

Identification of polar liquids using support vector machine based classification model

Thushara Haridas Prasanna¹, Mridula Shantha¹, Anju Pradeep¹, Pezhohil Mohanan²

¹Division of Electronics, School of Engineering, Cochin University of Science and Technology, Kerala, India

²Advanced Centre for Atmospheric Radar Research, Cochin University of Science and Technology, Cochin, Kerala, India

Article Info

Article history:

Received Dec 29, 2021

Revised May 20, 2022

Accepted Jun 18, 2022

Keywords:

Classification

Complex permittivity

Identification

Machine learning

Polar liquids

Support vector machine

ABSTRACT

The dispersive nature of polar liquids creates ambiguity in their identification process. It requires a long time and effort to compare the measured values with the available standard values to identify the unknown liquid. Nowadays machine learning techniques are being used widely to assist the measurement techniques and make predictions with great accuracy and less human effort. This paper proposes a support vector machine (SVM) based classification model for the identification of six polar liquids-butanol, dimethyl sulphoxide, ethanediol, ethanol, methanol and propan-1-ol for a temperature range of 10 °C–50 °C and frequency range of 0.1 GHz–5 GHz. The model is constructed using the data from the National Physical Laboratory (NPL) report MAT 23. The identification of unknown liquid is based on complex permittivity measurement. If the measurement error in complex permittivity is less than $\pm 6\%$ of the standard value in NPL report, the proposed model identifies the liquids with 100% accuracy in the entire temperature and frequency range. The performance of the model is validated by testing the model with data external to the dataset used. The findings show that the proposed model is a useful and efficient tool for identifying unknown polar liquids.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Thushara Haridas Prasanna

Division of Electronics, School of Engineering, Cochin University of Science and Technology

Cochin, Kerala, India 682022.

Email: thushahp@gmail.com

1. INTRODUCTION

Material characterization plays a major role in many applications like material processing, bioengineering, medical treatment and food industry. Materials can be characterized based on their electromagnetic properties like permittivity, permeability and conductivity. Measurements in the microwave frequency range focus on the complex permittivity (ϵ^*) rather than the permeability and conductivity. Complex permittivity gives insight into the structure of the material, the temperature in the surroundings and the number of impurities in it. The real component of complex permittivity reflects the dielectric medium's ability to retain energy, whereas the imaginary part describes the medium's energy losses. Dispersion is the fluctuation of ϵ^* with frequency. At microwave frequencies, the effect of orientation polarization is responsible for dispersion [1]. In the case of dispersive materials, repeated measurements at different temperatures and frequencies are required to study the dielectric dispersion characteristics [2]. This work looks at polar liquids that are dispersive in nature. These liquids are utilised in specific absorption rate (SAR) metrology because their complicated permittivity is comparable to that of biological tissue metrology [2], [3]. Polar liquids in their pure form can be employed as an excellent calibration material in the field of dielectric instrumentation. National Physical Laboratory (NPL) of UK has conducted a detailed study on the dispersion

characteristics of commonly used polar liquids using coaxial cell permittivity measurement technique. NPL report MAT 23 describes the ϵ^* of polar liquids-butanol, dimethyl sulphoxide (dms), ethanediol, ethanol, methanol and propan-1-ol for a frequency range of 0.1 GHz-5 GHz and temperature range of 10 °C-50 °C [2]. The dispersive nature of these liquids makes the identification process a complex task.

According to related studies, unknown liquids can be identified by measuring its properties like density, melting point, boiling point, solubility and then comparing the results to the values of known liquids. It takes lot of experimental procedures and is very time consuming. Nuclear magnetic resonance (NMR) spectroscopy followed by Fourier transform method has been used in the identification of unknown alcohols [4]. NMR spectroscopy is a non destructive technique but it is very expensive. Another method used to identify the liquids is using surface acoustic mode aluminum nitride (AlN) transducer [5]. This method is very useful to test small amount of liquids but the identification process is time consuming. Complex permittivity measurement is a powerful tool in the identification of liquids. The most popular measurement techniques are transmission and reflection line, open ended probe and resonant methods [6]. In the transmission and reflection line method, from the measured values of transmission and reflection coefficients the ϵ^* is extracted with the help of Nicholson-Ross-Weir method. Open ended coaxial probe method uses rational function model to extract ϵ^* . In resonant method, measurement of quality factor and shift in resonant frequency are used to extract ϵ^* . In all these cases related to complex permittivity measurement, identification of an unknown polar liquid requires measured value of complex permittivity followed by manual search in the available standard report for close matching. This takes a lot of time especially in the case of polar liquids because of its dispersive nature.

Support vector machine (SVM) based classification model is proposed in this paper for the identification of the polar liquids. Complex permittivity (ϵ' and ϵ'') of the liquid, frequency (f) and temperature (t) of the measurement system that are very relevant to all permittivity measurement techniques are used as the input features to identify the polar liquids. The paper is structured as: research method, results and discussion, graphical user interface and conclusion

2. RESEARCH METHOD

Machine learning (ML) algorithms have the ability to recognize data and separate them into categories. This process is known as classification. This can be used to identify the group membership of the new data instances. The workflow of the classification based ML model used in this work is shown in Figure 1. The data obtained from NPL report is used to develop the model. The parameters ϵ' , ϵ'' , f and t which are very relevant in a permittivity measurement system are taken as the input features. Model is trained using training set and hyperparameters are tuned to get the best accuracy. The performance of different ML techniques is evaluated using performance measures and the most suitable one is selected. Complex permittivity can be measured using several techniques in which the most commonly used methods are coaxial probe, coaxial cell and planar sensors. Measurement using coaxial probe and coaxial cell are well suited for wide range of frequencies whereas planar sensors have limited frequency of operation. Since coaxial cell based complex permittivity measurement is used in NPL report, the ability of the model to identify the polar liquids based on other measurement techniques is also verified in this work.

