

Comparative Assessment of Forest Optimization with Deep Ensembling Technique for Human Activity Recognition based on Data Collected from Wearable Devices

G. Pallavi¹; Dr.A. Rama^{2*}

¹Research Scholar, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu, India.

¹pallavi.chitti24@gmail.com

^{2*}Project Guide, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu, India,

^{2*}ramaa.sse@saveetha.com

Abstract

Aim: Improving the performance of Human Activity Recognition based on information sensed by wearable devices. **Materials and methods:** In this study we have considered two groups namely forest optimization with sample size of 1408 and deep ensemble techniques with sample size 1408 (Kane, Phar, and BCPS n.d.). Accuracy was computed for the dataset size of 9673 to recognise six various human activities (walking, jogging, standing, upstairs, sitting, downstairs). **Result:** It was observed that the forest optimization algorithm obtains accuracy as 96% and loss as 14%. Forest optimization technique appears to have better significance than deep ensemble technique with value of $p=0.000$. **Conclusion:** The result proves that forest optimization approaches with varying seed value have significant improvement in human activity recognition.

Key-words: Machine Learning, Activity Recognition, Time Axis of Signals, Magnitude, Automated Human Activity Recognition System, Entrepreneurship.

1. Introduction

Human Activity Recognition is the process of observing the series of actions carried out by people in various environmental conditions (Zhu et al. 2019). Human Activity Recognition based on information sensed by Wearable devices was the classification of accelerometer sequence data. It focuses on selection of various Activities based on features extracted from accelerometer data and segmentation of time series data. (Twomey et al. 2018) It was considered to be important as assistive technology for eldercare and healthcare. It helps to identify the person, their personality and

psychological state. The Human Activity recognition systems are applicable in (Sukthankar et al. 2014) smart home sensor systems, Healthcare monitoring, (Ahad, Antar, and Ahmed 2020) Monitoring and surveillance systems for Indoor and Outdoor Activities.

This study also specifies the methodologies that can have a good impact on entrepreneurship. An entrepreneur can introduce these human activity recognition techniques as an automated system and process the same to business, which have a great influence in health care. Predicting the patient problems and necessities through online are too demanding for physicians, however, the development and use of automated human activity recognition systems can help in monitoring the patient's health closely and reports doctors in identifying health risks of the specific person and to recommend preventive measures through online.

Nearly all 10 articles related to Human Activity Recognition using Wearable devices have been published in pubmed and 6 articles published in IEEE Explorer in over the past five years. (Sansano and Sansano, n.d.) proposed machine learning-based techniques for indoor localization and human activity recognition through wearable devices with the outcome of accuracy rate 82% and loss was 21%. (Z. Mohammed 2017; Pirttikangas, Fujinami, and Nakajima 2006) proposed human activity recognition using deep ensemble technique of data collected from wearable devices with the outcome of Accuracy 85% and loss was 22%. (Gupta and Dallas 2014) proposed human activity recognition using ensemble technique of wearable sensor data with the outcome of Accuracy 72%. (Guo et al. 2019) human activity recognition using multi classifier hierarchical fusion model based on entropy weight with outcome of accuracy 59% and loss was 36%. (Brophy et al. 2018) proposed Machine vision approach to human activity recognition using photoplethysmography sensor data with the outcome of low accuracy 62% and loss in 29%. (Gupta and Dallas 2014; Ghasemzadeh et al. 2015) proposed power-Aware computing in wearable sensor networks with the outcome of an optimal feature selection. (Chen and Chen 2015) proposed novel wrapper method for human activity recognition for feature selection and its applications with the outcome of archived accuracy rate was 59% and the loss rate was 32%. (Ghasemi and Pouyan 2016) human activity recognition in ambient assisted living environments using proposed convex optimization problem with outcome of Accuracy rate of 76% and loss 32%. (M. Mohammed, Khan, and Bashier 2016) machine learning : with proposed Algorithms and Applications with the outcome of a proved theoretical approach. Overall the best study article was (Sansano and Sansano, n.d.) proposed machine learning-based technique for indoor localization and human activity recognition through wearable devices with the outcome of accuracy rate was 82% and loss was 21%.

