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AN IMPROVED OPTIMIZATION BASED CLASSIFICATION MODEL FOR SENSOR BASED HUMAN ACTIVITY RECOGNITION

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ABSTRACT

Human Activity Recognition (HAR) is the field of study which infer insights for human activities. HAR plays vital role in various real-world applications includes checking regularly for a period of time about reducing the risk in daily living activities in healthcare systems, elder care and rehabilitation. There are plenty of conventional algorithms exists for HAR and still needs improvement in various factors such as privacy and accuracy. HAR can be classified as vision based such as surveillance video/image, and sensor based such as smartphones, smart watches and wearable devices. The vision based HAR use external devices to collect the data with issues such as privacy, data storage size, cost, infrastructure and accuracy. The sensor based HAR uses on-body smart devices in the wrist, chest, abdomen, ankle, leg and bell to collect the data. Sensors embedded in these devices provides privacy-aware relevant data with information for analysis. This research work aims to consider all aspects of sensor based human activity recognition, datasets, pre-processing techniques, optimization techniques, classification models and prediction accuracy by proposing Random Forest(RF) and Support Vector Machine Classifier (SVMC)based GSCV-RF and GSCV-SVM methods. These methods outperform in terms of prediction accuracy when compared with conventional models.

Keywords: *Classification, Human Activity Recognition, Machine Learning, Optimization, Prediction, Sensors.*

1. INTRODUCTION

Human Activity Recognition is a method for finding the movement of a person based on video/sensor data collected from a surveillance camera, wearable devices, accelerometer, magnetometer and gyroscope sensors in smartphone, smart watch and smart band to predict complicated actions. There are various HAR applications including senior citizen care, assistive living, rehabilitation, monitoring of sports activities and smart health care. The data collected from various sensors are applied in machine learning models to predict the physical activities of a person for better rehabilitation of patients and improve sports activities. Figure 1.a shows the accelerometer sensing x,y,z axis orientation and 1.(b) shows the gyroscope sensing angular orientation.

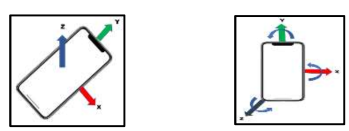

Figure 1.(A) Accelerometer Sensing X,Y,Z Axis Orientation 1.(B) Gyroscope Sensing Angular Orientation.

In this work, novel machine learning based optimization model has been proposed to predict human physical activities.

In section 2 we presented a literature review related to machine learning techniques for human activity recognition. Section 3 explains the proposed prediction model for human activity recognition. In section 4 we discussed the experimental results obtained using Python software. Finally, the conclusions and future works presented in section 5

2. LITERATURE REVIEW

This section explains the literature related to health care especially the recognition of human physical activities with respect to source of data, types of data, pre-processing, optimization techniques, classification and prediction models, measures for fitting the model.

The Wearable sensors and Body sensors can be used as a source of data to collect information about the human physical activities.

Generally, the optimization techniques in machine learning such as Simulated Annealing, Gradient descent, Stochastic Gradient descent, Adaptive Learning rate, Conjugate gradient method, Derivative free optimization, zeroth order optimization, meta learning and other population algorithms such as Genetic Algorithm and Particle Swarm Optimization (PSO) are also used to optimize the parameters for classification models.

2.1 Pre-processing techniques

B. A. Mohammed Hashim and R. Amutha[1], proposed fast feature dimensionality reduction technique to identify various physical activities by a human, applied in various classifiers such as Naïve Bayes, Random Forest(RF), Deep learning and k-Nearest neighbour. The experimental analysis shows that it achieved the high classification accuracy of 98.72% using random forest classifier for the human activity dataset collected from UCI machine learning repository.

2.2 Classification models

There are various classification models in machine learning based on decision tree, Neural Networks, Bayesian classification and Lazy learners. Min-Cheol Kwon and Sunwoong Choi[3], proposed Artificial Neural Network (ANN) classification for prediction of 11 human physical activities using smart watch based accelerometer sensors and achieved 95% classification accuracy.

