Monitoring Health Status and Quality Assessment of Leaves Using Terahertz Frequency

Adnan Zahid[1], Hasan Tahir Abbas[2], Fawad Sheikh[2], Thomas Kaiser[2], Ahmed Zoha[1], Muhammad Imran[1], and Qammer H. Abbasi[1]
[1]School of Electronics and Nanoscale Engineering, University of Glasgow, Glasgow, U.K.
[2]Institut für Digitale Signalverarbeitung, Universität Duisburg-Essen (UDE), Campus Duisburg, NRW, Germany
[1]Email: a.zahid.1@research.gla.ac.uk, {Hasan.Abbas, Ahmed.Zoha, Muhammad.Imran & Qammer.Abbasi@glasgow.ac.uk}

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ABSTRACT

The demand for effective use of water resources has increased due to ongoing global climate transformations in the agriculture science sector. Cost-effective and timely distributions of the appropriate amount of water are vital not only to maintain a healthy status of plants leaves but to drive the productivity of the crops and achieve economic benefits. This paper presents a novel, and non-invasive machine learning (ML) driven approach using terahertz waves with a swissto12 material characterization kit (MCK) in the frequency range of 0.75 to 1.1 THz in real-life digital agriculture interventions, aiming to develop a feasible and viable technique for precise estimation of water content (WC) in plants leaves on different days. For this purpose, multi-domain features are extracted from frequency, time, time-frequency domains using observations data to incorporate three different machine learning algorithms such as support vector machine, (SVM), K-nearest neighbour (KNN) and decision-tree (D-Tree). The results demonstrate SVM outperformed other classifiers using 10-fold and leave-one-observations-out cross-validation for different days classification with an overall accuracy of 98.8%, 97.15%, and 96.82% for coffee, pea-shoot, and spinach leaves respectively. In addition, using SFS technique, coffee showed a significant improvement of 15%, 11.9%, 6.5% in computational time for SVM, KNN and D-tree. For pea-shoot, 21.28%, 10.01%, and 8.53% of improvement was noticed in operating time for SVM, KNN and D-Tree classifiers. Lastly, in baby-spinach leaf, SVM exhibited an upgrade of 21.28%, 10.01%, and 8.53% was noticed in operating time for SVM, KNN and D-Tree classifiers and which eventually enhanced the classification accuracy. Thus, the proposed method incorporating ML using terahertz waves can be beneficial for precise estimation of WC in leaves and can provide prolific recommendations and insights for farmers to take proactive actions in relations to plants health monitoring.

Index terms: THz sensing, machine learning, terahertz, plant health

BIOGRAPHY

Qammer H. Abbasi, received his BSc and MSc degree in electronics and telecommunication engineering from University of Engineering and Technology (UET), Lahore, Pakistan (with distinction). He received his Ph.D. degree in Electronic and Electrical engineering from Queen Mary University of London (QMUL), U.K., in Jan., 2012. From 2012 to June 2012, he was Post-Doctoral Research Assistant in Antenna and Electromagnetics group, QMUL, UK. From 2012 to 2013, he was international young scientist under National Science Foundation China (NSFC), and Assistant Professor in University of Engineering and Technology (UET), KSK, Lahore. From August, 2013 to April 2017 he was with the Center for Remote healthcare Technology and Wireless Research Group, Department of Electrical and Computer Engineering, Texas A &M University (TAMUQ) initially as an Assistant Research Scientist and later was promoted to an Associate Research Scientist and Visiting lecture where he was leading multiple Qatar national research foundation grants. Currently Dr. Abbasi is a Lecturer (Assistant Professor) in James Watt school of engineering at University of Glasgow in addition to Visiting Lecturer with Queen Mary, University of London (QMUL). He has been mentoring several undergraduate, graduate students and postdocs. Dr. Abbasi has research portfolio of around £3.5 million and contributed to a patent, 7 books and more than 250 leading international technical journal and peer reviewed conference papers and received several recognitions for his research. Dr. Abbasi is an IEEE senior member and was Chair of IEEE young professional affinity group. He is an Associate editor for IEEE Journal of Electromagnetics, RF, and Microwaves in Medicine and Biology, IEEE Sensors, IEEE open access Antenna and Propagation and IEEE Access journal and acted as a guest editor for numerous special issues in top notch journals. He is a member of IET and commitee member for IET Antenna & Propagation and healthcare network. Dr. Abbasi has been a member of the technical program committees of several IEEE flagship conferences and technical reviewer for several IEEE and top notch journals including TPC chair for 4th international UCET conference 2019. He contributed in organizing several IEEE conferences, workshop and special sessions in addition to European school of antenna course. He received several recognitions for his research, which includes appearance in BBC, STV, dawnnews, local and international newspaper, cover of MDPI journal, most downloaded articles, UK exceptional talent endorsement by Royal academy of Engineering, National talent pool award by Pakistan, International Young Scientist Award by NSFC China, URSI Young Scientist award, National interest waiver by USA, 4 best paper awards and best representative image of an outcome by QNRF. His research interests include nano communication, biomedical applications of millimeter and terahertz communication, wearable and flexible sensors, compact antenna design for 5G and beyond, RF design and radio propagation, antenna interaction with human body, Implants, body centric wireless communication issues, wireless body sensor networks, non-invasive health care solutions, physical layer security for wearable/implant communication.

OUTLINE

- Introduction
- Motivation
- Proposed Method
- Measurements Setup
- Results
- Conclusions

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Introduction and Motivation

- By 2050, global food production will need to increase by an estimated 70% in developed countries and 100% in developing countries to match current trends in population growth In most countries, agriculture is considered as the spine in the overall development of countries especially in developing countries due to its significant role in enhancing economic development of country.

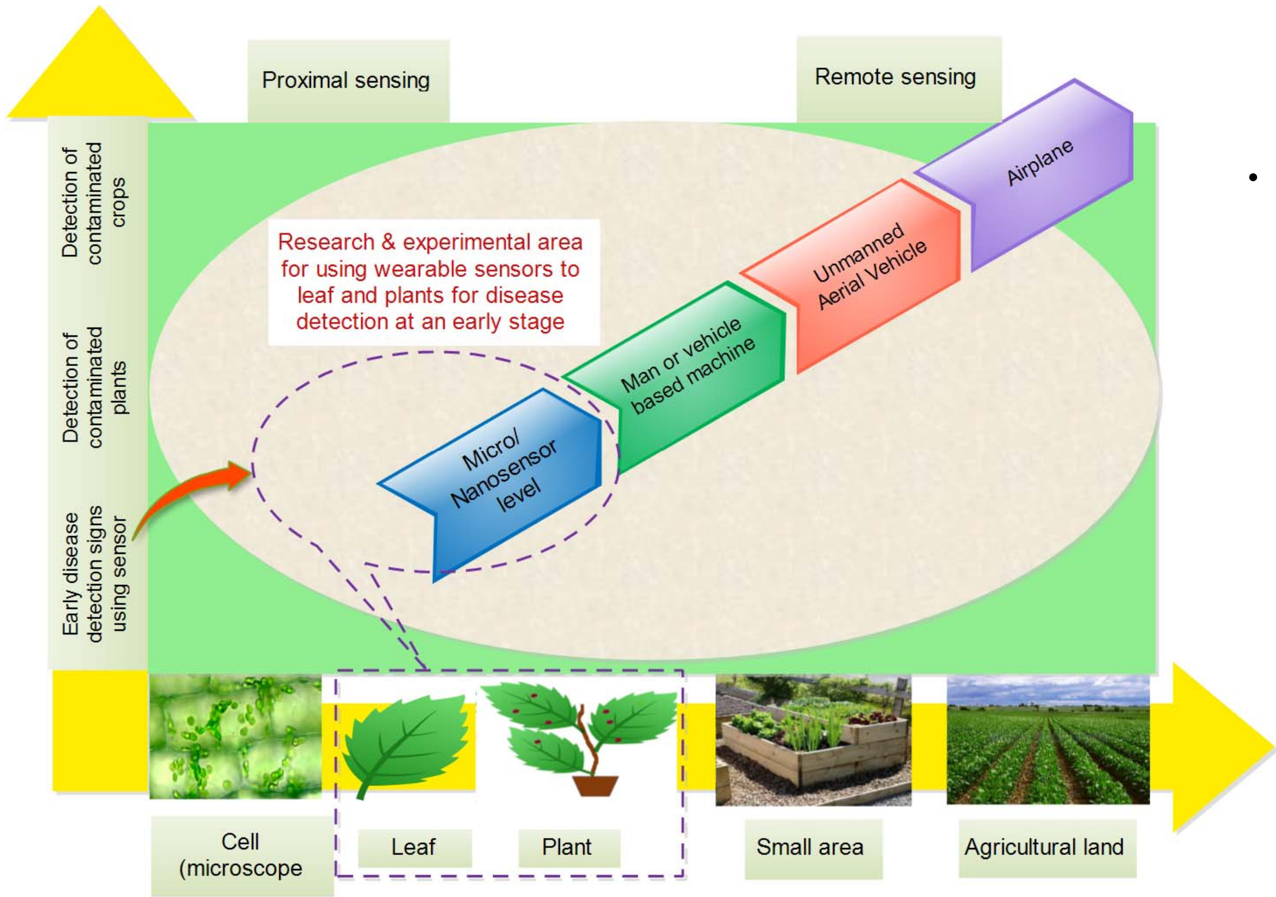
- Agriculture contributes approximately 20% of total greenhouse gas emission in Scotland and therefore makes a significant contribution to the total UK greenhouse gas emissions. Uncontrolled application of the pesticides, fertilisers and other resources are the major contributing factors

- Standard sensors and systems have been employed to meet the huge requirement of crops productivity, appropriate usage of fertilizers, capable of detecting small amounts of impurities in soil and pathogens in plants, nutrients deficiencies in plants have not obtained prolific results in agriculture sectors and clearly appears to be unfeasible and unachievable.

- This motivates our work to develop a novel and innovative approach employing nano-sensors and machine learning at molecular level in plants to improve reliability, enhancing the sensitivity in detecting the bacteria or fungus in plants with precise quantification at the early stage and at molecular level which would help in reducing usage of pesticides and effective use of fertilizers, and to produce less time consuming, portable, and cost-effective solution.