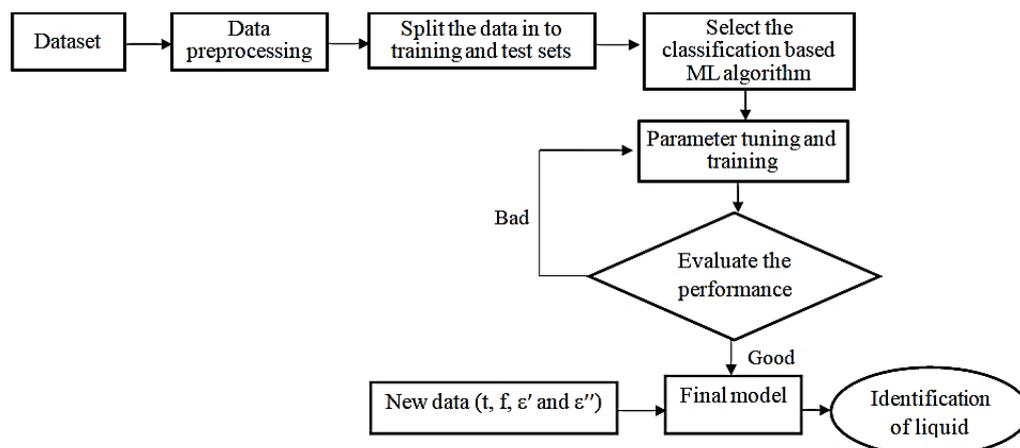


Figure 1. Workflow of the proposed methodology

2.1. Data gathering and pre-processing

The data for this work was gathered from NPL MAT 23 report. Table 1 shows the dataset description. The range of permittivity of six polar liquids for a temperature range of 10 °C-50 °C and frequency range of 0.1 GHz-5 GHz is shown in Table 2 [2]. This is a classification problem with multiple classes that includes the six polar liquids as the six classes. These classes are assigned with values from 1 to 6. For better use of the dataset of 1,000 samples, K-fold cross validation is performed on the whole data. This splits the dataset into subsets and performs training and testing on different parts of the dataset.

Table 1. Description of the dataset

Dataset Inputs			
No	Features	Values	
1	Frequency (f) in GHz	0.1-5	
2	Temperature (T) in °C	10-50	
3	Permittivity (Real part)	3.23-78.5	
4	Permittivity (Imaginary part)	0.3-18.56	
Output			
No	Liquid	Number of samples	Class
1	Butan-1-ol	140	1
2	Dimethyl Sulphoxide	140	2
3	Ethenediol	180	3
4	Ethanol	180	4
5	Methanol	180	5
6	Propan-1-ol	180	6

Table 2. Range of permittivity

Polar liquid	Permittivity	
	Real part	Imaginary part
Butan-1-ol	3.23-16.27	0.84-7.9
Dimethyl Sulphoxide	34.85-47.12	0.3-18.56
Ethenediol	6.93-43.48	0.94-18.3
Ethanol	4.93-26.18	0.82-11.13
Methanol	10.9-35.68	0.44-14.89
Propan-1-ol	3.66-20.35	1.1-9.35

2.2. Support vector machine classifier

The purpose of the SVM classifier is to find the optimum decision boundary that can separate n-dimensional space into classes and accurately classify a new data point. For multi-class classification, the one-against-all technique is utilised. SVM creates models for each class in this way. The mth SVM is trained with all of the data in the mth class having positive labels and all other samples having negative labels when using S classes. [7], [8]. Thus with l training data (x1, y1), ... (xl, yl), where xi ∈ Rⁿ, i = 1, . . . , l and yi ∈ {0, 1, . . . , S} is the class of xi and the mth SVM solves the following minimization

$$f = \min_{\omega^m, b^m, \xi^m} \frac{1}{2} (\omega^m)^T \omega^m + C \sum_{i=1}^l \xi_i^m \tag{1}$$

such that $(\omega^m)^T \varphi(x_i) + b^m \geq 1 - \xi_i^m$, if $y_i = m$
 $(\omega^m)^T \varphi(x_i) + b^m \leq -1 + \xi_i^m$, if $y_i \neq m$
 $\xi_i^m \geq 0, i = 1, 2, \dots, l$

The training data xi are mapped to a higher dimensional space by the function φ which is known as kernel. Here ω is the weight vector, b is the bias term, C is the penalty parameter and ξ is the slack variable [9]. By minimizing $\frac{1}{2} (\omega^m)^T \omega^m$ SVM tries to maximize the margin $\frac{2}{\|\omega\|}$ between the data in different classes. The penalty term $C \sum_{i=1}^l \xi_i^m$ tries to reduce the number of training errors. For (1) there are S decision functions

$$(\omega^1)^T \varphi(x) + b^1, \dots, (\omega^S)^T \varphi(x) + b^S$$

x is classified to the class that has largest value of decision function
 Class of x ≡ argmax_{m=1,2,...,S} ((ω^m)^T φ(x) + b^m).