Mekruksavanich S, Jitpattanakul A.[4], proposed CNN-LSTM hybrid model to improve the performance of classification for smartphone based human activity recognition. The Bayesian optimization technique is used for tuning hyper parameters. The CNN-LSTM hybrid model classification accuracy is increased up to 2.24%.

Tan T-H, Wu J-Y, Liu S-H, Gochoo M. [5], presented Ensemble Learning Algorithm with Smartphone Sensor Data using fully connected DNN and achieved prediction accuracy of 96.7% which is measured using f1 measure.

Ysenllari, E., Ottenbacher, J. & McLennan[6], proposed a two-dimensional convolutional neural network (2D-CNN) to recognize qualitative human activity and obtained the accuracy from 96.57% to 99.28% . They obtained Cohen's k value from 0.96 to 0.99.

Dua, N et.al [7], proposed Deep neural network based convolutional neural network and Gated Recurrent Unit (CNN-GRU) model using UCI-HAR, WISDM, and PAMAP2 datasets and achieved accuracy of 96.20%, 97.21%, and 95.27% respectively [7].

Mutegeki R, Han DS[8], proposed a CNN-LSTM approach to predict human activities and achieved the accuracy of 92.13 for UCI-HAR dataset.Prasad et.al[9] proposed CNN approach for human activity recognition of six activities performed by the subjects using WISDM dataset contains accelerometer sensor data present in cell phone and obtained the prediction accuracy of 89.67%. Vasanthanageswari, Prabhu P[11], presented a methods using optimization technique for the prediction of suitable crop. The model is tested with public datasets and outperformed with conventional models.

Mohsen, S et.al[11], presented a well-designed k-nearest neighbour (KNN) algorithm for human activity recognition. This algorithm parameters are tuned for improving the performance of classification accuracy. This algorithm is experimentally analysed using real-world datasets. The standard performance measures are used to test the performance of classifiers and achieved the classification accuracy of 90.37%.

Sivakami.M and Prabhu P [12] presented machine learning models to improve the accuracy of classification and testing using cardiac dataset. The model outperforms when compared with conventional models.

Prabhu P et.al[13-14] proposed business intelligence models for e-commerce recommender system using frequent item set and fuzzy logic. This model provides solution to recommend suitable items for ecommerce websites.

The conventional classifiers have the limitations in prediction accuracy, sparsity and scalability. These models may depend on more numbers of sensors, other devices which may cause side effects to the patients and also affects the privacy. Hence there is a need to provide parameter optimized accurate prediction and improved health care methods using mobile devices.

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The tree based Decision Tree methods, statistical based Bayesian methods and Neural Networks based methods are exists to provide solution to the HAR. This proposed work uses optimization methods before adapting classification to predict accurate physical activities.

This literature shows that still there is a need to improve the prediction models to achieve high accuracy and overcome other limitations such as scalability and sensitivity. Improved classifications are required especially in the filed of health care applications.

3. METHODOLOGY

In this section, proposed optimized classification model for human activity recognition is explained. The design of the developed model is depicted in figure 2.

