mean $\mathbf{C}_{\text{test}}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{W}$.

Note that in practical modelling scenarios, neither the noise level $\mathbf{h}(\mathbf{z})$ nor kernel parameters $\boldsymbol{\phi}_g$ are generally accessible, and they have to be learned from the given data. In this study, similar to the standard GP, the noise level is supposed to be constant across the input space, and hence the noise variance is defined as: $\mathbf{h}^2(\mathbf{z}) \equiv \boldsymbol{\alpha}^2$ and accordingly the noise matrix is represented as: $\mathbf{V} \equiv \alpha^2 \mathbf{I}$. The unknown parameters of the Gaussian process regression (GPR), including $\boldsymbol{\phi}_g$ and α_n , are then together referred to as GP hyperparameters, represented as $\boldsymbol{\phi}_w = \{\boldsymbol{\phi}_g, \alpha_n\} \equiv \{\alpha_g, \gamma, \alpha_n\}$.

4.3 PROPOSED METHODOLOGY

In the proposed problem[2] of finding the adulteration level of milk and parameter indices like sugar in biscuit, it is require to predict or estimate the output in terms of percentage adulteration level of milk and value of sugar content in biscuit. Here the data is collected by AS7265x sensor where it has total 18 channels with different wavelengths. This channels are capturing the data from a percular food sample depending on environmetal setup. So there are total 18 variables are present in one single input data set. And the sensor is taking data for a given time interval depending upon the need of input data set.

So here we got one input data set D_x for a particular sample of milk or biscuit as,

$$D_x = \{ X_A, X_B, \dots, X_L \}$$

Now in finding adulteration level of milk is forming a non-linear regression problem, where a prediction model best represented by a unknown function $f_y : \mathbb{R}^2 \rightarrow \mathbb{R}$, is learned by the trainig input data set $D_x = \{ X_j \}$ which is almost constant for a percular sample of milk or for a given adulterated milk, and giving a single scalar measured output as $Y_j \in \mathbb{R}$, as:

$$Y_j = f_y(x_j) + \epsilon_{y_j} \text{ with } \epsilon_{y_j} \approx N(0, h_y^2(x_j))$$

ϵ_{y_j} is measurement uncertainties which can be represented as the *equivalent modelling errors*. These equivalent modelling errors which are caused because of the uncertainties in input variables, are random variables and are assumed to be independently and normally distributed. The noise variance $h_y^2(x_j)$ is considered as constant throughout the input data set and defined as $h_y^2(x) = \boldsymbol{\alpha}_{ny}^2$. This model is used to predict or estimate \mathbf{y}_t for the given query 18 channel

signals from sensor module x_t as the output is scalar related to input with a nonlinear function of x_t input variable so we are using Gaussian process regression (GPR) to solve the mentioned problem. So to predict $Y_t = f_y(x_t) + \epsilon_{yt}$ for the query input x_t , for giving a training data set of $[x_1, x_2, x_3, \dots, x_N]^T$.

In this work, SE kernel has been selected as the covariance function. It is worth mentioning that, the input data have been standardized so that each dimension is weighted on the same scale.

The SE kernel, for any two given inputs \mathbf{x}_k and \mathbf{x}_l , is here defined as:

$$c(\mathbf{x}_k, \mathbf{x}_l) = \alpha^2_{fy} \exp [-(\mathbf{x}_k - \mathbf{x}_l)^2 / 2\gamma^2_{fy}]$$

SE kernel here is parameterized by $\phi_{fy} = \{\alpha_{fy}, \gamma_{fy}\}$, and the GP hyperparameters are given by $\phi_y = \{\alpha_{fy}, \gamma_{fy}, \alpha_{ny}\}$. With the definition $\mathbf{Y} = [y_1, y_2, y_3, \dots, y_N]^T$, a multivariate Gaussian distribution can be formed similar to (4.6) as follows

$$\begin{bmatrix} \mathbf{Y} \\ f_{yt} \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mathbf{0} \\ 0 \end{bmatrix}, \begin{bmatrix} \mathbf{C} + \mathbf{V} & \mathbf{C}_{x_t} \\ \mathbf{C}_{x_t}^T & c(x_t, x_t) \end{bmatrix} \right) \quad (4.11)$$

where f_{yt} denotes the value of the function f_y at the query input x_t

$$\mathbf{C} = \begin{bmatrix} c(\mathbf{x}_1, \mathbf{x}_1) & \dots & c(\mathbf{x}_1, \mathbf{x}_N) \\ \vdots & \ddots & \vdots \\ c(\mathbf{x}_N, \mathbf{x}_1) & \dots & c(\mathbf{x}_N, \mathbf{x}_N) \end{bmatrix}$$

$$\mathbf{C}_{x_t} = [c(\mathbf{x}_t, \mathbf{x}_1), c(\mathbf{x}_t, \mathbf{x}_2), c(\mathbf{x}_t, \mathbf{x}_3), \dots, c(\mathbf{x}_t, \mathbf{x}_N)]^T \quad (4.12)$$

and \mathbf{V} is the diagonal matrix of noise variances whose entries are: $[V]_{jj} = h^2_Y(X_j) = \alpha^2_{nx}$.