Sensing Technologies for Precision Agriculture

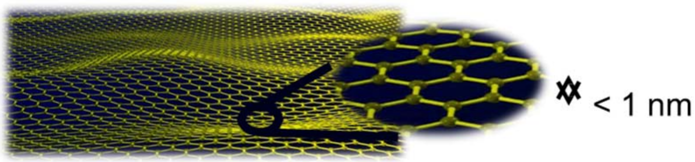
Sensing technologies applied at different stages to determine the contaminated crops

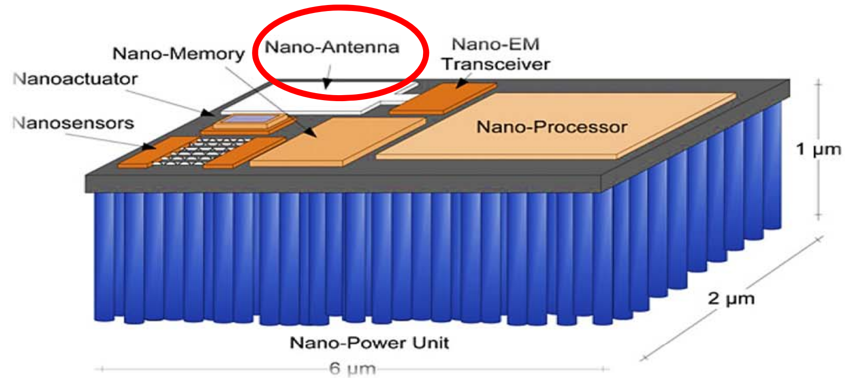


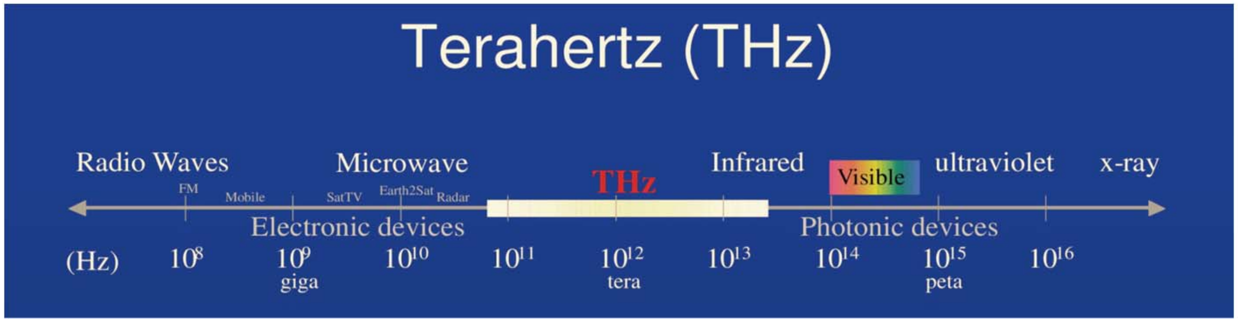
- Overview of current sensor technologies used for the automated detection and identification of host-plant interactions. These sensors can be implemented in precision agriculture applications and plant phenotyping on different scales from single cells to entire ecosystems. Depending on the scale, different platforms can be operated and consequentially different plant parameters can be observed

Nanosensor Device (Nano-Antenna)

Nanotechnology enables the development of nano-scale devices
Nanosensors are the most basic nano-devices that are able to perform sensing, actuation, and reporting,
The essential part of such a nanodevice is the communication unit. Graphene based Nano-antennas have been proposed to transmit signal in the THz band (0.1-10THz).



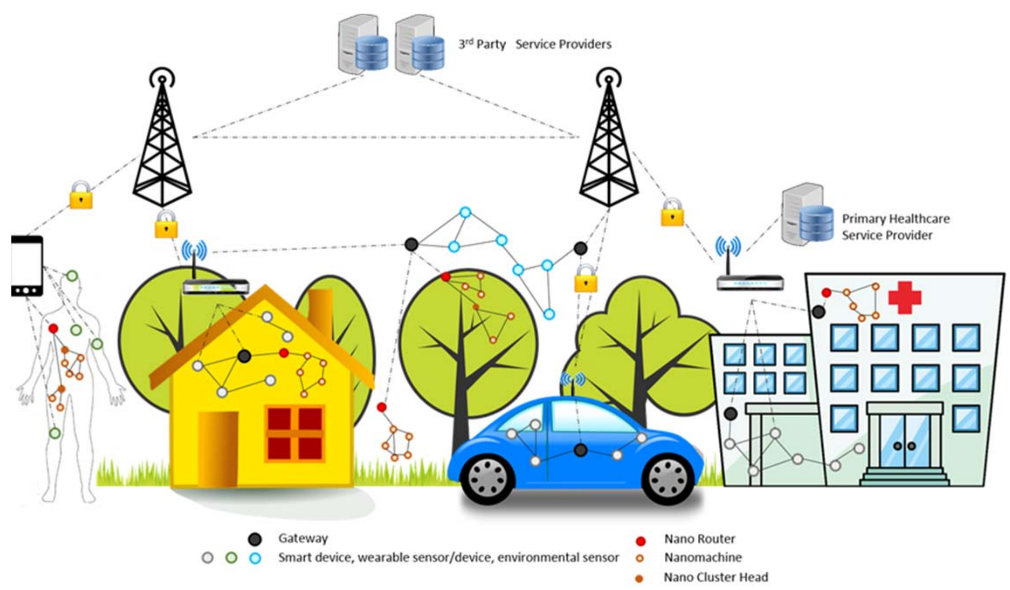




I. F. Akyildiz and J. M. Jornet, "Electromagnetic Wirelss Nanosensor Networks," *Nano Communication Networks,* 2010.

Internet of Nano Things (IoNT)

- The interconnection of nanonetworks with traditional networks and the Internet defines a new networking paradigm, known as the Internet of Nano Things

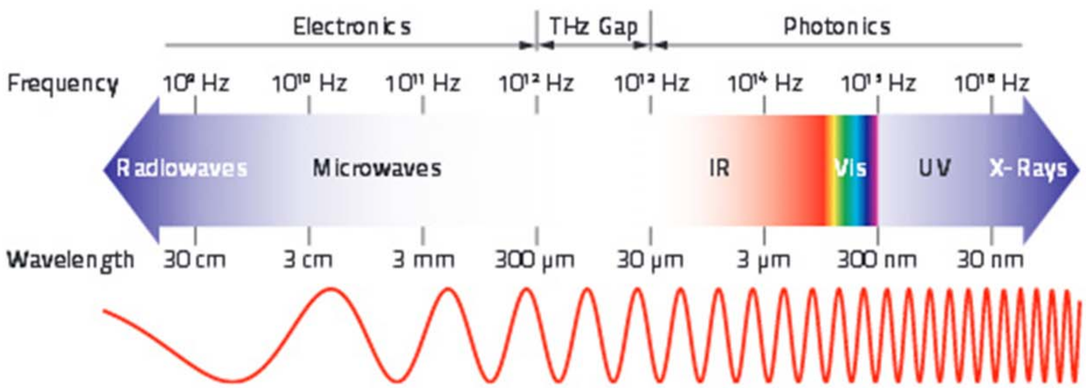


Nano-communication

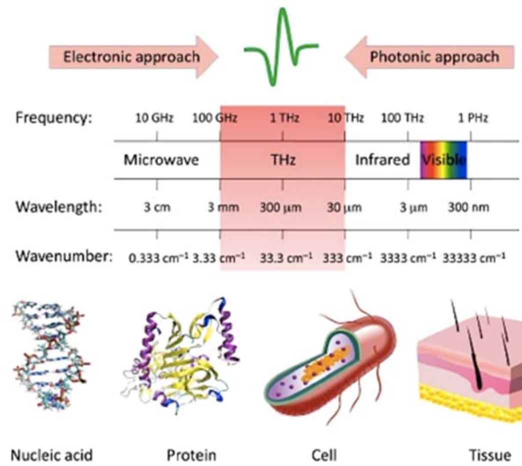
Two main paradigms emerge:

- ❖ Molecular communication
- ❖ **Electromagnetic communication**

The latest advancements in graphene-based electronics have opened the door to electromagnetic communication among nano-devices in the THz band.

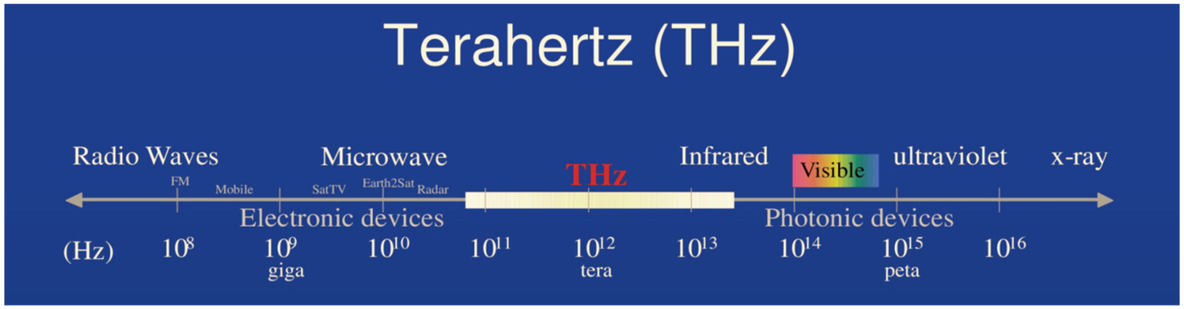


THz gap



The exploration of THz region from 100GHz to 10THz

Introduction Cont.

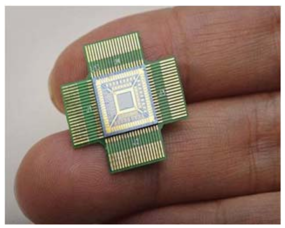


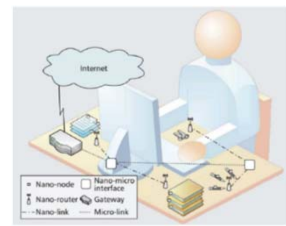
- How do nano-devices communicate with each other?
  - ➢ Molecular Communication
    - Diffusion-based Molecular Communication
    - Flow-based Molecular Communication
  - ➢ Electromagnetic Communication
  - ➢ Sonic Communication
  - ➢ and *etc.*

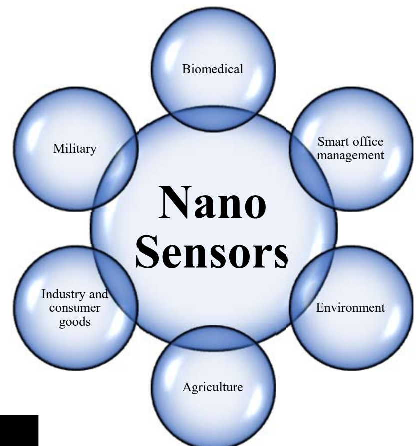
- THz Band channel is highly frequency selective and exhibits a unique distance-dependent bandwidth
- Terahertz frequencies are used its non ionization hazards for biological tissues, and less susceptibility to some of propagation (i.e., rayligh fading)

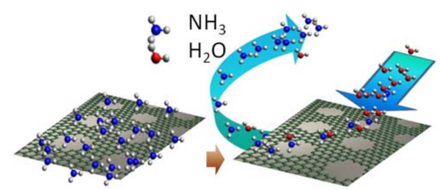
Applications of Nano-scale

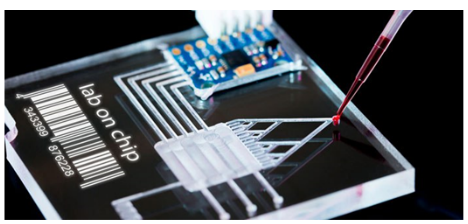
The nano-scale IoNT sensory data enables new applications that are limited or unavailable in the IoT e.g., Healthcare, Environmental, Agricultural monitoring, Military and Industry