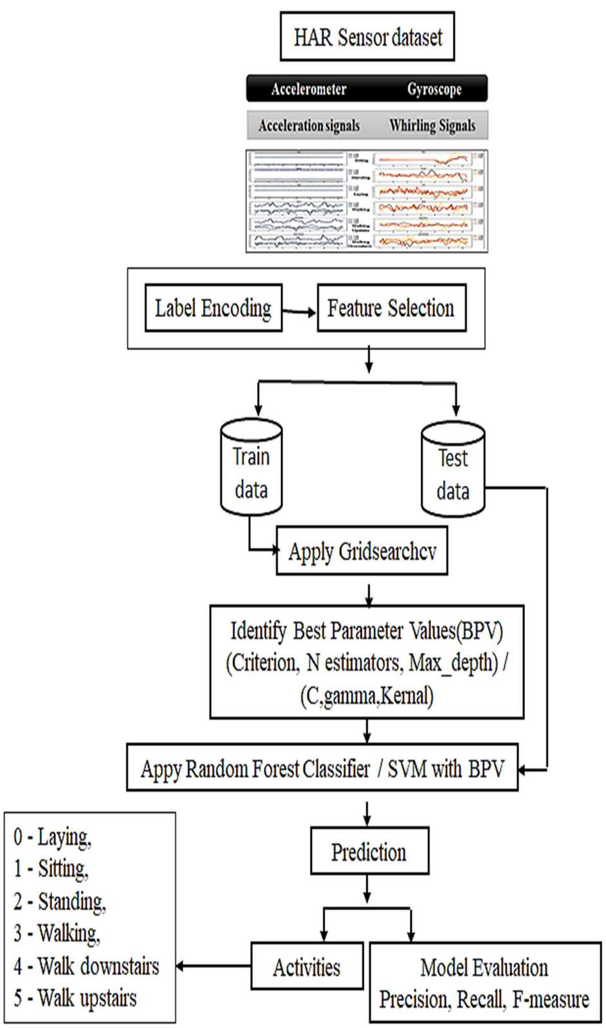

Figure 2. Optimization Based Prediction Model Design.

This model is divided into three phases namely pre-processing, modelling and evaluation. This proposed model first loads the human activity recognition input data received from accelerometer and gyroscope sensors. This dataset is then pre-processed for modelling using label encoding and dimension reduction method. The input dataset is divided into train and test data. The next step in the proposed model is to apply optimization technique for finding best parameter values of prediction model. The remainder of this section presents more details explanation about the proposed prediction model.

3.1 pre-processing

The dataset is pre-processed to verify any missing values, irrelevant data and inconsistencies. Dimensionality reduction technique plays vital role in reducing the number of attributes by removing least important attributes. The list of features from the dataset using highly accurate and interpretable Random Forest feature selection technique is selected as input for modelling. The dataset is split into train and test for modelling.

3.2 Training the model.

The next step in this proposed work is to train the model. Hyperparameters tuning play's major role in enhancing the prediction using classifier by finding the most suitable parameters. There are two approaches for hyperparameters tuning namely GridSearchCV and RandomizedSearchCV. In GridSearchCV the user is defining the all-possible values whereas in RandomizedSearchCV combinations are defined by random manner. When large number of values with less combination of parameters the RandomizedSearchCV model gives less time due to random selection.

3.2.1 GridSearchCV optimization

In this work, GridsearchCV method is cross validation technique used to find the best parameters from the given list of parameter values for the classifier using cross validation method. It uses a various combination of all hyperparameters and its values and finds the performance for each combination and selects the most suitable value for the hyperparameters. The considered hyper parameters for random forest classifiers are; the number of trees in the forest, maximum number of levels in each tree, maximum number of features and criteria (Gini and entropy) for impurity for construction of decision tree. The identified best paramters are criterion='entropy', max_depth=11, n_estimators=200 random_state=42. The considered hyper parameters for SVM classifiers are; C-regularization parameter, gamma and kernel. The identified best parameters for the SVM method is (C=100, gamma=0.001, kernel='rbf').

3.3 Activity Prediction and Evaluation

The last step in this model is to predict the suitable class for the new input data (i.e. Test data). When the test data is provided to the model, it compares the test data with the train data to give outcome. Once the best parameters are identified for the classifier model using optimization technique, these best parameters are applied in the classifier for the prediction on test data.

3.4 Proposed GSV-RF and GSV-SVM Algorithm

```
Input:
  HAR dataset D (feature vectors:561; classes c= 6)
Output:
  Predicted c physical activities.
  Precision(P),Recall(R),F measure(F) values.

Begin
  Load HAR sensor dataset D
  Initialize number of classes (c = 6);
  Do Label encoding
  Apply dimensionality reduction technique
  Apply feature selection
  Spilt the D into train (TR) and test dataset (TS)
  Apply GridSearchCV_optimization(TR) in RFC
   Identify Best Parameter Values (BPV) for RFC
//RFC(criterion, max_depth, N_estimators)
// Criterion – (gini, entropy),
//max_depth of the tree,
//N-estimators (Number of trees to build)
Apply GridSearchCV_optimization(TR) in SVMC
// Support Vector Machine (SVM)
//   SVM(C, gamma, kernel)
// C is the penalty parameter of the error term
// Kernal(Linear, Polynomial, RBF, and Sigmoid)
 Perform RFC(BPV) on TR
 Perform SVM(BPV) on TR
 Test the GSV-RFC using test dataset (TS)
 Test the GSV-SVMC using test dataset (TS)
 Evaluate model using precision, recall and f-measure.
End
```

