An Effective Framework for Automated Identification of Human Activity

Neha Bansal, Atul Bansal, Manish Gupta

Department of Electronics & Communication Engineering, GLA University, Mathura, UP India

Department of Electronics & Communication Engineering, GLA University, Mathura, UP India

Department of Electronics & Communication Engineering, GLA University, Mathura, UP India

Abstract

The integration of human-computer interaction technologies into everyday life has sparked the attention of researchers in creating increasingly sophisticated autonomous systems. These human-computer interaction systems can achieve success in practical applications by resolving the deficiencies in current methodologies. This study concentrates on a significant application of human-computer interaction called human activity recognition. Human activity recognition (HAR) refers to the process of identifying and categorising human gestures, activities, and different types of interactions. The system is trained and detects human behaviors utilizing video-based data streams and images as input. The sensor data utilises any accessible touch- or touchless sensing devices. Gyroscopes, Bluetooth, sound sensors, accelerometers, and other integrated sensors included in modern advanced smartphones serve as illustrations of sensing devices. This paper integrates both video-based and sensor-based activity identification. There are a total of four models suggested for the HAR system, consisting of two models that rely on sensors and two models that rely on video. The two models used are the Machine Learning-based Voting Classifiers for Human Activity Recognition (MLVC) and the Ensemble Convolutional Neural Networks. The proposed models are evaluated against the current leading strategies using the metric of recognition accuracy.

Keywords

Human activity recognition, Machine Learning, Convolutional Neural Networks, Classifiers, Bluetooth, Sound Sensors

1. Introduction

Human activity includes the movement of various portions of the body; the recognition of such movements is a key feature in the creation of autonomous systems as a practical application of HCI. [1]. To improve usability in detecting crime and preventing dangerous actions, human activity recognition (HAR) includes detecting regular daily activities [2]. The concept of HAR has aroused the interest of industrialists and academicians in developing intelligent recognition systems. However, recognizing human activities is challenging due to unsolved constraints such as camera resolution, camera deployment, sensor mobility, sensor deployment, disordered background, and inherent unpredictability regarding how different human activities are conducted.[3][4]. The effective recognition of activities can fulfill the future needs of building smart homes and intelligent monitoring systems. Many repetitive jobs performed by humans can be made easier or automated by HAR systems since they can recognize them. The HAR system is an application that aids in pattern recognition and expert systems [5]. Training and recognition are the two phases of this process of identifying human activities. Even though both phases include identical procedures, the first stage entails gaining knowledge of the activities. In contrast, the second step uses the knowledge gained during the training stage to accomplish accurate recognition. This approach indicates that the recognition step depends on the outcome of an earlier stage.

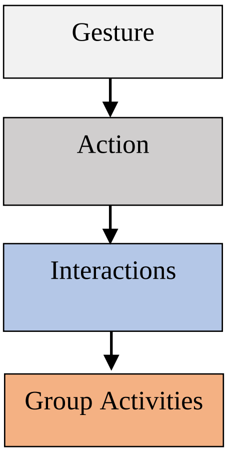

Figure 1: Levels of Human Activities

Gestures, actions, interactions, and group activities are examples of distinct levels of human activity [6] [7]. Figure 1 illustrates these levels. A gesture is the movement of a human body, such as raising an arm or waving a hand, waving, raising an arm, facial expressions, etc. The gesture is a simple activity that is performed within a short time duration. The next stage is action, which is essentially the combination of several motions. Actions such as jumping, running, walking, etc., show what a person is doing.
Further, interaction can be human-object interaction or human-human interaction. Human-object interaction can be between a human and a device. Still, human-to-human interactions, such as handshakes, arm wrestling, gift exchanging, etc., require the participation of at least two persons. Activities requiring many people, like marching or playing cricket, are group activities. Group activity is complex as it incorporates a series of interactions, actions, and gestures. The complexity of the activities increases from gestures to group activities [8].

Both sensor-based HAR and vision-based HAR are important for recognizing human activities [9]. Sensor devices are utilized for sensor-based HAR, and vision devices are used for vision-based HAR. The sensor-based devices can be either conventionally-operated or wirelessly operated, and they can use any special sensors or the in-built sensors found in modern mobile phones and other electronic devices [10]. The gyroscope and accelerometer are widely used kinematic sensors, while the magnetometer, GPS, pressure, gyroscope, and accelerometer are among the most notable in-built smartphone sensors. Vision-based devices are non-contact devices where a camera is used as the primary means of data acquisition [11]. Computer vision techniques can be applied to the acquired data to identify human actions. Figure 2 shows the classification system used for the HAR. The current approach combines sensor-based activity recognition with visual activity recognition.

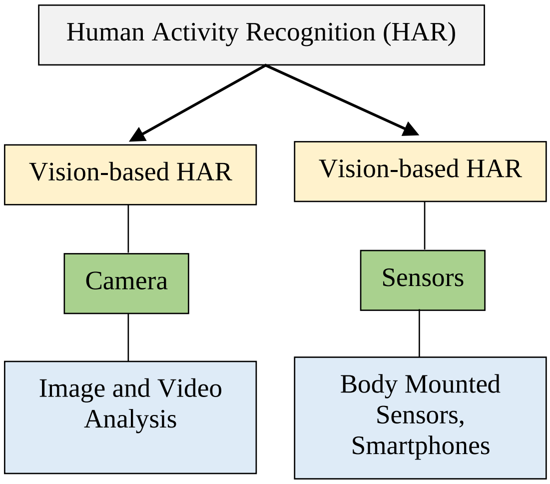

Figure 2: Taxonomy of HAR

Four modules make up the process of recognizing human activity: pre-processing, feature extraction, feature optimization, and classification. Figure 3 shows the different processes of HAR. The first module is the pre-processing module, which segments the background region from the foreground of Human Activity Recognition Vision-based HAR Camera Image and Video Analysis Sensor-based HAR Sensors Body Mounted Sensors Smartphones the image sequences in for the video data. The pre-processing module also detects the availability of humans and objects in the frame. The feature extraction module extracts the features required to recognize the activities. The features may be local or global. The local features, such as image edges, corners, blobs, etc. The global features are the overall visual content in the case of images. The instances of global features are texture, shape, contour, histogram orientation, etc.
Further, the feature selection or optimization filters the extracted features. The feature selection module removes redundant and irreverent features from the extracted feature set. The feature selection can be performed using optimization techniques such as ant colony optimization, particle swarm optimization [12], gravitational search algorithm, firefly algorithm, etc.

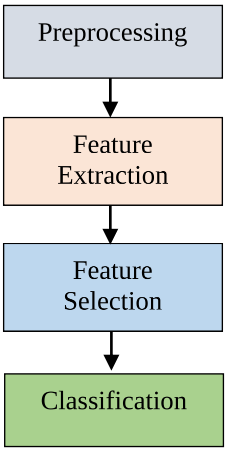

Figure 3: Process of HAR

The final step of the HAR process is the classification module. In this module, activities are categorized using different techniques, such as machine learning techniques and deep learning techniques [13] [14] [15].

2. Related works

In this section, we will discuss research on the real-time applicability of sensor-based HAR in a wide range of domains that has prompted researchers to investigate various techniques for developing advanced sensor-based HAR systems. The recent trends, datasets, and issues in the fields. The section discusses the contributions of researchers for the sensor-based HAR. Dernbach et al. [16] examined the numerous alternative methods for smartphone-based activity recognition that have been discovered, focusing primarily on straightforward tasks like a person moving from one location to another. Therefore, in addition to classifying simple activities, the authors investigated the competencies to recognize complex activities, such as cooking, cleaning, etc., by exploiting a smartphone. Algorithms for supervised machine learning were trained and tested using features that were derived from the inertial sensor data that was embedded in the phone's sensors. Akhter et al. [17]. The incorporated machine learning algorithms were k-star, best first tree (BFT), decision table (DT), Bayes net (BN), Naïve Bayes (NB), and multilayer perceptron (MLP). The outcomes of the experimental examination of 10 participants showed that straightforward tasks are simple to identify. On the other hand, the prediction model's performance on complicated activities was subpar. Fan et al. [18] found that Smartphones can be used to get rich and useful information that can be used for health care and fitness management.
People also carry Smartphones in different positions: bags, hands, side pockets, front pockets, and back pockets of trousers. Siirtola et al. [19] focused on the use of data collected from smartphone accelerometer sensors for the recognition of everyday activities. Two modes of experimentation were carried out: online and offline. These offline experiments showed that the suggested method is user and body position-independent. Chernbumroong et al. [20] used two devices for data collection purposes; one was a Chronos smart watch-wearable gadget, and the second was a heart rate monitor chest strap. For dataset generation, thirteen activities in any order, each lasting 10 minutes, are performed by twelve elderly participants. Zheng et al. [21] introduced a brand-new technique for high-accuracy HAR based on embedded acceleration sensors in mobile phones. The feature extraction phase and the classification phase served as the foundation for this study.

Many researchers are contributing their work to human activity recognition. Table 1 shows some researcher contributions.

Table 1: Researcher Contribution to HAR

Author and Year	Technique	Dataset	Remarks
Machado et al., 2015	K-Means, Affinity Propagation, Mean Shift and Spectral Clustering.	Accelerometer	The authors presented a novel approach for activity recognition using a single 3D accelerometer. The performance was efficient for most cases. Among the discussed cases, the accuracy of the subject-dependent cases was lower.
Ronao et al., 2016	Convnet	Benchmark Dataset	The authors suggested incorporating cross-channel pooling instead of max pooling, ensemble approach of time & frequency pooling, and a combined approach of Convnet & SVM.
Vavoulas et al., 2017	IBk (Instance Based Learner)	MobiAct	The work can be extended for improvement by incorporating advanced deep learning techniques.
Balli et	RF,	Sensor	The system

al., 2019	SVM, C4.5 and KNN Watch	data of Moto 360 Smart	performance can be further improved by recognizing more small step activities such as eating, smoking, cooking, etc.
Tarafdar and Bose, 2021	XgBoost, AdaBoost, Boosted C5.0	Public Dataset	The authors described to incorporate more efficient approaches such as deep learning and ensemble learning approaches to improve activity recognition
Tan et al., 2022	DNN ensembled with CNN stacked on the GRU.	UCI-HAR, UCIOpportunity, and UCI-WIDSM	The work can be extended to real-time applicability in hospitals to check the daily activities of COVID-19 affected patients.

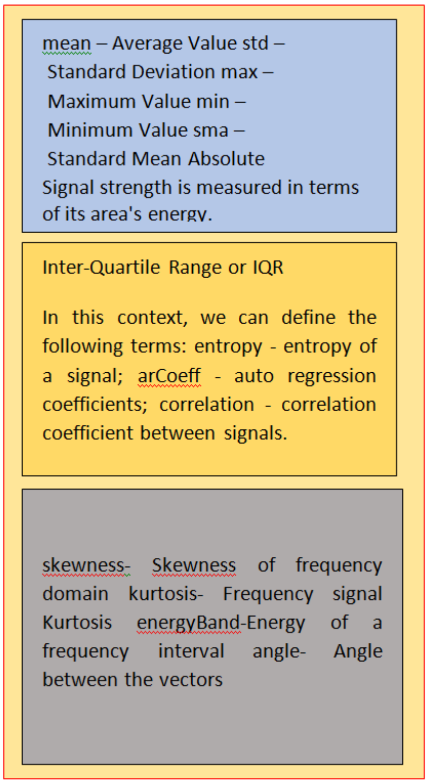

Figure 4: Terms used in HAR

3. Proposed Approach

To enhance the accuracy of activity classification inside its superset, Human Activity Recognition, we introduced the VC method in this section. To improve classification accuracy, a VC combines the knowledge of various independent classifiers. We performed data pre-processing and then used Principal Component Analysis (PCA) for dimension reduction before feeding the training dataset into the suggested model. See Figure 4 for a graphic display of the proposed architecture process. The method proposed for human action recognition using collected data from smart phones built-in sensors is illustrated in Figure 4. Thirty participants, aged 19 to 48, from the UCI Human Activity Recognition (UCI-HAR) benchmark dataset were used in the experiments. Positions include standing, sitting, lying down, walking, ascending, and descending. Smartphones with built-in gyroscopes and accelerometers make it possible to digitally record the participant's tri-axial angular velocity at a constant rate of 50Hz, as well as the participant's tri-axial linear acceleration. Variables in the time and frequency domains were calculated to produce feature vectors.

In this case, we employ Principal Component Analysis as a dimensionality reduction technique, implementing it in Python with the Scikit-learn module. Furthermore, PCA can be used to accelerate a machine learning method. The enormous data collection can be made more manageable and visually appealing by reducing the number of vectors or features, even if doing so reduces accuracy in some circumstances.
Automated procedures like the ones below were used to find the best possible features for a practical Python implementation of Principal Component Analysis.

3.1 Algorithm:

Principal Component Analysis using Machine Learning (PCAML)
Terms using PCAML:
dataset d, matrix m, eigenvectors evec, eigenvalues eval The projection matrix pm.
Input:
Dataset d.
Output:
k dimensional feature subspace

1. Standardized the values available in the d (With a mean of zero and a variance of one).
2. The covariance m between the dimensions has been calculated..

3. The eval and evac were acquired from the m referenced in Step II.
4. The pm has been constructed from the chosen k evac.
5. The new k-dimensional feature subspace Y was obtained by transforming the original d using pm.

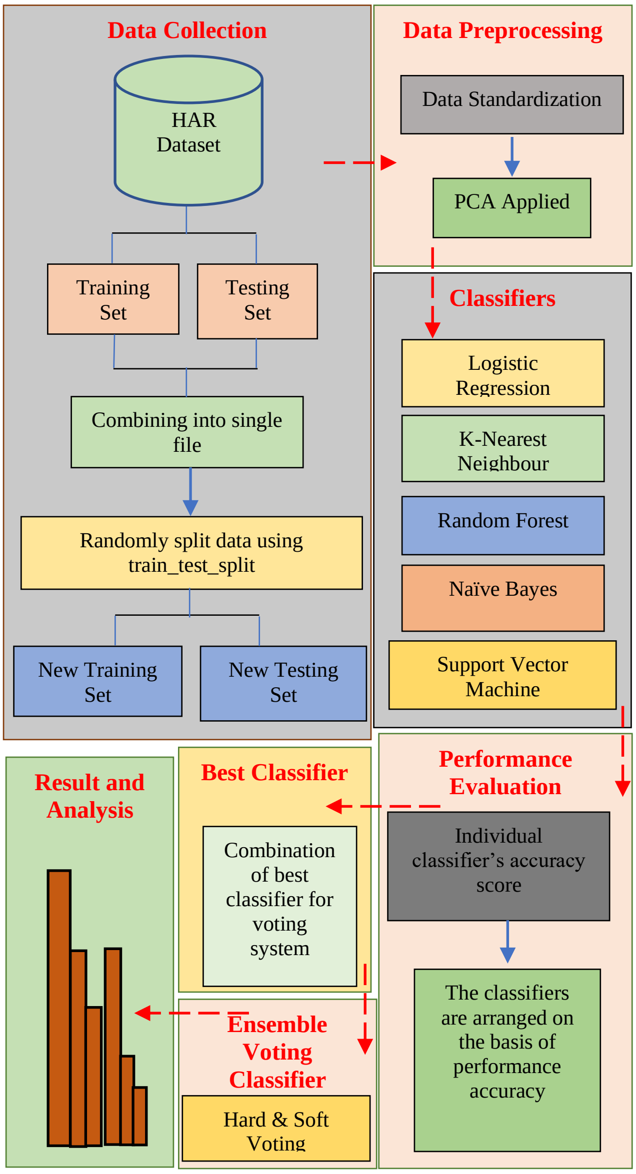

Figure 5: Flow of proposed approach.

The underlying principle of this technique is to reduce the dimensionality of a dataset composed of additional variables which are either weakly or strongly correlated without impacting the variance of the dataset. In this investigation, the dataset contains a total of 561 characteristics. In the suggested ensemble voting approach, 200 features are chosen after applying principal component analysis to minimize information loss and enhance accuracy. Using the PCA approach, which normalizes the raw image data, the features are decreased. The covariance matrix is then constructed from the picture data. Singular Value Decomposition (SVD) is next applied to the matrix information, and finally, picture information is projected onto the newly created foundation. The features that are ultimately employed in further processing are the reduced features. Following a feature reduction of the dataset, five distinct machine-learning classifiers are used to classify human actions. Classifiers include LR, KNN, NB, RF, and SVM. We are employing the Voting Classifier (VC) machine learning technique in this instance. It acts on an ensemble of distinct models and generates a result or class based on the results of their combined efforts, i.e., the class with the highest projected probability. In this work, both Hard Voting (HV) and Soft Voting (SV) classifiers are used.

One form of voting is "Hard Voting,", in which the class with the most votes from each classifier, or the class with the highest likelihood of being selected by each classifier, is projected as the output class. Class P was chosen as the winner since it was predicted by three out of the four classifiers (P, P, and Q). So, P is the last predicted category.

The voting method used in this case is called "Soft Voting". The final class is determined by averaging the probability that each classifier was originally assigned. If we have three models, the probabilities of class P and Q are respectively (0.27, 0.42, 0.32) and (0.27, 0.42, 0.32). (0.32, 0.28, 0.25). Since class P received the highest average probability from all classifiers, its probability is 0.3367, making it the clear winner. Class Q received the lowest average probability, 0.28.
After experimentation, the performance results of the studied ML classifiers and the combinations of the best and most consistent classifiers were selected for the proposed ensemble VC with two variations, namely HV and Soft Voting. In addition, the optimal tuning of hyperparameters and weighted voting have been used to experimental ML classifiers and suggested ensemble voting classifiers, respectively, to improve accuracy.

4. Experimental Results

Here, we assess how well the planned task would perform. Recognition accuracy, precision, recall, and f-measure are evaluated for each model. Eqs. 1–4 shows how these quantities can be formulated. Using a confusion matrix and a classification report, we assess the accuracy of the prediction. Table 2 displays the confusion matrix's settings. Precision (P), recall (R), F-measure (FM), recognition accuracy (RA), correctly classified instances (CCI), and total number of instances (TNI) are all metrics used to evaluate performance.

$$P = \frac{TP}{TP + FP} \quad \text{Eq. (1)}$$

$$R = \frac{TP}{TP + FN} \quad \text{Eq. (2)}$$

$$FM = 2 \times \frac{P \times R}{P + R} \quad \text{Eq. (3)}$$

$$RA = 2 \times \frac{CCI}{TNI} \quad \text{Eq. (4)}$$

If we denote True Positives (TP), False Negatives (FN), True Negatives (TN), and False Positives (FP), then we get the following distribution:.

Table 2: Parameters of Confusion Matrix

		Predicted Class	
		Yes	No
Actual Class	Yes	TP	FN
	No	FP	TN

An innovative hybrid algorithm based on ensemble voting classifiers has been introduced for behavior recognition in humans. On the one hand, total accuracy on the Benchmark dataset was used to rank the effectiveness of five ML classifiers from lowest to highest. The proposed ensemble voting classifiers, on the other hand, are machine learning algorithms that are trained on a collection of high-performing classification models that incorporate both hard and soft voting. Data from all domains are collected and then split 70:30 between training and testing sets to ensure that the experimental outcomes are objective. The training set has 7200 rows and 560 columns, while the testing set has only 3090 rows and 560 columns. Both sets have the same total of 560 numeric features. Maintaining a PCA value of 200 components allows for comparisons between research. The results of the various ML classifiers are summarized in table 3. The relative strengths of the different classifiers are shown in Table 3. Classifiers are ranked based on their recognition accuracy. Classifiers are ranked from 1 to 5 based on their recognition accuracy, with 1 being the classification with the highest accuracy and 5 being the classifier with the lowest accuracy. SVM, KNN, LR, RF, and NB are rated 1 through 5 in Table 3 as according to their recognition accuracies (89, 86.56, 83.92, 80, and 72, respectively). Indisputable evidence shows that SVM is the best classifier.
Metrics and parameters include, but are not limited to, Classifier C, Accuracy A, Precision P, Recall, F-Measure FM, and Rank. Two variants of the proposed ensemble voting classifier, HV and Soft Voting, use combinations of the highest-performing ML classifiers. In addition, the investigated ML algorithms and the suggested ensemble VC have been subjected to the optimal tuning of hyperparameters and weighted voting to improve accuracy. VC, algorithm combinations (AC), accuracy (A), precision (P), recall (R), and F-measure (FM) are some of the metrics and parameters that may be used.

Table 3: Performance analysis

Ordering of Classifiers based on Performance Analysis					
C	**A (%)**	**P (%)**	**R(%)**	**FM(%)**	**Rank**
LR	83	84	83	84	3
KNN	86	87	86	87	2
RF	80	81	80	80	4
NB	72	74	72	73	5
SVM	89	89	89	89	1
Performance analysis of Soft Voting Classifiers					
VC	**AC**	**A(%)**	**P(%)**	**R(%)**	**FM(%)**
I	SVM, KNN	91	92	91	91
II	SVM, KNN,LR	92	93	92	92
III	SVM, KNN, LR, RF	91	92	91	91
IV	SVM, KNN, LR, RF, NB	90	91	90	90
Performance analysis of Hard Voting Classifiers					
VC	**AC**	**A(%)**	**P(%)**	**R(%)**	**FM(%)**
I	SVM, KNN	90	90	90	90
II	SVM, KNN, LR	91	92	91	91
III	SVM, KNN, LR, RF	91	91	91	91
IV	SVM, KNN, LR, RF, NB	90	91	90	90
Performance Analysis of Voting Classifier – II with Individual Classifiers (C)					
Classifier	**A(%)**	**P(%)**	**R(%)**	**FM(%)**	
VC– II (SVC)	92	93	92	92	
VC–II (HVC)	91.	92	91	91	
LR	83	84	83	84	
KNN	86	87	86	87	
RF	80	81	80	80	
NB	72	74	72	73	
SVM	89	89	89	89	

The results of SV are displayed in Table 3, while the results of HV are displayed in Table 3 Section. The Voting Classifier-II (a combination of SVM, KNN, and LR) achieves the highest recognition accuracy (92 percent when using SV and 91 percent when using hard voting) of all the voting classifiers.
The results of the SV ensemble classifiers in Table 3 are superior to those of the HV ensemble classifiers. As an ensemble classifier, VC- II attained an overall accuracy of 92% with SV and 91% with hard voting. The VC- II is compared to the other individual classifiers in Table 3. Tabulated in Table 3 are contrasts between the findings of the Voting Classifier-II (a combination of SVM, KNN, and LR) and those of the individual classifiers. VC- II outperforms competing methods in terms of accuracy and speed. This happened because it incorporates a support vector machine, k-nearest neighbor, and LR. The visual representation of this disparity is shown in Figure 6.

Figure 6: Performance Analysis of Accuracy, Precision, Recall, and F-Measure using different Classifiers

The suggested technique results are shown in Figure 6; compared to hard voting; the accuracy attained using VC- II SV is 1.13% higher. VC- II (soft voting) outperforms LR by 8.86%, KNN by 6.2%, RF by 12.5%, NB by 20.7%, and SVM by 3.75 percentage points. This demonstrates the superiority of VC- II (soft voting). As a bonus, cutting-edge methods are used to evaluate the voting classifiers. Included studies may be found in [22], [23], and [24]. We propose combining the Gramian angular field (GAF) and the multi-dilated kernel residual network (Mdk-ResNet) for a novel approach to deep learning (Mdk-Res). The authors have also assessed the effectiveness of various combinations of GAF with GoogleNet, ResNet, Convolutional Neural Networks, Long Short-Term Memory, and Multilayer Perceptrons. There are adapted semi-supervised Recurrent Convolution Attention Model (SRCAM) methods for activity recognition [22, 23], [24]. An official name for this method is the “DTW-DBA approach”, and what it does is take an average of the barycenters' locations over time. A comparison of the proposed voting classifiers with several other approaches is presented in Table 3.

Table 4: Comparison of VC– II with State-of-the-art Techniques

Classifier	**Recognition Accuracy (%)**
VC–II (SVC)	92
VC-II (HVC)	91
WSTM	89
GAF+Fusion-Mdk-ResNet)	89
GAF+GoogLeNet	87
GAF+ResNet	87
GAF+Conv_2D	88
LSTM	80
Conv_1D	85
MLP	80
SRCAM	81
DTW-DBA	86

In Figure 7, we visualize the results of the Performance Evaluation of VC-II with an Individual Classifier. The findings for various classifiers' recognition levels of accuracy are presented.

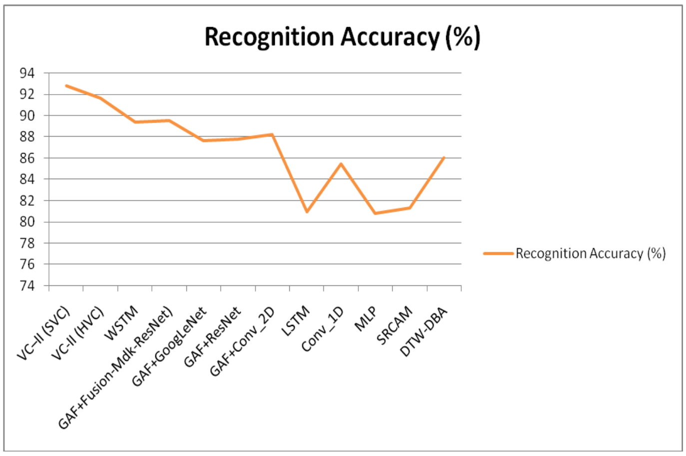

Figure 7: Performance Analysis of a Single Classifier Using VC-II

The suggested voting classifiers outperform some competing activity recognition methods compared to state-of-the-art methods.

5. Conclusion

In this work, we provide a method for utilizing machine learning algorithms in VC systems, which may also be applied to recognizing human activities. Recognition accuracy was assessed using five well-known machine processes (LR, KNN, RF, NB, and SVM). Compared to other methods on the standard-setting UCI-HAR dataset, SVM, KNN, LR, RF, and NB all score exceptionally well but progressively ascending. Additionally, the models with hard and SV have been nominated by this experimentation. Compared to other possible permutations of classifiers, those based on a mixture of three machine learning algorithms (SVM, KNN, and LR) have shown the most promise. This research shows that compared to other machine learning classifiers and state-of-the-art methods, the Voting Classifier-(a II's combination of SVM, KNN, and LR) SV approach yielded the highest accuracy (92.78%).

References

[1] D. K. Vishwakarma, R. Kapoor, and A. Dhiman, "A Proposed Unified Framework for the Recognition of Human Activity by Exploiting the Characteristics of Action Dynamics," Robotics and Autonomous Systems, Vol. 77, pp. 25-38, 2016.

[2] D. Wu, N. Sharma and M. Blumenstein, "Recent Advances in Video-based Human Action Recognition using Deep Learning: A Review," in Proc International Joint Conference on Neural Networks (IJCNN), IEEE, 2017, Anchorage, USA, pp. 2865-2872, 2017.

[3] P. Pareek, and A. Thakkar, "A Survey on Video-based Human Action Recognition: Recent Updates, Datasets, Challenges, and Applications," Artificial Intelligence Review, 54(3), pp. 2259-2322, 2021.

[4] M. Sornam, K. Muthusubash and V. Vanitha, "A Survey on Image Classification and Activity Recognition using Deep Convolutional Neural Network Architecture," in Proc Ninth International Conference on Advanced Computing (ICoAC), IEEE, Chennai, India, 2017, pp. 121-126.

[5] L. M. Dang, K. Min, H. Wang, M. J. Piran, C. H. Lee and H. Moon, "Sensor-based and Vision-based Human Activity Recognition: A Comprehensive Survey," Pattern Recognition, 108, pp. 1-24, 2020.

[6] S. Jindal, M. Sachdeva and AKS Kushwaha, "Deep Learning for Video Based Human Activity Recognition: Review and Recent Developments," In Proc. International Conference on Computational Intelligence and Emerging Power System, Springer, Singapore, pp. 71-83.

[7] J.K. Aggarwal and M.S. Ryoo, "Human Activity Analysis: A Review," ACM Computing Surveys (Csur), 43(3), pp. 1-43, 2011.

[8] P.K.Singh, S. Kundu, T. Adhikary, R. Sarkar, and D. Bhattacharjee, "Progress of Human Action Recognition Research in the Last Ten Years: a Comprehensive Survey," Archives of Computational Methods in Engineering, 29, pp. 2309–2349, 2021.

[9] O.D.Lara, A.J.Pérez, M.A. Labrador, and J. D. Posada, "Centinela: A Human Activity Recognition System based on Acceleration and Vital Sign Data," Pervasive and Mobile Computing, 8(5), pp. 717-729, 2012.

[10] P.Turaga, R. Chellappa, V.S. Subrahmanian, and O. Udrea, "Machine Recognition of Human Activities: A Survey," IEEE Transactions on Circuits and Systems for Video technology, 18(11), pp. 1473-1488, 2008.

[11] S.J. Berlin and M. John, "Particle Swarm Optimization with Deep Learning for Human Action Recognition," Multimedia Tools and Applications, 79(25), pp. 17349-17371, 2020.

[12] S.R. Ramamurthy and N. Roy, "Recent Trends in Machine Learning for Human Activity Recognition-A Survey," Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), pp. e1254(1-11), 2018.

[13] M. Sood, S. Verma and V.K. Panchal, "Optimal Path Planning using Swarm Intelligence based Hybrid Techniques," Journal of Computational and Theoretical Nanoscience, 16(9), pp. 3717-3727, 2019.

[14] M. Rani, A. Gupta and S. Kaushal, "Deep Learning Network Based Framework for Disaster Event Detection," Proc. Modern Approaches in 141 Machine Learning and Cognitive Science: A Walkthrough, Springer, Cham,pp. 195-202, 2022.

[15] S. Dernbach, B. Das, N.C. Krishnan, B.L. