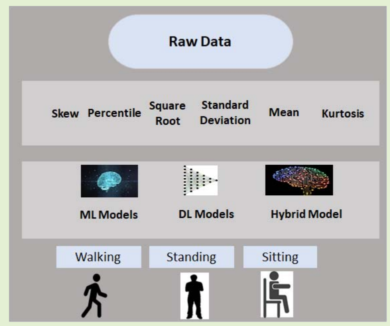
A Hybrid Posture Detection Framework: Integrating Machine Learning and Deep Neural Networks

Sidrah Liaqat, Kia Dashtipour, Kamran Arshad, *Senior Member, IEEE*, Khaled Assaleh, *Senior Member, IEEE*, and Naeem Ramzan, *Senior Member, IEEE*

***Abstract*—The posture detection received lots of attention in the fields of human sensing and artificial intelligence. Posture detection can be used for the monitoring health status of elderly remotely by identifying their postures such as standing, sitting and walking. Most of the current studies used traditional machine learning classifiers to identify the posture. However, these methods do not perform well to detect the postures accurately. Therefore, in this study, we proposed a novel hybrid approach based on machine learning classifiers (i. e., support vector machine (SVM), logistic regression (KNN), decision tree, Naive Bayes, random forest, Linear discrete analysis and Quadratic discrete analysis) and deep learning classifiers (i. e., 1D-convolutional neural network (1D-CNN), 2D-convolutional neural network (2D-CNN), LSTM and bidirectional LSTM) to identify posture detection. The proposed hybrid approach uses prediction of machine learning (ML) and deep learning (DL) to improve the performance of ML and DL algorithms. The experimental results on widely benchmark dataset are shown and results achieved an accuracy of more than 98%.**



***Index Terms*— Posture detection, hybrid approach, deep learning, machine learning.**

I. Introduction

THE posture detection is used in different applications such as healthcare, surveillance, virtual environment, indoor and outdoor monitoring, the reality for animation and entertainment. In addition, the posture detection can be used in framework of home-human interface. With the increased number of elderly population and limited healthcare resources, it is important to propose a technology which can support the remote monitoring of elderly and vulnerable people to live more independently. Maintain the good posture is significant to lead the healthy life. The posture is about how the people hold their body and position the limbs. Within the advancement of the technology, the human has chosen the sedentary lifestyle which leading to less physical activity and movement [1]–[5]. The long time sitting during the work or study leads to decrease in muscle strength. The sedentary lifestyle have negative impact on body human, not caring about correct posture or fault posture can lead pain in neck, back and shoulder. Therefore, it is important to control the human posture to maintain their health and safety during work or study. Considering the need, the paper reports three major contributions that are outlined below:

- In this paper, we implemented a novel CNN and LSTM architecture for automatically identify the posture detection. It is worth to mention, the deep learning classifiers unlike machine learning algorithms do not require hand-crafted features.
- In addition, a novel hybrid approach based on DL (1D-CNN, 2D-CNN, LSTM, BiLSMT) and ML (random forest, KNN, Naive Bayes, decision tree, LDA, QDA and SVM) methods developed to identify the posture.
- There is an extensive comparative experimental results that are conducted with state-of-the-art approaches to evaluate the performance of our proposed approach.

This paper discuss the machine learning (ML) and deep learning (DL) methods for posture detection which is used to

Manuscript received January 8, 2021; revised January 25, 2021; accepted January 26, 2021. Date of publication February 1, 2021; date of current version March 5, 2021. This work was supported in part by the Ajman University Internal Research Grant. The associate editor coordinating the review of this article and approving it for publication was Dr. Qammer H. Abbasi. *(Corresponding author: Sidrah Liaqat.)*

Sidrah Liaqat and Naeem Ramzan are with the School of Engineering and Computing, University of the West of Scotland, Paisley PA1 2BE, U.K. (e-mail: sidra193@gmail.com; naeem.ramzan@uws.ac.uk).

Kia Dashtipour is with the James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, U.K. (e-mail: kia.dashtipour@glasgow.ac.uk).

Kamran Arshad and Khaled Assaleh are with the College of Engineering and IT, Ajman University, Ajman, UAE (e-mail: k.arshad@ajman.ac.ae; k.assaleh@ajman.ac.ae).

Digital Object Identifier 10.1109/JSEN.2021.3055898

monitor human activity. In this study, we focus on the selection of ML, DL and hybrid methods to increase the performance of posture recognition. The activity which is recognised are sitting and standing. The sitting and standing is important posture to detect because human can monitor their own activity if they are sitting for long time, they can stand for some activity.

The paper is organised into the following sections. Section II provides detailed related work within the field of radar based motion detection. Section III presents the methodology of how the experimentation of this research has been done. Section IV discusses the results obtained through the experimentation. Section V gives the conclusion.

II. Related Work

In the literature, extensive research has been carried out to build different posture models. In this section, we summarize the related state-of-the-art approaches for detection of human postures.