3.3.1 Evaluation Measures

To test the quality of the prediction model, it is implemented and tested using Python environment with real-world datasets and evaluated using mathematical measures. The proposed prediction model is evaluated based on measures like Recall (Sensitivity), Precision, F-measure, macro average and weighted average from the number of True Positives (TP), False Positives (FP) and False Negatives (FN) obtained. Precision is the fraction of true positives with anything calculated as positives. F-measure balances the precision and recall values by finding the harmonic mean.

$$Precision = \frac{TP}{(TP+F\ \ )} \quad (1)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (2)$$

$$F\ measure = \frac{(\ 2\ X\ Precision\ X\ Recall)}{Precision + Recall} \quad (3)$$

4. RESULTS AND DISCUSSION

In this section, the experimental setup, the results of the developed human activity recognition prediction models are presented.

4.1 Experimental setup

4.1.1 Datasets description

The datasets for the HAR may be collected from real world and public datasets available in website. UCI machine learning repository Human Activity Recognition Using Smartphones Data Set, WISDM[15,16], Groupware, Wrist Sensor Dataset, Chest Sensor Dataset, Nottingham Trent University, UCI HAR Single Chest-Mounted Accelerometer dataset, Cornell Activity Dataset, SisFall, MobiSense, MobiAct and PAMAP2 datasets are commonly available public datasets.

In this work, human activity recognition using smart phone dataset taken from UCI machine learning repository [14] is used for testing the performance of this model. This dataset contains raw data collected from 30 volunteers and conducted 6 physical activities namely 0-laying, 1-sitting, 2-standing, 3-walking, 4-walk downstairs and 5- walk upstairs. It consists of 10299 samples with 561 attributes with time and frequency domain data. Each sample consists of triaxial acceleration, triaxial angular velocity, time domain variables, subject id and target class. The figure 3(a) shows the distribution of activities from UCI Machine learning repository Human Activity Recognition using smartphones dataset.

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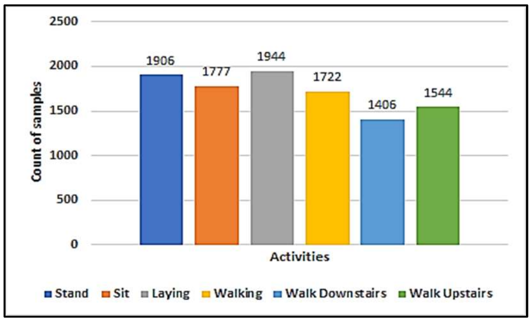


Figure 3. (A) Distribution Of Physical Activities In UCI – HAR Dataset.

Figure 3.(b) shows the sample of Accelerometer and gyroscope signals of six activities.

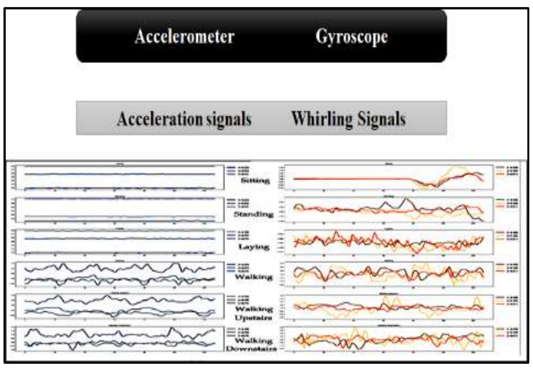


Figure 3.(B) Accelerometer And Gyroscope Signals Of Six Activities

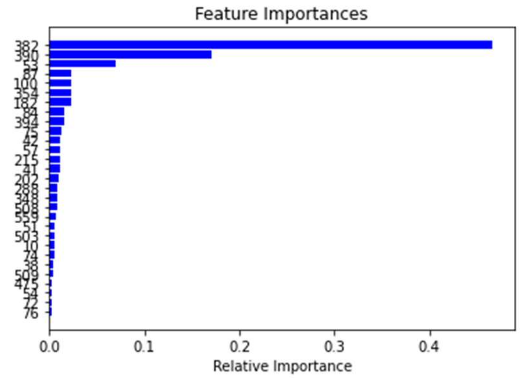
The Public UCI datasets [15] collected from website can also be used to test the performance of this prediction model.

4.1.2 Feature selection Results

4.1.2.1 Random forest feature selection

The selected features using Random Forest feature selection method are [76 72 54 475 509 38 74 10 503 51 559 508 348 288 202 41 215 57 42 75 394 84 182 354 100 87 53 390 382].

Figure 3.(c) shows the features selected using random forest feature selection method.



3.(C) Feature Selection Using Random Forest.

4.1.2.2 Best fit feature selection

Selected attributes Using Best fit method: [11,24,38,39,42,43,45,51,52,53,54,55,58,67,69,71,73,76,79,80,81,105,106,109,122,159,160,161,181,204,232,298,304,305,309,312,368,370,371,383,388,413,450,451,452,453,492,506,520,539,558,559,560, 561 : 54].

4.1.2.3 Greedy stepwise feature selection

Selected attributes using greedy stepwise method: [11,24,38,39,42,43,45,51,52,53,54,55,58,67,69,71,73,76,79,80,81,105,106,109,122,159,160,161,181,204,232,298,304,305,309,312,368,370,371,383,388,413,450,451,452,453,492,506,520,539,558,559,560, 561 : 54]

4.1.2 Software implementation description

This research work was implemented using Python 3.10 for Windows version using Intel(R) Core (TM) i7-8565U CPU @ 1.80GHz 1.99 GHz and RAM 8GB. The Python libraries Scilab, Numpy, Pandas, Tensorflow, sklearn, matplotlib and seaborn were used to develop the optimization based prediction model for Human Activity Recognition.

4.2 Results and discussion

4.2.1 Performance comparison

Generally, the precision, recall, F measure, sensitivity, specificity, ROC curve, Mean Absolute Error (MAE) and confusion matrix are used to evaluate the performance of prediction models.

Abdulhamit Subasi et al.,[2] presented the ways to perform HAR system to diagnose any health risks using two types of sensor data. The performance of various machine learning techniques in detecting critical condition were analysed experimentally and their results are discussed. Table

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1 shows the accuracy comparison of various conventional classifiers calculated using HAR dataset.

Table.1 Classification Accuracy Comparison Of Conventional Classifiers

Classifier	Measure		
	Precision	Recall	F-Measure
k_NN	96.32	96.27	96.26
Decision Tree	93.56	93.48	93.51
Naïve Bayes	93.00	93.00	93.00
AdaBoost	95.35	95.36	95.35
Random Forest	97.66	97.67	97.67
SVM	97.65	97.68	97.67
Multilayer Perceptron	98.00	98,00	98,00
Logistic Regression	98.12	98.12	98.12

Table 2 shows the accuracy comparison of various improved conventional classifiers calculated using HAR dataset. The Logistic Regression (LR) Classifier gives high f-measure accuracy of 98.12 when compared with other conventional models.