Similar to the Eq.(4.8) the conditional distribution $p(y_t | x_t, \phi_y, h_y, h_{yt}, D_y)$ is here obtained as

$$p(y_t | x_t, \phi_y, h_y, h_{yt}, D_y) \sim \mathcal{N} \left(\mathbf{C}_{x_t}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{Y}, c(x_t, x_t) - \mathbf{C}_{x_t}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{C}_{x_t} + \alpha^2_{ny} \right) \quad (4.13)$$

Here the best estimation or prediction of y_t is mean of the distribution Eq.(4.13) :

$$\bar{y}_t = \mathbf{C}_{x_t}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{Y} \quad (4.14)$$

and the uncertainty associated with the estimate is captured in its variance:

$$\text{Var}(y_t) = c(x_t, x_t) - \mathbf{C}_{x_t}^T (\mathbf{C} + \mathbf{V})^{-1} \mathbf{C}_{x_t} + \alpha^2_{ny} \quad (4.15)$$

4.4 EXPERIMENTAL RESULT

4.4.1 EXPERIMENTAL SETUP

As mentioned earlier, the data is collected by AS7265x sensor which has in built three sensors in which one AS72651 act as master and other two sensors AS72652 and AS72653 ae acting like slave. This sensor is individually having total 6 channels with different wavelengths having Ultraviolet, or visible, or near infrared spectrum of light. So, placing vertically 1 inch or 2inch apart from the food sample, this sensor module can capture a very distinct data for input x variable. The experimental setup is well designed in total 8 conditions as mentioned earlier. And depending on the respective setup the data are collected and they are different according to the test sample and environmental condition. As the outside light is not in our control so there must be some random error is also associated with data but for the sake of mathematical procedure we take it fixed error throughout the sample space.

This data can be transmitted by serial communication to a web server page through ESP-32 WIFI module and data are further process in some other location with some other PC. This make the system most advance in nature by instantly getting data of milk or other sample where the data is collected from other part of country.

4.4.2 DATA SET GENERATION

Based on given methodology, data is collected from AS7265x sensor which has total 18 channels so at a time instance total 18 channel data is produced. This 18channel data is forming a row of data set, so the dataset is having total 18 columns representing individual channel data from a particular sample of milk or biscuit We are taking data from a particular sample for about one minute. So, the data set is producing total 60 rows, hence the data set is having a matrix of 60 x 18 size. After every one second one row is generated by the sensor.

This procedure is repeated for each sample, so for each sample of milk is producing same 60 x18 matrix size data set. This data set is now sending to the web server called ‘ThingSpeak’ via ESP-32 WIFI module. Then, from this web page data is collected and further process on the given algorithm.

This data set is subdivided into two groups, one is for train the algorithm and other one is for test the algorithm. As our data set so constant in nature that the values corresponding to each channel is almost fixed for a fixed milk or food sample. So, we are free to reduce the data for train the model. So, we investigate by changing the ratio of training and testing and observe the robustness of model.

4.4.3 PERFORMANCE EVALUATION

Table 4.1 shows the performance evaluation in terms of accuracy in percentage of predicting percentage of adulterated milk.

Table 4.1. Performance of GPR milk adulteration problem on Amul Taza milk sample taking training : testing =7:3

Conditions	Accuracy	
	Mean In %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	99.89	0.005
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	36.69	0.028
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	29.33	0.005
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	64.33	0.005
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	31.48	0.069
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	100.00	0.00

Table 4.2. Performance of GPR milk adulteration problem on red cow milk sample taking training : testing =7:3

Conditions	Accuracy	
	Mean In %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	100.00	0.00

Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	57.66	0.036
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	39.71	0.005
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	67.33	0.005
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	39.41	0.07
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	98.66	0.005

Table 4.3. Performance of GPR milk adulteration problem on metro milk sample taking training : testing =7:3

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	25.64	0.089
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	37.89	0.005
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	69.33	0.005
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	45.69	0.07
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	100.00	0.00

Table 4.4. Performance of GPR milk adulteration problem on
super_T sample taking training : testing =7:3

Conditions	Accuracy	
	Mean In %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with glass container with 1 inch vertical Distance between milk surface and sensor module	54.87	0.006
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	11.54	0.005
Good illumination with steel container with 1 inch vertical Distance between milk surface and sensor module	100.00	0.00
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	67.89	0.005
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	41.56	0.074
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	87.33	0.004

Table 4.5. Performance of GPR milk adulteration problem on
Bhagirathi milk sample taking training : testing =7:3

Conditions	Accuracy	
	Mean In %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	98.33	0.046
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	64.98	0.058
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	10.12	0.005

Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	91.45	0.089
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	26.33	0.005
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	16.77	0.006
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	96.55	0.002

Table 4.6. Performance of GPR milk adulteration problem on
Local cow milk sample taking training : testing =7:3

Conditions	Accuracy	
	Mean In %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	98.36	0.004
Bad illumination with glass container with 1 inch vertical Distance between milk surface and sensor module	68.71	0.028
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	61.54	0.005
Good illumination with steel container with 1 inch vertical Distance between milk surface and sensor module	100.00	0.00
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	47.40	0.041
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	39.66	0.087
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	94.33	0.005

Following table 4.7 shows the prediction accuracy of GPR for predicting the total fat content in the given unknown milk sample. Here we fix testing and trainging ration as 7:3, under condition1 i.e. under good illumination keeping 1 inch vertical distance and with glass container. As in local cow milk we do not have any prerequisite data of total fat content so we ignore the local milk sample under this experiment.

Table 4.7: Performance accuracy of GPR to determine total fat content of cow milk sample

Milk sample	Performance Accuracy	
	Mean in %	Standard deviation
Amul Taaza	100.00	0.00
Red cow	99.05	0.066
Metro	100.00	0.00
Super_T	97.98	0.058
Bhagirathi	100.00	0.00

Now as seen from the performance result of GPR on various milk samples , we are getting very high accuracy on predicting percentage adulterated milk sample in a bright that is good illumination condition and with vertical distance of one inch or two inches so we next investigate the performance of GPR on finding percentage amount of adulterated milk for various testing and training ratios keeping fixed the best environmental conditions i.e. here we are keeping good illumination condition along with one inch vertical distance between sensor module and milk sample. Now from previous result we have observed that the container material is absolutely independent in the experiment so for rest of the experiments we considering only glass container.

Table 4.8. Performance of GPR for identifying level of adulteration of milk and determining total fat content for different testing and training ratios

Milk sample	Training: Testing	Accuracy of GPR to identifying level of milk adulteration		Accuracy of GPR to determine total fat content in given milk sample	
		Mean in %	Standard deviation	Mean in %	Standard deviation
Amul Taza	7:3	100.00	0.00	100.00	0.00
Amul Taza	6:4	98.00	0.060	99.97	0.008
Amul Taza	5:5	94.65	0.055	100.00	0.00
Amul Taza	4:6	87.63	0.089	100.00	0.00

Amul Taza	3:7	39.41	0.015	31.46	0.060
Amul Taza	2:8	21.26	0.027	23.68	0.090
Red Cow	7:3	100.00	0.00	99.05	0.066
Red Cow	6:4	96.36	0.06	100.00	0.00
Red Cow	5:5	89.65	0.006	98.87	0.006
Red Cow	4:6	55.89	0.078	41.66	0.031
Red Cow	3:7	26.15	0.045	36.89	0.070
Red Cow	2:8	20.00	0.09	11.25	0.047
Super_T cow milk	7:3	100.00	0.00	97.98	0.058
Super_T cow milk	6:4	99.36	0.005	97.36	0.005
Super_T cow milk	5:5	91.89	0.006	89.36	0.082
Super_T cow milk	4:6	81.46	0.005	78.96	0.059
Super_T cow milk	3:7	39.66	0.025	32.66	0.030
Super_T cow milk	2:8	29.54	0.005	34.78	0.031
Metro cow milk	7:3	100.00	0.00	100.00	0.00
Metro cow milk	6:4	97.99	0.005	98.35	0.069
Metro cow milk	5:5	74.56	0.049	78.33	0.089
Metro cow milk	4:6	51.26	0.047	58.66	0.090
Metro cow milk	3:7	49.21	0.005	52.69	0.082
Metro cow milk	2:8	10.46	0.005	20.67	0.045

Bhagirathi	7:3	98.33	0.046	100.00	0.00
Bhagirathi	6:4	94.35	0.049	97.84	0.047
Bhagirathi	5:5	86.33	0.005	87.22	0.005
Bhagirathi	4:6	74.22	0.032	76.66	0.036
Bhagirathi	3:7	54.36	0.056	57.66	0.005
Bhagirathi	2:8	17.39	0.004	14.11	0.030

Following table 4.9 shows the performance accuracy of GPR to determine added sugars and total fat content in given biscuit sample called 'Britannia Nutri Choice' under two different conditions taking testing to training ratio of 7:3.

Table 4.9: Performance of GPR to determine added sugars and total fat content in given biscuit sample 'Britannia Nutri Choice'

Conditions	Determination of total fat content		Determination of added sugars content	
	Mean in %	Standard deviation	Mean in %	Standard deviation
Under good illumination condition	100.00	0.00	100.00	0.00
Under bad illumination condition	39.67	0.005	48.33	0.089

Here as prerequisite values of total fat content is 12g per 100g and total added sugars content is 19.5g per 100g are taken as per figure 3.63 (a).

4.5 SUMMARY

Gaussian process regression is showing very convincing result on the spectroscopic data set of different adulterated milk sample as well as different company's milk sample. First for the adulteration problem of milk we have taken different adulterated milk sample from different brands, in the good illumination condition irrespective of one inch or 2 inch vertical distance between the surface of milk sample and sensor module the classification result of GPR is very satisfactory, for the different testing and training ratios are showing at least 30% of data are needed for train the model and hence the requirement of large number of data is not needed for conducting the experiment on ground level on any location and this gives our proposed system a robustness and effectiveness.

For the second case we found the total fat content in the given milk sample , here we produce different milk sample of different company with 100% pure form. Here also we found very convincing result and needed very samall sample data to predict the output in the form of fat value. Here evrything is depends on known value of fat of a particular milk sample that is given as input to the model and henece as many sample can we produce to train the model, it gives better result.

CHAPTER-5

REGULARISED ROBUST CODING IN IDENTIFYING MILK ADULTERATION

- **INTRODUCTION**
- **SPARSE CODING WITH MAP BASED ESTIMATION**
- **WEIGHT UPDATE RULE**
- **ALGORITHM OF RRC**
- **CLASSIFICATION STRATEGY IN RRC**
- **EXPERIMENTAL RESULTS**
- **SUMMARY**

5.1 INTRODUCTION

Nowadays, sparse representation-based classification methods are successfully introduced traditionally first in face recognition problem [1] and now we are using this method to solve the cow milk adulteration problem [2]. Here, the test data of spectroscopic sensor of 18 channels are represented as a linear sparse combination of all the training 18 channel data. These sparse coding models assume that the residual error i.e. difference between query data and the training data follows Gaussian or Laplacian distribution. These distribution models of the coding residuals, sometimes become unsuitable for describing the recognition systems effectively in a practical scenario. In view of this, later a new robust regression model, called regularized robust coding (RRC) [1] has been proposed. RRC [1] assumes that the coding residual and its coding coefficients are independent and identically distributed, which helps in robustly regressing a query signal here spectroscopic data, with regularized regression coefficients. The RRC [1] coding problem is solved with the help of maximum a posteriori (MAP) estimation of Bayesian probability. In this thesis, RRC [1] is used to solve the milk adulteration problem [2] by means of robust regression. Detailed experimental studies are reported to evaluate the effectiveness of this approach in milk adulteration problem [2]. The mathematical framework of RRC [1] along with experimental results are discussed in the subsequent sections of this chapter.

5.2 SPARSE CODING WITH MAP BASED ESTIMATION

The method of sparse representation or sparse coding, which is a particular type of redundant representation is gaining popularity day by day, especially in solving many signal processing problems particularly where a big size of data set is involve in computation. Sparse representation makes the distribution lesser dense and it allows the representation to have more degrees of freedom which helps the relationships becoming less non-linear in nature. This is essentially a technique of energy minimization which can be formulated as follows,

$$f(\underline{x}) = \frac{1}{2} \|\underline{x} - \underline{y}\|_2^2 + G(\underline{x}) \quad (5.1a)$$

Here, \underline{x} is the correct signal data and \underline{y} noise present in the signal both are in vector form, when we solve any signal denoising problem [6]. $G(\underline{x})$ is called the prior or regularization term. From the Bayesian point of view, this is nothing but an MAP estimation which tries to optimize the function $f(\underline{x})$ corresponding to the optimum value of \underline{x} [7]. The prior term can be of many forms, e.g. the dictionary decomposition based sparse coding uses,

$$G(\underline{x}) = k \|\underline{\alpha}\|_p^p,$$

$$\text{Where, } \underline{x} = \underline{\alpha} D \quad (5.1b)$$

Here, D is representing dictionary that made of atoms which are actually characteristics of the training data and we determine sparse vector denoted by $\underline{\alpha}$. As $\underline{\alpha}$ is the sparse vector so it consists very few non zero elements. Which allow us to formulate \underline{x} be the linear combination of those non zero elements and dictionary atoms. K is the scaling factor. And p in equation 5.1b is the sparsity constraint of the representation. If $p=0$, it is becoming a l_0 -norm problem which

is counting the number of non-zero entries and otherwise l_1 counts sum of magnitudes of non-zero values. In this case, let $\mathbf{y} \in \mathfrak{R}^n$ be an unknown signal of spectroscopic sensor suitably in the form a vector, which is to be coded over the dictionary $\mathbf{D} \in \mathfrak{R}^{n \times m}$ i.e. the training database of sensor signal from all classes, taking in different conditions using the sparse coding vector $\alpha \in \mathfrak{R}^m$. In case of AS7265x sensor database mentioned earlier, the experiments are conducted in different conditions with low illumination condition with different vertical distance between sensor module and surface of milk sample and hence specifically desires robust sparse representation. The residual error can be given as, $\mathbf{r} = \mathbf{y} - \mathbf{D}\alpha$, and the problem under consideration whose solution needs to be obtained can be represented [1] as,

$$\min_{\alpha} \|\mathbf{y} - \mathbf{D}\alpha\|_p^p \quad \text{s.t.} \quad \|\alpha\|_1 \leq \tau \quad (5.2)$$

If it is assumed by the prior that the residual follows Gaussian or Laplacian distribution, then Eq. (5.2) can be solved considering $p=2$ or $p=1$ respectively. The corresponding solutions obtained are known as maximum likelihood estimation (MLE) solution or l_1 -sparsity constrained MLE solution, respectively. An in-depth study revealed that, under the assumption that all elements r_i ($1 \leq i \leq n$) in \mathbf{r} are mutually independent and their distributions are identical, different probability distribution models can be fitted in such challenging situations, and an ideal distribution should have a sharp peak at zero and most importantly a longer asymptotic tail which mainly fits the low illumination condition signals. . If the probability density function (PDF) of this distribution is $f_S(r_i)$ where S is the set of parameters to tune distribution curve, then the l_1 - sparsity constrained MLE problem can be formulated as follows,

$$\min_{\alpha} \sum_{i=1}^n \rho_S(y_i - \mathbf{q}_i \alpha) \quad \text{s.t.} \quad \|\alpha\|_1 \leq \tau \quad (5.3)$$

Where q_i is the i^{th} row of \mathbf{D} , $\mathbf{D} = [\mathbf{q}_1; \mathbf{q}_2; \dots; \mathbf{q}_n]$, $\rho_S(r_i) = -\ln f_S(r_i)$ and $\tau > 0$ is a constant. This model was proposed as a robust sparse coding (RSC) model[8] with the assumption that the coding coefficients are distributed sparsely enough. Although it produced good results against bad illumination condition signals, the l_1 - sparsity constraint made the computational burden very high. To make life easy and lower the computational burden we are using [1] a more efficient, general purpose and less computation hungry model, namely regularized robust coding (RRC) has been proposed which tries to solve the problem using the maximum a posteriori (MAP) estimation of Bayesian probability [1]. It is assumed that all elements α_j ($1 \leq j \leq m$) in α are mutually independent and their distributions are identical, represented by the PDF $f_0(\alpha_j)$. If the testing signal \mathbf{y} is coded over the training dictionary \mathbf{D} , then the Bayesian formula-based MAP estimation gives the sparse coding vector as:

$$\hat{\alpha} = \arg \max_{\alpha} [\ln P(\mathbf{y} | \alpha) + \ln P(\alpha)] \quad (5.4)$$

Representing $P(\mathbf{y} | \alpha)$ in terms of the PDFs $f_S(r_i)$ and $P(\alpha)$ in term of PDFs $f_0(\alpha_j)$ in Eq-5.4 ,we can rewrite as :

$$\hat{\mathbf{a}} = \arg \max_{\mathbf{a}} \left[\prod_{i=1}^n f_s(y_i - \mathbf{q}_i \mathbf{a}) + \prod_{j=1}^m f_o(\alpha_j) \right] \quad (5.5)$$

By letting $\rho_s(r_i) = -\ln f_s(r_i)$ and $\rho_o(\alpha_j)$, this can be rewritten in minimization problem as follow,

$$\hat{\mathbf{a}} = \arg \min_{\mathbf{a}} \left[\sum_{i=1}^n \rho_s(y_i - \mathbf{q}_i \mathbf{a}) + \sum_{j=1}^m \rho_o(\alpha_j) \right] \quad (5.6)$$

This model is well performed in noisy signal because of the fidelity term $\sum_{i=1}^n \rho_s(y_i - \mathbf{q}_i \mathbf{a})$.