In smart city prediction and supervision of human health, using smart technology and portable system is an important part. Therefore, posture recognition in this paper is determined with multisensory and using LoRa (Long Range) technology. LoRa WAN technology has the advantage of long transmission distances and low cost. Using these two, multisensory and loRa technology, wearable clothes are designed which is comfortable in any given posture. In this paper multiprocessing is used because LoRa has low transmitting frequency and data transmission size is small. Hence, multiprocessing is done by sliding window, feature extraction, data processing and feature selection is done with Random forest. With three testers of 500 grouped data set better performance and accuracy is achieved [6]. Body postures and gestures are also non-verbal way of communication. In this paper, Augmented reality is used to determine the static posture by reducing cost and advanced body tracking technology. Also unsupervised machine learning on Kinect body posture sensors are used to detect group cooperation and learning [7]. Posture detection has also play an important role in performing yoga more accurately. Posture recognition is challenging task due to real-time bases and less available data set. Therefore, to overcome this issue large data set has been created with at least 5500 images of different yoga poses. For posture detection tf-pose estimation algorithm has been used which draws skeleton of human body on the real-time bases. Angles of the joints in the human body are extracted using the tf-pose skeleton which is used as a feature to implement various machine learning models (SVM, KNN, Logistic Regression, DT, NB and random forest). Among all Random forest model gives best accuracy [8]–[10].

In addition, there is another problem of posture in human being which occurs due to maximum time in sitting position. The poor and prolonged sitting effects physical and mental health. Posture training system is designed for sitting position and stretch pose data collection. Then for posture recognition, smart cushion using Artificial Intelligence (AI) and pressure sensing technologies is used. For more than 13 different postures, supervised machine learning models are trained which give better performances [11]. The sensor chair with pressure sensor tries to avoid wrong sitting position which may cause disease. In this posture detection, analysis is compared with decision tree and random forest. The classifier which gives better performance is random forest classifier [12]. For the improvement of sitting posture, sitting posture monitoring systems (SPMSs) is used. It has mounted sensors on backrest and seat plate of a chair. For this experiment 6 sitting postures are considered. Then various machine learning algorithms (SVM with RBF kernel, SVM linear, random forest, QDA, LDA, NB and DT) are applied on body weight ratio which is measured by SPMS. Result from SVM with RBF kernel gives better accuracy as compare to others [13]. There is also an intelligent systems design for the posture detection of sitting person on wheel chair. A network of sensors is used for data collection using neighbourhood rule (CNN), then data balancing is done with Kennard-stone algorithm and reduction in dimensions via principal component analysis. Finally k-nearest algorithm is applied to pre-processed and balanced data. In this amount of data is significantly reduced but result is remarkable [14].

A postural habit which has been formed cannot change easily so it is vital to form a proper postural habit since childhood. Therefore, machine learning algorithms CNN, NB, DT, NN, MLR and SVM are used for posture detection. Data is collected with a sensing cushion which is developed with (8×8) pressure sensor mat inside children chair seat cushion. Ten children are participated for five prescribed postures. The accuracy of CNN is the highest than other algorithms [15]. Dance is also a challenging task for posture recognition. It is multimedia in nature and its duration is over time as well as space. For dance analysis few things must be undertaken like segment of the dance video, recognition of the detected action element and recognition of the dance sequences. In this paper focus is on Indian classical dance, Bharatanatyam, which is driven by music as well as motion for posture recognition. Then recognition is done by machine and deep learning techniques which are GMM, SVM and CNN. In the final step Hidden Markov Model (HMM) is applied for data sequence recognition. The best recognition rate is with CNN classifier [16].

III. Methodology

This section describes our proposed approach for the detection of posture. The Fig shows the overall framework of posture detection.

A. Feature Extraction

There are total of six features are used for posture prediction. The features determine the posture are skew, percentile, square root (SR), standard deviation (SD), mean and kurtosis. The values for each feature is calculated individually for each window size. For example, the window size of 90 seconds is selected and the aforementioned features are calculated. After the feature extraction, the new dataset is created which consists of different features. It is to be noted that, after feature extraction, the most important task is to determines the combination

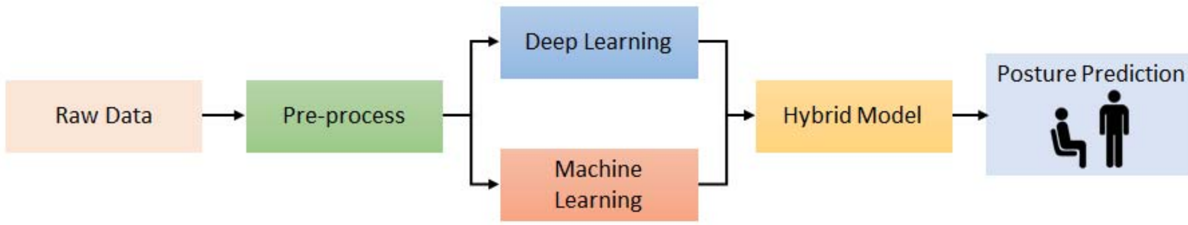


Fig. 1. Overview of the proposed framework for posture detection.

