Comparing the Performance of Different Classifiers for Posture Detection

Sagar Suresh Kumar[1], Kia Dashtipour[1,2(✉)], Mandar Gogate[2], Jawad Ahmad[2], Khaled Assaleh[3], Kamran Arshad[3], Muhammad Ali Imran[1,4], Qammer Abbasi[1], and Wasim Ahmad[1]

[1] James Watt School of Engineering, University of Glasgow, Glasgow, UK
[2] School of Computing, Edinburgh Napier University, Edinburgh, UK
k.dashtipour@napier.ac.uk
[3] Faculty of Engineering and IT, Ajman University, Ajman 346, UAE
[4] Artificial Intelligence Research Center (AIRC), Ajman University, Ajman, UAE

Abstract. Human Posture Classification (HPC) is used in many fields such as human computer interfacing, security surveillance, rehabilitation, remote monitoring, and so on. This paper compares the performance of different classifiers in the detection of 3 postures, sitting, standing, and lying down, which was recorded using Microsoft Kinect cameras. The Machine Learning classifiers used included the Support Vector Classifier, Naive Bayes, Logistic Regression, K-Nearest Neighbours, and Random Forests. The Deep Learning ones included the standard Multi-Layer Perceptron, Convolutional Neural Networks (CNN), and Long Short Term Memory Networks (LSTM). It was observed that Deep Learning methods outperformed the former and that the one-dimensional CNN performed the best with an accuracy of 93.45%.

Keywords: Machine learning · Deep learning · Detecting Alzheimer

1 Introduction

Human Posture Classification (HPC) has applications in a wide range of fields such as human computer interfacing, security surveillance, rehabilitation, remote monitoring, and so on [20]. There are broadly two kinds of sensor schemes that can be used for HPC: wearable and contactless. Wearable methods use sensors such as accelerometers, gyroscopes, magnetometers or even sensors that use physiological data such as Electromyogram (EMG), on different locations of the body while contactless ones rely on image or video processing, and also sensors in the proximity of the patient. Generally, wearable methods are obtrusive and cause discomfort. This is especially true for the elderly and the physically compromised. Hence, the research area of contactless HPC has gained popularity in the past few years [4,7,11,19,26,40,41,45].

HPC has been used to identify and correct several medical ailments in the past. Matar et al. used contactless bed-sheet pressure sensors to detect bed-posture and prevent pressure ulcers [38]. Lee et al. used inertial sensors to

M. Ur Rehman and A. Zoha (Eds.): BODYNETS 2021, LNICST 420, pp. 210–218, 2022.
https://doi.org/10.1007/978-3-030-95593-9_17

monitor squat exercises to prevent knee and leg injuries [33]. In camera based methods, Microsoft Kinect devices, which provides depth images using a combination of RGB and IR cameras and outputs the 3D coordinates of 32 joints, are quite popular. These solutions have benefited from the developments Machine and Deep Learning [3]. However, most of the past papers just use one or two classifiers without addressing in detail the classification schemes that produce optimal results. Hence, this work extensively compares the performance of different machine and deep learning classifiers and attempts to ascertain the optimum classifier(s) for posture data.

The rest of the paper is structured as follows. Section 2 provides the background information related to posture detection. Section 3 presents the proposed methodology. Section 4 provides the experimental results of the proposed posture detection and discussion, and finally Sect. 5 concludes the paper.

2 Related Work

Sidrah et al. [34] developed a novel approach based on hybrid approach used machine learning and deep learning approaches to detect human posture detection. However, the proposed approach can detect falling and standing and it cannot detect multiple posture detection. Panini et al. [42] presented an approach based on posture human detection in domotic application. The machine learning is used to generate the probability maps. The statistic classifier used to compare the probability maps and histogram profiles extracted from moving of people. The experimental results show that the results are robust and computational time are lowers as compared to state-of-the-art approaches such as [2, 8–10, 12–18, 27, 29, 30].