Previously our team has a rich experience in working on various research projects across multiple disciplines (Sathish and Karthick 2020; Varghese, Ramesh, and Veeraiyan 2019; S. R. Samuel, Acharya, and Rao 2020; Venu, Raju, and Subramani 2019; M. S. Samuel et al. 2019; Venu, Subramani, and Raju 2019; Mehta et al. 2019; Sharma et al. 2019; Malli Suresh Babu et al. 2019; Krishnaswamy et al. 2020; Muthukrishnan et al. 2020; Gheena and Ezhilarasan 2019; Vignesh et al. 2019; Ke et al. 2019; Vijayakumar Jain et al. 2019; Jose, Ajitha, and Subbaiyan 2020). Now the growing trend in this area motivated us to pursue this project.

Most of the research in Human Activity Recognition has been done based on the depth sensors, as it becomes more popular due to low cost and high sample rate while comparing the effectiveness of the existing system such as robust and expensive. The lacunae in the existing research was inadequate accuracy rate in recognising human activities due to the shadows and illumination changes or alleviated by the acquisition of the depth channel. And this recognition still persists for depth sensors such as occlusion as well as limitations of sensors. The Aim of study was to improve recognition rate of human activities using forest optimization algorithms of data collected from wearable devices.

2. Materials and Methods

The study setting of the proposed work has been done in our university. Two classifier groups identified for this study namely Forest Optimization and Deep ensemble Technique.

Data Description

This Dataset used for the experiment was collected from UCI-REPOSITORY (“Human Activity Recognition” 2013). The dataset consists of human activity signals that was carried out in thirty volunteers of age ranging between nineteen and thirty five. Human activities considered namely (Walking, sitting, jogging, standing, running). The classification has been done based on the features Time Axis of Signals, Time domain and frequency domain. In this Time includes (Mean, Median, variance), frequency includes wavelength Analysis. The G-power was calculated as 0.8 for the given data samples. The sample size was computed as 2816 for two groups

Deep Ensemble Technique

Deep Ensembling tense to explore distinct methods in function space, and it observes the training networks individually with random initialization. (Twomey et al. 2018)

Step 1: Dataset identified and preprocessed.

Step 2: Dividing the dataset into training and test sets with 80% and 20% respectively.

Step 2: Construction of Deep Ensembling Model

- i. Apply Bootstrapped samples randomly to the original dataset with replacement.
- ii. Diverse classifiers are trained on each of these different subsets of the original dataset.
- iii. Aggregation all the predictions of every base model.
- iv. Several classifiers are combined to predict the output of a final model and use the probability score of all the base learners.

Evaluate the final prediction of the ensemble models.

Forest Optimization Algorithm

Random Forest Optimization was an ensemble learning technique, which formulates the nodes and levels of the decision tree while training the model and predicts the output. It performs good in non-linear data and also reduces over fitting.

In this experiment forest optimization technique was used and the parameter was tuned by varying the random seed value to improve accuracy. The accuracy value varies with respect to the random seed number, and performs prediction.

Step 1. Initialize forest with 0-Aged people

Step 2. Local seeding on 0-Aged trees

Step 3. population limiting and form the candidate population

Step 4. Global seeding on the selected trees from the candidate population.

Step 5. Update with best activity recognition.

Step 6. Stop the condition.

Step 7. Evaluate the final prediction rate.

The proposed work uses Google colab cloud platform for testing forest optimization and deep ensemble technique. Where Google colab is an online browser based platform which helps to train and test models. The testing setup has Runtime type-GPU'S (12 GB of V-RAM, intel xeon processor with course @2.20 GHZ and 13.GB RAM). The testing procedure as follows

1. Forest optimization is constructed by varying the input samples to the decision tree in forest.

- i. Dividing the population of forest into sub-population
 - ii. Sub-populations are generated by KNN Algorithms.
 - iii. Population size randomly varies.
2. Generate and train the model.
 3. calculate the average Accuracy.

In this experiment Sample size was computed using various baseline scenarios for the control group of two. The input data of size 9673 was considered and they were classified into 6 classes namely walking, standing, sitting, jogging, getting down stairs and upstairs with accuracy of 96%. We have used a dataset from UCI repository, which was already preprocessed.