TABLE I
MACHINE LEARNING METHODS WITH THEIR PARAMETERS

Algorithm	Parameters	Training time
KNN	Eculidean distance	2 m 30 s
SVM	RBF Kernal	3 m 41 s
Random Forest	Max depth = 2	3 m 27 s
K-nearest neighbors	3	3 m 2 s
Logistic regression	Penalty = l2	3 m 41 s
QDA	tol = 0.0001	2 m 31 s
Naive Bayes	sample weight = none	2 m 48 s
LDA	number of components = 5	3 m 28 s
LSTM	10-layered	10 m 23 s
BiLSTM	Adam optimizer	7 m 13 s
1D-CNN	dropout = 0.2	9 m 16 s
2D-CNN	dropout = 0.2	8 m 2 s

of best features for posture prediction in term of accuracy. In total six features and combination of these features are evaluated using different ML models. In total combination of features for posture prediction is time consuming therefore, we employed DL methods which dp not require any feature engineering and they usually obtain superior performance as compared to ML models.

B. Machine Learning (ML) Methods

After feature extraction, there are different machine learning classifiers, including SVM, logistic regression, KNN, decision tree, naive bayes, random forest, LDA and QDA have been applied in order to evaluate the performance of the approach. Table I shows the parameters that are used to trained the machine learning methods. The scikit-learn package is used to train the machine learning classifiers. In addition, the training time for each models has been presented in Table I.

C. Deep Learning (DL) Methods

In next section, we discuss our proposed hybrid model which integrates the machine learning and DNN methods including 1D-CNN, 2D-CNN, LSTM and BiLSTM. The deep learning can be used in different various application such as cyber-security, sentiment analysis, speech enhancement and etc. However, in this paper we proposed a novel framework to detect posture prediction.

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 parameters of CNN framework are shown in Table II

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.

D. Hybrid Models

The hybrid methods consists of different classifiers and combining their prediction to train meta-learning model. The hybrid is used to enhance the performance of specific system. In this study, the prediction of ML classifiers (logistic regression, random forest, KNN, Naïve Bayes, decision tree, linear discriminant analysis, quadratic discriminant analysis and SVM) and DL classifiers (CNN, LSTM) are used as input of CNN, LSTM architecture. Fig 2 shows the architecture of proposed hybrid of ML and DL for posture detection. It is to be noted that, the parameters of each classifier has been set-up empirically after several simulation experiments.

IV. EXPERIMENTAL RESULTS

In order to classify the posture prediction, standard (logistic regression, random forest, KNN, Naïve Bayes, decision tree, linear discriminant analysis, quadratic discriminant analysis and SVM) and deep learning classifiers such as (1D-CNN, 2D-CNN, LSTM, BiLSTM) are trained. We extracted different features including skew, percentile, SR, SD, mean and kurtosis. It is worth to mention that, there are total thirteen experiments have been done. In addition, the 10-fold cross-validation is used to perform the experiments. In order to evaluate the performance of the proposed approach, precision, recall, F-score and accuracy metrics were used:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F\_measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Human Body Posture Detection: In order to evaluate the performance of the approach. The online widely benchmark

TABLE II

CNN ARCHITECTURE (CONV - CONVOLUTIONAL LAYER, MAXPOOL - MAXPOOLING LAYER, GLOBALMAXPOOL - GLOBAL MAX POOLING LAYER, FC - FULLY CONNECTED LAYER, RELU - RECTIFIED LINEAR UNIT ACTIVATION

Layer	1	2	3	4	5	6	7	8	9	10
Type	Conv	Max Pool	Conv	Max Pool	Conv	Max	Conv	Global Max Pool	Fc	Fc
Filters	16		32		64		128			
Kernal Size	3	2	3	2	3	2	3			
Neurons									128	2
Activation	ReLU		ReLU		ReLU		ReLU		ReLU	SoftMax