And the other term $\sum_{j=1}^m \rho_o(\alpha_j)$ depends solely on the prior probability distribution model and can be regularized easily. This RRC model in Eq.5.6 is the generalized model compared to the fixed RSC model shown in Eq.5.3 in above section as the distribution f_s and hence ρ_s need not be a fixed Gaussian or Laplacian model, but can have an adaptive shape depending on the input query sensor signal y . Now, the minimization problem in MAP estimation in Eq. (5.6) can be efficiently solved by approximating it as an iteratively reweighted regularized coding problem.

Summation of all the logarithmic PDF $\rho_s(r_i)$ values of the residual errors r_i can be given as

$$\hat{P}_s(\mathbf{r}) = \sum_{i=1}^n \rho_s(r_i) \quad (5.7)$$

Now as per Taylor Series expansion $\hat{P}_s(\mathbf{r})$ can be approximated in the near of \mathbf{r}_0 as

$$P_s(\mathbf{r}) = P_s(\mathbf{r}_0) + (\mathbf{r} - \mathbf{r}_0)^T P'_s(\mathbf{r}_0) + \Delta(\mathbf{r}) \quad (5.8)$$

All the higher order terms are considered together as the residual $\Delta(\mathbf{r})$ If ρ'_s is the derivative of ρ_s then we can write $\mathbf{P}'_s(\mathbf{r}_0) = [\rho'_s(r_{0,1}); \rho'_s(r_{0,2}); \rho'_s(r_{0,3}); \dots; \rho'_s(r_{0,n})]$ with $r_{0,1}$ be the i^{th} element of \mathbf{r}_0 vector. In a bid to achieve an easier minimization, $\mathbf{P}'_s(\mathbf{r})$ is desired to be converted to a convex function. For this reason residual $\Delta(\mathbf{r})$ can be approximated as $\Delta(\mathbf{r}) \approx 0.5(\mathbf{r} - \mathbf{r}_0)^T \mathbf{W}(\mathbf{r} - \mathbf{r}_0)$. This \mathbf{W} is the weight matrix which must be a diagonal matrix with all of its off-diagonal elements zero, as all the elements r_i in \mathbf{r} are independent of each other. If the desired PDF of $f_s(\mathbf{r})$ is symmetric, differentiable and monotonic then both $\hat{P}_s(\mathbf{r})$ and its approximation $P_s(\mathbf{r})$ will become their minimum values at $\mathbf{r} = \mathbf{0}$, and we let $P'_s(\mathbf{0}) = \mathbf{0}$, the corresponding entries in the weight matrix can be calculated as:

$$\mathbf{W}_{i,i} = \omega_s(r_{0,i}) = \frac{\rho'_s(r_{0,i})}{r_{0,i}} \quad (5.9)$$

Where $W_{i,i}$ is the positive scalar value, which giving us

$$P_s(\mathbf{r}) = \frac{1}{2} \|\mathbf{W}^{1/2} \mathbf{r}\|_2^2 + k \quad (5.10)$$

Where k is a constant, a function of \mathbf{r}_0 . In RRC, Eq. (5.6) is approximated by ignoring this k which makes the minimization problem solvable using iteratively reweighted l_2 -regularized coding, where \mathbf{W} is modified iteratively in the Eq. (5.9). Therefore, the locally approximated version of Eq. (5.6) becomes:

$$\hat{\mathbf{a}} = \arg \min_{\mathbf{a}} \left[\frac{1}{2} \|\mathbf{W}^{1/2} (\mathbf{y} - \mathbf{D}\mathbf{a})\|_2^2 + \sum_{j=1}^m \rho_v(\alpha_j) \right] \quad (5.11)$$

This is showing the different point of view, where calculating \mathbf{W} the diagonal matrix becoming the main point of focus.

5.3 WEIGHT UPDATE RULE

The elements of weight matrix, \mathbf{W} are the weight values given to each of the signal of the bad illumination or degraded query signal. It is very clear that the occluded or degraded signals, should be assigned smaller weights so that they exercise less influence in determining the coding result and the non-corrupted signal should be assigned higher weight values or data which are very much related with its previous value must be taken as higher preference regarding data selection which are taken in good environmental illumination condition are giving the higher weight value. As a result, signals with larger residuals \mathbf{r}_i will be assigned smaller weights $\omega_s(\mathbf{r}_{0,i})$ and vice versa, as it is reflected in Eq. (5.9). As ρ_s is differentiable, symmetric and monotonic which has its minimum at origin. They assumed that $\omega_s(\mathbf{r}_{0,i})$ is a bounded function in the range of 0 to 1 and proposed the following type of logistic function for calculating the weight values[1][9]:

$$\omega_s(r_i) = \frac{\exp(-\mu r_i^2 + \mu\delta)}{1 + \exp(-\mu r_i^2 + \mu\delta)} \quad (5.12)$$

Where μ and δ are two positive constant that is shaping the function i.e. its decreasing rate and the point of inflection. δ is the parameter which determines the demarcation point, and μ is controlling decreasing rate of weight $W_{i,i}$. Utilizing Eq. (5.9) and performing integration suitably, we get [1]:

$$\rho_s(r_i) = -\frac{1}{2\mu} (\ln(1 + \exp(-\mu r_i^2 + \mu\delta)) - \ln(1 + \exp \mu\delta)) \quad (5.13)$$

This distribution curve performs better than both Gaussian and Laplacian distribution as it is able to address the corrupted signal better by fitting all the higher residual values within its longer tail. If $\omega_s(r_i)$ from Eq. (5.12) is a constant valued term, it gives rise to l_2 -norm fidelity. In that case all the signals would be assigned equal weights, which will produce erroneous

result for the occluded corrupted signal. Whereas a choice of $\omega_s(r_i) = 1/|r_i|$ gives rise to l_1 - norm fidelity, and in this case, the system zero.

5.4 ALGORITHM OF RRC

Weight update of the diagonal weight matrix W in Eq. (5.11) makes the minimization of RRC via iteratively reweighted l_2 - regularized coding, where W is updated as per Eq. (5.9). To get desire coding vector α we update iteratively the weight W . Algorithm 5.1 shows the steps of iteratively reweighted regularized robust coding (IR³C) for solving the RRC minimization problem [1].

