Comparative performance exploration of different machine learning and deep learning algorithms for classification of hand wrist gestures

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Abstract— **In the current scenario, reliable recognition and classification of hand wrist gestures are gaining high demand for numerous applications including health care application, for Sign language recognition, and in robotics for managing mobile robots etc. This paper highlights the comparative evaluation of various machine learning and deep learning algorithms for classification of hand wrist gestures in terms of classification accuracies, confusion matrix, recall, and precision. This research presents the experiment conducted on ten different subjects demonstrates six different hand wrist gestures for creation of dataset based on variation in scattering parameters of designed wearable Antennas.**

Keywords- Machine learning, deep learning, Body worn antenna, hand wrist gestures, classification algorithm

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I. INTRODUCTION

The application of Wireless Body Area Networks (WBAN) in healthcare sector integrated with body movements and activities recognition systems is gaining interest now-a-days. The relevant technologies and applications, issues and challenges in WBAN implementation are reviewed [1]. The compact Ultra Band Antenna (UWB) is designed and simulated. The effect of using different substrates materials on antenna performance characteristics are comparatively analyzed in terms of return loss, VSWR, Impedance bandwidth [2].Miniaturized sensor based devices are widely preferred for WBAN utility. In this regards, the dimensions of circular antenna can be optimized and reduced by bisecting and slitting micro strip patch of antenna into quadrants. The on-body effect of developed antenna is analyzed through simulation as well as from experimentation [3].Antenna geometry optimization, channel characterization, and propagation model is discussed for WBAN particularly for biomedical applications [4]. The Terahertz (THz) band has been explored for compact and high gain antenna design based on Alumina, RT Duroid 6010, and Gallium Arsenide substrate as an emerging application in human health and activity monitoring wireless systems [5].

The flexible monopole wideband antenna is designed, fabricated, and tested for simulation and measurement observations for antenna radiation performance parameters [6].A small sized UWB antenna is developed for on body WBAN utility. For evaluating antenna performance in terms of electromagnetic radiation patterns, return loss, etc. are considered in free space and on- body condition using human voxel model. The time domain characteristics of antenna are also highlighted [7]. A novel deep learning technique is applied as amalgamation of 3 D convolutional neural networks (3D-CNN) with Long Short-Term Memory (LSTM) architecture for real time human activity classification. The classifiers based on deep learning concept are designed using Keras, and Tensorflow etc. libraries of Python [8].

Human activities can be categorized into simple, complex and heterogeneous activities. The classification of complex and heterogeneous still poses challenge. The advancement in recognition techniques for such activities is required for enhancing effectiveness of WBAN systems. A novel human activity recognition system is developed by integration of Convolutional Neural Networks (for extraction of features) and Recurrent Neural Networks (for determining appropriate patterns in time-series sequential data). The three different datasets are utilized for classification purpose [9].

For human to device communication, traditional classifiers that manually extract features such as Random forest, Decision Trees, etc. can be utilized. But it has limitation when application is for multiple persons with varied characteristics where manual extraction of person specific features is not feasible. Deep neural network is beneficial in those cases as it leads to automatically extraction of subject specific features [10]. To achieve classification practical results three datasets i.e. LoDVP dataset, UCF50 dataset, and MOD20 dataset were utilized for CNN based on Kernelized rank pooling based on feature subspaces (KRP-FS) and basic Kernelized rank pooling (BKRP) [11].

The DCNN classifier based on convolutional filter, an activation function, and a pooling layer having multiple layers connected consecutively is utilized [12].For classifying human activities, a deep learning CNN model is presented based on 3 dimensional feature extraction using Euclidean distance This effect of considering appropriate window size is also described in the study [13]. The time-varying frequency signatures spectrograms that are considered as images for DCNN, are observed for six human activities .Although many conventional as well deep learning techniques can be applied for classification but deep learning method poses enhanced performance in context to accuracy and computational complexity. DCNN have a multi-layer structure that greatly enhances the generalization and abstraction performance [14-15].

The circularly polarized patch antenna is designed and explored for Human activity Classification (HAC) systems. Dynamic time Warping (DTW) algorithm is implanted on observed antenna reflection coefficients datasets for three arm activities [16]. RNNs can be applied for sequential data or time series varying data such as EEG data. RNN units enables interconnections between the subsequent layers as well as to from previous inputs. LSTM is a kind of RNN that performs better by learning both long- and short-term dependencies. Attention mechanism can made further improvement in the performance of LSTM. Deep Learning (DL) is a ML technique for complex problems that combines feature extraction and classification simultaneously as it deploys multiple layers of artificial neural networks [17-18].The remote detection of movements by human can be performed using machine learning classifiers by analyzing the data signal observed from pacemakers deployed inside patient's body. The quantitative model has been developed considering propagation using channel models [19].

The related work in literature comprises a wide variety of classification techniques and algorithms for classifying diverse human body postures and motion related activities. Majority of comparable work are based on sensors implemented for data collection. In the presented work, eight classification algorithms are implemented on observed hand gestures datasets and their performance is compared to determine most accurate classifier for the current scenario.

The major considerations of the presented work include:

1) Implementation of body worn Ultra Wide Band Antennas for classification based on antenna performance characteristics.

2) Application of ensemble classifier approach to achieve enhanced accuracy.

3) Performance evaluation and comparison of hand gesture classification algorithms.

The literature review regarding UWB antennas for WBAN systems and related work of classification of human body movements is mentioned in Section 1. The presented antenna implementation set up for data set creation discussed in Section II. The classification results are demonstrated in Section III. The section IV concludes the current work.

II. DATASET COLLECTION

In this paper, the compact textile (denim substrate) based UWB transmitting and receiving antennas presented in [20-21] are utilized for data set observation for six hand wrist gestures. The considered hand gestures considered are highlighted in Table I and Fig.1 .The sample of created dataset is shown in Table II.

TABLE I. HAND GESTURES CONSIDERED FOR EXPERIMENT

Category of body activities	**Classes of wrist gesture movements**	**Applications**
Hand/wrist movements	[A] hand at rest (neutral position) [B] hands open [C] hands close [D] wrist flexion [E] wrist extension [F] wrist deviation	Sign language recognition, health care application in elderly care, robotics in managing mobile robots etc.

Antennas are deployed on human body at two placement locations: on chest and on hand wrist. Ten persons with an average age of 23 years were participated in the experimental observation process by performing six different right hand wrist gestures with repetitions.

TABLE II. SAPMLE OF DATASET OBSERVED

S_{11}	S_{21}	Position	Subject	Hand gesture	Wrist gesture names
-21.48	-98.90	2	4	1	hand at rest
-22.67	-98.14	1	7	1	hand at rest
-21.85	-68.53	1	3	2	hands open
-21.32	-68.21	3	5	2	hands open
-21.98	-80.97	2	2	3	hands close
-22.12	-81.33	2	3	3	hands close
-19.53	-98.47	3	8	4	wrist flexion
-18.97	-82.17	3	2	4	wrist flexion
-18.98	-85.97	1	10	5	wrist extension
-18.60	-86.80	2	4	5	wrist extension
-22.58	-80.79	3	5	6	wrist deviation
-23.12	-81.33	1	7	6	wrist deviation

The antenna characteristics S_{11} and S_{21} were observed for each hand wrist gestures through Anritsu MS46322A Vector Network Analyzer. For each observed antenna performance parameter such as S_{11} and S_{21}, 2400 data sets (10 human subjects ×6 wrist gesture activities × 2 frequencies × 10 repetitions ×2 locations of antenna placement ×3 positions) were created using body worn antennas implemented for classification purpose.

(a) Hands at rest (b) hands open (c) hands close (d) Wrist flexion (e) Wrist extension (f) Wrist deviation

Fig. 1. Six different hand/ wrist gestures considered in the experimental study

III. Classification Result and Discussion

A. Classification Techniques

Some conventional machine learning techniques such as the Random Forest (RF), Support Vector Machine (SVM), and the K-Nearest Neighbor (KNN), Extreme Gradient Boosting (XGB) are implemented for presented hand gesture classification after the feature extracting stage. The 1D CNN and Multilayer Perceptron (MLP) are also implemented on observed datasets. The one dimensional CNN is implemented in present study as it is applicable for signal or vector data processing unlike 2D or 3D CNN mainly for applicable for video and image classification. For analysis of tabular data ensemble methods of machine learning is proved to be better than deep learning. The decision tree ensemble has been proven superior to neural networks on tabular data as associated information gets already extracted. Extreme Gradient Boosting (XGB) is machine learning classifier for handling tabular data accurately.