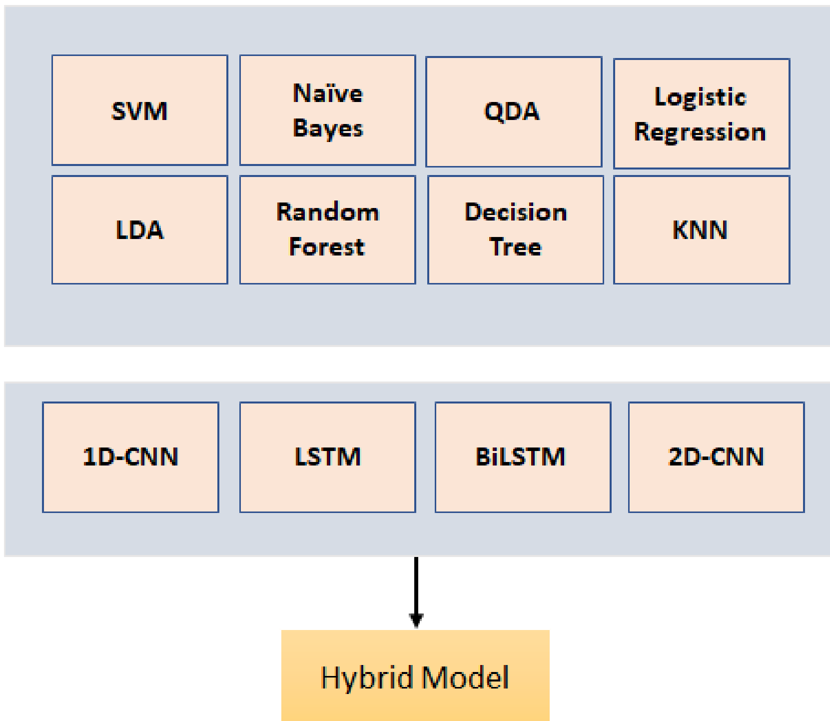


Fig. 2. Proposed Hybrid Classifier.

dataset called human body using galvanic skin response have been used. The data is collected for five different subjects, and it has been classified into three different categories such as standing, sitting and walking. In addition, the data is recorded at a resolution of 16 bits in samples of 5 min to 15 min and the sampling rate is 1 MHz (maximum precision position on the BITalino Kit) [17]. There are different machine learning methods to train the classifiers for classifying the posture such as standing, sitting and walking. In order to evaluate the performance of the approach, the data used in our study is collected from five different individuals, the dataset consists of four males and females for different ethnicity, all the bracket of 25 to 30 years of age.

The machine learning algorithms are trained based on the 10-fold cross-validation and train/test used Python variables containing the data and comparing the prediction of the data to the actual labels of the data. There are different evaluation metrics such as accuracy, precision, recall and f-measure are used to compare the current algorithms. It is worth to mention that, the scikit-learn with Tensorflow background is used to implement the deep learning approaches.

TABLE III

SUMMARY OF LOGISTIC REGRESSION FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	87.37	0.87	0.87	0.87
Mean, SD	87.31	0.87	0.87	0.87
Mean, SD, SR	89.44	0.90	0.89	0.89
Mean, SD, SR, percentile	94.75	091	0.89	0.95
Mean, SD, SR, percentile, kurtosis	94.75	0.91	0.89	0.95
Mean, SD, SR, percentile, kurtosis, skew	95.98	0.93	0.92	0.96

Table III shows the summary of results for selected features using logistic regression. The experimental results show the combination of all features achieved better performance and mean feature achieved less accuracy.

TABLE IV
SUMMARY OF RANDOM FOREST FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	87.88	0.85	0.92	0.88
Mean, SD	86.15	0.84	0.89	0.87
Mean, SD, SR	90.23	0.91	0.89	0.90
Mean, SD, SR, percentile	90.12	0.91	0.89	0.91
Mean, SD, SR, percentile, kurtosis	90.3	0.90	0.91	0.90
Mean, SD, SR, percentile, kurtosis, skew	90.59	0.90	0.91	0.91

TABLE V
SUMMARY OF KNN FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	81.94	0.79	0.87	0.83
Mean, SD	82.51	0.79	0.88	0.83
Mean, SD, SR	82.05	0.79	0.87	0.83
Mean, SD, SR, percentile	82.69	0.80	0.88	0.84
Mean, SD, SR, percentile, kurtosis	82.6	0.80	0.79	0.80
Mean, SD, SR, percentile kurtosis,skew	82.7	0.81	0.81	0.81

TABLE VI
SUMMARY OF NAIVE BAYES FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	91	0.91	0.91	0.91
Mean, SD	92.91	0.91	0.95	0.93
Mean, SD, SR	92.37	0.90	0.95	0.93
Mean, SD, SR, percentile	88.68	0.89	0.89	0.89
Mean, SD, SR, percentile, kurtosis	90.69	0.90	0.92	0.91
Mean, SD, SR, percentile, kurtosis, skew	90.85	0.90	0.92	0.91

TABLE VII
SUMMARY OF DECISION TREE FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	89.95	0.89	0.89	0.89
Mean, SD	83.24	0.83	0.83	0.83
Mean, SD, SR	87.85	0.87	0.86	0.87
Mean, SD, SR, percentile	89.21	0.89	0.88	0.89
Mean, SD, SR, percentile, kurtosis	90.21	0.90	0.90	0.90
Mean, SD, SR, percentile, kurtosis, skew	91.32	0.91	0.90	0.91

TABLE VIII
SUMMARY OF LDA FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	88.23	0.89	0.87	0.88
Mean, SD	87.98	0.89	0.86	0.88
Mean, SD, SR	88.02	0.87	0.89	0.88
Mean, SD, SR, percentile	88.3	0.88	0.88	0.88
Mean, SD, SR, percentile, kurtosis	87.29	0.85	0.90	0.88
Mean, SD, SR, percentile, kurtosis, skew	86.92	0.84	0.92	0.88

TABLE IX
SUMMARY OF SVM FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	92.51	0.93	0.92	0.92
Mean, SD	91.4	0.91	0.92	0.91
Mean, SD, SR	91.45	0.91	0.91	0.91
Mean, SD, SR, percentile	91.42	0.90	0.89	0.90
Mean, SD, SR, percentile, kurtosis	91.95	0.93	0.92	0.93
Mean, SD, SR, percentile, kurtosis, skew	95.3	0.93	0.91	0.92

Table IV shows the summary of results for selected features using random forest. The experimental results show the combination of all features achieved better performance. In the other hand, mean and SD feature achieved less accuracy.

Table V shows the summary of results for selected features using KNN. The experimental results show the combination of all features achieved better performance. In the other hand, mean feature achieved less accuracy.

Table VI shows the summary of results for selected features using Naive Bayes. The experimental results show the mean and SD and also mean, SD and SR features achieved better performance. In the other hand, mean, SD, SR and percentile features achieved less accuracy.

Table VII shows the summary of results for selected features using decision tree. The experimental results show the combination of all features achieved better performance. In the other hand, mean and SD features achieved less accuracy.

Table VIII shows the summary of results for selected features using LDA. The experimental results show the mean, SD, SR and percentile features achieved better performance. In the other hand, combination of all feature achieved less accuracy.

Table IX shows the summary of results for selected features using SVM. The experimental results show the combination of all features achieved better performance. In the other hand, mean and SD features achieved less accuracy.

Table X shows the summary of results for selected features using QDA. The experimental results show the mean feature achieved better performance. In the other hand, mean, SD and SR features achieved less accuracy.

Table XI shows the summary of results for selected features using 1D-CNN. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean feature achieved less accuracy.

Table XII shows the summary of results for selected features using 2D-CNN. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean and SD features achieved less accuracy.

TABLE X
SUMMARY OF QDA FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	89.84	0.89	0.91	0.90
Mean, SD	77.71	0.69	0.68	0.69
Mean, SD, SR	71.25	0.70	0.70	0.70
Mean, SD, SR, percentile	72	0.72	0.71	0.72
Mean, SD, SR, percentile, kurtosis	72.1	0.72	0.72	0.72
Mean, SD, SR, percentile, kurtosis, skew	74.59	0.71	0.70	0.71

TABLE XI
SUMMARY OF 1D-CNN FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	88.74	0.88	0.88	0.88
Mean, SD	89.26	0.89	0.89	0.89
Mean, SD, SR	91.23	0.91	0.92	0.92
Mean, SD, SR, percentile	9189	0.92	0.92	0.92
Mean, SD, SR, percentile, kurtosis	92.1	0.92	0.91	0.92
Mean, SD, SR, percentile, kurtosis, skew	92.8	0.91	0.91	0.91
Raw data	94.56	0.94	0.93	0.94

TABLE XII
SUMMARY OF 2D-CNN FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	87.26	0.87	0.86	0.87
Mean, SD	86.55	0.86	0.85	0.86
Mean, SD, SR	88.21	0.88	0.87	0.88
Mean, SD, SR, percentile	89.1	0.89	0.88	0.89
Mean, SD, SR, percentile, kurtosis	89.6	0.89	0.88	0.88
Mean, SD, SR, percentile, kurtosis, skew	90.23	0.90	0.89	0.90
Raw data	91.23	0.92	0.91	0.92

TABLE XIII
SUMMARY OF LSTM FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	88.51	0.88	0.87	0.88
Mean, SD	89.09	0.89	0.89	0.89
Mean, SD, SR	90.6	0.90	0.90	0.90
Mean, SD, SR, percentile	90.6	0.91	0.90	0.91
Mean, SD, SR, percentile, kurtosis	90.89	0.91	0.91	0.91
Mean, SD, SR, percentile, kurtosis, skew	91.21	0.91	0.90	0.91
Raw data	91.8	0.91	0.90	0.91

TABLE XIV
SUMMARY OF BILSTM FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	88.54	0.88	0.88	0.88
Mean, SD	88.9	0.89	0.88	0.88
Mean, SD, SR	89.17	0.89	0.89	0.89
Mean, SD, SR, percentile	90.2	0.90	0.89	0.90
Mean, SD, SR, percentile, kurtosis	90.83	0.90	0.90	0.90
Mean, SD, SR, percentile, kurtosis, skew	90.92	0.90	0.90	0.90
Raw data	91.32	0.91	0.91	0.91

TABLE XV
SUMMARY OF HYBRID (CNN) FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	93.29	0.93	0.92	0.93
Mean, SD	93.87	0.93	0.93	0.93
Mean, SD, SR	94.29	0.94	0.94	0.94
Mean, SD, SR, percentile	95.61	0.95	0.95	0.95
Mean, SD, SR, percentile, kurtosis	95.89	0.95	0.95	0.95
Mean, SD, SR, percentile, kurtosis, skew	97.29	0.97	0.97	0.97
Raw data	98.14	0.98	0.98	0.98

Table XIII shows the summary of results for selected features using LSTM. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean feature achieved less accuracy.

