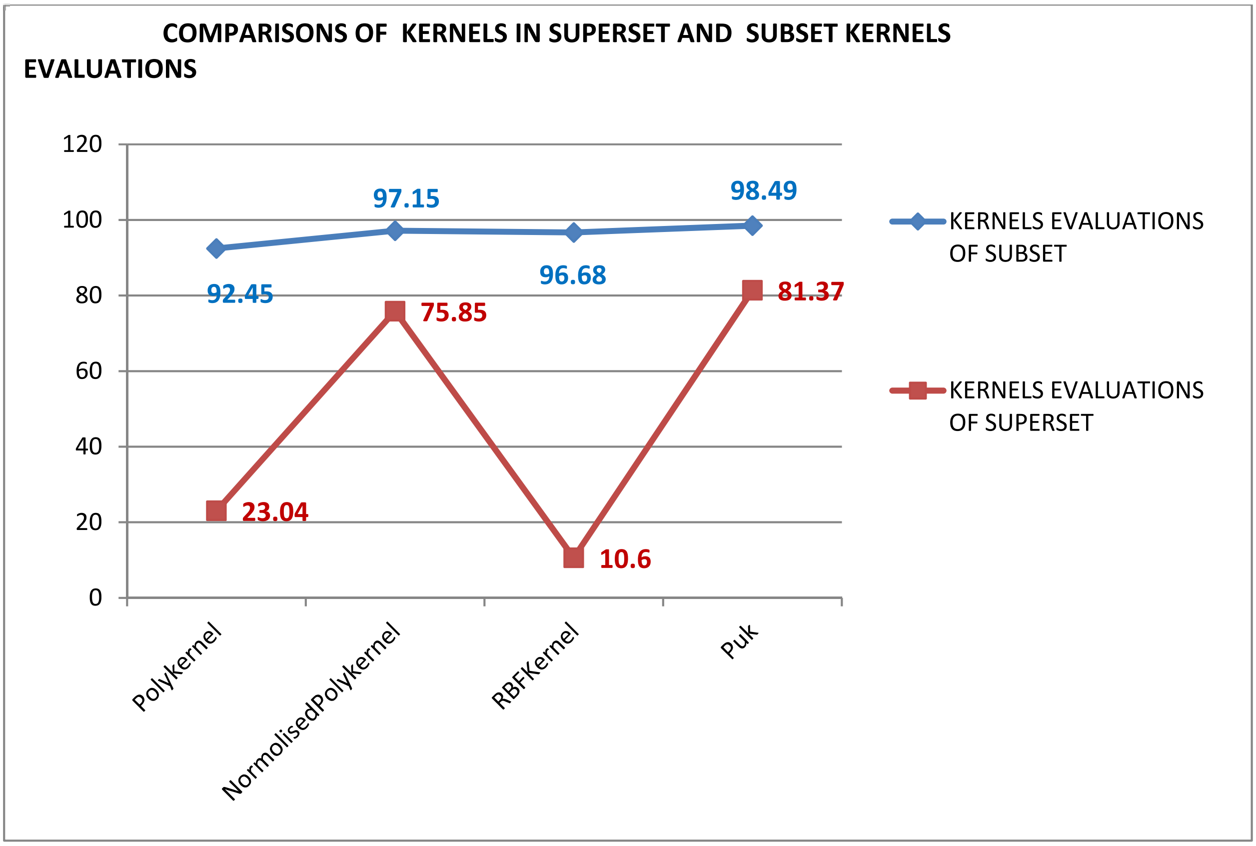

Figure 7: Various Kernels Vs Kernels Evaluations of subset and superset in Wireless Indoor Localization Data Set

Above diagram clearly depicts on various kernels Vs Kernels Evaluations in subset of Wireless Indoor Localization Data Set. Polykernel has 92.45, NormolisedPolykernel has 97.15, RBFKernel has 96.68 and Puk Kernel has 98.49. So, Puk Kernel has highly evaluated in kernels compares than other kernels.

Above diagram clearly depicts on various kernels Vs Kernels Evaluations in subset of Wireless Indoor Localization Data Set. Polykernel has 23.04, NormolisedPolykernel has 75.85, RBFKernel has 10.6 and Puk Kernel has 81.37. So, Puk Kernel has highly evaluated in kernels compares than other kernels.

V CONCLUSION

We performed tenfold cross validation and recorded the average of ten folds as the classification accuracy. From the results obtained we conclude that the support vector machine using regression with Puk kernel has less error and high co relation coefficient and it has taken less time complexity to build the model compare than other kernel parameters tuning in Support Vector Machine classifier.

REFERENCES

[1] Jayant G. Rohra et.al, User Localization in an Indoor Environment Using Fuzzy Hybrid of Particle warm Optimization & Gravitational Search Algorithm with Neural Networks, Proceedings of Sixth International Conference on Soft Computing for Problem Solving, Advances in Intelligent Systems and Computing 546,2017.
[2] Salazar, A.M., Warden, D.L., Schwab, K., Spe.ctor, J., Braverman, S., Walter, J.,Ellenbogen, R.G.: Cognitive rehabilitation for traumatic brain injury a randomized trial.JAMA 283(23), 3075–3081 (2000)
[3] Nguyen, N.T., Bui, H.H., Venkatsh, S., West, G.: Recognizing and monitoring high-level behaviors in complex spatial environments. In: Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 2, II-620. IEEE (2003)
[4] Pei, L., Liu, J., Guinness, R., Chen, Y., Kuusniemi, H., Chen, R.: Using LS-SVM based motion recognition for smartphone indoor wireless positioning. Sensors 12(5), 6155–6175 (2012)
[5] Cho, S.B.: Exploiting machine learning Techniques for location recognition and prediction with smartphone Logs. Neurocomputing (2015)
[6] Zou, H., Lu, X., Jiang, H., Xie, L.: A fast and precise indoor localization algorithm based on an online sequential extreme learning machine. Sensors 15(1), 1804–1824 (2015)
[7] Zadeh, L.A.: Fuzzy sets. Inform. control 8(3), 338–353 (1965)
[8] Jang, J.S., Sun, C.T.: Neuro-fuzzy modeling and control. Proc. IEEE 83(3), 378–406 (1995)
[9] Eberhart, R.C., Kennedy, J.: A new optimizer using particle swarm theory. In: Proceedings of the Sixth International Symposium on Micro Machine and Human Science, vol. 1, pp. 39–43 (1995)
[10] Bulusu, N., Heidemann, J., Estrin, D.: GPS-less low-cost outdoor localization for very smalldevices. IEEE Personal Commun. 7(5), 28–34 (2000).

[11] Dr.G.Ayyappan Ensemble Classifications for Student Academics Performance Data Set Indian Journal of Computer Science and Engineering 10(1) (2019) DOI : 10.21817/indjcse/2019/v10i1/191001009
[12] Dr.G.Ayyappan Ensemble Classifications for Sequential minimal optimization classification approach for caesarian section classification dataset data set by applying various kernels 9(6) (2018) DOI : 10.21817/indjcse/2018/v9i6/180906012