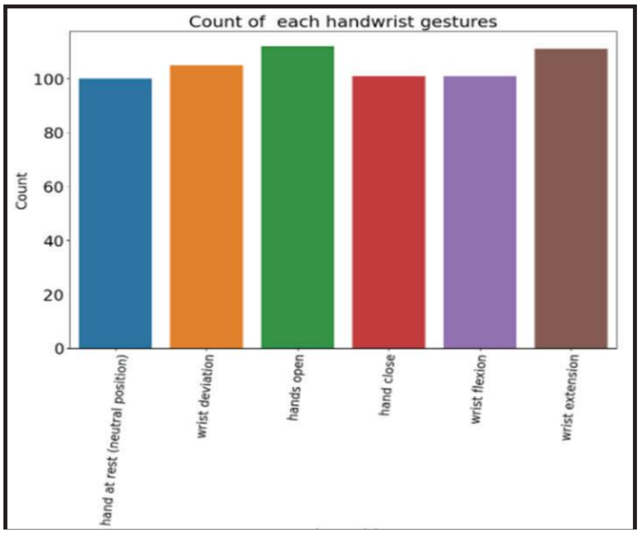

Fig. 2. Wrist gestures with number of activities

B. Classification results

The performance of various hand gestures recognition and classification algorithms have been evaluated on self-observed datasets for six different wrist gestures illustrated in Fig 1and Fig 2. For evaluation purpose, we analyzed Accuracy, Precision, Recall, and F1-score as classification performance metrics as shown in Table III, V, VII and IX for RF, SVM, KNN, and XGB Classifier respectively. The Confusion matrix are shown in Table IV, VI, VIII and X for RF, SVM, KNN, and XGB Classifier respectively. The result of neural network implementation is shown in Fig.3.

TABLE III. RF CLASSIFIER RESULTS

Wrist gesture	*Classifier*	*Precision*	*Recall*	*F1-score*
hand at rest		1.00	1.00	1.00
hand open		1.00	0.96	0.98
hand close		0.96	1.00	0.98
wrist flexion	**RF**	1.00	0.93	0.96
wrist extension		0.94	1.00	0.97
wrist deviation		1.00	1.00	1.00

TABLE IV. CONFUSION MATRIX USING RF CLASSIFIER

Hand gesture	[A]	[B]	[C]	[D]	[E]	[F]
[A]	37	0	0	0	0	0
[B]	0	45	2	0	0	0
[C]	0	0	46	0	0	0
[D]	0	0	0	38	3	0
[E]	0	0	0	0	45	0
[F]	0	0	0	0	0	54

TABLE V. SVM CLASSIFIER RESULTS

Wrist gesture	*Classifier*	*Precision*	*Recall*	*F1-score*
hand at rest		0.90	1.00	0.95
hand open		1.00	0.96	0.98
hand close		0.96	0.98	0.97
wrist flexion	**SVM**	1.00	0.90	0.95
wrist extension		0.94	0.98	0.96
wrist deviation		1.00	0.98	0.99

TABLE VI. CONFUSION MATRIX USING SVM CLASSIFIER

Hand gesture	[A]	[B]	[C]	[D]	[E]	[F]
[A]	37	0	0	0	0	0
[B]	0	45	2	0	0	0
[C]	1	0	45	0	0	0
[D]	1	0	0	37	3	0
[E]	1	0	0	0	44	0
[F]	1	0	0	0	0	53

TABLE VII. KNN CLASSIFIER RESULTS

Wrist gesture	*Classifier*	*Precision*	*Recall*	*F1-score*
hand at rest		0.97	1.00	0.99
hand open		0.97	0.96	0.96
hand close		0.94	0.96	0.95
wrist flexion	**KNN**	1.00	0.78	0.88
wrist extension		0.78	1.00	0.87
wrist deviation		1.00	0.89	0.94