All analyses are conducted using SPSS(statistical package for social and sciences) for the experiment. Descriptive statistics(Mean, standard deviation, standard error) is carried out for forest optimization and deep ensemble technique. The independent variables are time axis of signals, hidden correlation between neighbouring signals, time-domain and frequency-domain, where time-domain includes mean, median, variance, and frequency domain includes wavelet analysis. The dependent variables were walking, upstairs, standing, sitting, jogging, downstairs.

Independent t-test is performed to compare the performance of an algorithm. Based on Analysis done it has been proved that Accuracy rate was improved. Therefore in this comparison forest optimization algorithm Accuracy (96%) appears to be better than deep ensemble technique (87%)

3. Results

For the first time, we conducted a comprehensive review of recent action recognition frameworks based on semantic information. Pose, poselet, object/scene meaning, and attributes are added as part of a semantic space. We explore how semantic representations capture essential information and are immune to visual changes.

Table-1 represents that tabulation of accuracy for forest optimization and deep ensemble technique with varying the seed value randomly. The software package That used for statistical Analysis in this experiment was SPSS.

Table 1 - Predicted Accuracy of Human Activity Recognition (Forest optimization accuracy Of 96% and Deep ensemble technique accuracy of 87%)

S.NO	Random Seed Value	Accuracy of Forest optimization (%)	Deep Ensemble technique (%)
1	37	90	82
2	45	96	73
3	42	92	82
4	28	89	86
5	36	86	87
6	24	85	84
7	29	81	85
8	32	87	83
9	20	81	81
10	22	84	82

Table-2 represents By the average of two algorithms standard mean values have been defined in Group Statics. The mean value of forest optimization appears to be better mean=86.8.

Table 2 - Group statics results (Mean of Forest optimization 86.8 was more compared with Deep ensemble technique 82.5 and std. Error Mean for Forest optimization was 1.33 and Deep Ensemble was 1.22)

Group	N	Mean	Std. Deviation	Std. Error mean
Accuracy forest optimization	10	86.8000	4.21110	1.33167
Deep ensemble	10	82.5000	3.86580	1.22247
Loss forest optimization	10	35.8000	10.84025	3.42799
Deep ensemble	10	45.2000	7.71434	2.43949

Table-3 represents the significance value was given in the Independent Sample test. The significance value $p=0.000$ which was less than value $p=0.005$ ($p=0.000 > 0.005$). This Analysis was done by comparing the forest optimization and Deep ensemble technique with the Accuracy value for varying seed value randomly.

Table 3 - Independent Sample T-test Result was applied for dataset fixing Accuracy as 96% and level of significance as 0.05 (Forest optimization appears to perform significantly better than deep ensemble technique, with the value $p=0.000$)

	Levene's Test for Equality of Variances		T-test for Equality of Means						
	F	sig	t	df	sig(2-tailed)	Mean difference	Std.error difference	95% confidence interval of the difference	
								lower	upper
Accuracy Equal variances Assumed.	.628	0.10	2.379	18	.000	4.30000	1.80770	.50216	8.09784
Equal variances Not Assumed			2.379	17.870	.001	4.30000	1.80770	.50018	8.09982
Loss Equal variances Assumed.	.815	0.20	-2.234	18	.000	-9.40000	4.20740	-18.23942	-56058
Equal Variances Not Assumed			-2.234	16.255	.001	-9.40000	4.20740	-18.30793	-49207

In fig-1 the graphical representation of Accuracy for train and test data of human activity recognition using forest optimization. The outcome percentage of the training set was 70% and testing was 30%. In that graph the blue colour graphical line represents the train and pink colour represents the test.

Fig. 1 - Accuracy percentage of with train and test data(Forest Optimization Algorithm)

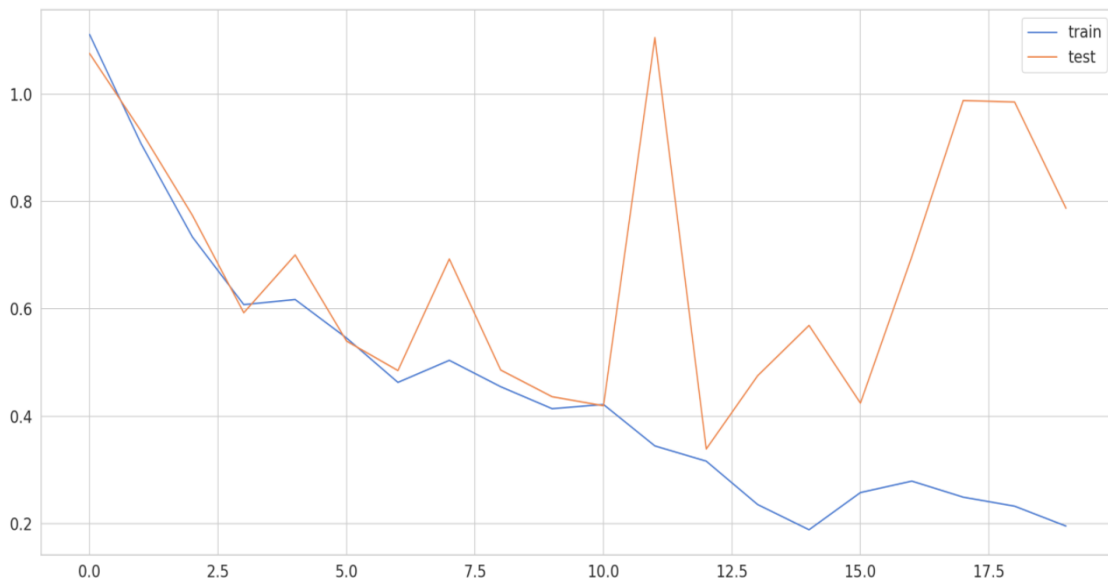
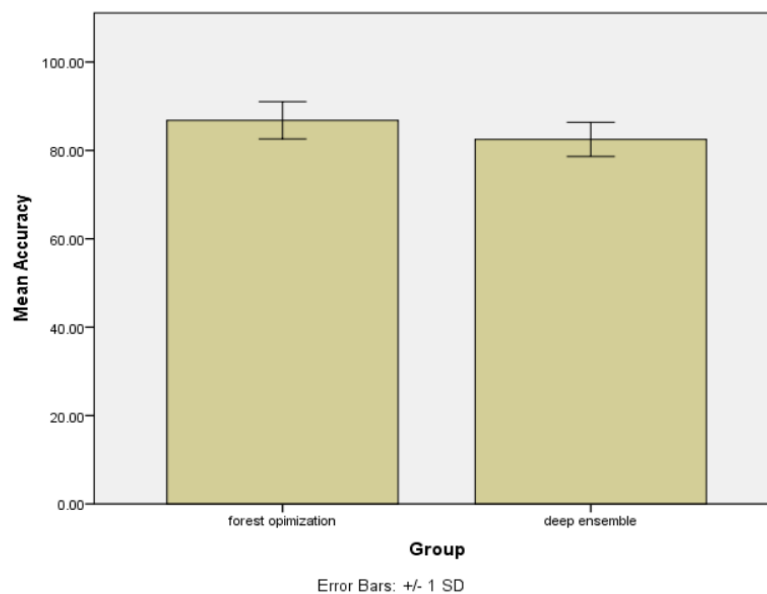


Fig-2 Box Plot graphical representation of the comparison of mean accuracy of Forest Optimization and Deep Ensemble Technique. The mean Accuracy of forest optimization appears to be better than Deep ensemble technique and the standard deviation of forest Optimization appears to be better than Deep ensemble technique. X Axis: Forest optimization vs Deep ensemble technique Y Axis: Mean Accuracy of detection ± 1 SD

→ GGraph



In fig-2 the box plot graph represents the comparison of accuracy of forest optimization with deep ensemble technique. Forest optimization got the most consistent result than deep ensemble technique. There was a statistical significance between forest optimization and deep ensembling algorithm where it has $p=0.000$ for independent sample t-test. since the forest optimization technique appears to give better accuracy than deep ensembling for human activity recognition.

4. Discussion

In this study it was observed that Random forest optimization Algorithm proves to have better Accuracy (96%) than Deep ensemble Technique (Accuracy-85%).

Most of the research used various classification algorithms for human activity recognition like (Pirttikangas, Fujinami, and Nakajima 2006) achieved 72% of accuracy in recognising the human activities using deep ensemble technique. (Munoz-Organero 2019) outlier detection in wearable sensor data for HAR based proposed DRNNs with the outcome of 79% accuracy.

(Nweke et al. 2018) analysis of multi-sensor fusion for mobile and wearable sensor fusion for wearable sensors based human activity recognition with the outcome of 82% accuracy.

(Cai, Yang, and Zhang 2014) real-time physical activity recognition using a single triaxial accelerometer based on HMM with the outcome of accuracy 84%. (Ghasemzadeh et al. 2015) power-Aware computing in wearable sensors networks for an optimal feature selection with the outcome of archived accuracy rate was 86%. (Ghasemi and Pouyan 2016) proposed human activity recognition in ambient assisted living environments using a convex optimization problem with the outcome with accuracy of 81%. (Valentin 2014) Gestural activity recognition for canine-human communication with the outcome of accuracy 82% and loss was 59%. (“Human Activity Recognition” 2013) proposed human activity recognition using deep ensemble technique with the outcome of accuracy 84% and loss 43%. It can be implemented for analysis human activity recognition in wearable devices Detecting the recognition of human activities using forest optimization with a modified proposed system with many sensors like wearable devices which can be used in healthcare monitoring systems, smart home appliances etc. were some of new findings. And many cited literature used algorithms got less accuracy than forest optimization. Forest optimization was used for human activity recognition in surveillance and monitoring of health care systems.

Our institution is passionate about high quality evidence based research and has excelled in various fields ((Vijayashree Priyadarshini 2019; Ezhilarasan, Apoorva, and Ashok Vardhan 2019;

Ramesh et al. 2018; Mathew et al. 2020; Sridharan et al. 2019; Pc, Marimuthu, and Devadoss 2018; Ramadurai et al. 2019). We hope this study adds to this rich legacy.

The limitations of this study include each person's place, distance, location, and date and time of the performance of an activity where the person done was not well defined. The future scope of Human activity recognition can benefit various applications such as health care monitoring services and smart home applications. Many sensors have been utilized for human activity recognition such as wearable devices.

5. Conclusion

Human activity recognition for the data collected from wearable devices using forest optimization algorithms has obtained the accuracy of (96%), which appears to perform better with varying the seed values. The highest mean value of forest optimization was 86.8%. In order to improve the mean recognition rate scale invariant and local dependence of sensor variables are to be considered in future.

Declarations

Conflict of Interests: No conflict of interests in this manuscript

Author Contribution

Author Gp. was involved in data collection, data analysis, manuscript writing. Author AR was involved in conceptualization, data validation, and critical review of manuscript.

Acknowledgment

The authors would like to express their gratitude towards Saveetha school of engineering, Saveetha Institute of Medical and Technical Sciences(Formerly Known as Saveetha University) for providing the necessary infrastructure to carry out this work successfully.

Fundings: we thank the following organizations for providing financial support that enabled us to complete the study.