In this work, for six polar liquids the number of classes is taken as $S=6$. K-fold cross validation is applied on the dataset and hyperparameters are tuned to get the best performance from the model [8], [10]–[13]. For reliable estimates and best results 5-fold cross validation is selected and the hyperparameter C is tuned to the value 21 and the kernel is the radial basis function (RBF). (ϕ) [14], [15]. At a time, the 5-fold cross validation on the 1,000 sample dataset creates a training set of 800 samples and a test set of 200 samples.

3. RESULTS AND DISCUSSION

The complex permittivity of polar liquids varies non-linearly with frequency and temperature. Several classifiers are applied to the dataset to learn the complex relationship among data. The performance of various classifiers is evaluated using performance measures (accuracy, error, specificity and sensitivity) and is presented in Table 3. It is observed that the hyperparameter tuning of SVM with RBF kernel and penalty parameter $C=21$ can separate the six polar liquids with 100% accuracy. The suitability of SVM is thus confirmed. The receiver operating characteristics curve (ROC) is shown in Figure 2. The ideal point on the figure is in the top left corner, where the false positive rate is 0 and the real positive rate is 1. The area under the curve for each class is obtained as 1 [16], [17]. This shows that all the six polar liquids are classified with an accuracy of 1.

Table 3. Performance comparison

Model	Accuracy (%)	Error (%)	Specificity (%)	Sensitivity (%)
Naive Bayes	59	41	91	59
Decision Tree	87	13	96	86
KNN	95	5	99	94
Random Forest	93	7	93	98
SVM	1	0	1	1

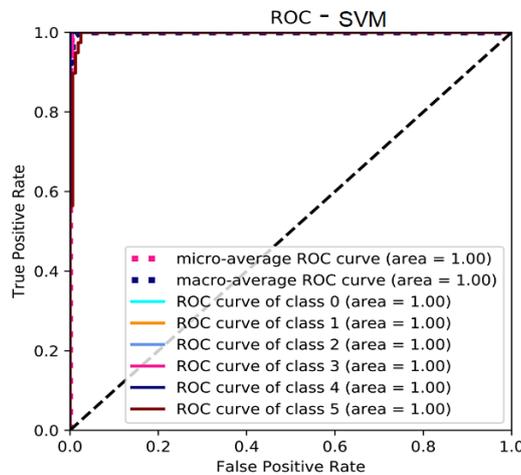


Figure 2. ROC for the proposed model

The accuracy of the proposed SVM model for 5-fold cross validation is obtained as 100% in all the 5 sets. This confirms the stability of the proposed model. The overfit condition is tested using three different methods. Firstly, the confusion matrix of both the training set and test set of the SVM classification is shown in Figure 3(a) and Figure 3(b) respectively. The diagonal elements indicate the correct predictions [16]–[18]. This shows that the SVM classifier performs well in both the training and the test set and the model is not overfitted. Secondly, the accuracy of the model is plotted for the training and test set by varying the penalty parameter C as shown in Figure 4. It shows that the model performs well in both the training set and test set and the accuracy is one when $C=21$. This also indicates that the model is not overfitted. Finally, the support vectors for each of the six classes have been identified and are shown in Table 4. The number of support vectors in each class is substantially smaller than the number of samples in each class [11]. This confirms that the model is not overfitted. All codes are written in the programming language Python 3.5 with the associated Scikit-learn library [10]. The average training time is 0.02s and the average time taken to test a

new data is 0.002s in a computer with an Intel Core i5 processor running at a clock speed of 1.6 GHz and equipped with 8 GB of RAM.