Algorithm 5.1 Iteratively Reweighted Regularized Robust Coding

Input: Test sensor signal \mathbf{y} , dictionary \mathbf{D} composed of l_2 - normalized training signals uniformly initialized sparse vector α^1 .

Output: Optimized sparse vector $\hat{\alpha}$.

Set an iteration counter $j=1$:

1. l_2 - normalize the test signal first and hence compute its corresponding residual $\mathbf{r}^j = \mathbf{y} - \mathbf{D} \alpha^j$
2. Calculate the weight matrix $W_{i,l} = \omega_s(r_{0,l})$ using Eq. (5.12) .
3. Solve the minimization problem to obtain $\hat{\alpha}^j$.

$$\hat{\alpha} = \arg \min_{\alpha} \left\{ \left\| W^{\frac{1}{2}} (\mathbf{y} - \mathbf{D} \alpha) \right\|_2^2 + \lambda \|\alpha\|_2^2 \right\}$$

We consider here the Gaussian distribution. In case of Laplacian it would be $\|\alpha\|_1$ and λ is the constant depends on particular distribution.

4. For $j>1$, coefficient vector is updated as $\alpha^{j+1} = \alpha^j + \beta (\hat{\alpha}^j - \alpha^j)$ here β is factor of acceleration , and it should be taken so carefully that the cost function Eq.(5.6) is converging.
5. Convergence criteria: $\|W^{j+1} - W^j\|_2 / \|W^j\|_2 < \varepsilon$, where, ε being a small positive constant.

Update the iteration counter $j=j+1$

5.5 CLASSIFICATION STRATEGY IN RRC

After the convergence of the iteratively reweighted regularized coding problem, following Algorithm 5.1 there has to be a classification strategy for query test sensor signals. The classification strategy used in milk adulteration problem via sparse representation is also used by Yang et al. in RRC [1]. In this method, the test signal \mathbf{y} is classified as:

$$\text{class}(\mathbf{y}) = \arg \min_{cl} \{E_{cl}\} \quad (5.14)$$

Where ,

$$E_{cl} = \left\| \mathbf{W}_0^{1/2} (\mathbf{y} - \mathbf{D}_{cl} \hat{\boldsymbol{\alpha}}_{cl}) \right\|,$$

\mathbf{D}_{cl} is the sub-dictionary associated with class cl , $\hat{\boldsymbol{\alpha}}_{cl}$ is the optimized coding vector for class cl , and \mathbf{W}_0 is the final weight matrix.

5.6 EXPERIMENTAL RESULTS

The experiment was conducted in the Instrumentation and Cyber Physical System Laboratory of Electrical Engineering Department, Jadavpur University, Kolkata. The experiment was conducted to solve the milk adulteration problem with taking different milk sample of different concentration. As mentioned earlier the data from the milk sample was taken under different environmental condition such as good and bad illumination condition, different vertical distance between sensor module and milk surface and with different container namely glass and steel container. The data is made of total 18 channels starting from A to L i.e. from 410 nm wavelength to 940 nm wavelength. Every single channel is capturing a fixed value corresponds to a fixed milk sample with fixed condition. Situations are made of total 8 combination namely,

Table 5.1: Different experimental conditions under RRC

Number of conditions	Conditions
1	Good illumination condition with glass container with 1inch vertical distance between sample surface and sensor module
2	Good illumination condition with glass container with 2inch vertical distance between sample surface and sensor module
3	Bad illumination condition with glass container with 1inch vertical distance between sample surface and sensor module
4	Bad illumination condition with glass container with 2inch vertical distance between sample surface and sensor module
5	Good illumination condition with steel container with 1inch vertical distance between sample surface and sensor module
6	Good illumination condition with steel container with 2inch vertical distance between sample surface and sensor module
7	Bad illumination condition with steel container with 1inch vertical distance between sample surface and sensor module
8	Bad illumination condition with glass container with 2inch vertical distance between sample surface and sensor module

Above total 8 different conditions are applied for every sample of milk. So that the variation of sample and record are prepared to train the algorithm. The entire database is randomly split into training and testing sets in a ratio of 7:3, and the dictionary D in the training dataset, comprises atoms with low lighting conditioned signals, in all the cases.

The following table 5.2 is showing the Experimental results for above varying condition which are evaluated by RRC algorithm. It is clearly observed that the data coming from the sensor is well organised and distinct enough for recognise by RRC algorithm and give better classification accuracy.

Table 5.2: Performance of RRCL1 for Amul Taaza milk sample
For different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	98.66	0.005
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	95.79	0.005
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	77.36	0.028
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	79.59	0.032
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	99.89	0.005
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	63.33	0.029
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	61.46	0.026
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	89.66	0.002

From the above table it is clearly understood that the variation of accuracy of RRC [1] is not varying for different vertical distances here 1 inch and 2inch but the accuracy is degraded drastically for low illumination condition and it is obvious as from the data set of low illumination condition most of the channel data are having very low value in magnitude also sometimes 0 is coming, so the accuracy is very high for good illumination condition. Also, the accuracy is not depending upon the variation of different container materials. So, in practice we can test any milk sample in any container as the light rays from sensor is actually reflected from top surface of milk sample, so here container is independent of experimental setup.

Following table 5.3 is showing accuracy of RRCL2 on the Amul taza data set for different conditions.

Table 5.3: Performance of RRCL2 for Amul taaza milk sample

For different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	99.66	0.005
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	97.79	0.005
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	71.36	0.028
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	64.36	0.006
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	96.78	0.005
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	69.67	0.03
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	59.36	0.029
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	94.77	0.004

Now the data is taken for Red cow milk sample for the same different conditions as mentioned earlier. So, the expected result is very same as result came for Amul taza cow milk sample. So, it is clear that we can classify and predict the adulterated milk based on given methodology.