1. Ipharmed Services private Limited, Bangalore.
2. Saveetha University

3. Saveetha Institute of Medical and Technical Sciences.
4. Saveetha school of engineering.

References

- Ahad, Md Atiqur Rahman, Anindya Das Antar, and Masud Ahmed. 2020. *IoT Sensor-Based Activity Recognition: Human Activity Recognition*. Springer Nature.
- Brophy, Eoin, Jose Juan Dominguez Veiga, Zhengwei Wang, and Tomas E. Ward. 2018. "A Machine Vision Approach to Human Activity Recognition Using Photoplethysmography Sensor Data." *2018 29th Irish Signals and Systems Conference (ISSC)*. <https://doi.org/10.1109/issc.2018.8585372>.
- Cai, Jun, Ke Quan Yang, and Yi Zhang. 2014. "Real-Time Physical Activity Recognition Using a Single Triaxial Accelerometer Based on HMM." *Applied Mechanics and Materials*. <https://doi.org/10.4028/www.scientific.net/amm.602-605.2221>.
- Chen, Gang, and Jin Chen. 2015. "A Novel Wrapper Method for Feature Selection and Its Applications." *Neurocomputing*. <https://doi.org/10.1016/j.neucom.2015.01.070>.
- Ezhilarasan, Devaraj, Velluru S. Apoorva, and Nandhigam Ashok Vardhan. 2019. "Syzygium Cumini Extract Induced Reactive Oxygen Species-Mediated Apoptosis in Human Oral Squamous Carcinoma Cells." *Journal of Oral Pathology & Medicine: Official Publication of the International Association of Oral Pathologists and the American Academy of Oral Pathology* 48 (2): 115–21.
- Ghasemi, Vahid, and Ali Akbar Pouyan. 2016. "Human Activity Recognition in Ambient Assisted Living Environments Using a Convex Optimization Problem." *2016 2nd International Conference of Signal Processing and Intelligent Systems (ICSPIS)*. <https://doi.org/10.1109/icspis.2016.7869899>.
- Ghasemzadeh, Hassan, Navid Amini, Ramyar Saeedi, and Majid Sarrafzadeh. 2015. "Power-Aware Computing in Wearable Sensor Networks: An Optimal Feature Selection." *IEEE Transactions on Mobile Computing*. <https://doi.org/10.1109/tmc.2014.2331969>.
- Gheena, S., and D. Ezhilarasan. 2019. "Syringic Acid Triggers Reactive Oxygen Species-Mediated Cytotoxicity in HepG2 Cells." *Human & Experimental Toxicology* 38 (6): 694–702.
- Guo, Ming, Zhelong Wang, Ning Yang, Zhenglin Li, and Tiantian An. 2019. "A Multisensor Multiclassifier Hierarchical Fusion Model Based on Entropy Weight for Human Activity Recognition Using Wearable Inertial Sensors." *IEEE Transactions on Human-Machine Systems*. <https://doi.org/10.1109/thms.2018.2884717>.
- Gupta, Piyush, and Tim Dallas. 2014. "Feature Selection and Activity Recognition System Using a Single Triaxial Accelerometer." *IEEE Transactions on Biomedical Engineering*. <https://doi.org/10.1109/tbme.2014.2307069>.
- "Human Activity Recognition." 2013. *Human Activity Recognition*. <https://doi.org/10.1201/b16098-7>.
- Jose, Jerry, Ajitha, and Haripriya Subbaiyan. 2020. "Different Treatment Modalities Followed by Dental Practitioners for Ellis Class 2 Fracture – A Questionnaire-Based Survey." *The Open Dentistry Journal* 14 (1): 59–65.
- Kane, Sean P., Phar, and BCPS. n.d. "Sample Size Calculator." Accessed March 25, 2021. <https://clincalc.com/stats/samplesize.aspx>.

Ke, Yang, Mohammed Saleh Al Aboody, Wael Alturaiki, Suliman A. Alsagaby, Faiz Abdulaziz Alfaiz, Vishnu Priya Veeraraghavan, and Suresh Mickymaray. 2019. "Photosynthesized Gold Nanoparticles from Catharanthus Roseus Induces Caspase-Mediated Apoptosis in Cervical Cancer Cells (HeLa)." *Artificial Cells, Nanomedicine, and Biotechnology* 47 (1): 1938–46.

Krishnaswamy, Haribabu, Sivaprakash Muthukrishnan, Sathish Thanikodi, Godwin Arockiaraj Antony, and Vijayan Venkatraman. 2020. "Investigation of Air Conditioning Temperature Variation by Modifying the Structure of Passenger Car Using Computational Fluid Dynamics." *Thermal Science* 24 (1 Part B): 495–98.

Malli Sureshbabu, Nivedhitha, Kathiravan Selvarasu, Jayanth Kumar V, Mahalakshmi Nandakumar, and Deepak Selvam. 2019. "Concentrated Growth Factors as an Ingenious Biomaterial in Regeneration of Bony Defects after Periapical Surgery: A Report of Two Cases." *Case Reports in Dentistry* 2019 (January): 7046203.

Mathew, M. G., S. R. Samuel, A. J. Soni, and K. B. Roopa. 2020. "Evaluation of Adhesion of Streptococcus Mutans, Plaque Accumulation on Zirconia and Stainless Steel Crowns, and Surrounding Gingival Inflammation in Primary" *Clinical Oral Investigations*. <https://link.springer.com/article/10.1007/s00784-020-03204-9>.

Mehta, Meenu, Deeksha, Devesh Tewari, Gaurav Gupta, Rajendra Awasthi, Harjeet Singh, Parijat Pandey, et al. 2019. "Oligonucleotide Therapy: An Emerging Focus Area for Drug Delivery in Chronic Inflammatory Respiratory Diseases." *Chemico-Biological Interactions* 308 (August): 206–15.

Mohammed, Mohssen, Muhammad Badruddin Khan, and Eihab Bashier Mohammed Bashier. 2016. *Machine Learning: Algorithms and Applications*. CRC Press.

Mohammed, Zouiten. 2017. "Machine Learning Algorithms for Oncology Big Data Treatment." *Proceedings of the 2nd International Conference on Computing and Wireless Communication Systems - ICCWCS'17*. <https://doi.org/10.1145/3167486.3167565>.

Munoz-Organero, Mario. 2019. "Outlier Detection in Wearable Sensor Data for Human Activity Recognition (HAR) Based on DRNNs." *IEEE Access*. <https://doi.org/10.1109/access.2019.2921096>.

Muthukrishnan, Sivaprakash, Haribabu Krishnaswamy, Sathish Thanikodi, Dinesh Sundaresan, and Vijayan Venkatraman. 2020. "Support Vector Machine for Modelling and Simulation of Heat Exchangers." *Thermal Science* 24 (1 Part B): 499–503.

Nweke, Henry Friday, Ying Wah Teh, Uzoma Rita Alo, and Ghulam Mujtaba. 2018. "Analysis of Multi-Sensor Fusion for Mobile and Wearable Sensor Based Human Activity Recognition." *Proceedings of the International Conference on Data Processing and Applications - ICDPA 2018*. <https://doi.org/10.1145/3224207.3224212>.

Pc, J., T. Marimuthu, and P. Devadoss. 2018. "Prevalence and Measurement of Anterior Loop of the Mandibular Canal Using CBCT: A Cross Sectional Study." *Clinical Implant Dentistry and Related Research*. <https://europepmc.org/article/med/29624863>.

Pirttikangas, Susanna, Kaori Fujinami, and Tatsuo Nakajima. 2006. "Feature Selection and Activity Recognition from Wearable Sensors." *Ubiquitous Computing Systems*. https://doi.org/10.1007/11890348_39.

Ramadurai, Neeraja, Deepa Gurunathan, A. Victor Samuel, Emg Subramanian, and Steven J. L. Rodrigues. 2019. "Effectiveness of 2% Articaine as an Anesthetic Agent in Children: Randomized Controlled Trial." *Clinical Oral Investigations* 23 (9): 3543–50.