Ma et al. [37] proposed a cushion-based posture detection system used to process sensor for human detection in the wheelchair. The method is consists of three different steps such as classification for posture, backward selection of sensor configuration, and comparison with state-of-the-art approaches [1, 5, 6, 21–25, 28, 31, 32, 35, 36, 46, 47].

Nasirahmadi et al. [39] proposed an approach to identify whether a two-dimensional imaging system along with deep learning approaches to detecting standing and lying postures with CNN and ResNet features extraction of RGB images were used. Sacchetti et al. [44] developed an approach to classify human posture detection in classroom ambience. The posture can be divided into confident and non confident aiming for teacher evaluation, interested/non interested. The approach presents some concepts about postures and how effectively detect openpose library and finally neural network is used measure the effectiveness of the approach.

3 Methodology

In this section, we discussed the proposed methodology for human posture detection. The Fig. 1 displays the overview framework of the approach.

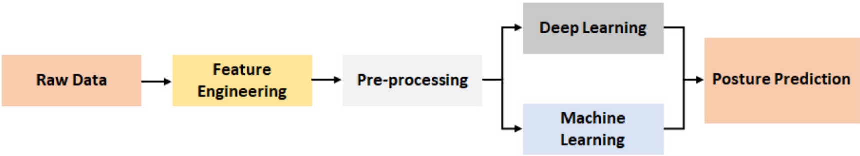

Fig. 1. Overview proposed approach

3.1 Classifiers

A wide range of machine and deep learning classifiers were used and are illustrated in Table 1 and Table 2. The Waikato Environment for Knowledge Analysis (WEKA) platform was used in this study to implement these algorithms. Among machine learning algorithms, the Naive Bayes Classifier's prior probabilities were set to 0, the Logistic Regression model used L2 loss, the K-nearest neighbours algorithm used 30 neighbours, and the the Random Forests classifier used 100 decision trees.

Convolutional Neural Network: For comparison, the novel CNN framework is developed. The implemented CNN consists of input, hidden and output layers. Our proposed CNN framework contains convolutional, max pooling and fully connected layers. The 10-layered CNN framework achieved the most promising results. The Fig. 2 shows the architecture for CNN.

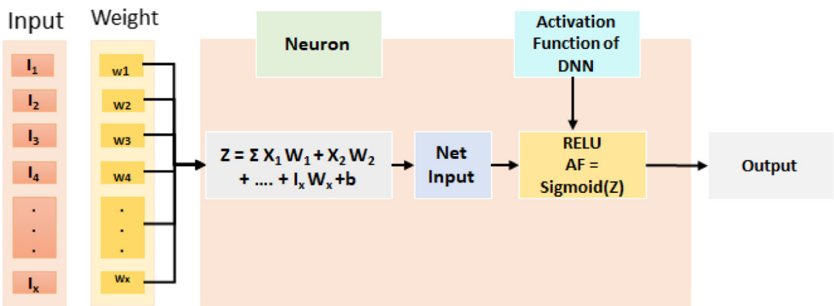

Fig. 2. Overview architecture of CNN

Long Short Term Memory (LSTM): The long short term memory (LSTM) proposed architecture contains input layer, two different stacked LSTM and one output as fully connected layer. Particularly, the LSTM architecture consists of two different stacked bidirectional layers (contains 128 cells and 64 cells) with dropout 0.2 and a dense layer with two neurons and softmax activation.

Among deep learning algorithms, both 1D and 2D Convolutional Neural Networks were used and their structures consisting of max pooling, convolution, and fully connected layers (total 10) are illustrated. Both unidirectional and bidirectional Long Short Term Memory (LSTM) Networks were used consisting of 2 stacked layers of 128 and 64 cells and a dense layer of softmax activation function. The Multilayer Perceptron (MLP) consisted of 2 hidden layers and used the ReLu activation function. K fold cross validation was used and K values of 10, 5, and 2 were tested.

4 Results and Discussion

The Deep Learning based classifiers have outperformed the Machine Learning Classifiers in general, as shown in Table 1 and 2. As expected, as the number of K-folds decreased, the accuracies decreased as well. Among Machine Learning methods, the Support Vector Machine with Radial Basis Function (RBF) Kernel performed the best with an overall accuracy of 83.42% while the Naive Bayes performed the worst with an accuracy of 74.56%. In Deep Learning methods, CNNs and LSTMs were superior to the traditional MLP networks. Although the latter 2 had similar accuracies, the 1D-CNN performed the best with an accuracy of 93.45%. Thus, future work should focus on optimizing the structure and performance of this network in posture detection.

Dataset: The data from [43] was used in this study, in which Microsoft Kinect V2 cameras were used to extract posture information of six users and three activities: sitting, standing, and lying down. Although the cameras obtain 75 points, which represent the x,y, and z coordinates of 25 body joints, 7 location independent features are extracted from them to reduce the computational load. These include the height,left hip angle, right hip angle, left knee angle, right knee angle, chest angle, and chest-knee angle. They were calculated from the body joints depth coordinates using cosine formula.

Table 1 shows the summary of results of machine learning and their performance using 10-fold cross validation. As shown in Table 1 the SVM outperforms other machine learning classifiers.

Table 1. Machine Learning classifiers and their performance with 10 fold cross validation

Classifier	Accuracy	Recall	Precision	F1 score
SVM (RBF)	83.42%	0.83	0.82	0.81
Naive Bayes	74.56%	0.74	0.73	0.74
Logistic Regression	80.91%	0.80	0.79	0.80
KNN	76.98%	0.76	0.75	076
Random Forests	77.08%	0.77	0.76	0.77

Table 2 shows the summary of results of deep learning and their performance using 10-fold cross validation. As shown in Table 2 the 1D-CNN outperforms other deep learning classifiers such as 2D-CNN, LSTM, BiLSTM.

Table 2. Deep Learning classifiers and their performance with 10-fold cross validation

Classifier	Accuracy	Recall	Precision	F1 score
MLP	82.56%	0.82	0.82	0.82
1D-CNN	93.45%	0.93	0.92	0.93
2D-CNN	91.59%	0.91	0.90	0.91
LSTM	88.19%	0.88	0.87	0.88
BiLSTM	90.87%	0.90	0.90	0.90

Table 3 shows the summary of results of machine learning and their performance using 5-fold cross validation. As shown in Table 3 the MLP outperforms other machine learning classifiers.

Table 3. Machine Learning classifiers and their performance with 5-fold cross validation

Classifier	Accuracy	Precision	Recall	F-measure
MLP	81.56	0.81	0.8	0.81
SVM	81.02	0.81	0.8	0.81
Naive Bayes	71.36	0.71	0.7	0.71
Logistic Regression	71.26	0.71	0.7	0.71
KNN	74.87	0.75	0.74	75
Random Forest	76.34	0.76	0.76	0.76

Table 4 shows the summary of results of deep learning and their performance using 5-fold cross validation. As shown in Table 4 the 1D-CNN outperforms other deep learning classifiers.

Table 4. Deep Learning classifiers and their performance with 5-fold cross validation

Classifier	Accuracy	Precision	Recall	F-measure
1D-CNN	91.51	0.91	0.91	0.91
2D-CNN	90.96	0.91	0.9	0.91
LSTM	89.56	0.89	0.88	0.89
BiLSTM	88.98	0.89	0.88	0.89

Table 5 shows the summary of results of machine learning and their performance using 2-fold cross validation. As shown in Table 5 the SVM outperforms other machine learning classifiers.

Table 5. Machine Learning classifiers and their performance with 2-fold cross validation

Classifier	Accuracy	Precision	Recall	F-measure
MLP	80.42	0.8	0.79	0.8
SVM	81.01	0.81	0.81	0.81
Nave Bayes	70.94	0.7	0.7	0.7
Logistic Regression	70.59	0.7	0.7	0.7
KNN	74.29	0.74	0.74	74
Random Forest	75.63	0.75	0.74	0.75

Table 6 shows the summary of results of deep learning and their performance using 2-fold cross validation. As shown in Table 6 the 1D-CNN outperforms other deep learning classifiers.

Table 6. Deep Learning classifiers and their performance with 2-fold cross validation

Classifier	Accuracy	Precision	Recall	F-measure
1D-CNN	90.23	0.9	0.89	0.9
2D-CNN	89.67	0.89	0.88	0.89
LSTM	88.19	0.88	0.87	0.88
BiLSTM	87.76	0.87	0.86	0.87

5 Conclusion

The human posture detection is important in remote monitoring of patient. However, most of the current approaches cannot perfectly detect different human postures such as sitting, standing and lying down. Therefore, in this study, we proposed an approach based on the machine learning and deep learning approaches to detect different posture detection.

Acknowledgement. This work is supported in part by the Ajman University Internal Research Grant.

References

1. Adeel, A., Gogate, M., Hussain, A.: Contextual deep learning-based audio-visual switching for speech enhancement in real-world environments. Inf. Fusion **59**, 163–170 (2020)
2. Ahmed, R., et al.: Deep neural network-based contextual recognition of Arabic handwritten scripts. Entropy **23**(3), 340 (2021)

3. Alaoui, H., Moutacalli, M.T., Adda, M.: AI-enabled high-level layer for posture recognition using the azure Kinect in Unity3D. In 2020 IEEE 4th International Conference on Image Processing, Applications and Systems (IPAS), pp. 155–161 (2020)
4. Alqarafi, A.S., Adeel, A., Gogate, M., Dashitpour, K., Hussain, A., Durrani, T.: Toward's Arabic multi-modal sentiment analysis. In: Liang, Q., Mu, J., Jia, M., Wang, W., Feng, X., Zhang, B. (eds.) CSPS 2017. LNEE, vol. 463, pp. 2378–2386. Springer, Singapore (2019). https://doi.org/10.1007/978-981-10-6571-2_290
5. Asad, S.M., et al.: Mobility management-based autonomous energy-aware framework using machine learning approach in dense mobile networks. Signals **1**(2), 170–187 (2020)
6. Asad, S.M., Dashtipour, K., Hussain, S., Abbasi, Q.H., Imran, M.A.: Travelers-tracing and mobility profiling using machine learning in railway systems. In: 2020 International Conference on UK-China Emerging Technologies (UCET), pp. 1–4. IEEE (2020)
7. Churcher, A., et al.: An experimental analysis of attack classification using machine learning in IoT networks. Sensors **21**(2), 446 (2021)
8. Dashtipour, K., Gogate, M., Adeel, A., Algarafi, A., Howard, N., Hussain, A.: Persian named entity recognition. In: 2017 IEEE 16th International Conference on Cognitive Informatics and Cognitive Computing (ICCI* CC), pp. 79–83. IEEE (2017)
9. Dashtipour, K., Gogate, M., Adeel, A., Hussain, A., Alqarafi, A., Durrani, T.: A comparative study of Persian sentiment analysis based on different feature combinations. In: Liang, Q., Mu, J., Jia, M., Wang, W., Feng, X., Zhang, B. (eds.) CSPS 2017. LNEE, vol. 463, pp. 2288–2294. Springer, Singapore (2019). https://doi.org/10.1007/978-981-10-6571-2_279
10. Dashtipour, K., Gogate, M., Adeel, A., Ieracitano, C., Larijani, H., Hussain, A.: Exploiting deep learning for Persian sentiment analysis. In: Ren, J., et al. (eds.) BICS 2018. LNCS (LNAI), vol. 10989, pp. 597–604. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-00563-4_58
11. Dashtipour, K., Gogate, M., Adeel, A., Larijani, H., Hussain, A.: Sentiment analysis of Persian movie reviews using deep learning. Entropy **23**(5), 596 (2021)
12. Dashtipour, K., Gogate, M., Cambria, E., Hussain, A.: A novel context-aware multimodal framework for persian sentiment analysis. arXiv preprint arXiv:2103.02636 (2021)
13. Dashtipour, K., Gogate, M., Li, J., Jiang, F., Kong, B., Hussain, A.: A hybrid Persian sentiment analysis framework: integrating dependency grammar based rules and deep neural networks. Neurocomputing **380**, 1–10 (2020)
14. Dashtipour, K., Hussain, A., Gelbukh, A.: Adaptation of sentiment analysis techniques to Persian language. In: Gelbukh, A. (ed.) CICLing 2017, Part II. LNCS, vol. 10762, pp. 129–140. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-77116-8_10
15. Dashtipour, K., Hussain, A., Zhou, Q., Gelbukh, A., Hawalah, A.Y.A., Cambria, E.: PerSent: a freely available Persian sentiment Lexicon. In: Liu, C.-L., Hussain, A., Luo, B., Tan, K.C., Zeng, Y., Zhang, Z. (eds.) BICS 2016. LNCS (LNAI), vol. 10023, pp. 310–320. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-49685-6_28
16. Dashtipour, K., et al.: Multilingual sentiment analysis: state of the art and independent comparison of techniques. Cogn. Comput. **8**(4), 757–771 (2016)

17. Dashtipour, K., Raza, A., Gelbukh, A., Zhang, R., Cambria, E., Hussain, A.: PerSent 2.0: Persian sentiment lexicon enriched with domain-specific words. In: Ren, J., et al. (eds.) BICS 2019. LNCS (LNAI), vol. 11691, pp. 497–509. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-39431-8_48
18. Dashtipour, K., et al.: Public perception towards fifth generation of cellular networks (5G) on social media. Front. Big Data (2021)
19. Gepperth, A.R.T., Hecht, T., Gogate, M.: A generative learning approach to sensor fusion and change detection. Cogn. Comput. **8**(5), 806–817 (2016). https://doi.org/10.1007/s12559-016-9390-z
20. Ghazal, S., Khan, U.S.: Human posture classification using skeleton information. In: 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), pp. 1–4 (2018)
21. Gogate, M., Adeel, A., Hussain, A.: Deep learning driven multimodal fusion for automated deception detection. In: 2017 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1–6. IEEE (2017)
22. Gogate, M., Adeel, A., Hussain, A.: A novel brain-inspired compression-based optimised multimodal fusion for emotion recognition. In: 2017 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1–7. IEEE (2017)
23. Gogate, M., Adeel, A., Marxer, R., Barker, J., Hussain, A.: DNN driven speaker independent audio-visual mask estimation for speech separation. arXiv preprint arXiv:1808.00060 (2018)
24. Gogate, M., Dashtipour, K., Adeel, A., Hussain, A.: CochleaNet: a robust language-independent audio-visual model for real-time speech enhancement. Inf. Fusion **63**, 273–285 (2020)
25. Gogate, M., Dashtipour, K., Hussain, A.: Visual speech in real noisy environments (vision): A novel benchmark dataset and deep learning-based baseline system. In: 2020 Proceedings of the Interspeech, pp. 4521–4525 (2020)
26. Gogate, M., Hussain, A., Huang, K.: Random features and random neurons for brain-inspired big data analytics. In: 2019 International Conference on Data Mining Workshops (ICDMW), pp. 522–529. IEEE (2019)
27. Guellil, I., et al.: A semi-supervised approach for sentiment analysis of Arab(ic+izi) messages: Application to the Algerian dialect. SN Comput. Sci. **2**(2), 1–18 (2021). https://doi.org/10.1007/s42979-021-00510-1
28. Huma, Z.E., et al.: A hybrid deep random neural network for cyberattack detection in the industrial internet of things. IEEE Access **9**, 55595–55605 (2021)
29. Hussain, A., et al.: Artificial intelligence-enabled analysis of UK and us public attitudes on Facebook and twitter towards COVID-19 vaccinations. medRxiv (2020)
30. Hussien, I.O., Dashtipour, K., Hussain, A.: Comparison of sentiment analysis approaches using modern Arabic and Sudanese dialect. In: Ren, J., et al. (eds.) BICS 2018. LNCS (LNAI), vol. 10989, pp. 615–624. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-00563-4_60
31. Ieracitano, C., et al.: Statistical analysis driven optimized deep learning system for intrusion detection. In: Ren, J., et al. (eds.) BICS 2018. LNCS (LNAI), vol. 10989, pp. 759–769. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-00563-4_74
32. Jiang, F., Kong, B., Li, J., Dashtipour, K., Gogate, M.: Robust visual saliency optimization based on bidirectional markov chains. Cogn. Comput. 1–12 (2020)
33. Lee, J., Joo, H., Lee, J., Chee, Y.: Automatic classification of squat posture using inertial sensors: deep learning approach. Sensors **20**(2), 361 (2020)

34. Liaqat, S., Dashtipour, K., Arshad, K., Assaleh, K., Ramzan, N.: A hybrid posture detection framework: integrating machine learning and deep neural networks. IEEE Sens.J. **21**(7), 9515–9522 (2021)
35. Liaqat, S., Dashtipour, K., Arshad, K., Ramzan, N.: Non invasive skin hydration level detection using machine learning. Electronics **9**(7), 1086 (2020)
36. Liaqat, S., Dashtipour, K., Zahid, A., Assaleh, K., Arshad, K., Ramzan, N.: Detection of atrial fibrillation using a machine learning approach. Information **11**(12), 549 (2020)
37. Ma, C., Li, W., Gravina, R., Fortino, G.: Posture detection based on smart cushion for wheelchair users. Sensors **17**(4), 719 (2017)
38. Matar, G., Lina, J.M., Kaddoum, G.: Artificial neural network for in-bed posture classification using bed-sheet pressure sensors. IEEE J. Biomed. Health Inf. **24**(1), 101–110 (2020)
39. Nasirahmadi, A., et al.: Deep learning and machine vision approaches for posture detection of individual pigs. Sensors **19**(17), 3738 (2019)
40. Nisar, S., Tariq, M., Adeel, A., Gogate, M., Hussain, A.: Cognitively inspired feature extraction and speech recognition for automated hearing loss testing. Cogn. Comput. **11**(4), 489–502 (2019). https://doi.org/10.1007/s12559-018-9607-4
41. Ozturk, M., Gogate, M., Onireti, O., Adeel, A., Hussain, A., Imran, M.A.: A novel deep learning driven, low-cost mobility prediction approach for 5G cellular networks: the case of the control/data separation architecture (CDSA). Neurocomputing **358**, 479–489 (2019)
42. Panini, L., Cucchiara, R.: A machine learning approach for human posture detection in domotics applications. In: 12th International Conference on Image Analysis and Processing, 2003. Proceedings, pp. 103–108. IEEE (2003)
43. Qassoud., Bolic., Rajan.: Posture-and-fall-detection-system-using-3d-motion-sensors (2018)
44. Sacchetti, R., Teixeira, T., Barbosa, B., Neves, A.J., Soares, S.C., Dimas, I.D.: Human body posture detection in context: the case of teaching and learning environments. SIGNAL 2018 Editors **87**, 79–84 (2018)
45. Shiva, A.S., Gogate, M., Howard, N., Graham, B., Hussain, A.: Complex-valued computational model of hippocampal CA3 recurrent collaterals. In: 2017 IEEE 16th International Conference on Cognitive Informatics and Cognitive Computing (ICCI* CC), pp. 161–166. IEEE (2017)
46. Taylor, W., Shah, S.A., Dashtipour, K., Zahid, A., Abbasi, Q.H., Imran, M.A.: An intelligent non-invasive real-time human activity recognition system for next-generation healthcare. Sensors **20**(9), 2653 (2020)
47. Yu, Z., et al.: Energy and performance trade-off optimization in heterogeneous computing via reinforcement learning. Electronics **9**(11), 1812 (2020)