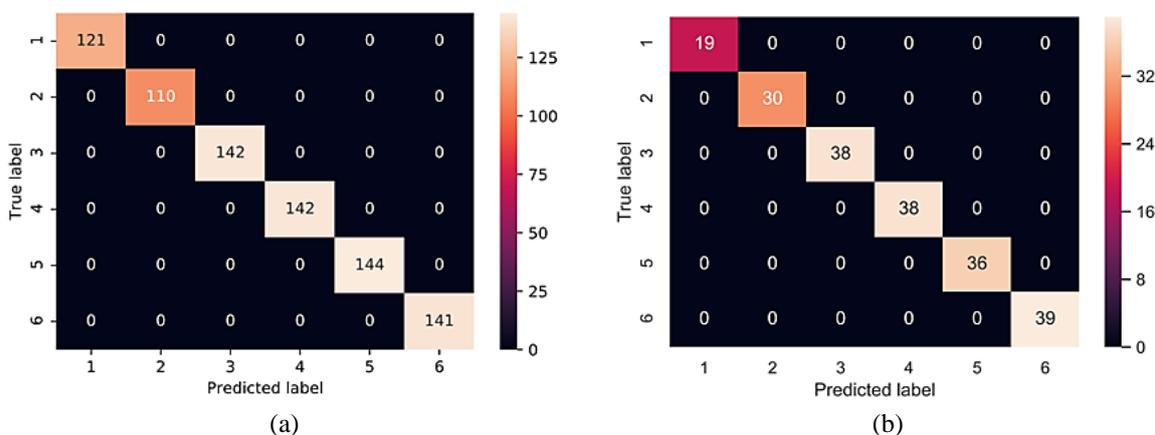


Figure 3. Confusion matrix (a) Training set, and (b) Test set

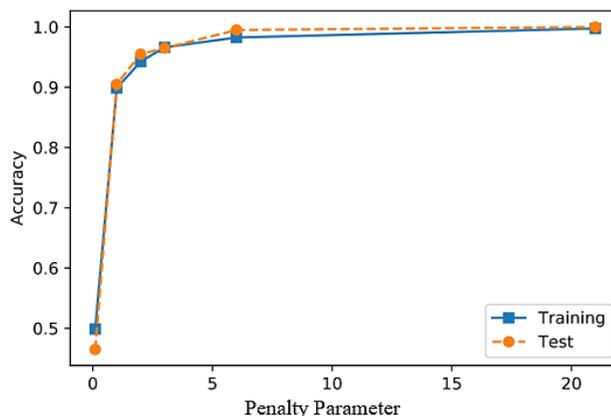


Figure 4. Accuracy vs penalty parameter (C)

Table 4. Support vectors for the proposed model

Class	Polar liquid	Number of samples in the dataset	Number of support vectors
1	Butan-1-ol	140	29
2	DMSO	140	17
3	Ethanediol	180	44
4	Ethanol	180	42
5	Methanol	180	32
6	Propan-1-ol	180	42

Alcohols like methanol and ethanol are highly volatile and evaporate rapidly. This changes the liquid temperature and hence the permittivity. Polar liquids like DMSO and ethanediol are hygroscopic, absorb water from atmosphere leading to variation in permittivity. Values of complex permittivity obtained from the NPL report are based on the coaxial cell measurement technique. Complex permittivity can be measured using different measurement techniques. Robustness of the proposed model needs to be tested for data obtained using other measurement techniques as well. The most widely used permittivity measurement techniques for liquids using coaxial probe, planar sensors and transverse electromagnetic cell (TEM) are considered for this purpose. It has been noted that the measured values of ϵ^* differ from the standard value in NPL report and the variation depends on the measurement technique, temperature, frequency and the liquids used [19]–[29]. The measurement errors in ϵ^* associated with different measurement techniques are

calculated for all the six liquids and shown in Table 5. This variation is expressed as the maximum percentage of error (E) in measured value with respect to the standard value. The measurement error is found to be minimum in the case of TEM cell because of the closed structure. A new test set is formed considering these measured values and the response of the proposed model is noted. The number of samples in the new test set is 40. While preparing the new test set, focus is given to those values in which considerable variations occur with respect to the standard value. The proposed model is able to predict all the liquids with 100% accuracy. The confusion matrix for the new test set is shown in Figure 5.

Table 5. Robustness of the proposed model

Liquid [Ref.No]	Measurement Technique	T (°C)	F (GHz)	Maximum error in permittivity E (%)			Number of samples supplied to the model	Number of samples identified
				Real part (ϵ')	Imaginary Part (ϵ'')	F (GHz)		
Butan-1-ol [20]	Probe	30	0.1-1	-16.72	-0.62	0.1	10	10
DMSO [22]	Sensor	25	1.58	2.88	-37.6	1.58	1	1
Ethenediol [23]	TEM Cell	24.2	0.1-4	0.07	0.3	1	6	6
Ethanol [24]	Probe	25	1-5	10.15	8.04	5	10	10
Methanol [24]	Probe	25	1-5	10.49	-0.75	1.5	9	9
Propan-1-ol [25]	Probe	30	0.1-1	-3.68	4.55	0.4	4	4
Total							40	40

