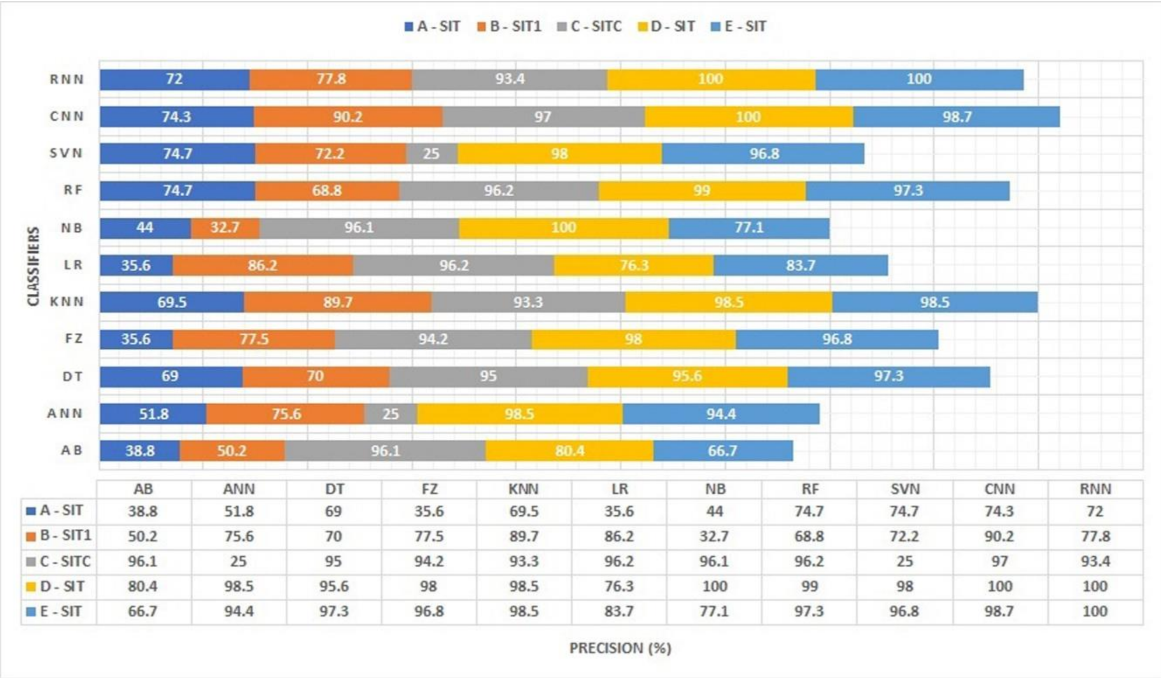
EAI Endorsed Transactions
on ______________________________ Research Article EAI.EU



	AB	ANN	DT	FZ	KNN	LR	NB	RF	SVN	CNN	RNN
A - SIT	38.8	51.8	69	35.6	69.5	35.6	44	74.7	74.7	74.3	72
B - SIT1	50.2	75.6	70	77.5	89.7	86.2	32.7	68.8	72.2	90.2	77.8
C - SITC	96.1	25	95	94.2	93.3	96.2	96.1	96.2	25	97	93.4
D - SIT	80.4	98.5	95.6	98	98.5	76.3	100	99	98	100	100
E - SIT	66.7	94.4	97.3	96.8	98.5	83.7	77.1	97.3	96.8	98.7	100

(a) static activities (sitting).

	AB	ANN	DT	FZ	KNN	LR	NB	RF	SVN	CNN	RNN
A - WLK	65.6	70	69.6	69.5	72	69.5	72.8	73.8	73.8	71.7	71.7
B - WLK1	35.3	30	28.6	33.3	100	71.4	81.6	92.1	84.4	42.9	86.3
C - AMB	63.7	98.7	85	88.6	86.1	95.3	63.7	95.3	98.7	96.9	93.6
D - WLK	74.4	84	91.3	89.6	84	45.7	50	98.6	89.6	99	100
E - WLK	91.3	87	94.8	92.2	97.3	93.9	96.3	96.5	92.2	97.1	97.7

(b) Transactional activity (walking)

Figure 4. Precision comparison analysis for static activity (sitting) and transactional activity (walking) of all classifiers. One activity from each dataset can be seen. Each activity is represented as <Dataset Representation >- <Activity abbreviation denoted in table 2 >. A represents AReM dataset, B represents HAPT dataset, OLDPPL is represented by C, D represents PAMAP2 dataset and E represents WISDM dataset.

and logistic regression classifier provides good sensitivity and specificity rate after CNN, LSTM, Random forest and SVM classifiers.