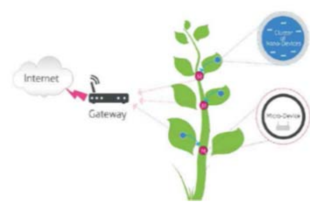




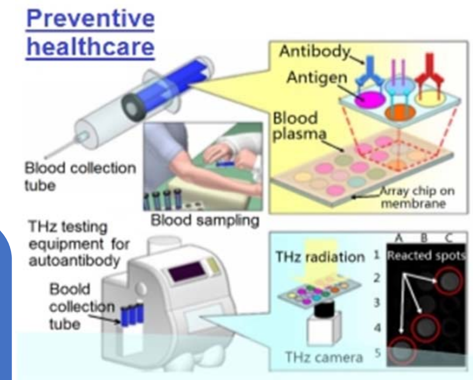








Applications of Nano-scale



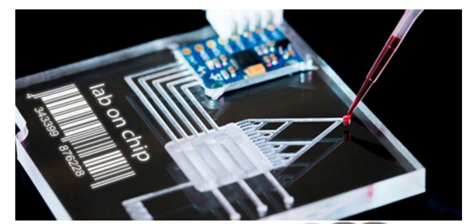
Security

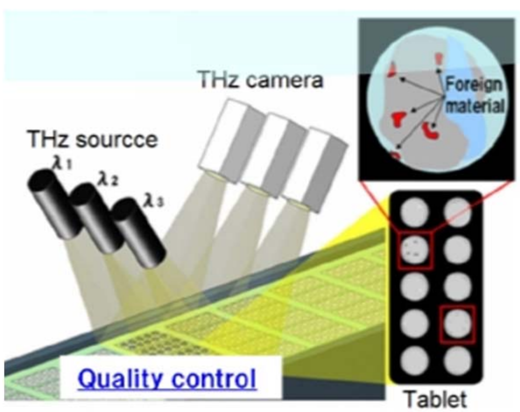
Healthcare

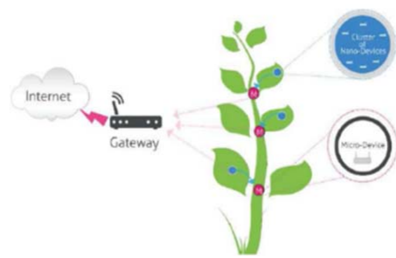
Terahertz Sensing Technology

Quality Control

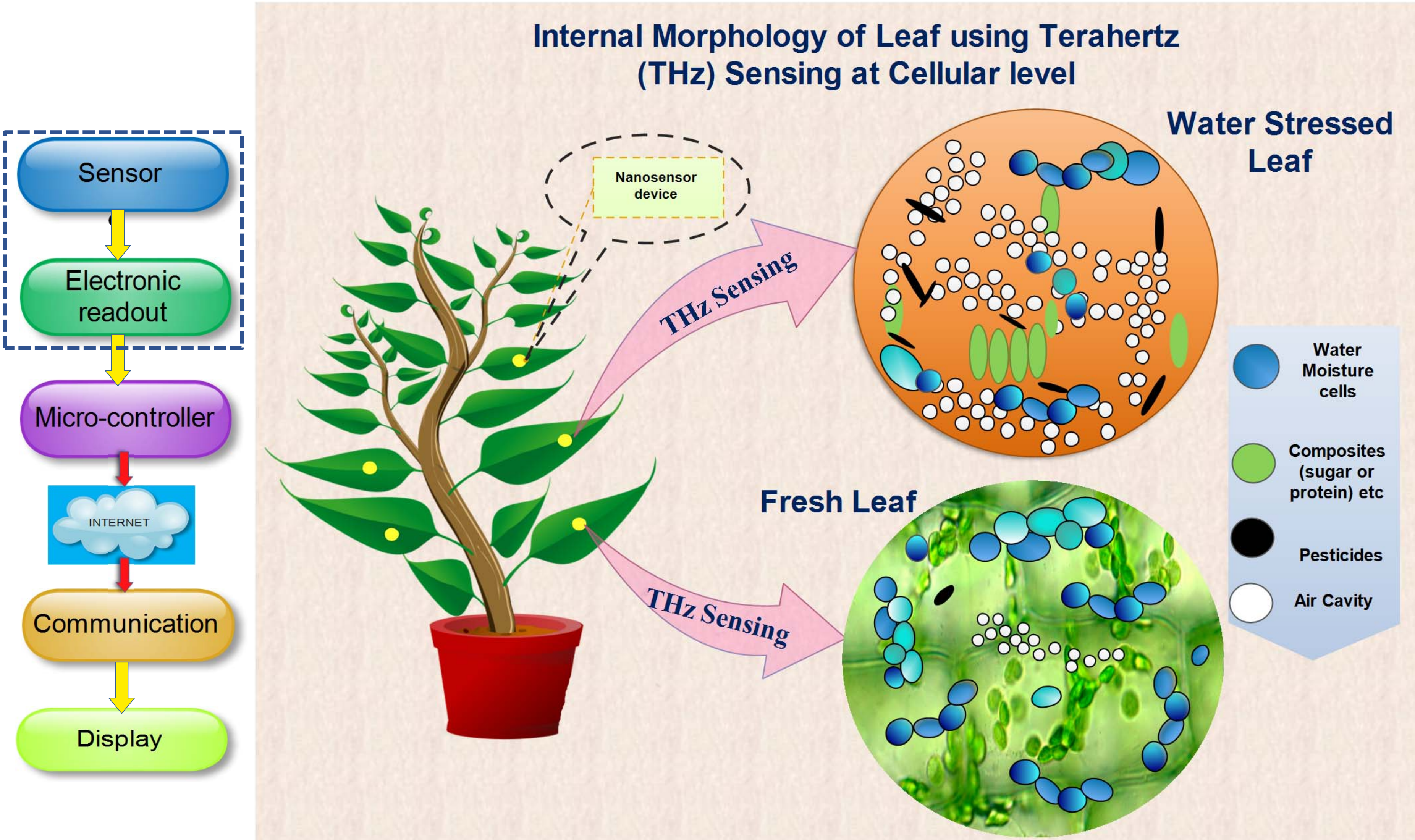
Communications



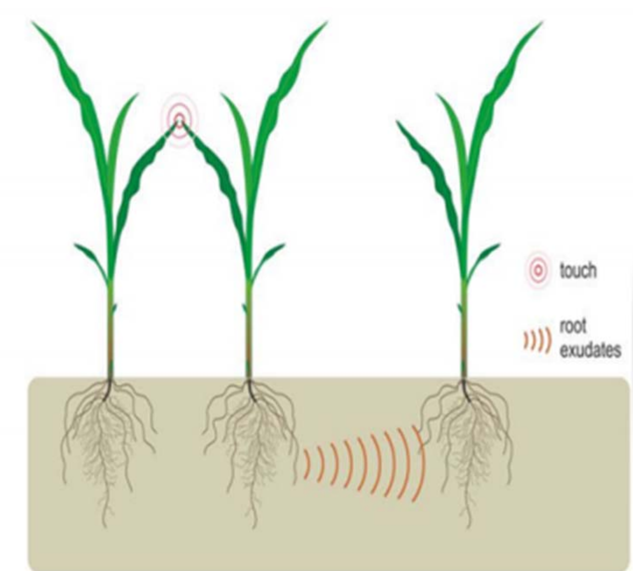




Nano-Sensor on Leaves Using THz Sensing



Terahertz Existing technologies for Monitoring Health Status and Water Content of Leaves



- Time Domain Spectroscopy
- Hyper-spectral Imaging
- Magnetic Resonance Imaging
- Thermal Imaging

Water content in monitoring health status of leaves

- In the past decade, climate transformations have predicted an increment in the occurrence of scarcity of water resources in many parts of world.
- This growing deficiency of water has caused enormous challenges in various fields of plant science sector.
- The realization of water as an important and fundamental component requires in photosynthesis, nutritional transport, and to the timely growth of plant leaves.
- In this work, a novel and non-invasive technique is presented to estimate the water content (WC) at cellular level in plants leaves in using a terahertz sensing

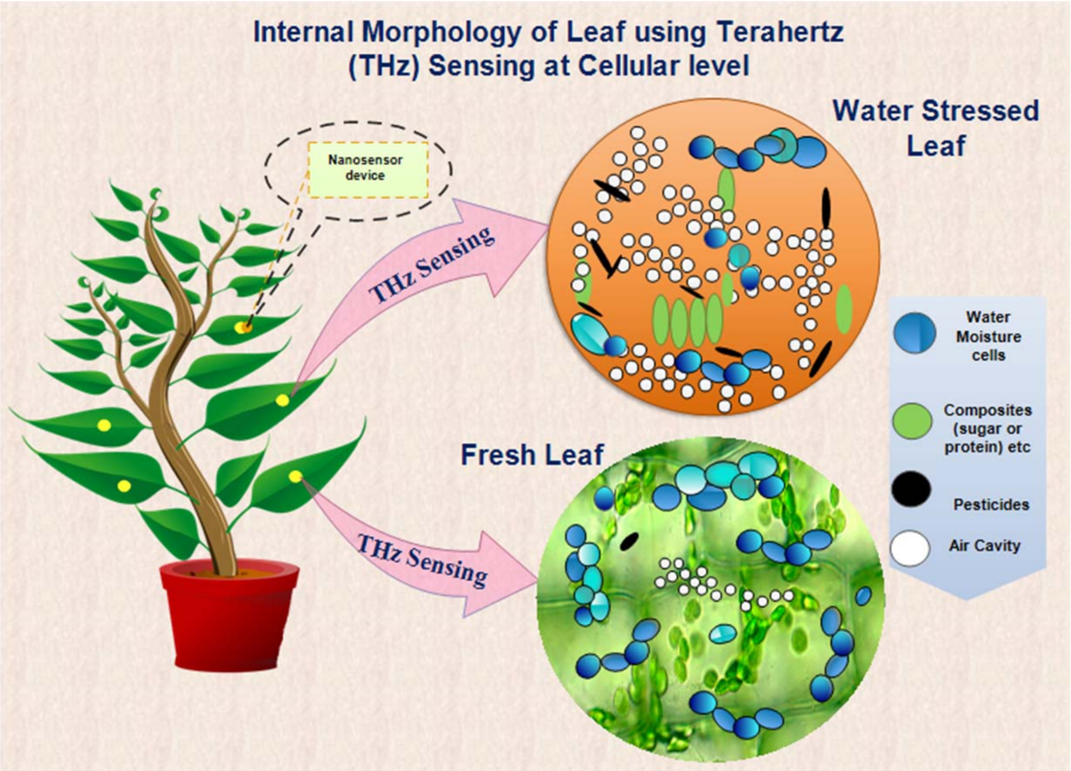
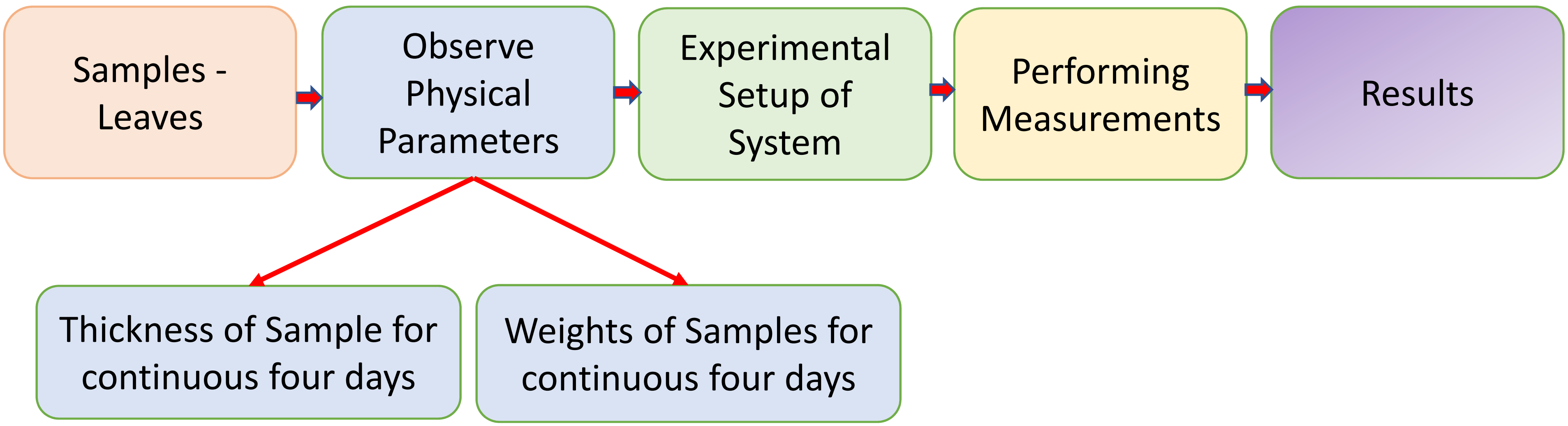


