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An Efficient Deductive Learning Approach on LPWAN for Optimizing Power Consumption by Using Gaussian Process

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***Abstract* - In the last years, the Internet of Things (IoT) has emerged as a key application context in the design and evolution of technologies in the transition toward a 5G ecosystem. More and more IoT technologies have entered the market and represent important enablers in the deployment of networks of interconnected devices. As network and spatial device densities grow, energy efficiency and consumption are becoming an important aspect in analyzing the performance and suitability of different technologies. In this framework, this survey presents an extensive review of IoT technologies, including both Low-Power Short-Area Networks (LPSANs) and Low-Power Wide-Area Networks(LPWANs), from the perspective of energy efficiency and power consumption. A low-power wide-area network or low-power wide-area network or low-power network is a type of wireless telecommunication wide area network designed to allow long-range communications at a low bit rate among things, such as sensors operated on a battery. This proposed system finds that the efficient model for producing best optimal solution. Here, all the kernels are producing strongly correlated coefficient which is from 0.77 to 0.82 of correlation coefficient. The Normalized kernel is having highest correlation coefficient value which is 0.82. The RBF kernel is having lowest correlation coefficient which is 0.77. The Poly kernel has highest mean absolute error value which is 288.08%.The Lowest mean absolute error value is 218.94% which is produced by Normalized kernel of Gaussian approach. The Poly kernel of Gaussian approach has highest root mean squared error value which is 364.63%. The least root mean squared error value is 212.24% which is produced by Normalized kernel of Gaussian approach. Poly kernel of Gaussian classifier has highest relative absolute error value which is 94.48%. The least relative absolute error value is 81.43% which is produced by Normalized kernel of Gaussian classifier. The Poly kernel of Gaussian approach has highest root relative squared error value which is 95.95%. The least root relative squared error value is 79.71% which is produced by Normalized kernel of Gaussian approach. This system finds that the Normalized kernel of Gaussian classifier model gives more efficient result compare with other models.**

***Index Terms* - Puk kernel, LPWAN, Gaussian approach, Mean Absolute Error, Poly kernel.**

I.INTRODUCTION

The Internet of Things (IoT) paradigm was introduced over two decades ago, and its deployment has been ongoing for almost one. In its most general definition, IoT is a network of devices, that is, the things, which gather and exchange data possibly over the Internet. The ultimate goal of IoT is to enhance existing services and applications or deliver new ones to users, with little to no human intervention [1-3,5]. The extreme heterogeneity of application domains and involved devices has led to different requirements and expectations. Therefore, a large variety of wireless communication technologies has gradually emerged for enabling IoT, and is expected to connect up to75 billion devices by 2025, with an economic impact of around $11.1 trillion per year [5-8]. Considering the first important aspect in IoT systems, that is, the coverage area of the adopted technologies, a rough taxonomy in short-range vs. wide-range systems can be identified. Moreover, by taking into account energy efficiency and power consumption aspects, the two above categories identify so-called Low-Power Short-Area Networks(LPSAN) and Low-Power Wide-Area Networks (LPWAN).[9-13].

This paper governs that the section 2 has related research works; In section 3 focuses materials and methods; In section 4 shows that results and discussions and finally section 5 represents conclusion.

II LITERATURE SURVEY

A primary target for all the above technologies is to deliver their services while taking into account energy efficiency and power consumption aspects, at both device and network levels.[14-17] These aspects are extremely important for the IoT development, and for this reason recent years have seen a rising research-and-development interest toward (i) the design and implementation of techniques and mechanisms for energy efficiency, including power saving modes at the device level and cooperation schemes across the network, and (ii) the derivation of theoretical and empirical models for the power consumption and battery lifetime of the above classes of devices.[18-25] The peculiarity in terms of constraints and requirements of the IoT systems and scenarios requires significant extensions of mechanisms and theoretical analyses already implemented and derived for non-IoT wireless communication technologies, which however provide a reliable and valid starting point of analysis, as will be also discussed in the following [25-28].