5. Conclusion

In today's world, the sensors and smart phone based human activity recognition area is proving to be vital in assisting human beings in different areas of life. In this paper, we used 5 benchmarks on different datasets to implement multi-class classification techniques and used a GUI based analytics platform KNIME and MATLAB. We used Ada boost, artificial neural network, decision tree, K-NN, logistic regression, Naive Bayes, random forest, support vector machine, convolutional neural network and Long Short Term Memory networks classifiers. The methods we applied in this study produced some outstanding classification, specifically for convolutional neural network and Long Short-Term Memory networks classifiers which produced over 90% overall classification rate, while random forest and support vector machine produced up to 80% accuracy rate. (One number is classification rate and other number is accuracy..? Should be the same thing when comparing. Either classification rate or accuracy) The primary reason for CNN and LSTM to perform better is their ability to work on sequential data.

Some other finding in this paper is the pattern of an activity recognition. For example, random forest and KNN are best for static activities, convolutional neural network and Long Short Term Memory networks are best for almost each activity, especially for cycling and jump forward and backward. Random forest classifiers are other classifiers which produced better results. We concluded that deep learning models (CNN, LSTM) and Random forest from classical machine learning are more stable and best performance classification algorithms for human activity recognition.

Table 4. Classifier Recall of Activities for all datasets

Datasets	Activity\Classifier	AB	ANN	DT	FZ	KNN	LR	NB	RF	SVN	CNN	LSTM
AReM	BND1	70.9	70.4	87.7	72.2	88.4	72.2	71	89.2	89.2	89.9	87.7
	BND2	70.9	70.4	87.7	72.2	88.4	72.2	71	89.2	89.2	85.1	84.5
	CYL	75.4	57.5	79.2	20.5	76.7	20.5	76.1	79.4	79.4	69.4	68.5
	LYN	47.6	61.9	64.9	57.2	66.4	57.2	71.9	69.3	69.3	99	95.9
	SIT	68.6	89.2	96.3	79	97.8	79	84.2	98.4	98.4	71.1	70.1
	STD	58.7	44.8	70	84.7	69.2	84.7	68.8	74.4	74.4	78.2	77.8
	WLK	41.4	64.1	73.6	10.7	76.6	10.7	23.4	78.8	78.8	76.3	77.6
HAPT	STD1	51.8	86.7	77.6	82.3	93.7	92.2	18.1	76.5	86.3	94.8	73.2
	WKU1	53.3	73.3	40	28.6	53.3	66.7	87.5	62.5	50	66.7	20
	WKD2	33.3	33.3	66.7	41.2	66.7	55.6	42.9	57.5	1.1	68.8	57
	WKU2	58.8	41.2	58.8	43.8	47.1	47.1	75	100	75	60	50
	SIT1	71.1	83.2	71.1	75.8	83.8	85.3	94.4	61.1	72.2	84	87.5
	STD2	78.5	89	87.2	91.7	92.4	93	70.3	81.1	83.6	96.2	81
	LYDN	18.2	32.4	47.6	40.8	44	40.7	80	73.3	66.7	59	60
	SIT2	56.7	81.2	57	64	71.3	70	28.6	64.3	57.1	75.7	73.3
	LYD2	63.6	72	72.4	69.3	65.4	72	70.6	35.3	35.3	81.3	60
	WLK1	75	37.5	25	14.3	62.5	62.5	36.5	91.4	91	60	96.1
	WLK2	75	0	25	75	100	100	89	93	93	50	94.8
	WKD1	64.3	57.1	57.1	35.7	64.3	50	59.9	86.8	77.2	60	86.1
OLDPPL	SITD	92	97.9	97.2	97.5	94.9	98.7	92	98.7	97.9	98.9	97.7
	LYNG	100	100	99.9	99.9	99.9	99.9	100	99.9	100	99.9	99.9
	AMB	55.4	35	81.7	75.8	75.1	79.2	55.4	79.2	35	74.8	60.9
	SITC	24.6	0.1	94.9	94.3	93.8	96	24.6	96	0.1	97.7	95.4
	LYN	93.9	99	96.9	96.4	99	91.8	88.3	98	96.4	98.5	99.5
	FLND	73.6	98.9	97.8	98.9	98.9	80.9	28.1	100	98.9	99	99
	HCL	75.4	87.7	95.5	93.1	87.7	57	44.1	98.3	93.1	98.9	100
	SIT	62	96.6	95.1	95.6	96.6	43.9	39.5	96.6	95.6	96.7	97.2

PAMAP2	PSC	88	65.1	98.3	94.8	65.1	72.6	65.7	99.4	94.8	100	100
	RJMP	84.3	94.3	98.1	97.6	94.3	37.6	66.7	99	97.6	98	100
	STD	26.5	95.7	92.4	95.1	95.7	85.3	26.5	99.5	95.1	100	100
	WLK	43.9	81.6	84.4	88.7	81.6	34.9	10.8	96.7	88.7	98	100
	RUN	60.8	87.3	92.5	91.4	87.3	34	89.2	99.1	91.4	99.5	99.5
	CYL	81.6	95.1	96.2	95.6	95.1	96.2	27.6	99.5	95.6	95.1	97.5
	NWLK	46.2	82.4	89.4	89.7	82.4	19.1	8	99.5	89.7	99.5	100
	WTV	99	99	100	100	99	97.6	92.9	99	100	99.5	99.5
WISDM	WLK	94.2	97.7	94.2	95.1	98.2	90.3	95.3	97.4	95.1	98.8	98.5
	JOG	88.4	96.3	88.4	96.4	96.4	83	89.7	95.6	96.4	96.9	97.4
	UPS	12.8	15.4	57.4	11.1	70.9	8.1	36.5	62.5	11.1	66.1	72
	DNS	7.2	22.1	62.8	3.1	70.1	32.7	25.3	57.5	3.1	55.3	62.8
	SIT	98.5	90.7	96	93.8	100	96	90	96	93.8	100	98.6
	STD	59	89.1	89.1	89.7	94.9	69.6	72.7	97.8	89.7	89.5	89.5

6. Future work

Despite a comprehensive comparative study, we have not tested the human activity recognition datasets against some other deep learning models such as deep belief network. In addition, the use of feature transformation techniques such as restricted Boltzmann machine and auto-encoders can be utilized to further optimize the classification technique and improve the accuracy and other matrices. In future work, we also plan to work on a real time HAR system. The system is anticipated to be a cloud based solution that system will communicate with different IoT devices. In the proposed system, we will use deep learning techniques CNN and LSTM for Human activity recognition.

References

[1] Wu WH, Bui AA, Batalin MA, Au LK, Binney JD, Kaiser WJ. MEDIC: Medical embedded device for individualized care. Artificial intelligence in medicine. 2008; Feb 1;42(2):137-52.

[2] Long X, Yin B, Aarts RM. Single-accelerometer-based daily physical activity classification. In2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2009; Sep 3 (pp. 6107-6110). IEEE.

[3] Tognetti A, Lorussi F, Bartalesi R, Quaglini S, Tesconi M, Zupone G, De Rossi D. Wearable kinesthetic system for capturing and classifying upper limb gesture in post-stroke rehabilitation. Journal of NeuroEngineering and Rehabilitation. 2005; Dec;2(1):1-6.

[4] Tognetti A, Lorussi F, Tesconi M, Bartalesi R, Zupone G, De Rossi D. Wearable kinesthetic systems for capturing and classifying body posture and gesture. In2005 IEEE Engineering in Medicine and Biology 27th Annual Conference 2006; Jan 17 (pp. 1012-1015). IEEE.

[5] Hassan MM, Uddin MZ, Mohamed A, Almogren A. A robust human activity recognition system using smartphone sensors and deep learning. Future Generation Computer Systems. 2018; Apr 1;81:307-13.

[6] Ignatov A. Real-time human activity recognition from accelerometer data using Convolutional Neural Networks. Applied Soft Computing. 2018; Jan 1;62:915-22.

[7] Chen Y, Shen C. Performance analysis of smartphone-sensor behavior for human activity recognition. Ieee Access. 2017; Mar 1;5:3095-110.

[8] Reyes-Ortiz JL, Oneto L, Sama A, Parra X, Anguita D. Transition-aware human activity recognition using smartphones. Neurocomputing. 2016; Jan 1;171:754-67.

[9] Ignatov AD, Strijov VV. Human activity recognition using quasiperiodic time series collected from a single tri-axial accelerometer. Multimedia tools and applications. 2016; Jun;75(12):7257-70.

[10] Shoaib M, Bosch S, Scholten H, Havinga PJ, Incel OD. Towards detection of bad habits by fusing smartphone and smartwatch sensors. In2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops) 2015; Mar 23 (pp. 591-596). IEEE.

[11] Ronao CA, Cho SB. Deep convolutional neural networks for human activity recognition with smartphone sensors. InInternational Conference on Neural Information Processing 2015; Nov 9 (pp. 46-53). Springer, Cham.

[12] Chen Z, Zhu Q, Soh YC, Zhang L. Robust human activity recognition using smartphone sensors via CT-PCA and online SVM. IEEE Transactions on Industrial Informatics. 2017; Jun 7;13(6):3070-80.

[13] Chen Z, Zhang L, Cao Z, Guo J. Distilling the knowledge from handcrafted features for human activity recognition. IEEE Transactions on Industrial Informatics. 2018; Jan 5;14(10):4334-42.

[14] Dao MS, Nguyen-Gia TA, Mai VC. Daily human activities recognition using heterogeneous sensors from smartphones. Procedia computer science. 2017; Jan 1;111:323-8.

[15] Xu Z, Zhao J, Yu Y, Zeng H. Improved 1D-CNNs for behavior recognition using wearable sensor network. Computer Communications. 2020; Feb 1;151:165-71.

[16] Wang L, Liu R. Human activity recognition based on wearable sensor using hierarchical deep LSTM networks. Circuits, Systems, and Signal Processing. 2020; Feb;39(2):837-56.

[17] Palumbo F, Gallicchio C, Pucci R, Micheli A. Human activity recognition using multisensor data fusion based on reservoir computing. Journal of Ambient Intelligence and Smart Environments. 2016; Jan 1;8(2):87-107.

[18] Anguita D, Ghio A, Oneto L, Parra X, Reyes-Ortiz JL. A public domain dataset for human activity recognition using smartphones. InEsann 2013; Apr 24 (Vol. 3, p. 3).

[19] Torres RL, Ranasinghe DC, Shi Q, Sample AP. Sensor enabled wearable RFID technology for mitigating the risk of falls near beds. In2013 IEEE international conference on RFID (RFID) 2013; Apr 30 (pp. 191-198). IEEE.
[20] Reiss A, Stricker D. Introducing a new benchmarked dataset for activity monitoring. In2012 16th international symposium on wearable computers 2012; Jun 18 (pp. 108-109). IEEE.
[21] Reiss A, Stricker D. Creating and benchmarking a new dataset for physical activity monitoring. InProceedings of the 5th International Conference on PErvasive Technologies Related to Assistive Environments 2012; Jun 6 (pp. 1-8).
[22] Kwapisz JR, Weiss GM, Moore SA. Activity recognition using cell phone accelerometers. ACM SigKDD Explorations Newsletter. 2011; Mar 31;12(2):74-82.
[23] Freund Y, Schapire RE. A decision-theoretic generalization of on-line learning and an application to boosting. Journal of computer and system sciences. 1997; Aug 1;55(1):119-39.
[24] Freund Y, Schapire RE. A short introduction to boosting: Journal of Japanese Society for Artificial Intelligence, v. 14. 1999; 771-780.
[25] Van Der Malsburg C. Frank rosenblatt: Principles of neurodynamics: Perceptrons and the theory of brain mechanisms. InBrain theory 1986; (pp. 245-248). Springer, Berlin, Heidelberg.
[26] McClelland JL, Rumelhart DE, PDP Research Group. Parallel distributed processing. Cambridge, MA: MIT press; 1986.
[27] Rinderle S, Reichert M, Dadam P. Correctness criteria for dynamic changes in workflow systems—a survey. Data & knowledge engineering. 2004; Jul 1;50(1):9-34.
[28] Liu B, Abbas HA, McKay B. Classification rule discovery with ant colony optimization. InIEEE/WIC International Conference on Intelligent Agent Technology, 2003; IAT 2003. 2003 Oct 13 (pp. 83-88). IEEE.
[29] Gabriel TR, Berthold MR. Influence of fuzzy norms and other heuristics on “mixed fuzzy rule formation”. International Journal of Approximate Reasoning. 2004; Feb 1;35(2):195-202.
[30] Berthold MR. Mixed fuzzy rule formation. International journal of approximate reasoning. 2003; Feb 1;32(2-3):67-84.
[31] Fix E, Hodges JL. Discriminatory analysis. Nonparametric discrimination: Consistency properties. International Statistical Review/Revue Internationale de Statistique. 1989; Dec 1;57(3):238-47.
[32] Cover T, Hart P. Nearest neighbor pattern classification. IEEE transactions on information theory. 1967; Jan;13(1):21-7.
[33] Landwehr N, Hall M, Frank E. Logistic model trees. Machine learning. 2005; May 1;59(1-2):161-205.
[34] Cristianini N, Shawe-Taylor J. An introduction to support vector machines and other kernel-based learning methods. Cambridge university press; 2000; Mar 23.
[35] El-Naqa I, Yang Y, Wernick MN, Galatsanos NP, Nishikawa R. Support vector machine learning for detection of microcalcifications in mammograms. InProceedings IEEE International Symposium on Biomedical Imaging 2002; Jul 7 (pp. 201-204). IEEE.
[36] Han JW, Lane PC, Davey N, Sun Y. Comparing the performance of single-layer and two-layer support vector machines on face detection. Proceedings of UKCI, London. 2007.
[37] Hearst MA, Dumais ST, Osuna E, Platt J, Scholkopf B. Support vector machines. IEEE Intelligent Systems and their applications. 1998; Jul;13(4):18-28.
[38] Herold J, Friedenberger M, Bode M, Rajpoot N, Schubert W, Nattkemper TW. Flexible synapse detection in fluorescence micrographs by modeling human expert grading. In2008 5th IEEE International Symposium on Biomedical Imaging: From Nano to Macro 2008; May 14 (pp. 1347-1350). IEEE.
[39] Mjolsness E, DeCoste D. Machine learning for science: state of the art and future prospects. science. 2001; Sep 14;293(5537):2051-5.
[40] Nattkemper TW, Twellmann T, Ritter H, Schubert W. Human vs. machine: evaluation of fluorescence micrographs. Computers in biology and medicine. 2003; Jan 1;33(1):31-43.
[41] Wei N, You J, Friehs K, Flaschel E, Nattkemper TW. An in situ probe for on-line monitoring of cell density and viability on the basis of dark field microscopy in conjunction with image processing and supervised machine learning. Biotechnology and bioengineering. 2007; Aug 15;97(6):1489-500.
[42] LeCun Y, Bengio Y, Hinton G. Deep learning. nature. 2015; May;521(7553):436-44.
[43] Hubel DH, Wiesel TN. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. The Journal of physiology. 1962; Jan 1;160(1):106-54.
[44] Fukushima K, Miyake S. Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition. InCompetition and cooperation in neural nets 1982; (pp. 267-285). Springer, Berlin, Heidelberg.
[45] LeCun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proceedings of the IEEE. 1998; Nov;86(11):2278-324.
[46] LeCun Y, Boser B, Denker JS, Henderson D, Howard RE, Hubbard W, Jackel LD. Backpropagation applied to handwritten zip code recognition. Neural computation. 1989; Dec;1(4):541-51.
[47] Hammerla NY, Halloran S, Plötz T. Deep, convolutional, and recurrent models for human activity recognition using wearables. arXiv preprint arXiv:1604.08880. 2016; Apr 29.
[48] Inoue M, Inoue S, Nishida T. Deep recurrent neural network for mobile human activity recognition with high throughput. Artificial Life and Robotics. 2018; Jun;23(2):173-85.
[49] Edel M, Köppe E. Binarized-blstm-rnn based human activity recognition. In2016 International conference on indoor positioning and indoor navigation (IPIN) 2016; Oct 4 (pp. 1-7). IEEE.
[50] Zhu, Jianping, Haiquan Chen, and Wenbin Ye. "A hybrid CNN–LSTM network for the classification of human activities based on micro-Doppler radar." IEEE Access 8 (2020): 24713-24720.
[51] Rakesh, Y. Joy, R. Kavitha, and J. Julian. "Human Activity Recognition Using Wearable Sensors." In Intelligent Data Engineering and Analytics, pp. 527-538. Springer, Singapore, 2021.