Fig. 1: Internal Morphology of Leaf Using Terahertz (THz) Sensing at Cellular Level

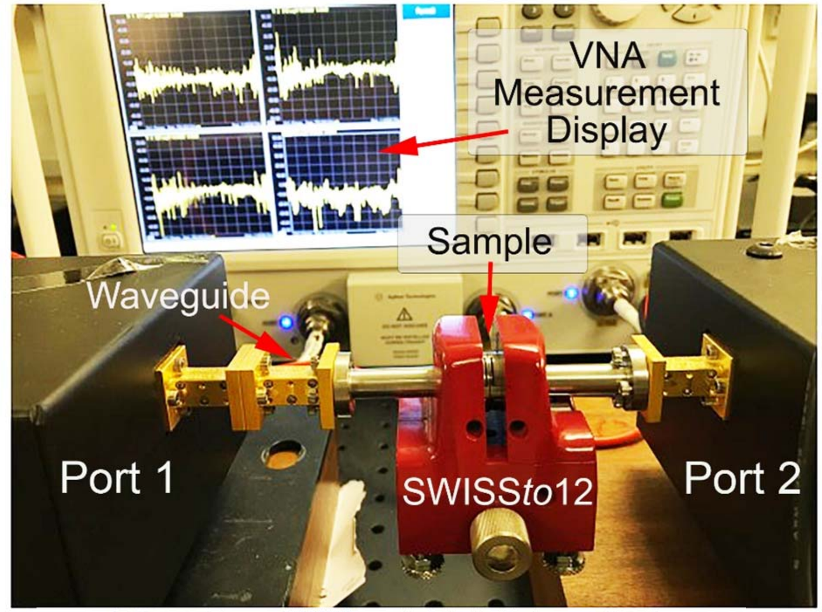
Overall Approach of Proposed Technique



Measurements Setup

Network Analyzer

- **Swiss*to*12 THz system** (0.75 to 1.1 THz)
- A waveguide system
- Polytetrafluoroethylene (PTFE) caps

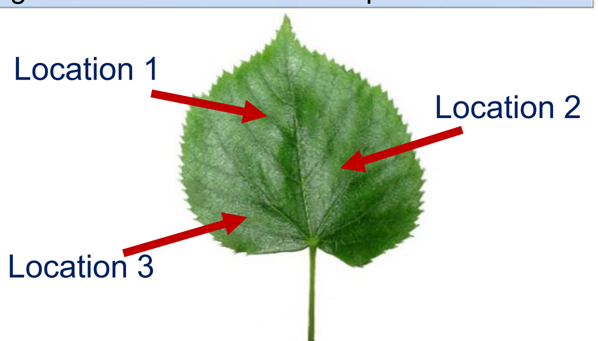


Calibration Kit (wR – 1.0)

- Transmission Electron Microscope (TEM)
- Scanning Electron Microscope (SEM)

Samples

- Fresh leaves (Baby leaf, Peashoot, Spinach)
- Digital scale and Vernier Calliper



Results

Statistical Analysis of Leaves

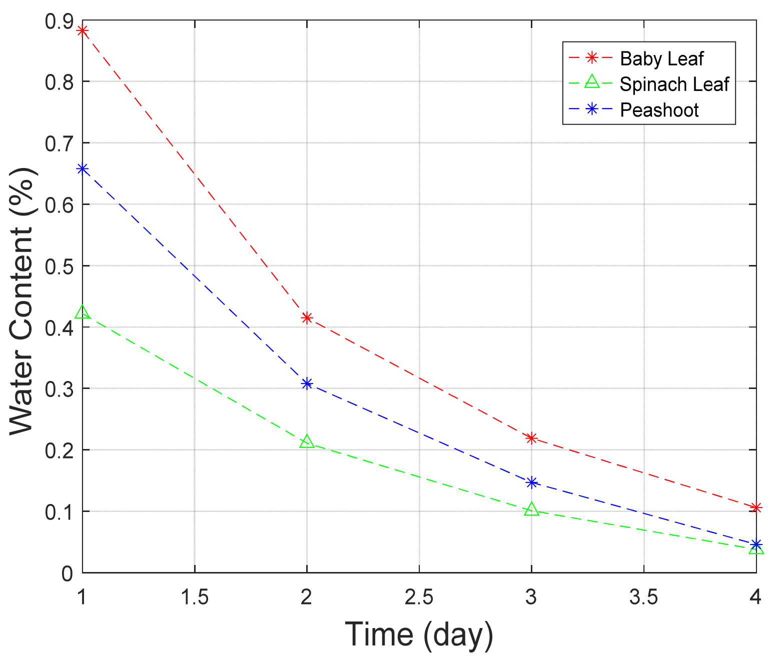


Fig. Water content of the leaves from day 1 to day 4

Fig. 3: Demonstration of Measuring the weight and thickness of leaves using digital scale and Vernier calliper respectively

$$WC = \frac{W_{time} - W_{dry}}{W_{fresh}} \times 100\%$$

- It was aimed to analyse the variations of water content (WC) in all three leaves for four consecutive days and its effect on absorption.
- It was noticed that baby-leaf contained a high volumetric WC followed by pea-shoot and spinach leaf.
- As days progressed, the weights of all leaves were drastically reduced due to the evaporation of WC from leaves, thus, creating more air-cavity in leaves.

Nicolson-Ross-Weir (**NRW**) **method**

Real and Imaginary Permittivity

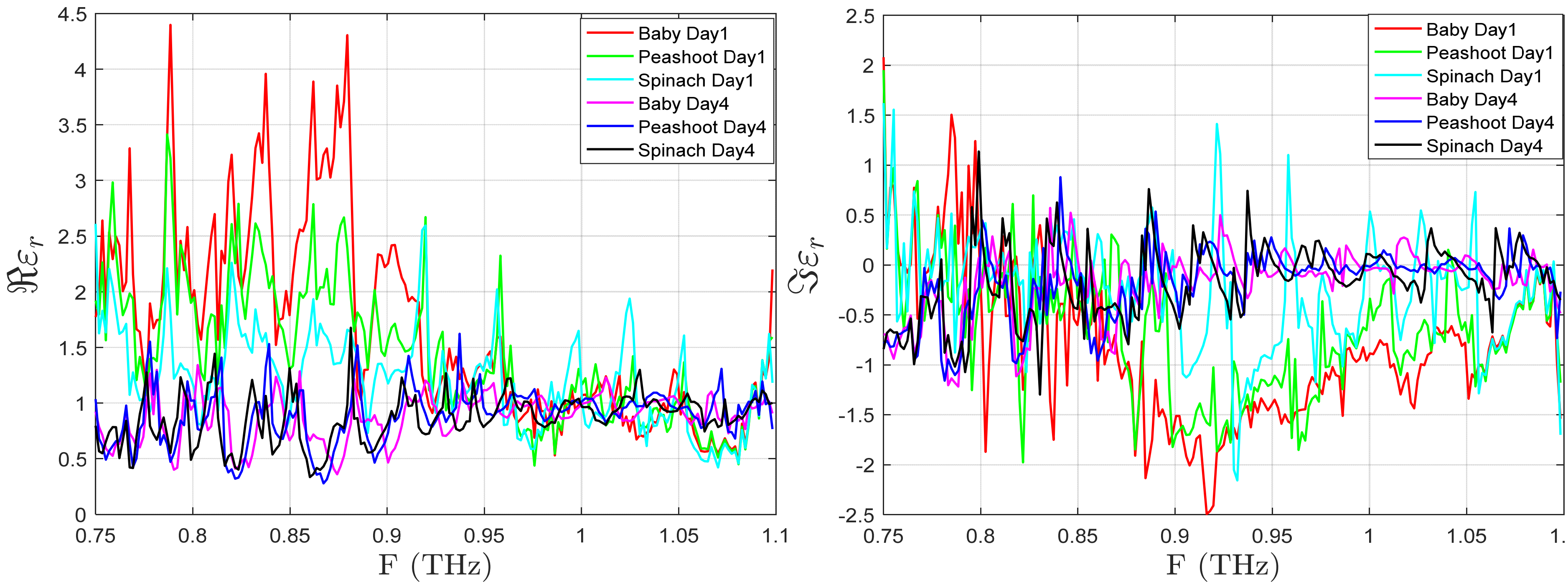
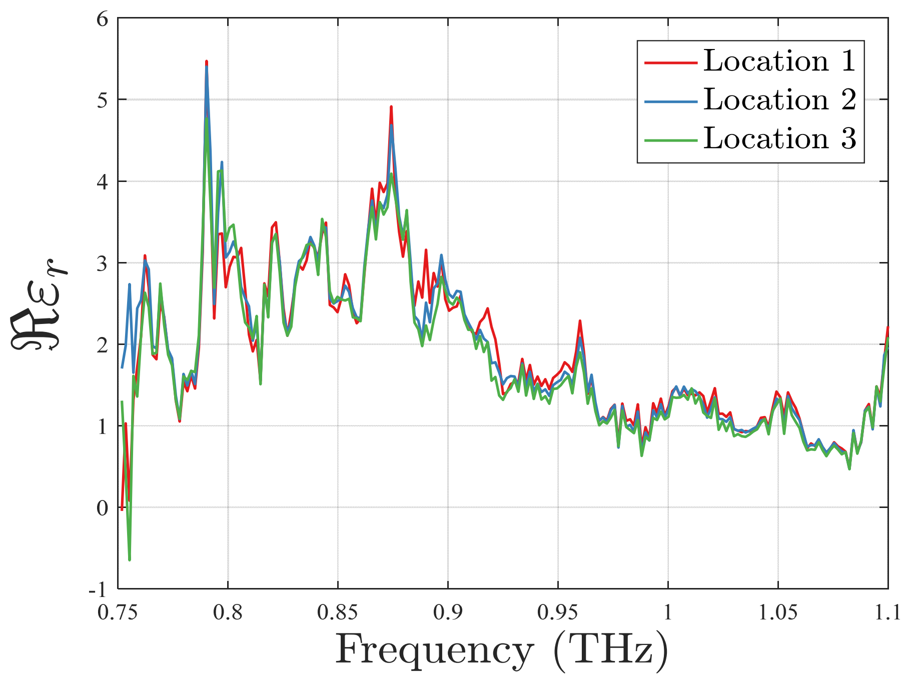
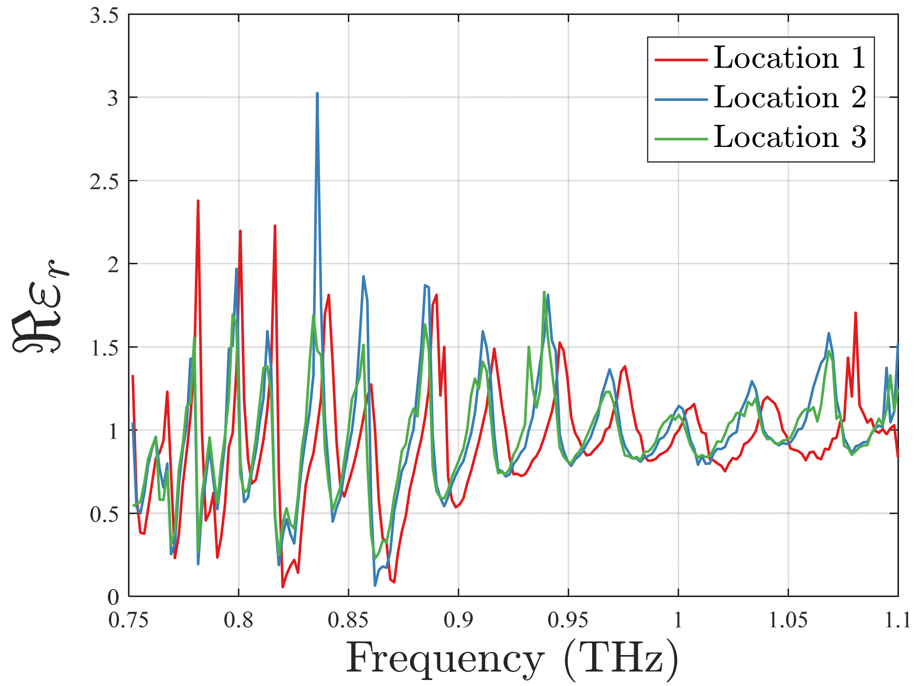