III MATERIALS AND METHODS

In this section focuses on the materials and methods of this research work. The Low power consumption Wide Area using IOT dataset borrowed fromhttp://archive.ics.uci.edu/ml/datasets/GNFUV+Unmanned+Surface+Vehicles+Sensor+Data.The data-set contains four (4) sets of mobile sensor readings data (humidity, temperature) corresponding to a swarm of four (4) Unmanned Surface Vehicles (USVs) in a test-bed in Athens (Greece).

Description of Attributes

Attribute	Description	Data type
Device	USV ID	String
Humidity	sensed from the USV	Float
Temperature	sensed from the USV	Float
Experiment	1	Constant
Time	the sensing and reporting time	Float

Machine Learning Algorithms:
Implements Gaussian processes for regression without hyper parameter-tuning.
In this work focuses on below kernel. They are

- Poly kernel
- Puk
- Normalized Kernel
- RBF Kernel
- String Kernel

Material: The Weka 3.9.5 open-source data mining tools for finding an optimal models.
This work considers 10:90-fold cross validation for training and testing processes of borrowed dataset.

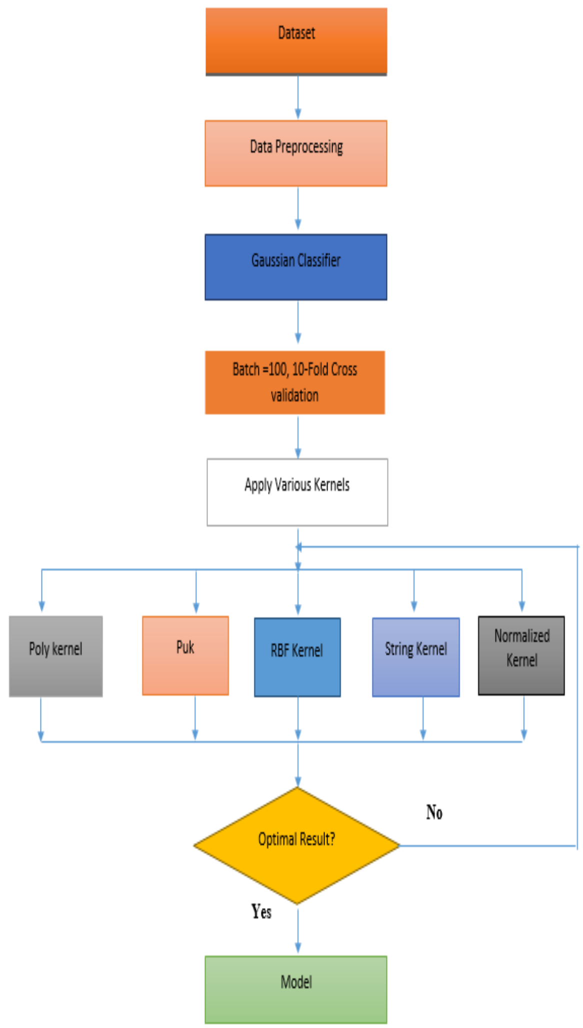

Figure 1: Proposed System

IV RESULTS AND DISCUSSIONS

This work focuses on the Gaussian Processes by changing various kernels namely Poly kernel, Puk, RBF Kernel, String Kernel and Normalized Kernel for getting optimal output. This work governs on the various results namely Correlation Coefficient, Mean Absolute Error, Root Mean Squared Error, Relative Absolute Error, Root Relative Squared Error and Time taken to build the model.

Table 2: Various Kernels in Gaussian approach and Their Measurements

S.No	Kernel	Correlation Coefficient	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Root Relative Squared Error	Time taken to build model (Seconds)
1	Poly Kernel	0.79	288.08	364.63	94.48%	95.95%	3.29
2	String Kernel	0.74	222.69	278.47	81.94%	81.10%	2.21
3	Normalized Kernel	0.82	218.94	212.24	81.43%	79.71%	3.34
4	Puk Kernel	0.81	245.04	307.6	91.36%	91.87%	2.39
5	RBF Kernel	0.77	229.72	288.57	81.47%	82.04%	4.45

By applying Poly kernel in Gaussian classifier has taken the time to build the model is 3.29 seconds. It has correlation coefficient is 0.79; It has 288.08of Mean Absolute Error value. It has 364.63of Root Mean Squared Error value. It has 94.48% of Relative Absolute Error value. This model has 95.95% of Root Relative Squared Error value. By using String kernel in Gaussian classifier has taken the time to build the model is 0.31 seconds. It has correlation coefficient is 0.74; It has 222.69 of Mean Absolute Error value. It has 278.47 of Root Mean Squared Error value. It has 81.94% of Relative Absolute Error value. This model has 81.10% of Root Relative Squared Error value. By implementing Normalized kernel in Gaussian classifier has taken the time to build the model is 3.34 seconds. It has correlation coefficient is 0.57; It has 21881.84 of Mean Absolute Error value. It has 27415.14 of Root Mean Squared Error value. It has 83.33% of Relative Absolute Error value. This model has 82.61% of Root Relative Squared Error value.

By applying Puk kernel in Gaussian classifier has taken the time to build the model is 2.39 seconds. It has correlation coefficient is 0.81; It has 245.04of Mean Absolute Error value. It has 307.6of Root Mean Squared Error value. It has 91.36% of Relative Absolute Error value. This model has 91.87% of Root Relative Squared Error value. By using RBF kernel in Gaussian classifier has taken the time to build the model is 4.45 seconds. It has correlation coefficient is 0.77; It has 229.72 of Mean Absolute Error value. It has 288.57 of Root Mean Squared Error value. It has 81.47% of Relative Absolute Error value. This model has 82.04% of Root Relative Squared Error value.

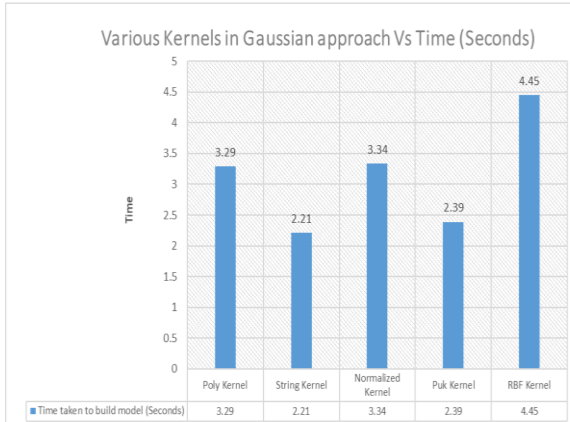

Figure 2: Various Kernels in Gaussian Classifier Vs Time

The above diagram clearly shows that Gaussian classifier while applying the Sting Kernel takes a less time consumption to build a model which is 2.21 seconds. The Gaussian Classifier using RBF Kernel takes more time consumption to build a model which is 4.45 seconds. Puk Kernel in Gaussian classifier takes 2.39 seconds which is more or less nearest to construction of String kernel in Gaussian model. The Normalized Kernel and Poly kernel are taking 3.34 seconds and 3.29 seconds to build the models.

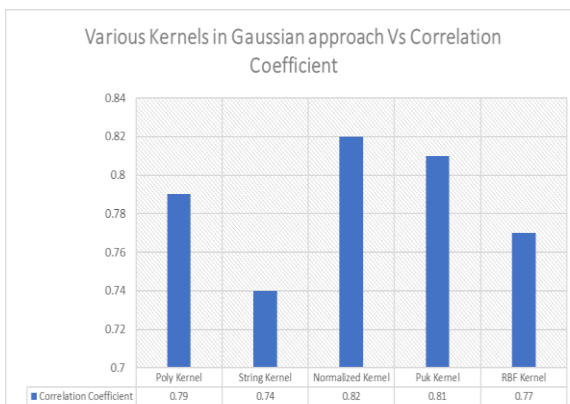

Figure 3: Various Kernels in Gaussian Classifier Vs Correlation Coefficient

The above diagram shows that the performance of various kernels in Gaussian classifier and correlation coefficient. All the kernels are producing strongly correlated coefficient which is from 0.77 to 0.82 of correlation coefficient. The Normalized kernel is having highest correlation coefficient value which is 0.82. The RBF kernel is having lowest correlation coefficient which is 0.77.