Table 5.4: Performance of RRCL1 for red cow milk sample

For different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical Distance between milk surface and sensor module	99.36	0.005
Good illumination with glass container with 2inch vertical Distance between milk surface and sensor module	100.00	0.00
Bad illumination with glass container with 1 inch vertical		

Distance between milk surface and sensor module	14.94	0.023
Bad illumination with glass container with 2inch vertical Distance between milk surface and sensor module	11.67	0.009
Good illumination with steel container with 1 inch vertical Distance between milk surface and sensor module	100.00	0.005
Good illumination with steel container with 2inch vertical Distance between milk surface and sensor module	97.33	0.004
Bad illumination with steel container with 1 inch vertical Distance between milk surface and sensor module	15.78	0.032
Bad illumination with steel container with 2inch vertical Distance between milk surface and sensor module	39.36	0.030
Good illumination with glass container with 1 inch and 2 inch together vertical Distance between milk surface and sensor module	100.00	0.00

Table 5.5: performance of RRCL2 for red cow milk sample

For different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	85.62	0.052
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	90.89	0.051
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	46.33	0.024
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	54.36	0.006
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	78.86	0.005
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	99.64	0.005
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	39.67	0.032
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	57.36	0.036
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	77.31	0.053

Now the experiment is conducted for local cow milk and the results are depicted in table 5.6 and table 5.7

Table 5.6: Performance of RRCL1 for local cow milk sample
for different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	87.86	0.056
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	99.64	0.005
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	11.57	0.029
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	26.35	0.032
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	41.25	0.076
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	36.67	0.005
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	90.27	0.005

Table 5.7: Performance of RRCL2 for local cow milk sample
for different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	87.86	0.056
Good illumination with glass container with 2 inch vertical distance between milk surface and sensor module	79.64	0.005
Bad illumination with glass container with 1 inch vertical	29.34	

distance between milk surface and sensor module		0.029
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	58.33	0.064
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	94.38	0.004
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	81.33	0.054
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	15.99	0.005
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	27.69	0.067
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	81.34	0.007

Now the data collected for SuperT cow milk and performance of RRCL1 and RRCL2 is depicted in table 5.8 and table 5.9 as follows,

Table 5.8: Performance of RRCL1 for SuperT milk sample
For different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	94.42	0.063
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	98.33	0.014
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	15.67	0.006
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	19.36	0.005
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	96.35	0.025
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	79.36	0.046
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	28.33	0.001
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	58.36	0.026
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	80.00	0.024

Table 5.9: performance of RRCL2 for SuperT milk sample

For different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	98.99	0.041
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	11.36	0.014
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	34.36	0.074
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	76.78	0.052
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	99.99	0.026
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	41.78	0.039
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	27.33	0.063
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	85.64	0.046

Now the experiment is conducted for Metro cow milk and the corresponding results are given in table 5.10 and table 5.11

Table 5.10: performance of RRCL1 for metro milk sample

for different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	89.65	0.041
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	79.64	0.011
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	11.67	0.074
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	36.07	0.052
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00

Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	87.69	0.056
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	29.67	0.025
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	56.69	0.028
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	71.49	0.067

Table 5.11: Performance of RRCL2 for metro milk sample
For different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	84.56	0.036
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	51.06	0.010
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	16.97	0.080
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	69.98	0.048
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	79.68	0.045
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	26.68	0.052
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	14.74	0.005
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	96.35	0.089

Now we have conducted the experiment for Bhagirathi milk sample for the same given conditions and the performance accuracy is given in table 5.12 and table 5.13

Table 5.12: performance of RRCL1 for Bhagirathi milk sample
for different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	90.55	0.029
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	43.33	0.005
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	47.84	0.005
Good illumination with steel container with 1 inch vertical distance between milk surface and sensor module	100.00	0.00
Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	89.87	0.044
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	28.48	0.004
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	39.96	0.045
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	74.77	0.052

Table 5.13: Performance of RRCL2 for Bhagirathi milk sample
for different conditions

Conditions	Accuracy	
	Mean in %	Standard deviation
Good illumination with glass container with 1 inch vertical distance between milk surface and sensor module	89.65	0.054
Good illumination with glass container with 2inch vertical distance between milk surface and sensor module	97.95	0.039
Bad illumination with glass container with 1 inch vertical distance between milk surface and sensor module	16.67	0.004
Bad illumination with glass container with 2inch vertical distance between milk surface and sensor module	41.64	0.082
Good illumination with steel container with 1 inch vertical Distance between milk surface and sensor module	82.85	0.052

Good illumination with steel container with 2inch vertical distance between milk surface and sensor module	100.00	0.00
Bad illumination with steel container with 1 inch vertical distance between milk surface and sensor module	31.33	0.005
Bad illumination with steel container with 2inch vertical distance between milk surface and sensor module	38.43	0.071
Good illumination with glass container with 1 inch and 2 inch together vertical distance between milk surface and sensor module	75.69	0.007

As shown in the result we can say that the performance or accuracy of RRC for good illumination condition is very high compared to the data collected in low or bad illumination condition so it is very much clear that the experiment should be conducted in good illumination condition. And the importance of different materials for container of milk is none i.e. we can conduct for any materials steel or glass. So, for further investigation for checking accuracy of RRC we conduct the experiment for good illumination condition and taking glass container with only 2 inches vertical separation.

Now we are investigating the performance of RRC for different training and testing ratios as follows,

Table 5.14 shows Performance of RRC for different training and testing ratios for good illumination condition taking glass container with 2inch vertical gap between milk sample and sensor module.