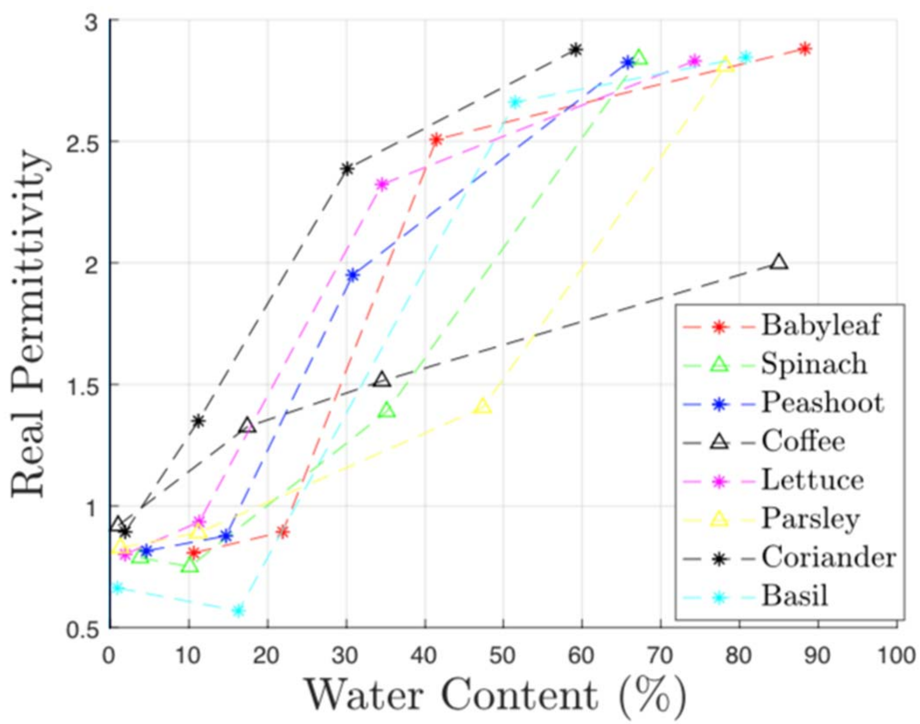
Fig. Permittivity (Real and Imaginary) response of all three leaves from day 1 to 4 using a frequency range from 0.75 THz to 1.1 THz.

Permittivity Response of Leaves at Three Various Locations-





Correlation of Real Permittivity and Loss of Water Content in Leaves Over four Consecutive Days



Machine Learning Applications

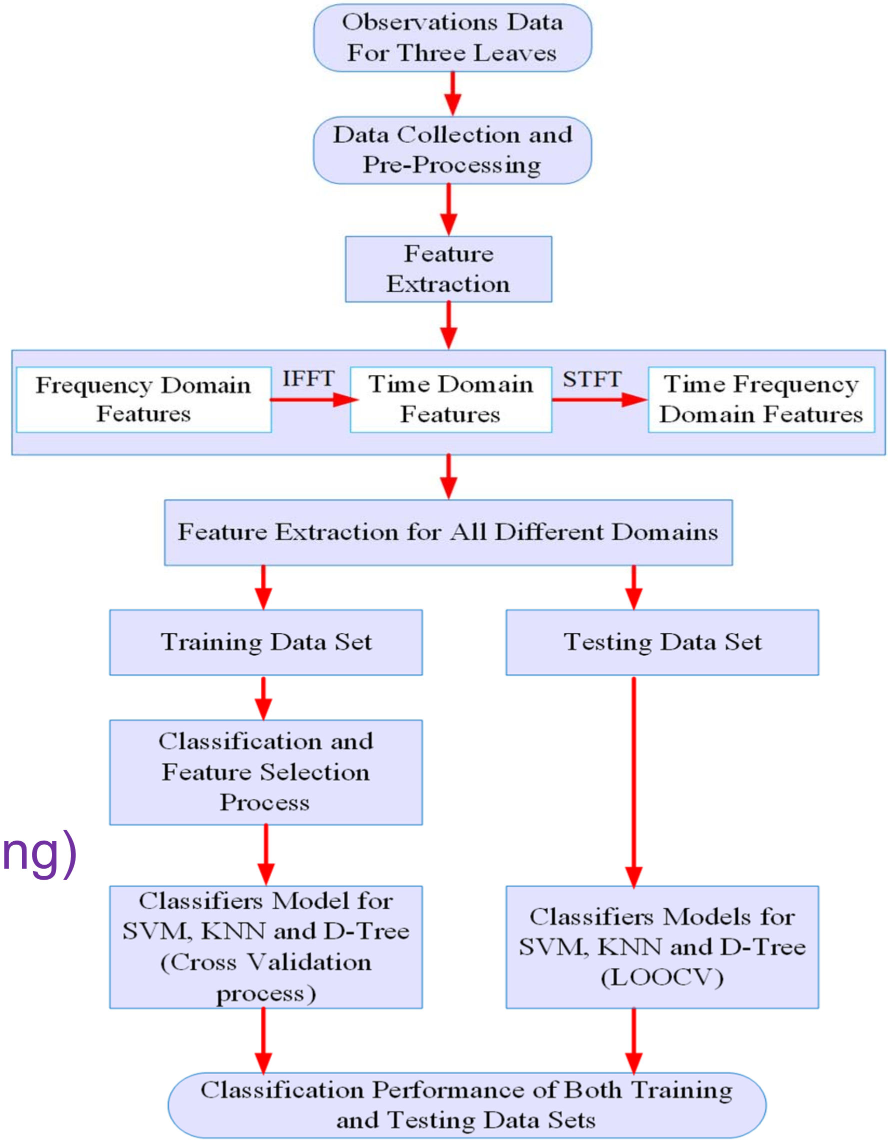
Some of the prominent and notable contributions where ML have been extensively used is the healthcare sector, food security, meteorology, medicine, meteorology, economic sciences etc

Furthermore, researchers are very keen to discover its possibilities, specifically in modern agriculture systems, to enhance yield production by utilizing the water distribution effectively

Flow Chart – An approach followed

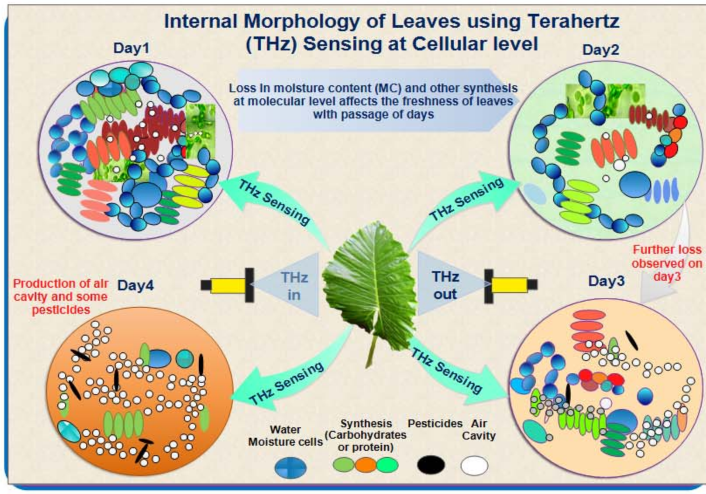
Steps Followed:

- Data Collection and Pre-Processing --
- Classification of all Frequency features (Raw Data)
- Feature Extraction
- Feature Selection
- Classification Model (Training and Testing)
- Output

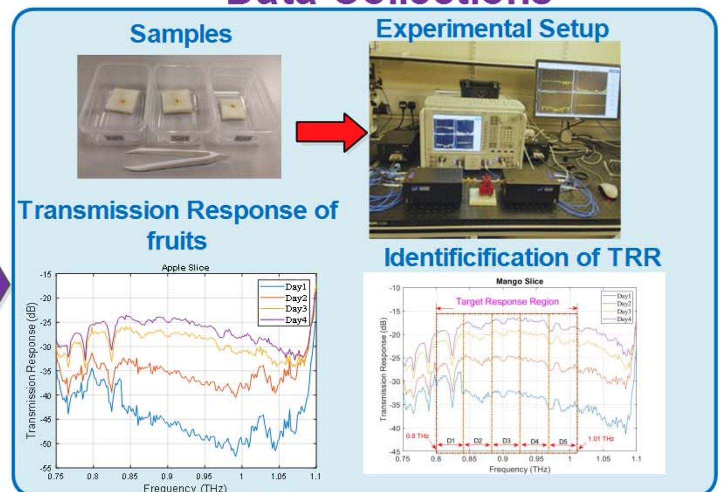


Graphical Representation

Internal Morphology of Leaves

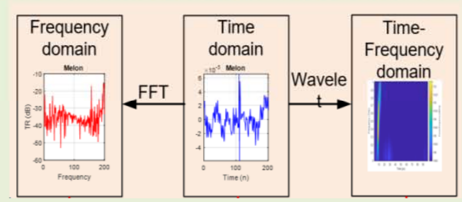


Non-invasive Sensing Setup and Data Collections



Classification Model

Feature Extraction & Selection



Selection of Parameters → Developed a classification Model → Training Data 70% / Testing Data 30%

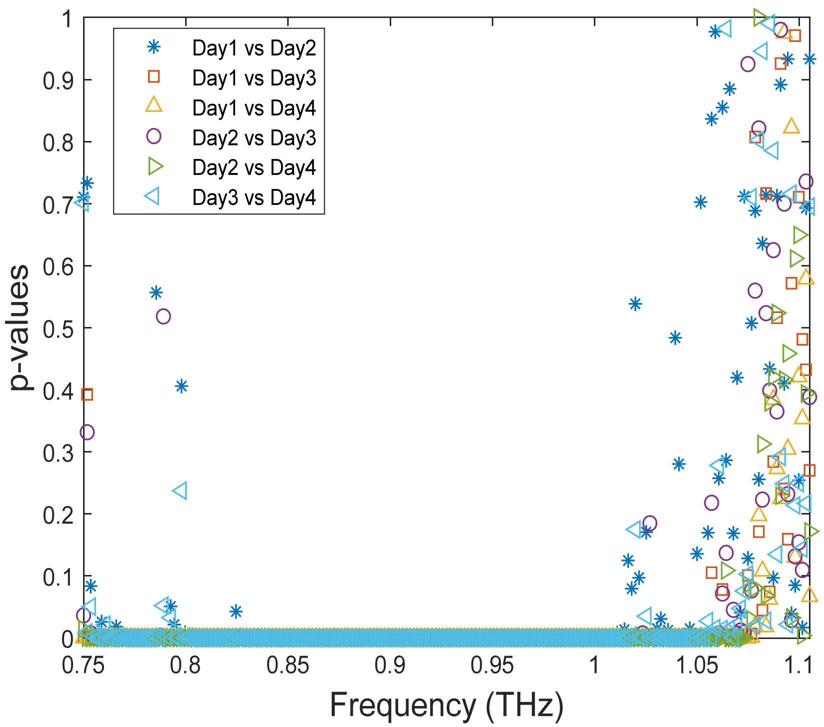
Classification Results

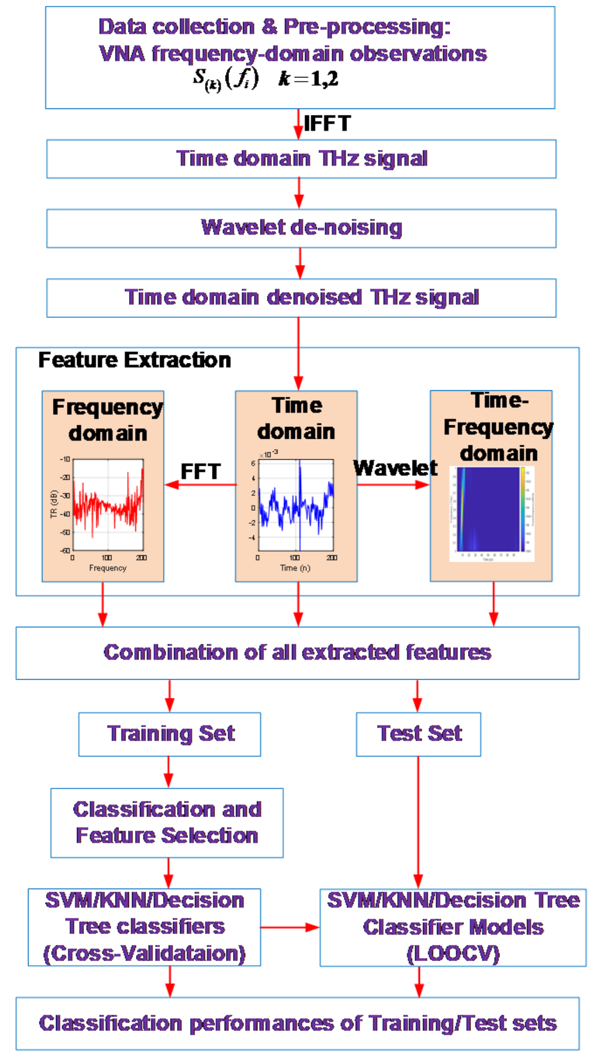
Classification Accuracy for leave-one-observation-out cross-validation

Samples	Classes	Classifiers Test Accuracy Performance (%) SVM	KNN	D-Tree	Water Content (%)
Coffee Leaf	Day1	100	100	100	82.84
	Day2	95.2	88.1	100	41.22
	Day3	100	92.6	92.3	12.34
	Day4	100	100	100	0.71
	Variance	0.58	1.09	0.92	
Peashoot Leaf	Day1	100	100	100	76.84
	Day2	100	87.5	87.5	49.22
	Day3	93.6	78.4	74.2	18.91
	Day4	95.0	89.3	91.7	0.21
	Variance	1.55	2.27	3.60	
Spinach Leaf	Day1	100	100	100	71.14
	Day2	100	100	100	34.22
	Day3	92.6	88.6	75.5	10.34
	Day4	94.7	89.7	91.3	0.10
	Variance	1.76	2.90	4.60	

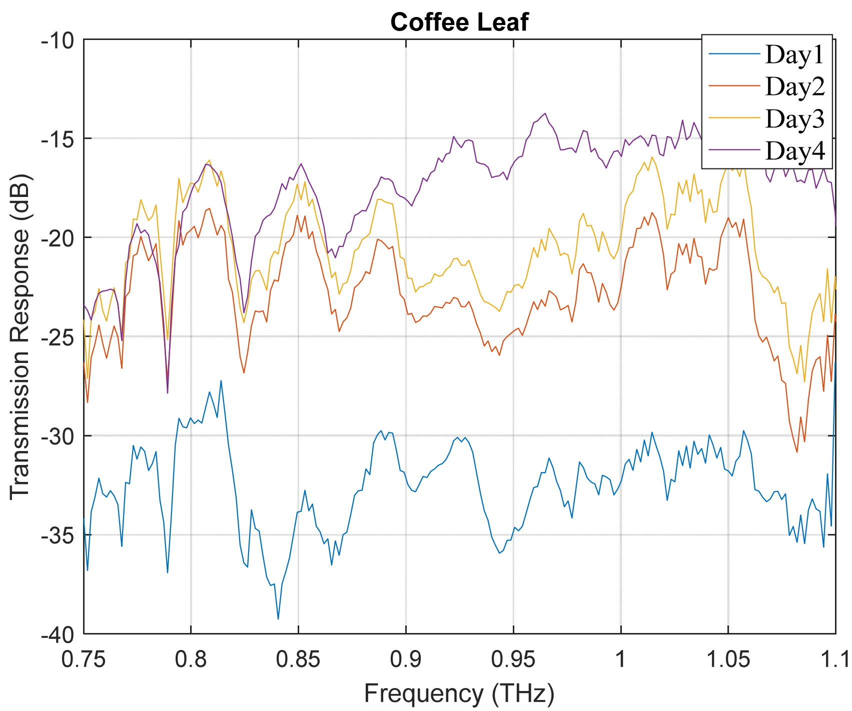
Classification of days: flow chart and identification of TRR

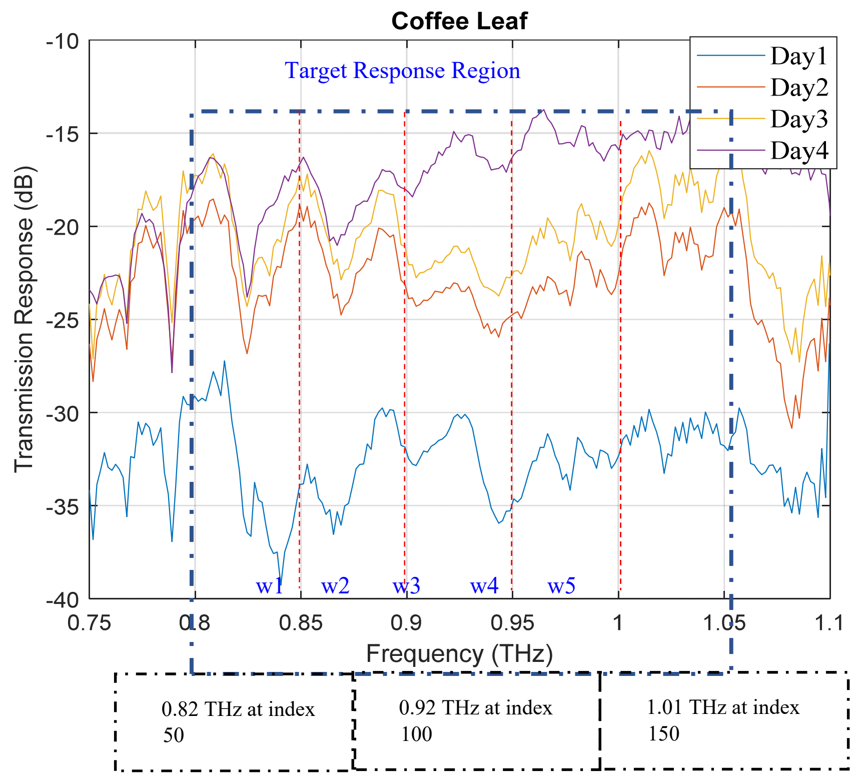
- From cumulative distribution function (CDF) of the probability of t-test, the observations in the frequency range from 0.8 THz to 1.05 THz exhibited a significant difference with the value of probability p near to 0 between the different days based on MC of fruit slice.
- Target Response Region (TRR) for feature extraction of classification.





1. Data Collection
2. Establish a Target Response Region
3. To find optimum features



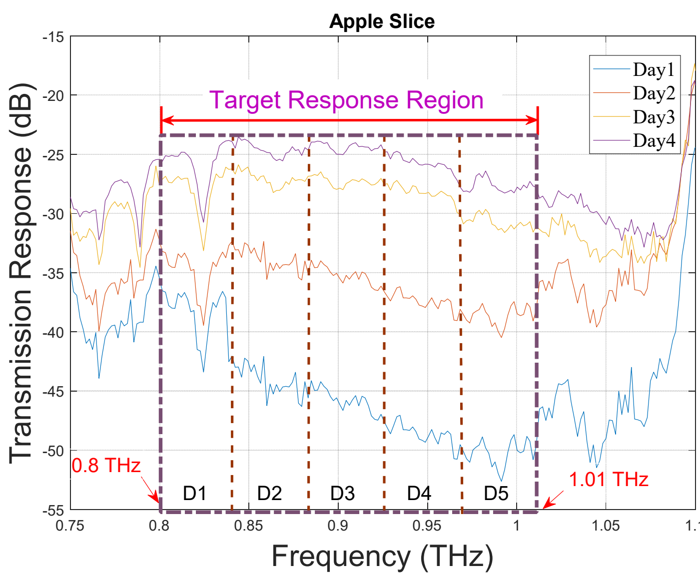


• Feature extraction of frequency domain (10 features)

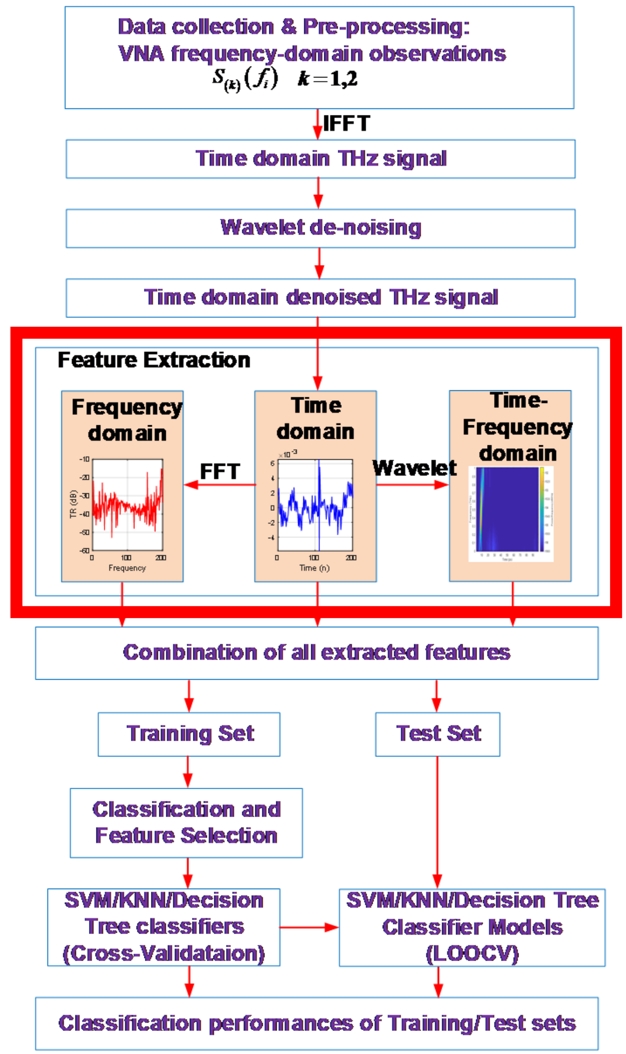
- The observations obtained from VNA were in frequency domain form, which can be used to extract the frequency domain features in TRR range directly. The variance of the Power Spectral Density (PSD) and the peak value of Cross Power Spectral Density (CPSD) :

$$\mathrm{PSD}\{S_{kk}(\omega)\} = \frac{1}{D} E\left\{\left(S_{(k)}^{(n)}(\omega)^{*} \cdot S_{(k)}^{(n)}(\omega)\right)\right\}$$

$$\mathrm{CPSD}\ \{S_{rk}(\omega)\} = max\ \langle \frac{1}{D} E\left\{\left(R(\omega)^{*} \cdot S_{(k)}^{(n)}(\omega)\right)\right\}\rangle$$

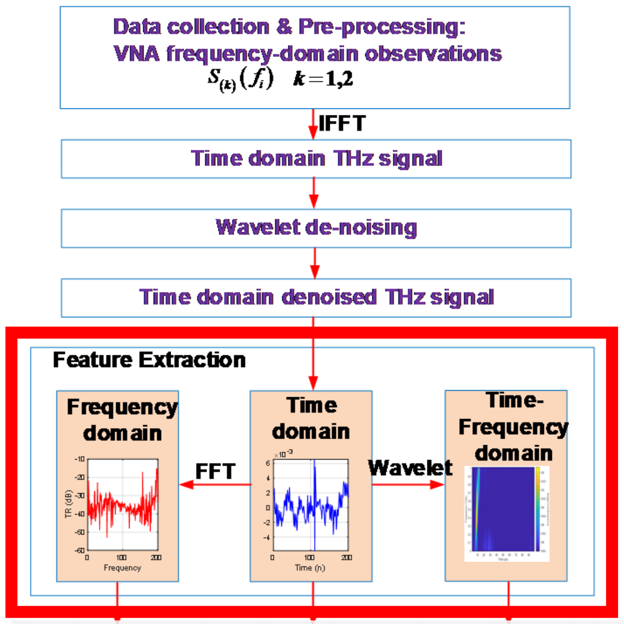


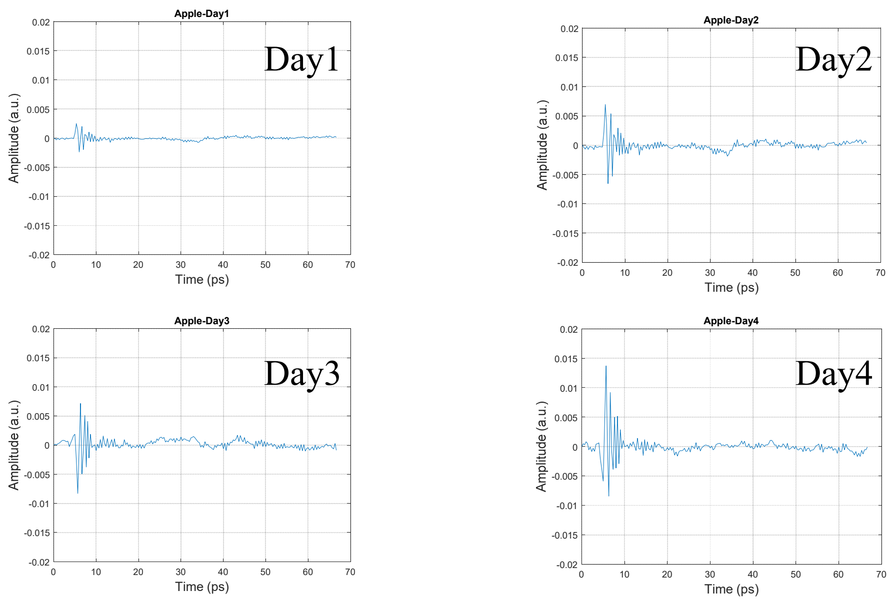
- In the TRR range, five frequency windows, D1,…,D5, with equal width of each frequency window were taken into.

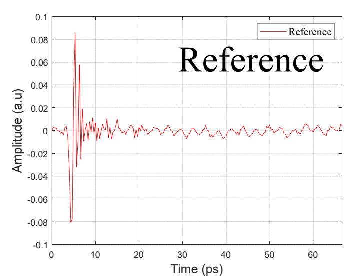


• Feature extraction of time domain (11 features)

By applying IFFT to transmission response of observations





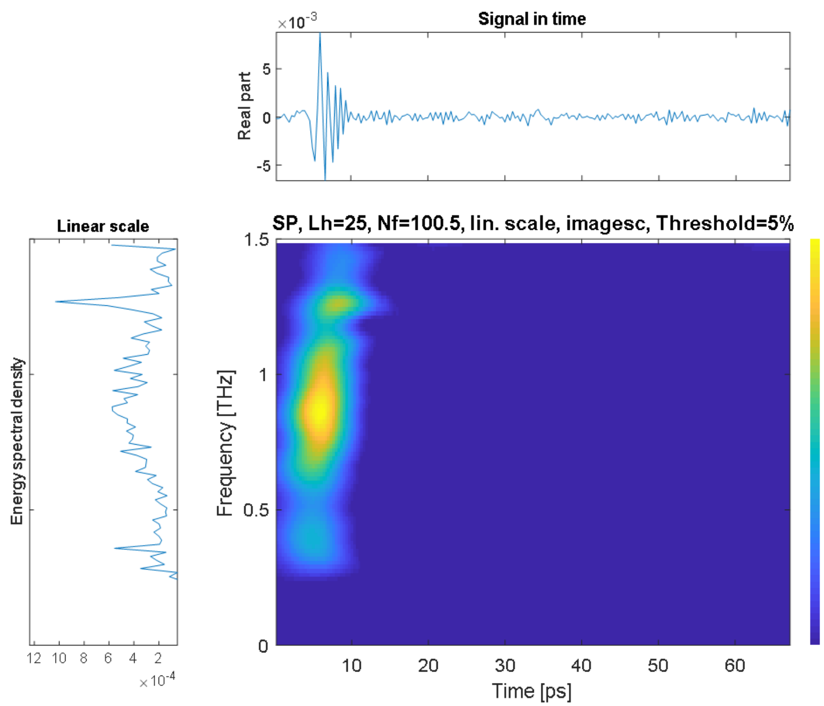


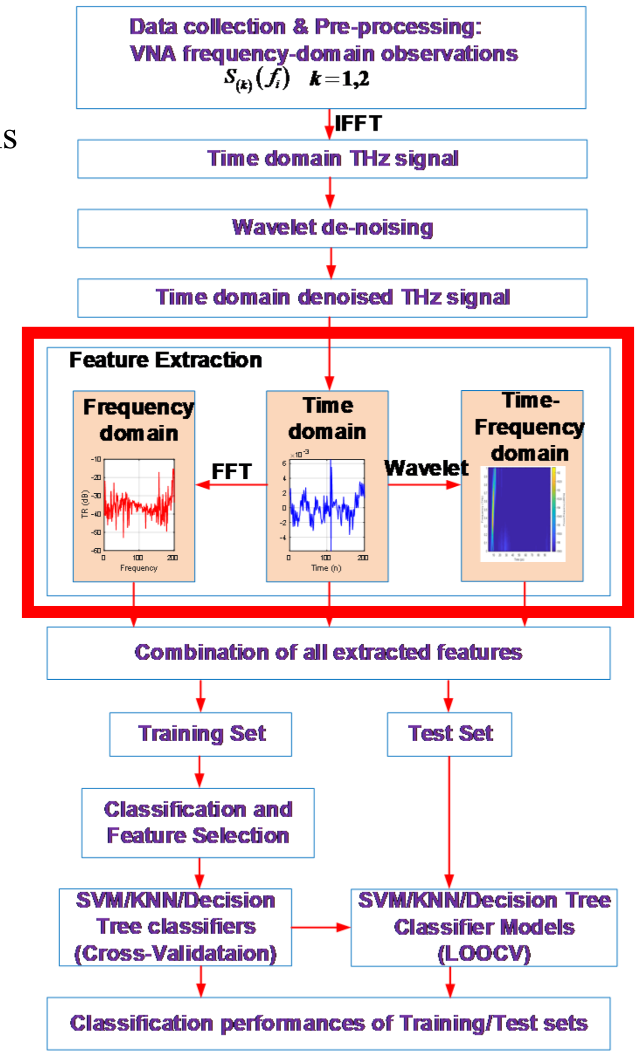
- Mean
- Mean of AV (MAV)
- STD
- Mean of AD (MAD)
- Skewness
- Kurtosis
- PCC
- 25th percentile (Q_1)
- 75th percentile (Q_3)
- IQR

Reference signal: measured by connecting the two halves of the corrugated waveguides of the MCK without sample between them together.