- Ramesh, Asha, Sheeja Varghese, Nadathur D. Jayakumar, and Sankari Malaiappan. 2018. "Comparative Estimation of Sulfiredoxin Levels between Chronic Periodontitis and Healthy Patients - A Case-Control Study." *Journal of Periodontology* 89 (10): 1241–48.
- Samuel, Melvin S., Jayanta Bhattacharya, Sankalp Raj, Needhidasan Santhanam, Hemant Singh, and N. D. Pradeep Singh. 2019. "Efficient Removal of Chromium(VI) from Aqueous Solution Using Chitosan Grafted Graphene Oxide (CS-GO) Nanocomposite." *International Journal of Biological Macromolecules* 121 (January): 285–92.
- Samuel, Srinivasan Raj, Shashidhar Acharya, and Jeevika Chandrasekar Rao. 2020. "School Interventions-Based Prevention of Early-Childhood Caries among 3-5-Year-Old Children from Very Low Socioeconomic Status: Two-Year Randomized Trial." *Journal of Public Health Dentistry* 80 (1): 51–60.
- Sansano, Emilio, and Emilio Sansano Sansano. n.d. "Machine Learning-Based Techniques for Indoor Localization and Human Activity Recognition through Wearable Devices." <https://doi.org/10.6035/14101.2020.180044>.
- Sathish, T., and S. Karthick. 2020. "Wear Behaviour Analysis on Aluminium Alloy 7050 with Reinforced SiC through Taguchi Approach." *Journal of Japan Research Institute for Advanced Copper-Base Materials and Technologies* 9 (3): 3481–87.
- Sharma, Parvarish, Meenu Mehta, Daljeet Singh Dhanjal, Simran Kaur, Gaurav Gupta, Harjeet Singh, Lakshmi Thangavelu, et al. 2019. "Emerging Trends in the Novel Drug Delivery Approaches for the Treatment of Lung Cancer." *Chemico-Biological Interactions* 309 (August): 108720.
- Sridharan, Gokul, Pratibha Ramani, Sangeeta Patankar, and Rajagopalan Vijayaraghavan. 2019. "Evaluation of Salivary Metabolomics in Oral Leukoplakia and Oral Squamous Cell Carcinoma." *Journal of Oral Pathology & Medicine: Official Publication of the International Association of Oral Pathologists and the American Academy of Oral Pathology* 48 (4): 299–306.
- Sukthankar, Gita, Christopher Geib, Hung Hai Bui, David Pynadath, and Robert P. Goldman. 2014. *Plan, Activity, and Intent Recognition: Theory and Practice*. Newnes.
- Twomey, Niall, Tom Diethe, Xenofon Fafoutis, Atis Elsts, Ryan McConville, Peter Flach, and Ian Craddock. 2018. "A Comprehensive Study of Activity Recognition Using Accelerometers." *Informatics*. <https://doi.org/10.3390/informatics5020027>.
- Valentin, Giancarlo. 2014. "Gestural Activity Recognition for Canine-Human Communication." *Proceedings of the 2014 ACM International Symposium on Wearable Computers Adjunct Program - ISWC '14 Adjunct*. <https://doi.org/10.1145/2641248.2642733>.
- Varghese, Sheeja Saji, Asha Ramesh, and Deepak Nallaswamy Veeraiyan. 2019. "Blended Module-Based Teaching in Biostatistics and Research Methodology: A Retrospective Study with Postgraduate Dental Students." *Journal of Dental Education* 83 (4): 445–50.
- Venu, Harish, V. Dhana Raju, and Lingesan Subramani. 2019. "Combined Effect of Influence of Nano Additives, Combustion Chamber Geometry and Injection Timing in a DI Diesel Engine Fuelled with Ternary (diesel-Biodiesel-Ethanol) Blends." *Energy* 174 (May): 386–406.
- Venu, Harish, Lingesan Subramani, and V. Dhana Raju. 2019. "Emission Reduction in a DI Diesel Engine Using Exhaust Gas Recirculation (EGR) of Palm Biodiesel Blended with TiO₂ Nano Additives." *Renewable Energy* 140 (September): 245–63.

Vignesh, R., Ditto Sharmin, C. Vishnu Rekha, Sankar Annamalai, and Parisa Norouzi Baghkomeh. 2019. "Management of Complicated Crown-Root Fracture by Extra-Oral Fragment Reattachment and Intentional Replantation with 2 Years Review." *Contemporary Clinical Dentistry* 10 (2): 397–401.

Vijayakumar Jain, S., M. R. Muthu Sekar, M. F. Baig, P. Senthilnathan, S. Loganathan, P. U. Abdul Wahab, M. Madhulakshmi, and Yogaen Vohra. 2019. "Evaluation of Three-Dimensional Changes in Pharyngeal Airway Following Isolated Lefort One Osteotomy for the Correction of Vertical Maxillary Excess: A Prospective Study." *Journal of Maxillofacial and Oral Surgery* 18 (1): 139–46.

Vijayashree Priyadarshini, Jayaseelan. 2019. "In Silico Validation of the Non-Antibiotic Drugs Acetaminophen and Ibuprofen as Antibacterial Agents against Red Complex Pathogens." *Journal of Periodontology* 90 (12): 1441–48.

Zhu, Ran, Zhuoling Xiao, Ying Li, Mingkun Yang, Yawen Tan, Liang Zhou, Shuisheng Lin, and Hongkai Wen. 2019. "Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning." *IEEE Access*. <https://doi.org/10.1109/access.2019.2922104>.