Table 2. Accuracy Of Various Improved Conventional Classifiers

Classifier	Type of classifier	Accuracy %
k-NN[10]	Nearest Neighbour	90.37
k-NN-FFDRT[1]	Nearest Neighbour	98.45
Random Forest-FFDRT[1]	Decision Tree	98.72
Naïve-Bayes-FFDT[1]	Bayes Theorem	93.00
ANN[3]	Neural Network	95.00
2D-CNN[6]	Neural Network	96.57 to 99.28
Deep learning-FFDRTT[1]	Neural Network	98.68
CNN-LSTM	Neural Network	92.13
CNN[9]	Neural Network	89.67

The 2D-CNN[6] based method provides high accuracy of classification up to 99.28%. The figure 4 shows the ROC curve shows false positive rate vs. True positive rate value of 0.998 of sitting activity classified using Random Forest Method.

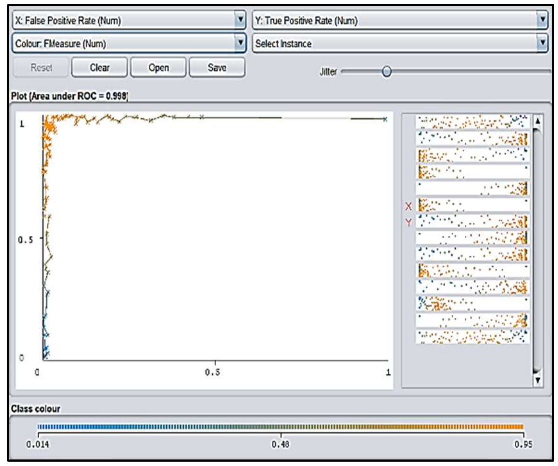

Figure 4 ROC Curve Shows False Positive Rate Vs. True Positive Rate Value Of Sitting Activity Classified Using Random Forest Method.

The confusion matrix is a performance evaluation metrics using for visualizing the performance of classifiers.

Figure 5 shows the confusion matrix of proposed GridSearchCV + SVM classifier using UCI machine learning HAR smartphone dataset.

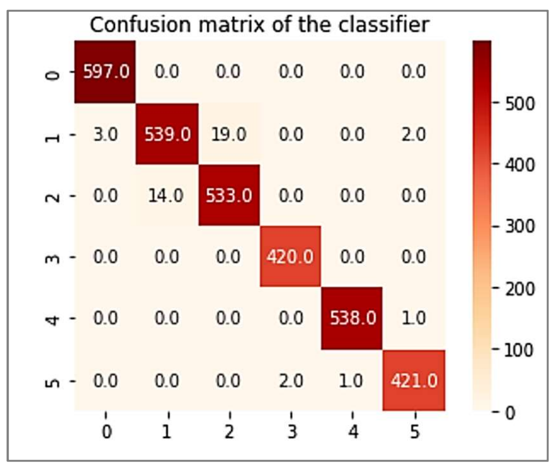

Figure 5. Confusion Matrix Of Proposed GSCV+SVM Classifier.

Table 3 shows the activity wise precision, recall and f1 score accuracy of SVM classifier calculated using HAR smartphone dataset. The Walk-downstairs activity gets high f1 score of 0.9950. The overall accuracy obtained for all activities is 0.9754.

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Table 3 Activity Wise Accuracy Of SVM Classifier Using HAR Dataset.

Activity	Precision	Recall	F-Score
Laying	0.9917	0.9983	0.9950
Sitting	0.9395	0.9378	0.9387
Standing	0.9482	0.9378	0.9430
Walking	0.9929	0.9952	0.9941
Walk-downstairs	0.9963	0.9963	0.9963
Walk-upstairs	0.9906	0.9953	0.9929
Accuracy			0.9754
Macro average	0.9765	0.9768	0.9767
Weighted Average	0.9753	0.9754	0.9753

Table.4 shows the activity wise precision, recall and f1 measure accuracy of proposed GridSearchCV+ SVM classifier calculated using HAR dataset. The Walk-downstairs activity gets high f1 score of 0.9981. The overall accuracy obtained is 0.9764.

Table 4 Activity Wise Accuracy Of Gridsearchcv+Svm Classifier Using Har Dataset.