Table XIV shows the summary of results for selected features using BiLSTM. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean feature achieved less accuracy.

Table XV shows the summary of results for selected features using hybrid CNN. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean feature achieved less accuracy. It is worth to mention that, CNN frame-work consists of convolutional, max pooling and fully connected layers. The 10-layered CNN framework achieved the most promising results. In addition, the true positive for hybrid CNN 1625, true negative 2164, the false positive 31 and the false negative is 20.

Table XVI shows the summary of results for selected features using hybrid 2D-CNN. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean feature achieved less accuracy.

Table XVII shows the summary of results for selected features using hybrid LSTM. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean feature achieved less accuracy.

Table XVIII shows the summary of results for selected features using hybrid BiLSTM. The experimental results show the raw data (without any feature selection) achieved better performance. In the other hand, mean feature achieved less accuracy.

TABLE XVI
SUMMARY OF HYBRID (2D-CNN) FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	92.19	0.92	0.92	0.92
Mean, SD	92.8	0.92	0.92	0.91
Mean, SD, SR	93.9	0.93	0.93	0.93
Mean, SD, SR, percentile	94.29	0.94	0.94	0.94
Mean, SD, SR, percentile, kurtosis	94.51	0.94	0.94	0.94
Mean, SD, SR, percentile, kurtosis, skew	96.51	0.96	0.96	0.96
Raw data	96.23	0.96	0.95	0.96

TABLE XVII
SUMMARY OF HYBRID (LSTM) FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	91.26	0.91	0.91	0.91
Mean, SD	92.63	0.92	0.92	0.92
Mean, SD, SR	92.89	0.92	0.92	0.92
Mean, SD, SR, percentile	93.44	0.93	0.93	0.93
Mean, SD, SR, percentile, kurtosis	94.87	0.94	0.93	0.94
Mean, SD, SR, percentile, kurtosis, skew	95.18	0.95	0.94	0.95
Raw data	96.5	0.96	0.96	0.96

TABLE XVIII
SUMMARY OF HYBRID (BiLSTM) FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	90.29	0.90	0.90	0.90
Mean, SD	91.9	0.91	0.91	0.91
Mean, SD, SR	92.78	0.92	0.91	0.92
Mean, SD, SR, percentile	92.99	0.92	0.92	0.92
Mean, SD, SR, percentile, kurtosis	93.73	0.93	0.93	0.93
Mean, SD, SR, percentile, kurtosis, skew	93.8	0.93	0.93	0.93
Raw data	94.52	0.94	0.94	0.94

A. Discussion

The comparative experimental results show that the hybrid deep learning method achieved better performance as compared to traditional machine learning and deep learning classifiers. The performance achieved on the dataset is to identify the posture prediction shows that the unique hybrid DL approaches outperformed the ML and DL technique. In order to train the DL classifiers, the NVIDIA GeForce 940M GPU with 384 Cuda cores and 2 GB DDR3 has been used. The main advantage of hybrid DL classifiers is that their ability to identify the posture. However, the dataset is only limited to three posture including standing, sitting and walking. The main disadvantage of the approach is DL classifiers are computationally expensive. Table XIX shows the comparison of state-of-the-art approaches with our proposed approach. The comparison results show that our approach achieved superior performance in term different evaluation metrics including accuracy, precision, recall and f-measure as compared to other approaches.

TABLE XIX
COMPARISON WITH STATE-OF-THE-ART APPROACHES

Ref	Accuracy	Precision	Recall	F-score
Rizwan et al. [17]	71.21	0.71	0.71	0.71
Xu et al. [18]	85.69	0.85	0.85	0.85
Castellini et al. [19]	79.08	0.88	0.73	0.76
Sanghvi et al. [20]	81.23	0.81	0.80	0.81
Winters et al. [21]	82.64	0.79	0.76	0.77
Winters et al. [21]	82.64	0.79	0.76	0.77
Lee et al. [3]	75.04	0.75	0.74	0.75
Our Approach	98.14	0.98	0.98	0.98

V. CONCLUSION

The remote health monitoring is important for providing independent living to elderly and vulnerable. Therefore, in this paper, we proposed a novel architecture based on deep learning classifiers to identify posture including standing, sitting and walking. In addition, the novel hybrid approach are developed based on the DL methods to identify the posture prediction. The hybrid approach contains different prediction of machine learning and deep learning to train the meta-learning. The experimental results show that the proposed hybrid approach achieved better performance as compared to DL and ML methods.

REFERENCES

[1] A. Koubâa *et al.*, "Activity monitoring of islamic prayer (salat) postures using deep learning," in *Proc. 6th Conf. Data Sci. Mach. Learn. Appl. (CDMA)*, Mar. 2020, pp. 106–111.

[2] A. Adeel *et al.*, "A survey on the role of wireless sensor networks and IoT in disaster management," in *Geological Disaster Monitoring Based on Sensor Networks*. Singapore: Springer, 2019, pp. 57–66.

[3] J. Lee, H. Joo, J. Lee, and Y. Chee, "Automatic classification of squat posture using inertial sensors: Deep learning approach," *Sensors*, vol. 20, no. 2, p. 361, Jan. 2020.

[4] F. Jiang, K. Dashtipour, and A. Hussain, "A survey on deep learning for the routing layer of computer network," in *Proc. UK/China Emerg. Technol. (UCET)*, Aug. 2019, pp. 1–4.

[5] F. Jiang, B. Kong, J. Li, K. Dashtipour, and M. Gogate, "Robust visual saliency optimization based on bidirectional Markov chains," *Cogn. Comput.*, pp. 1–12, 2020.

[6] J. Han *et al.*, "LoRa-based smart IoT application for smart city: An example of human posture detection," *Wireless Commun. Mobile Comput.*, vol. 2020, Aug. 2020, Art. no. 8822555.

[7] I. Radu, E. Tu, and B. Schneider, "Relationships between body postures and collaborative learning states in an augmented reality study," in *Proc. Int. Conf. Artif. Intell. Educ.* Cham, Switzerland: Springer, Jul. 2020, pp. 257–262.

[8] Y. Agrawal, Y. Shah, and A. Sharma, "Implementation of machine learning technique for identification of yoga poses," in *Proc. IEEE 9th Int. Conf. Commun. Syst. Netw. Technol. (CSNT)*, Apr. 2020, pp. 40–43.

[9] M. A. I. R. Ghannam and Q. Abbasi, *Engineering and Technology for Healthcare*. Hoboken, NJ, USA: Wiley, 2021.

[10] I. O. Hussien, K. Dashtipour, and A. Hussain, "Comparison of sentiment analysis approaches using modern Arabic and Sudanese dialect," in *Proc. Int. Conf. Brain Inspired Cogn. Syst.* Cham, Switzerland: Springer, Jul. 2018, pp. 615–624.

[11] K. Bourahmoune and T. Amagasa, "AI-powered posture training: Application of machine learning in sitting posture recognition using the LifeChair smart cushion," in *Proc. 28th Int. Joint Conf. Artif. Intell.*, Aug. 2019, pp. 5808–5814.

[12] M. Sandybekov, C. Grabow, M. Gaiduk, and R. Seepold, "Posture tracking using a machine learning algorithm for a home AAL environment," in *Intelligent Decision Technologies*. Singapore: Springer, 2019, pp. 337–347.

[13] J. Roh, H.-J. Park, K. Lee, J. Hyeong, S. Kim, and B. Lee, "Sitting posture monitoring system based on a low-cost load cell using machine learning," *Sensors*, vol. 18, no. 2, p. 208, Jan. 2018.
[14] P. D. Rosero-Montalvo, D. H. Peluffo-Ordonez, V. F. Lopez Batista, J. Serrano, and E. A. Rosero, "Intelligent system for identification of wheelchair user's posture using machine learning techniques," *IEEE Sensors J.*, vol. 19, no. 5, pp. 1936–1942, Mar. 2019.
[15] Y. Kim, Y. Son, W. Kim, B. Jin, and M. Yun, "Classification of children's sitting postures using machine learning algorithms," *Appl. Sci.*, vol. 8, no. 8, p. 1280, Aug. 2018.
[16] T. Mallick, P. P. Das, and A. K. Majumdar, "Posture and sequence recognition for Bharatanatyam dance performances using machine learning approach," 2019, *arXiv:1909.11023*. [Online]. Available: http://arxiv.org/abs/1909.11023
[17] A. Rizwan *et al.*, "Non-invasive hydration level estimation in human body using galvanic skin response," *IEEE Sensors J.*, vol. 20, no. 9, pp. 4891–4900, May 2020.
[18] W. Xu, M.-C. Huang, N. Amini, L. He, and M. Sarrafzadeh, "ECushion: A textile pressure sensor array design and calibration for sitting posture analysis," *IEEE Sensors J.*, vol. 13, no. 10, pp. 3926–3934, Oct. 2013.
[19] C. Castellini, E. Gruppioni, A. Davalli, and G. Sandini, "Fine detection of grasp force and posture by amputees via surface electromyography," *J. Physiol.-Paris*, vol. 103, nos. 3–5, pp. 255–262, May 2009.
[20] J. Sanghvi, G. Castellano, I. Leite, A. Pereira, P. W. McOwan, and A. Paiva, "Automatic analysis of affective postures and body motion to detect engagement with a game companion," in *Proc. 6th Int. Conf. Human-Robot Interact. (HRI)*, 2011, pp. 305–312.
[21] M. Winters *et al.*, "Knowledge engineering for unsupervised canine posture detection from IMU data," in *Proc. 12th Int. Conf. Adv. Comput. Entertainment Technol.*, Nov. 2015, pp. 1–8.

Sidrah Liaqat is pursuing the Ph.D. degree with the School of Engineering and Computing, University of the West of Scotland. She is working on remote healthcare technologies and machine learning.

Kia Dashtipour received the M.Sc. degree in advanced computer system development and the Ph.D. degree in computing science from the University of Stirling in 2014 and 2019, respectively. He was a Postdoctoral Research Associate with the Edinburgh Napier University from 2018 to 2019. He is currently a Research Associate with the James Watt School of Engineering, University of Glasgow. His main research interests include natural language processing, machine learning, and speech enhancement.

Kamran Arshad (Senior Member, IEEE) is currently the Dean of Graduate Studies and Research and a Professor in Electrical Engineering with Ajman University, UAE. Prior to joining Ajman University, in January 2016, he has been with the University of Greenwich, U.K., as a Senior Lecturer and the Program Director of M.Sc. Wireless Mobile Communications Systems Engineering. He is also a Senior Fellow of the U.K. Higher Education Academy (SFHEA). He led a number of locally and internationally funded research projects encompassing the areas of cognitive radio, LTE/LTE advanced, 5G, optimization, and cognitive Machine-to-Machine (M2M) communications. He has contributed to several European and international large-scale research projects. He has over 130 technical peer-reviewed articles in top quality journals and international conferences, received three Best Paper Awards, one best Research and Development Track Award, and chaired technical sessions in several leading international conferences. He is an Associate Editor of the *EURASIP Journal on Wireless Communications and Networking*.

Khaled Assaleh (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the University of Jordan in 1988, the master's degree in electronic engineering from Monmouth University, NJ, USA, in 1990, and the Ph.D. degree in electrical engineering from Rutgers, The State University of New Jersey in 1993. From 2002 to 2017, he was with the American University of Sharjah (AUS) as a Professor of Electrical Engineering and the Vice Provost for Research and Graduate Studies. Prior to joining AUS, he had a nine-year R&D career in the Telecom Industry in the USA with Rutgers, Motorola, and Rockwell/Skyworks. He is currently the Vice Chancellor for Academic Affairs and a Professor of Electrical Engineering at Ajman University. He holds 11 U.S. patents and has published over 120 articles in signal/image processing and pattern recognition and their applications. His research interests include bio-signal processing, biometrics, speech and image processing, and pattern recognition. He has served on organization committees of several international conferences including ICIP, ISSPA, ICCSPA, MECBME, and ISMA. He has also served as a Guest Editor for several special issues of journals.

Naeem Ramzan (Senior Member, IEEE) received the M.Sc. degree in telecommunications from the University of Brest, France, in 2004, and the Ph.D. degree in electronics engineering from the Queen Mary University of London, London, U.K., in 2008.

He is currently a Full Professor of Artificial Intelligence and the Director of the Affective and Human Computing for Smart Environment (AHCSE) Research Centre, University of the West of Scotland (UWS), U.K. He has authored or coauthored more than 200 research publications, including journals, book chapters, and standardization contributions. He has authored a book and coedited some books as well. His research interests are cross-disciplinary and industry focused and include AI/machine learning, affective computing and multimedia processing, analysis and communication, video quality evaluation, brain-inspired multi-modal cognitive technology, big data analytics, affective computing, the IoT/smart environments, natural multi-modal human–computer interaction, and eHealth/connected Health. His article was awarded the Best Paper Award 2017 of the IEEE Transactions on Circuits and Systems for Video Technology and a number of conference papers were selected for the Best Student Paper Award. He has been a Lead Researcher in various nationally or EU sponsored multimillion funded international research projects (total funding as PI secured over £20m). He has been awarded the Scottish Knowledge Exchange Champion Award 2020 and numerous other awards, such as the Staff Appreciation and Recognition Scheme (STARS) Award for Leadership in 2019 and awarded STARS award 2015 and 2017 for Outstanding Research and Knowledge Exchange (the University of the West of Scotland) and Awarded Contribution Reward Scheme 2011 and 2009 for outstanding research and teaching activities (The Queen Mary University of London). He is a Senior Fellow of the Higher Education Academy (HEA), the Co-Chair of MPEG HEVC verification (AHG5) Group, and a Voting Member of the British Standard Institution (BSI). In addition, he holds key roles in the Video Quality Expert Group (VQEG), such as the Co-Chair of the Ultra High Definition (UltraHD) Group, the Co-Chair of the Visually Lossless Quality Analysis (VLQA) Group, and the Co-Chair of the Psycho-Physiological Quality Assessment (PsyPhyQA). He is also the Co-Editor-in-Chief of *VQEG eLetter*. He has served as a Guest Editor for a number of journals. He is also a Founding Associate Editor of the *Journal of Quality and User Experience* (Springer) and an Associate Editor of number of journals. He has chaired/co-chaired/organized more than 25 workshops, special sessions, and tracks in international conferences. He has developed a highly innovative portfolio of post graduate studies, including the M.Sc. degrees in advanced computing, big data, the IoT, and eHealth/digital health.