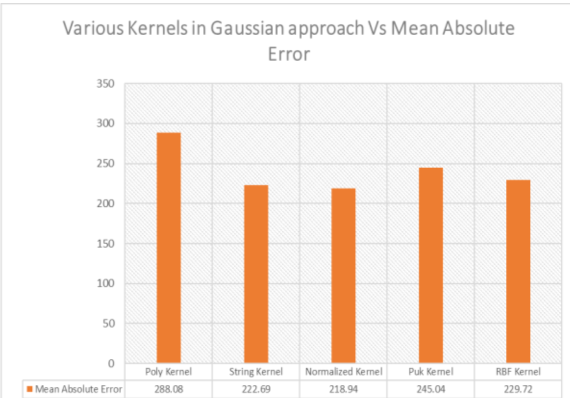

Figure 4: Various Kernels in Gaussian Classifier Vs Mean Absolute Error

The above diagram shows that the mean absolute error value of various kernels are using in Gaussian approach. The Poly kernel has highest mean absolute error value which is 288.08%.The Lowest mean absolute error value is 218.94% which is produced by Normalized kernel of Gaussian approach. The String Kernel, PukKenrel and RBF kernel has 222.69% of Mean Absolute Error, 245.04% of Mean Absolute Error and 229.72% of Mean Absolute Error value.

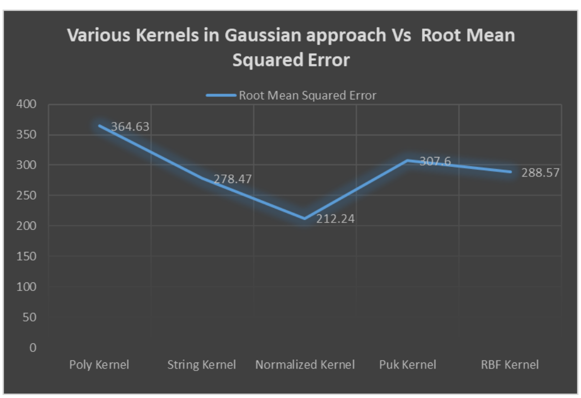

Figure 5: Various Kernels in Gaussian Classifier Vs Root Mean Squared Error

The above diagram shows that the Root Mean Squared Error value of various kernels in Gaussian classifier. The Poly kernel of Gaussian approach has highest root mean squared error value which is 364.63%. The least root mean squared error value is 212.24% which is produced by Normalized kernel of Gaussian approach.

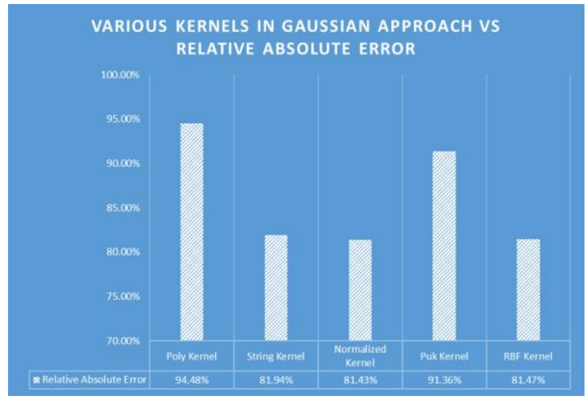

Figure 6: Various Kernels in Gaussian Classifier Vs Relative Absolute Error

The above diagram shows that the Relative Absolute Error value of various Inductive Learning Classification approaches. Poly kernel of Gaussian classifier has highest relative absolute error value which is 94.48%. The RBF Kernel, String Kernel and Normalized kernel have more or less same Relative Absolute Error values which are 81.47% of relative Absolute Error value, 81.94% of Relative Absolute Error Value and 81.43% of Relative Absolute Error value respectively. The least relative absolute error value is 81.43% which is produced by Normalized kernel of Gaussian classifier.