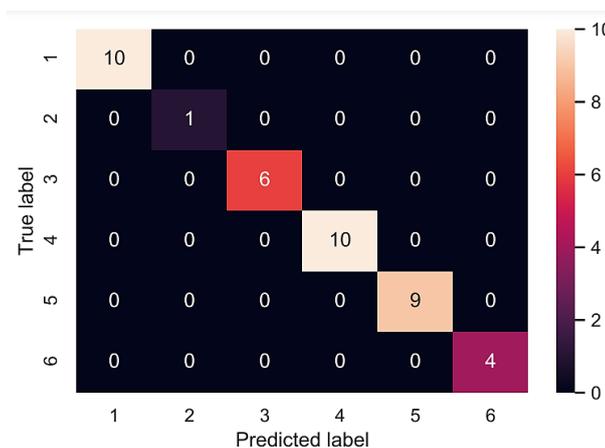


Figure 5. Confusion matrix for the new test set

Permittivity plot of the six liquids in the frequency range of 0.1GHz to 5GHz and room temperature 25 °C is shown in Figure 6. Real part of permittivity is shown in Figure 6(a) whereas imaginary part is shown in Figure 6(b). While the real part of permittivity (ϵ') decreases with increasing frequency, the imaginary part (ϵ'') increases with frequency, reaches a peak at a frequency known as the relaxation frequency (f_r) and then decreases. In the case of DMSO f_r is 8.32 GHz which is above the frequency range specified in Figure 6. Since the identification of these liquids are based on the measured value of complex permittivity (ϵ' and ϵ''), the error in measurement leads to misclassification. For varied temperatures in the range of 10 °C to 50 °C, a modified test set is created by manually incorporating the measurement error that might occur in the entire frequency range (0.1 GHz to 5 GHz) during the permittivity measurement as a step variation of $\pm 0.5\%$ of the standard value of both ϵ' and ϵ'' . The performance of the model in each step is evaluated and the maximum measurement error in ϵ^* that the model can accommodate without any misclassification is found out. For a particular temperature, this test set consists of 120 samples with 20 samples for each liquid. It is observed that if the measurement error introduced in both ϵ' and ϵ'' is equal to 6% of the standard value, the first misclassification occurs in the case of butan-1-ol at 10 °C and 0.1 GHz as seen from row 1 of Table 6. The accuracy of the model drops to 99 %. For all other temperatures and frequencies the measurement error that the model can accommodate without misclassification is greater than 6%. The details of first misclassification observed at different temperatures are shown in Table 6. Since most of the measurements happen at room temperature 25 °C, the details of misclassification observed is also found out and presented in row 4 of Table 6. At 25 °C the first misclassification is observed at 0.1 GHz when the measured value of

both ϵ' and ϵ'' decreases by 7.5% of the standard value. The complex permittivity plot at 25 °C and 0.1 GHz with a measurement error of -7.5% incorporated is illustrated in Figure 7 and the confusion matrix for the same is shown in Figure. 8. These results indicate that if the identification of an unknown liquid is to be carried out using the proposed model, well calibrated complex permittivity measurement systems with measurement error less than $\pm 6\%$ is to be used to eliminate the chance of misclassification.

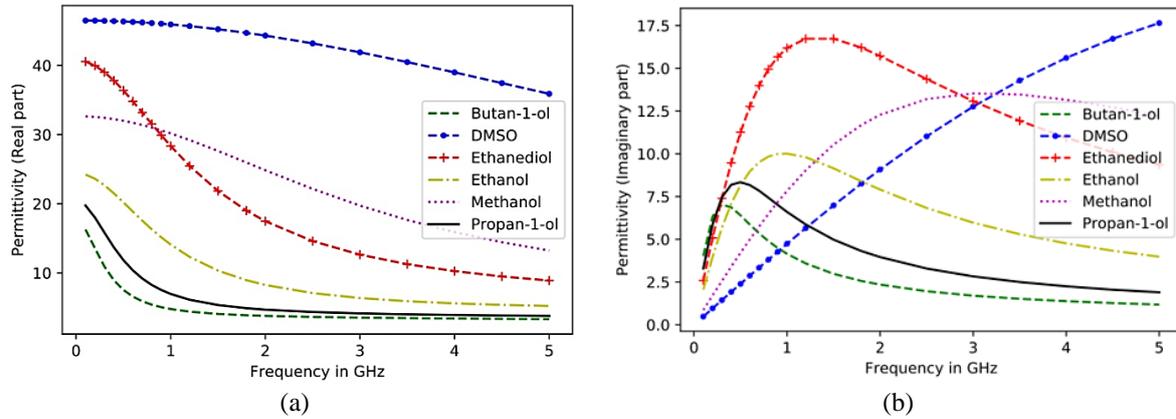


Figure 6. Permittivity plot at 25 °C (a) Real part, and (b) Imaginary part

Table 6. Misclassification test of the proposed model

T (°C)	Error introduced in ϵ^* (%)	Misclassification first observed		Misclassified result	Accuracy of the proposed model (%)
		Frequency (GHz)	Liquid		
10	+ 6	0.1	Butan-1-ol	Propan-1-ol	99
15	-9	0.2	Ethanol	Propan-1-ol	98
15	-9	0.1	Propan-1-ol	Butan-1-ol	98
20	- 8	0.1	Propan-1-ol	Butan-1-ol	99
25	-7.5	0.1	Propan-1-ol	Butan-1-ol	99
30	+ 10	0.1	Butan-1-ol	Propan-1-ol	99
35	- 8	0.1	Butan-1-ol	Propan-1-ol	99
40	-8.5	0.2	Propan-1-ol	Butan-1-ol	99
45	-8	0.1	Propan-1-ol	Butan-1-ol	99
50	-8	0.1	Propan-1-ol	Butan-1-ol	99
10-50	Less than $\pm 6\%$	-	-	-	100

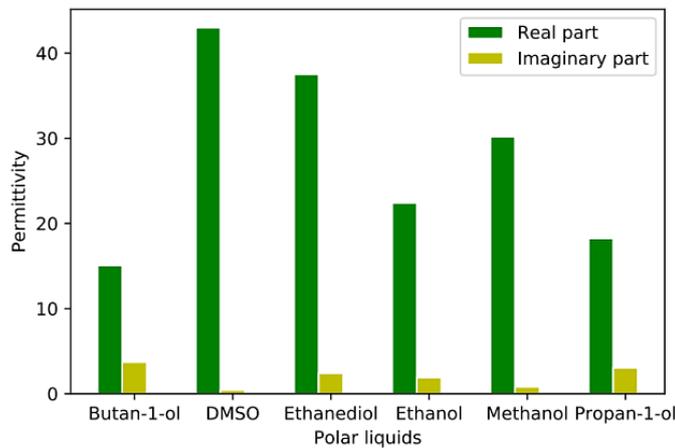


Figure 7. Permittivity plot at 25 °C and 0.1 GHz with a measurement error of -7.5%