Table 5.14: Performance of RRCL1 and RRCL2 for different testing and training ratio for predicting level of adulteration of milk

Milk sample	Training: Testing	Accuracy of RRCL1		Accuracy of RRCL2	
		Mean in %	Standard deviation	Mean	Standard deviation
Amul taza	7:3	95.79	0.005	97.79	0.005
Amul taza	6:4	91.00	0.052	89.69	0.052
Amul taza	5:5	84.44	0.063	81.89	0.041
Amul taza	4:6	63.36	0.024	51.26	0.047
Amul taza	3:7	41.25	0.028	45.69	0.057
Amul taza	2:8	11.39	0.021	19.67	0.089
Red cow	7:3	100.00	0.00	90.89	0.051
Red cow	6:4	87.89	0.058	81.11	0.082

Red cow	5:5	71.58	0.005	80.00	0.002
Red cow	4:6	64.85	0.052	74.88	0.025
Red cow	3:7	49.58	0.056	70.25	0.069
Red cow	2:8	19.35	0.089	16.67	0.056
Local cow milk	7:3	99.64	0.005	79.64	0.005
Local cow milk	6:4	91.25	0.052	81.66	0.054
Local cow milk	5:5	89.99	0.005	87.77	0.006
Local cow milk	4:6	74.46	0.027	71.86	0.089
Local cow milk	3:7	45.89	0.048	39.87	0.049
Local cow milk	2:8	17.89	0.006	14.96	0.069
Super_T cow milk	7:3	98.33	0.014	98.99	0.041
Super_T cow milk	6:4	91.47	0.056	90.00	0.053
Super_T cow milk	5:5	89.67	0.005	81.26	0.067
Super_T cow milk	4:6	74.58	0.005	69.71	0.058
Super_T cow milk	3:7	41.33	0.004	36.66	0.056
Super_T cow milk	2:8	23.36	0.047	29.96	0.030
Metro cow milk	7:3	79.64	0.011	84.56	0.036
Metro cow milk	6:4	81.22	0.052	86.64	0.028
Metro cow milk	5:5	76.35	0.056	80.00	0.027

Metro cow milk	4:6	79.68	0.054	71.46	0.087
Metro cow milk	3:7	51.11	0.005	49.88	0.078
Metro cow milk	2:8	11.87	0.006	17.67	0.004
Bhagirathi	7:3	100.00	0.00	97.95	0.039
Bhagirathi	6:4	98.96	0.048	95.64	0.056
Bhagirathi	5:5	91.25	0.047	89.99	0.005
Bhagirathi	4:6	87.88	0.041	83.33	0.057
Bhagirathi	3:7	69.89	0.039	74.56	0.004
Bhagirathi	2:8	14.52	0.006	13.69	0.028

So from the given result we can say that as the data is not varying for a particular channels i.e. for a (particular wavelength in nm) for a fixed sample with fixed condition so RRC is very robust in this case and as per data the performance is very satisfactory .As the data are not changing for a particular channels so for train the model we just need few sample data that is why whether we are train the model with 70% samples or 40% samples the performance of algorithm is very high. Only a few variations are shown in the data for a particular channel so if we train the model only 20% or 30% data then the performance is not satisfactory.

5.7 SUMMARY

The chapter is discussing about the method of regularized robust coding (RRC) [1], based on robust regression analysis, and its usefulness in milk adulteration problem [2]. As discussed earlier for the different milk samples of different conditions the experiment was conducted and we observed that for a particular channel the data is almost constant for a particular condition hence the model is trained with very small sample will serve our purpose. The accuracy is very high for good illumination condition so in future for industrial usage one must recommend to explore the sensor system in good illumination condition. All the different milk samples are working correctly on the given model .As in the given thesis we are preparing our sample for a particular milk with 10%, 20%, 30%, and 50% water -milk solution and RRC is classifying with very high accuracy almost 80% to 100% .So in future we can prepare more milk adulterated samples with gap of 5% so we can have more number of samples which can give more flexibility us to predict more sensible milk adulteration scheme.

CHAPTER 6

CONCLUSION

- **SYNOPSIS**
- **FUTURE SCOPE OF WORK**

6.1 SYNOPSIS

In the present work author developed a system which is capable of identifying the different adulterated milk sample and determine the different food constituents by means of spectroscopic sensor AS7265x. In the experimental setup author prepared different physical conditions like changing the vertical gap between the sensor and milk or food sample, two containers steel and glass, different illumination conditions and hence got several outcomes from sensor system. Author used several milk brands with their 5 different adulteration levels for carry out the experiment and got different outcomes so that author can classify among them with the level of adulteration in percentage.

Author is using two different signal processing and decision-making techniques namely GPR and RRC which qualify the developed system to classify different milk samples. Author got very high accuracy result from the developed system as the channel data are absolutely unique and ideal for feeding to decision making techniques GPR and RRC, and hence getting result with very high accuracy.

Author developed the system in a such a manner so that system can transmit the data in both way via WIFI and via wired, the system is well recognised and acceptable for its online version, so that one can collect and send data from any parts of the world and can communicate through WIFI mode. This feature gives user to get instant data from the any part of the country and analyse through different decision-making techniques like GPR, RRC.

6.2 FUTURE SCOPE OF WORK

The developed system has immense potential to work in many different problems as the sensor readings are so unique that it can get data from many other samples like fruits, oil, different spices and water quality monitoring by getting the information about nitrogen of water etc. So, the spectroscopic data are unique in terms of classify the different food samples, as in the present thesis work author gives the sight of getting one or two food constituents but in future work one can explore the same methodology and get the outcome as more than two different constituents.

In the present thesis work author demonstrated WIFI communication feature of transmitting data by using 'ThinSpeak' website for visualizing spectroscopic data. In future one can apply the same principle of transmitting data via WIFI in some self-developed personalised server and can make a complete graphical user interface to get the sights of different spectroscopic data.

In future one can get a sensor fusion system by adding different sensors like temperature sensor, humidity sensor and many more along with spectral sensor AS7265x to get more information about the food sample.

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