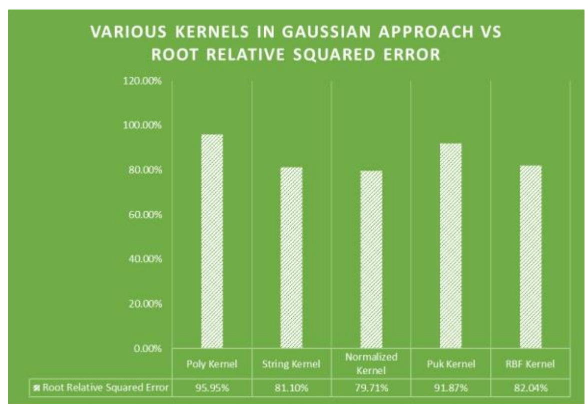

Figure 7: Various Kernels in Gaussian Classifier Vs Root Relative Squared Error

The above diagram shows that the Root Relative Squared Error value of various kernels in Gaussian approach. The Poly kernel of Gaussian approach has highest root relative squared error value which is 95.95%. The RBF Kernel, String kernel and Normalized kernel have more or less same Root Relative Squared Error values which are 82.04% of root relative squared error value, 81.10% of root relative squared error value and 79.71% of root relative squared error value respectively. The least root relative squared error value is 79.71% which is produced byNormalized kernel of Gaussian approach.

V CONCLUSION

This research work concludes that all the kernels are producing strongly correlated coefficient which is from 0.77 to 0.82 of correlation coefficient. The Normalized kernel is having highest correlation coefficient value which is 0.82. The RBF kernel is having lowest correlation coefficient which is 0.77.The Poly kernel has highest mean absolute error value which is 288.08%.The Lowest mean absolute error value is 218.94% which is produced by Normalized kernel of Gaussian approach. The Poly kernel of Gaussian approach has highest root mean squared error value which is 364.63%. The least root mean squared error value is 212.24% which is produced by Normalized kernel of Gaussian approach. Poly kernel of Gaussian classifier has highest relative absolute error value which is 94.48%.The least relative absolute error value is 81.43% which is produced by Normalized kernel of Gaussian classifier. The Poly kernel of Gaussian approach has highest root relative squared error value which is 95.95%.The least root relative squared error value is 79.71% which is produced by Normalized kernel of Gaussian approach. This system recommends that the Normalized kernel of Gaussian classifier model gives more efficient result compare with other models.

REFERENCES

[1] Harth, N. and Anagnostopoulos, C. (2018) Edge-centric Efficient Regression Analytics. In: 2018 IEEE International Conference on Edge Computing (EDGE), San Francisco, CA, USA, 02-07 Jul 2018
[2] Harth, N., Anagnostopoulos, C., (2017) Quality-aware Aggregation & Predictive Analytics at the Edge. IEEE International Conference on Big Data (IEEE Big Data 2017), December 11-14, 2017, Boston, MA, USA.
[3] http://archive.ics.uci.edu/ml/datasets/GNFUV+Unmanned+Surface+Vehicles+Sensor+Data
[4] Zanaj, E.; Caso, G.; DeNardis, L.; Mohammadpour, A.; Alay,Ö.; Di Benedetto, M.-G. Energy Efficiency in Short and Wide-Area IoT Technologies—A Survey. Technologies2021, 9, 22. https://doi.org/10.3390/technologies9010022
[5] Atzori, L.; Iera, A.; Morabito, G. The internet of things: A survey. Comput. Netw. 2010, 54, 2787–2805. [CrossRef]
[6] ITU. Internet of Things Global Standards Initiative. 2015. Available online: https://www.itu.int/en/ITU-T/gsi/iot/Pages/ default.aspx (accessed on 18 March 2021).
[7] Gillis, A.; Rosencrance, L.; Shea, S.; Wigmore, I. Internet of things (IoT). 2016. Available online: https://internetofthingsagenda.techtarget.com/definition/Internet-of-Things-IoT (accessed on 18 March 2021).
[8] Barker, P.; Hammoudeh, M. A survey on low power network protocols for the internet of things and wireless sensor networks.In Proceedings of the International Conference on Future Networks and Distributed Systems, Cambridge, UK, 19–20 July 2017;pp. 1–8.
[9] Andersson, M. Short range low power wireless devices and Internet of Things (IoT). Digi-Key Corp. 2015, 1, 1–16.
[10] Díaz-Zayas, A.; García-Pérez, C.A.; Recio-Pérez, A.M.; Merino, P. 3GPP standards to deliver LTE connectivity for IoT. In Proceedings of the 2016 IEEE First International Conference on Internet-of-Things DESIGN and Implementation (IoTDI), Berlin, Germany, 4–8 April 2016; pp. 283–288.
[11] Hoglund, A.; Bergman, J.; Lin, X.; Liberg, O.; Ratilainen, A.; Razaghi, H.S.; Tirronen, T.; Yavuz, E.A. Overview of 3GPP Release 14Further Enhanced MTC. IEEE Commun. Stand. Mag. 2018, 2, 84–89. [CrossRef]
[12] Nordic Semiconductor. What is Cellular IoT? Available online: https://blog.nordicsemi.com/ getconnected/what-is-cellular-iot(accessed on 18 March 2021).
[13] Anastasi, G.; Conti, M.; Di Francesco, M.; Passarella, A. Energy conservation in wireless sensor networks: A survey. Ad Hoc Netw.2009, 7, 537–568. [CrossRef]
[14] Feng, D.; Jiang, C.; Lim, G.; Cimini, L.J.; Feng, G.; Li, G.Y. A survey of energy-efficient wireless communications. IEEE Commun.Surv. Tutor. 2012, 15, 167–178. [CrossRef]
[15] Rault, T.; Bouabdallah, A.; Challal, Y. Energy efficiency in wireless sensor networks: A top-