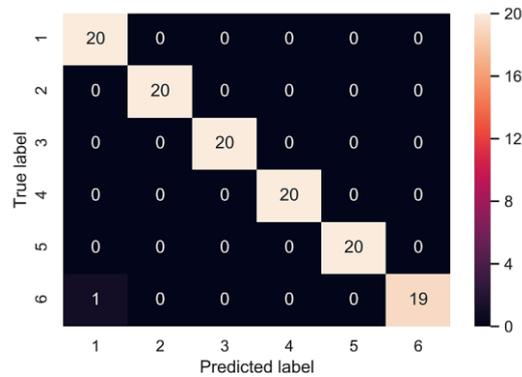


Figure 8. Confusion matrix for the modified test set at 25 °C and 0.1 GHz with a measurement error of -7.5%

4. GRAPHICAL USER INTERFACE

The proposed method is aimed to be used as a support tool to assist the measurement techniques. Graphical user interface (GUI) is designed for testing of unknown liquids. The inputs to the interface are the measured value of complex permittivity of unknown liquid, temperature and the frequency of the measurement system. The model identifies the unknown liquid within a fraction of a second. The front end of the GUI is designed using hypertext markup language (HTML) and the appearance is improved using cascading style sheet (CSS). The back end consists of the machine learning model and the web framework which are written in Python. Flask framework is used for the development of the interface [30]. It is a micro web framework that loads the machine learning model, takes the input from the front end and returns the predicted result. This GUI can be used for the temperature range of 10 °C to 50 °C, frequency range of 0.1–5 GHz. A warning message is displayed in the front end if the inputs exceed this range and also if the measured permittivity is not within the range of the dataset. The appearance of the GUI and an example of the predicted result are shown in Figure 9.

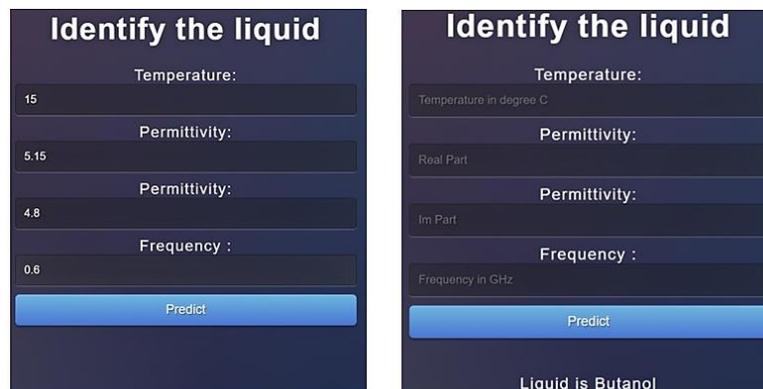


Figure 9. Graphical user interface

5. CONCLUSION

Measurements of complex permittivity in the microwave frequency range are well suited for the identification of unknown materials. But in the case of polar liquids, because of the dispersive nature, it is difficult to identify the liquid even though the permittivity is known or measured. In this work, SVM based classification model is implemented using Python for the identification of six polar liquids-Butan-1-ol, DMSO, Ethanol, Methanol and Propan-1-ol for a temperature range of 10 °C-50 °C and frequency range of 0.1 GHz-5 GHz. The identification is done with minimum number of parameters. The input parameters are the complex permittivity, frequency and temperature, which are very relevant in a measurement system. The accuracy achieved is 100% for the specified temperature and frequency range. The performance of the model is validated to confirm that the model is not overfitted. The robustness of the model is tested using an external dataset and the performance of the model is found to be good. A GUI is

designed for the identification of unknown liquids. Probability of misclassification is also tested by manually introducing measurement error in complex permittivity to the standard NPL data. It is observed that the first misclassification happens when the measured values of complex permittivity deviates by 6% of standard value in the NPL report. All complex permittivity measurement techniques with measurement error less than $\pm 6\%$ can be incorporated with the proposed model to identify the unknown polar liquid for the temperature range of 10 °C-50 °C and frequency range of 0.1 GHz-5 GHz without any misclassification. The response is fast and the ambiguity in the identification process is eliminated. The model may be extended to identify polar liquid mixtures by suitably extending the dataset.

REFERENCES

- [1] S. Mehrotra, A. Kumbharkhane, and A. Chaudhari, *Binary polar liquids*. Elsevier, 2017.
- [2] A. P. Gregory and R. N. Clarke, "Tables of the complex permittivity of dielectric reference liquids at frequencies up to 5ghz," Jan. 2012.
- [3] A. P. Gregory and R. N. Clarke, "A review of RF and microwave techniques for dielectric measurements on polar liquids," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 13, no. 4, pp. 727–743, Aug. 2006, doi: 10.1109/tdei.2006.1667730.
- [4] P. H. Chamberlain, "Identification of an alcohol with ¹³C NMR spectroscopy," *Journal of Chemical Education*, vol. 90, no. 10, pp. 1365–1367, Sep. 2013, doi: 10.1021/ed300833s.
- [5] T. Bui, B. Morana, A. Akhnouk, T. C. Duc, and P. M. Sarro, "Liquid identification by using a micro-electro-mechanical interdigital transducer," *The Analyst*, vol. 142, no. 5, pp. 763–771, 2017, doi: 10.1039/c6an01804a.
- [6] R. A. Alahnomi *et al.*, "Review of recent microwave planar resonator-based sensors: techniques of complex permittivity extraction, applications, open challenges and future research directions," *Sensors*, vol. 21, no. 7, p. 2267, Mar. 2021, doi: 10.3390/s21072267.
- [7] V. N. Vapnik, *Statistical learning theory*. Wiley, 1998.
- [8] C.-W. Hsu, C.-C. Chang, and C.-J. Lin, "A practical guide to support vector classification," National Taiwan University, 2016.
- [9] F. F. Chamasemani and Y. P. Singh, "Multi-class support vector machine (SVM) classifiers -- an application in hypothyroid detection and classification," in *2011 Sixth International Conference on Bio-Inspired Computing: Theories and Applications*, Sep. 2011, pp. 351–356, doi: 10.1109/bic-ta.2011.51.
- [10] S. Raschka and V. Mirjalili, *Python machine learning: Machine learning and deep learning with Python, scikit-learn, and TensorFlow 2*. Packt Publishing Ltd., 2019.
- [11] D. P. Penumuru, S. Muthuswamy, and P. Karumbu, "Identification and classification of materials using machine vision and machine learning in the context of industry 4.0," *Journal of Intelligent Manufacturing*, vol. 31, no. 5, pp. 1229–1241, Nov. 2019, doi: 10.1007/s10845-019-01508-6.
- [12] S. Ibrahim, N. Amirah Zulkifli, N. Sabri, A. Amilah Shari, and M. R. M. Noordin, "Rice grain classification using multi-class support vector machine (SVM)," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 8, no. 3, pp. 215–220, Dec. 2019, doi: 10.11591/ijai.v8.i3.pp215-220.
- [13] Y. Zhang, S. Wang, and Z. Dong, "Classification of alzheimer disease based on structural magnetic resonance imaging by kernel support vector machine decision tree," *Progress In Electromagnetics Research*, vol. 144, pp. 171–184, 2014, doi: 10.2528/pier13121310.
- [14] B. Scholkopf *et al.*, "Comparing support vector machines with Gaussian kernels to radial basis function classifiers," *IEEE Transactions on Signal Processing*, vol. 45, no. 11, pp. 2758–2765, 1997, doi: 10.1109/78.650102.
- [15] B. Scholkopf, C. J.C.Burges, and A. J. Smola, *Advances in kernel methods: support vector learning*. Cambridge, MA, USA: MIT Press, 1999.
- [16] N. Sowmya and V. Ponnusamy, "Development of spectroscopic sensor system for an IoT application of adulteration identification on milk using machine learning," *IEEE Access*, vol. 9, pp. 53979–53995, 2021, doi: 10.1109/access.2021.3070558.
- [17] P. de Toledo, P. M. Rios, A. Ledezma, A. Sanchis, J. F. Alen, and A. Lagares, "Predicting the outcome of patients with subarachnoid hemorrhage using machine learning techniques," *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 5, pp. 794–801, Sep. 2009, doi: 10.1109/titb.2009.2020434.
- [18] E. A. A. Alaoui, S. C. K. Tekouabou, S. Hartini, Z. Rustam, H. Silkan, and S. Agoujil, "Improvement in automated diagnosis of soft tissues tumors using machine learning," *Big Data Mining and Analytics*, vol. 4, no. 1, pp. 33–46, Mar. 2021, doi: 10.26599/bdma.2020.9020023.
- [19] R. T. Blakey and A. M. Morales-Partera, "Microwave dielectric spectroscopy, 'A versatile methodology for online, non-destructive food analysis, monitoring and process control,'" *Engineering in Agriculture, Environment and Food*, vol. 9, no. 3, pp. 264–273, Jul. 2016, doi: 10.1016/j.eaef.2016.02.001.
- [20] A. D. Vyas, V. A. Rana, S. P. Bhatnagar, and V. M. Vashisth, "Dielectric dispersion and relaxation mixtures of 1-butanol and phenol at lower microwave frequencies," *Dielectric dispersion and relaxation mixtures of 1-butanol and phenol at lower microwave frequencies*, vol. 49, pp. 47–52, Jan. 2011.
- [21] Y.-Z. Wei and S. Sridhar, "Technique for measuring the frequency-dependent complex dielectric constants of liquids up to 20 GHz," *Review of Scientific Instruments*, vol. 60, no. 9, pp. 3041–3046, Sep. 1989, doi: 10.1063/1.1140601.
- [22] Z. Wei *et al.*, "A high-sensitivity microfluidic sensor based on a substrate integrated waveguide re-entrant cavity for complex permittivity measurement of liquids," *Sensors*, vol. 18, no. 11, p. 4005, Nov. 2018, doi: 10.3390/s18114005.
- [23] D. Zhao, G. Rietveld, and G. M. Teunisse, "A multistep approach for accurate permittivity measurements of liquids using a transmission line method," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 7, pp. 2267–2274, Jul. 2011, doi: 10.1109/tim.2010.2096930.
- [24] M. Abdolrazzagh, M. Daneshmand, and A. K. Iyer, "Strongly enhanced sensitivity in planar microwave sensors based on metamaterial coupling," *IEEE Transactions on Microwave Theory and Techniques*, vol. 66, no. 4, pp. 1843–1855, Apr. 2018, doi: 10.1109/tmtt.2018.2791942.
- [25] A. N. Prajapati, A. D. Vyas, V. A. Rana, and S. P. Bhatnagar, "Dielectric relaxation and dispersion studies of mixtures of 1-propanol and benzonitrile in pure liquid state at radio and microwave frequencies," *Journal of Molecular Liquids*, vol. 151, no. 1, pp. 12–16, Jan. 2010, doi: 10.1016/j.molliq.2009.10.010.
- [26] R. J. Sengwa, "A comparative dielectric study of ethylene glycol and propylene glycol at different temperatures," *Journal of Molecular Liquids*, vol. 108, no. 1–3, pp. 47–60, Nov. 2003, doi: 10.1016/s0167-7322(03)00173-9.

- [27] P. D. Muley and D. Boldor, "Investigation of microwave dielectric properties of biodiesel components," *Bioresource Technology*, vol. 127, pp. 165–174, Jan. 2013, doi: 10.1016/j.biortech.2012.10.008.
- [28] X.-Q. Yang, L.-J. Yang, K.-M. Huang, W.-Y. Tian, and H. Shang, "Experimental and the theoretical studies of the dielectric properties of DMSO–H₂O mixtures," *Journal of Solution Chemistry*, vol. 39, no. 6, pp. 849–856, Jun. 2010, doi: 10.1007/s10953-010-9543-8.
- [29] C. Guoxin, "Calibration-independent measurement of complex permittivity of liquids using a coaxial transmission line," *Review of Scientific Instruments*, vol. 86, no. 1, p. 14704, Jan. 2015, doi: 10.1063/1.4905362.
- [30] M. Grinberg, *Flask web development*. USA: O'Reilly Media, Inc., 2014.

BIOGRAPHIES OF AUTHORS



Thushara Haridas Prasanna     received the B.Tech. degree in electronics and communication from Cochin University of Science and Technology (CUSAT), in 2003 and in 2015, she received her M.Tech. in electronics from CUSAT. She is now working on her Ph.D. at CUSAT's School of Engineering. Since 2005, she has been teaching undergraduate engineering students in colleges and is presently serving as Assistant Professor, Model Engineering College, Thrikkakara, Cochin, India. Planar antennas, material characterization, and machine learning are among her research interests. She can be contacted at email: thushahp@gmail.com.



Dr. Mridula Shantha     (Senior Member IEEE) she obtained her B.Tech. in electronics and communication from Kerala University in Kerala, India in 1988 and in 1999, she received her M.Tech. in electronics from Cochin University of Science and Technology (CUSAT), India. She received her Ph.D. in microwave electronics from CUSAT in 2006. For achieving the top position in the university, she received the K. G. Nair Endowment Gold Medal. She is currently Professor, Division of Electronics Engineering, School of Engineering, CUSAT, with over 31 years of teaching experience in several professional institutions in Kerala. Planar antennas, dielectric-resonator antennas, metamaterials, flexible antennas, and material characterization are among her research interests. She is a life member of the Institute of Electronics and Telecommunication Engineers (India) and a senior member of the IEEE. She is also a life member of the Indian Society for Technical Education. She can be contacted at email: mridula@cusat.ac.in.



Dr. Anju Pradeep     (Senior Member IEEE) received the BTech degree in Electronics and Communication from Kerala University in 1993. Cochin University of Science and Technology awarded her MTech degree in Microwave and Radar Engineering in 2008. (CUSAT). She is currently a Professor at CUSAT's School of Engineering's Division of Electronics Engineering. Since 1995, she has been teaching undergraduate engineering students in colleges. At the first Kerala Women's Science Congress in 2010, she received the Young Scientist Award in the category of physical sciences for the best paper presentation. Metamaterials and optimization approaches are two of her research interests. She is a life member of the Indian Society for Technical Education and a senior member of the IEEE. She can be contacted at email: anjupradeep@cusat.ac.in.



Dr. Pezholil Mohanan     (Senior Member, IEEE) In 1985, he earned his Ph.D. in microwave antennas from Cochin University of Science and Technology (CUSAT) in Cochin, India. He worked as an engineer at Bharat Electronics' Antenna Research and Development Laboratory in Ghaziabad, India. He then became a faculty member at CUSAT's Department of Electronics. Subsequent to his retirement in 2016 as Professor, he worked as BSR Emeritus Professor. Currently, he serves as the coordinator at the Advanced Centre for Atmospheric Radar Research CUSAT. He has over 300 peer-reviewed academic articles and several conference papers to his credit. He also owns a number of patents in the fields of antennas and materials science. Microstrip antennas, superconducting microwave antennas, radar cross section reduction, chip less RFID, dielectric diplexer, and polarization agile antennas are among his research interests. Dr. Mohanan was awarded the Dr. S. Vasudev Award 2011 by the Kerala State Council for Science, Technology and Environment in 2012, as well as the Career Award by the University Grants Commission in Engineering and Technology in 1994. He can be contacted at email: drmohan@gmail.com.