Activity	Precision	Recall	F-Score
Laying	0.9950	1.0000	0.9975
Sitting	0.9747	0.9574	0.9659
Standing	0.9656	0.9744	0.9700
Walking	0.9953	1.0000	0.9976
Walk-downstairs	0.9981	0.9981	0.9981
Walk-upstairs	0.9929	0.9929	0.9929
Accuracy			0.9864
Macro average	0.9869	0.9871	0.9870
Weighted Average	0.9864	0.9864	0.9864

Figure 6 shows the accuracy of activities calculated using GridSearchCV+SVM classifier. The Walk-downstairs activity gets high f1 score of 0.9981 in the bar chart. The overall accuracy obtained is 0.9764.

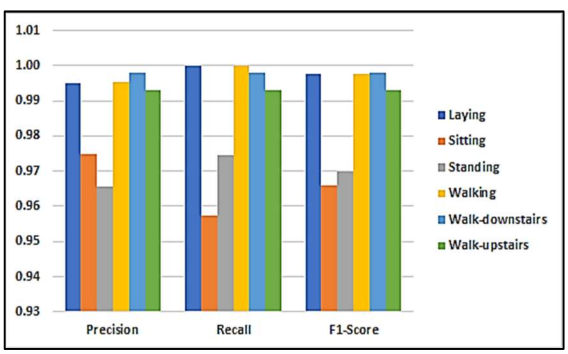

Figure 6 Accuracy Of Activities Calculated Using Gridsearchcv+SVM Classifier

Table.5 shows the accuracy comparison of various conventional classifiers with proposed GridSearchCV classifiers calculated using HAR dataset.

Table 5. Classification Accuracy Of Conventional Vs. Proposed Method

Classifiers	Accuracy %
k-NN	96.26
Decision Tree	93.51
Naïve Bayes	93.00
Random Forest (RF)	97.67
GSCV+ RF	97.72
Support Vector Machine (SVM)	97.67
GSCV+SVM	98.70

Figure.7 shows the accuracy comparison of various conventional classifiers with proposed GridSearchCV classifiers calculated using HAR dataset.

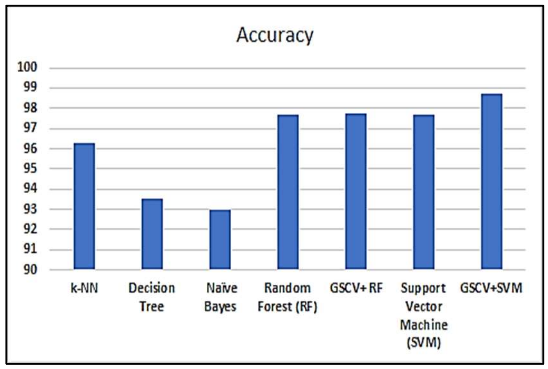

Figure 7 Accuracy Of Conventional Classifiers With Proposed Gridsearchcv Classifiers.

The proposed improved grid search optimization model performance is tested using Random Forest and SVM classifier. The performance of grid search optimized Random Forest model accuracy improved from 97.67% to 97.72% and improved optimized SVM model from 97.67% to 98.70%. GridSearchCV (GSCV)optimized SVM model gives better accuracy.

Still there are some problems and open research issues such as usage of patient's real world data collected from hospitals may be tested to assess this model performance. The improvement in the prediction accuracy more may be required because of this study is in the field of health care systems.

In this proposed work three feature selection methos have been used and grid search and random forest optimization methods are used to find the optimal parameters for various classifiers.

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5. CONCLUSION:

Human Activity Recognition is a major challenging field of study in elder care and health care. In this paper, grid search optimization based machine learning model is proposed to predict various human physical activities. The accuracy of various classifiers is also identified and discussed. The main work of the paper is discussed as; a novel model is proposed to predict the human physical activities using sensor data collected through smartphones. The experimental results show that the proposed model outperforms in prediction of human activities. The improved classifier using optimized parameters is used for prediction. When compared with other conventional optimization models, this model provides better accuracy. This prediction model can be further tested using different optimization techniques. The neural network based deep neural networks may be used to proposed the models. The datasets collected from other public repository or real world data can be used to test the performance benchmark.

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