down survey. Comput. Netw. 2014, 67,104–122. [CrossRef]
[16] Erol-Kantarci, M.; Mouftah, H.T. Energy-efficient information and communication infrastructures in the smart grid: A survey oninteractions and open issues. IEEE Commun. Surv. Tutor. 2014, 17, 179–197. [CrossRef]
[17] Bedi, G.; Venayagamoorthy, G.K.; Singh, R.; Brooks, R.R.;Wang, K.C. Review of internet of things (IoT) in electric power andenergy systems. IEEE Internet Things J. 2018, 5, 847–870. [CrossRef]
[18] Buzzi, S.; Chih-Lin, I.; Klein, T.E.; Poor, V.H.; Yang, C.; Zappone, A. A survey of energy-efficient techniques for 5G networks and challenges ahead. IEEE J. Sel. Areas Commun. 2016, 34, 697–709. [CrossRef]
[19] Weinstein, R. RFID: a technical overview and its application to the enterprise. IT Prof. 2005, 7, 27–33. [CrossRef]
[20] Want, R. An introduction to RFID technology. IEEE Pervasive Comput. 2006, 5, 25–33. [CrossRef]
[21] Lalitha, V.; Kathiravan, S. A review of manchester, miller, and fm0 encoding techniques. SmartCR 2014, 4, 481–490.
[22] Gislason, D. Zigbee Wireless Networking; Newnes: Oxford, UK, 2008.
[23] Chen, B.; Wu, M.; Yao, S.; Binbin, N. ZigBee technology and its application on wireless meter-reading system. In Proceedings ofthe 2006 4th IEEE International Conference on Industrial Informatics, Singapore, 16–18 August 2006; pp. 1257–1260.
[24] Zimmermann, H. OSI reference model-the ISO model of architecture for open systems interconnection. IEEE Trans. Commun.1980, 28, 425–432. [CrossRef]
[25] Farahani, S. ZigBee Wireless Networks and Transceivers; Newnes: Oxford, UK, 2011.
[26] IEEE Standard for Local and Metropolitan Area Networks. IEEE standard for local and metropolitan area networks—Part 15.4:Low-rate wireless personal area networks (lr-wpans). IEEE Stand. 2011, 802, 4–2011.
[27] Ramya, C.M.; Shanmugaraj, M.; Prabakaran, R. Study on ZigBee technology. In Proceedings of the 2011 3rd International Conference on Electronics Computer Technology, Kanyakumari, India, 8–10 April 2011; Volume 6, pp. 297–301.
[28] Specification, Z. Document 053474r20; ZigBee Standards Organization: Davis, CA, USA, 2012.