Feature extraction of time-frequency domain (4 features)

By applying STFT or Wavelet to time domain signal of observations

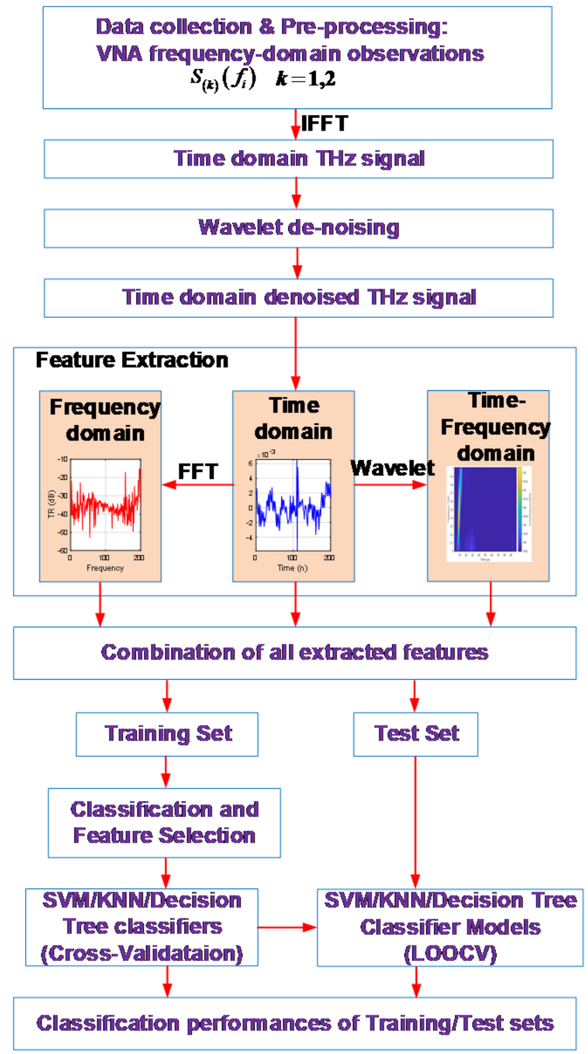




Classification of days

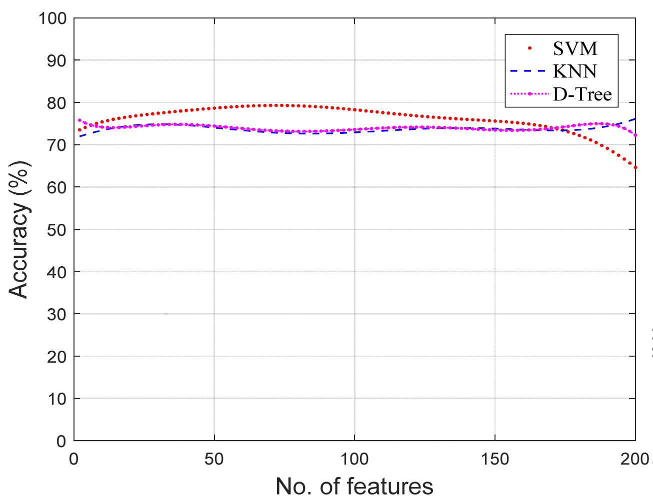
- Features extracted from time-, frequency-, and time-frequency domain.

Time Domain	Serial No.	Frequency Domain	Serial No.	Time-Frequency Domain (Wavelet)	Serial No.
Mean	1	PSD (D1)	12	Subband1	22
Variance	2	PSD (D2)	13	Subband2	23
MAV	3	PSD (D3)	14	Subband3	24
STD	4	PSD (D4)	15	Subband4	25
MAD	5	PSD (D5)	16		
Skewness	6	CPSD (D1)	17		
Kurtosis	7	CPSD (D2)	18		
PCC	8	CPSD (D3)	19		
Q_1	9	CPSD (D4)	20		
Q_3	10	CPSD (D5)	21		
IQR	11				
No of Features: 11		No of Features: 10		No of Features: 4	

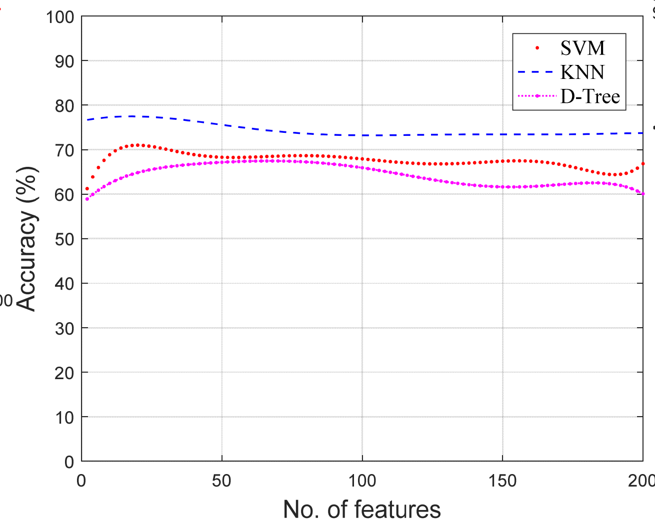


Classification Accuracy Results for Raw Data

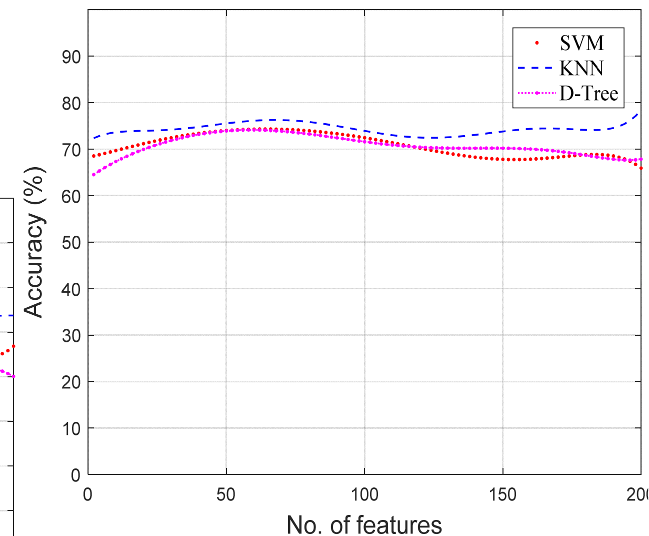
Accuracy (%)	Coffee	Peashoot	Baby Spinach
(SVM) %	88.22	89.26	77.78
(KNN) %	80.1	78.95	76.98
(DTree) %	86.24	81.58	76.93



Coffee



Pea-shoot



Baby-Spinach

Optimization and Feature Selection

Table 4. Classification Results for Coffee leaf

Classification Accuracy (%)	Time domain features (11)	Frequency domain features (10)	Time-frequency domain features (4)
SVM	92.6%	93.0%	91.6%
KNN	90.0%	91.8%	89.4%
Decision Tree	91.2%	90.7%	91.2%

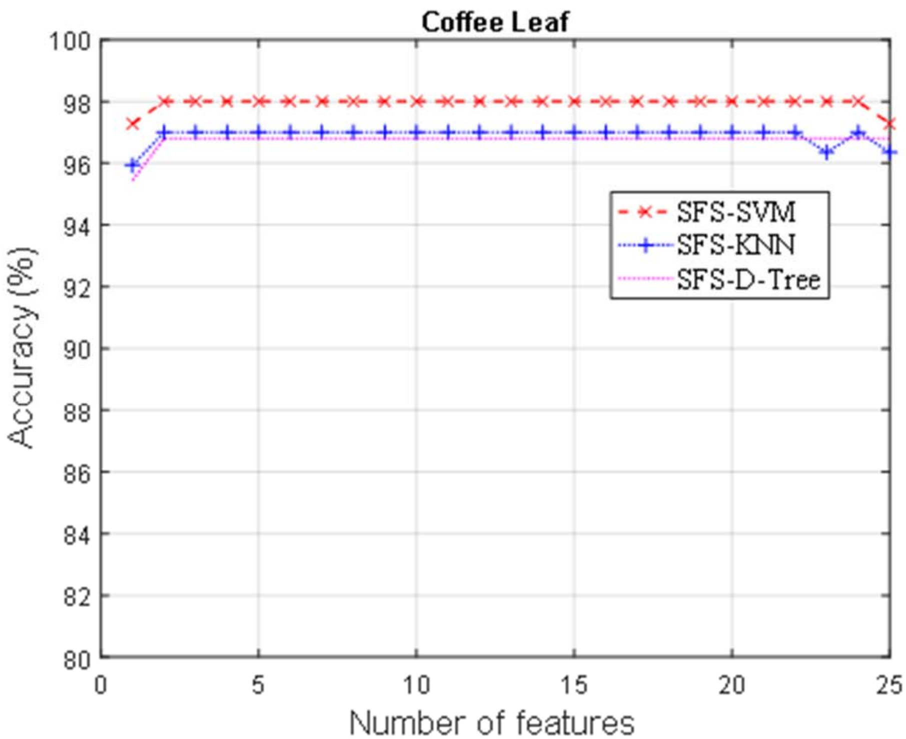


Table 7. Classification Results of Hybrid Combination Features for all leaves

Classification Accuracy (%) of Leaves	SVM	KNN	D-Tree
Coffee	94.46%	93.76%	91.15%
Pea-shoot	93.4%	91.62%	90.64%
Baby-spinach	91.13%	90.38%	89.01%

Table 8. Classification performance of for Coffee leaf by applying 10-fold validation using proposed algorithms with selected features

Feature Selection Methods	Classifiers	Serial Num. of Features	Total No of features	Accuracy (%)
SFS	SVM	24	1-19, 21-25	98.5
	KNN	22	1-6, 8-11, 13-21, 23-25	97.2
	D-Tree	24	1-23, 24	96.5
SBS	SVM	24	1-19,21-25	98.6
	KNN	24	1-21,23-25	97.6
	D-Tree	24	1-23,25	96.2
Relief-F	SVM	10	2,4,10,11,17-21,25	97.1
	KNN			95.9
	D-Tree			96.8

Table 11: Classification performance of all classifiers by applying 10-fold validation using proposed algorithms with selected features

Feature types and feature selection methods	Computation time (s)		
	SVM	KNN	Decision Tree
Coffee leaf:			
Extracted Features	0.7282	0.5309	0.4021
Selected Features:			
SFS	0.5706	0.4123	0.3371
SBS	0.6456	0.4240	0.3202
Relief-F	0.6252	0.4842	0.3582

The confusion accuracy with leave-one-observation-out cross validation method for each day along with monitoring the moisture content values for each day.

Samples	Classes	Classifiers Test Accuracy Performance (%)			Water Content (%)
		SVM	KNN	D-Tree	
Coffee Leaf	Day1	100	100	100	82.84
	Day2	95.2	88.1	100	41.22
	Day3	100	92.6	92.3	12.34
	Day4	100	100	100	0.71
	Variance	0.58	1.09	0.92	

Conclusion

In this paper, a novel and non-invasive method is presented using THz frequency for the characterisation of the plants' leaves utilizing the electromagnetic parameters.

Moreover, the loss of WC is also monitored for four days consecutively. It is observed that the WC in leaves show a strong correlation with the permittivity. The average decaying response observed from day 1 to 4 in permittivity is attributed to the loss of WC in leaves.

Thus, the study showed that proposed machine learning technique using terahertz waves pave the way for establishing a novel, robust direction for assessing the real-time information of estimating a water content in leaves non-invasively. Thus, results in the paper also demonstrated that timely detection of water stress in leaves could help to take proactive action in relation to plants health monitoring, and for precision agriculture applications, which is of high importance to improve the overall productivity.

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University of Glasgow

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a.zahid.1@student.gla.ac.uk

@UofGCSI

www.melabresearch.com

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