TABLE VIII. CONFUSION MATRIX USING KNN CLASSIFIER

Hand gesture	[A]	[B]	[C]	[D]	[E]	[F]
[A]	37	0	0	0	0	0
[B]	0	45	2	0	0	0
[C]	1	0	44	0	1	0
[D]	0	0	1	32	8	0
[E]	0	0	0	0	45	0
[F]	0	2	0	0	4	48

TABLE IX. XGB CLASSIFIER RESULTS

Wrist gesture	*Classifier*	*Precision*	*Recall*	*F1-score*
hand at rest		1.00	1.00	1.00
hand open		1.00	1.00	1.00
hand close		0.98	1.00	1.00
wrist flexion	**XGB**	1.00	1.00	1.00
wrist extension		1.00	1.00	0.98
wrist deviation		1.00	1.00	1.00

TABLE X. CONFUSION MATRIX USING XGB CLASSIFIER

Hand gesture	**[A]**	**[B]**	**[C]**	**[D]**	**[E]**	**[F]**
[A]	37	0	0	0	0	0
[B]	0	46	21	0	0	0
[C]	0	0	46	0	0	0
[D]	0	0	0	41	0	0
[E]	0	0	0	0	45	0
[F]	0	2	1	0	0	48

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 784)               0

 dense_4 (Dense)             (None, 100)               78500

 dense_5 (Dense)             (None, 10)                1010

=================================================================
Total params: 79510 (310.59 KB)
Trainable params: 79510 (310.59 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig. 3. Neural Network implementation

Table XI highlights the classification results in terms of Accuracy of the implemented machine learning and neural network classifiers on observed datasets. From the comparative exploration, it has been found that the XGB classifier is preferable for current tabular data of S_{11} and S_{21} parameters as it achieves better classification performance characteristics.

TABLE XI. PERFORMANCE OF PRESENTED CLASSIFICATION TECHNIQUES

[Sr. No.]	*Method*	*Accuracy (%)*
[1]	RF	97.77
[2]	SVM	96.76
[3]	KNN	97.25
[4]	XGB	99.75
[5]	1D-CNN	94.6
[6]	MLP	89.25

Table XII comparatively summarize the presented work with related work of recognition of body movements and activities. It has been demonstrated that the current work exhibits enhanced classification performance in comparison to comparable work in the area of human activity recognition.

TABLE XII. COMPARISON OF PRESENTED WORK WITH PREVIOUS LITERATURE

[Ref. No.]	**Activities considered**	**Datasets**	**Classification technique**	**Accuracy**
11	Body movements activities	MOD20 dataset	BKRP and KRP-FS based CNN	66.55 % and 74.00%
12	Hand gestures	Doppler signatures measured by Doppler radar	DCNN	93.1 %
13	nine movemnts activities	Florence 3D public dataset Euclidean distance.	CNN	94.08 %
14	Six different activities	spectrogram of S_{11} and S_{21}	DCNN	97.1% using S_{11} 8.8% using S_{21}
15	hand gestures	micro-Doppler signatures on spectrogram	DCNN	93.1%
16	3 arm activities	Near field of compact patch antenna	DTW	Not reported
17	Hand movements	EEG Movement Database	LSTM +Attention	83.2 % (Cross subject) 98.3 % (Intra subject)
Proposed	Six hand /wrist gestures	Transmission coefficient, reflection	RF SVM KNN	97.77 % (RF) 96.76 % (SVM) 97.25% (KNN)

[Ref. No.]	Activities considered	Datasets	Classification technique	Accuracy
		coefficient of UWB antennas	XGB 1D-CNN MLP	99.75% (XGB) 94.6% (CNN) 89.25% (MLP)

IV. Conclusion

The recognition and classification of six human wrist gestures is presented in this research work. The antenna characteristics of UWB antenna design has been explored as basis of implementation of an efficient and reliable hand wrist gesture recognition and classification system. From comparative performance analysis, the most suitable classification algorithm for observed datasets is XGB in context to classification accuracy. The current work highlights the highest accuracy of 99.76% for all wrist gesture activity types. The highest accuracy obtained by implemented XGB classifier on tabular data of scattering parameters data sets. As a future work the existing work can be extended by incorporating more number of human hand gesture movements and activities and by developing novel algorithm for classification with superior performance

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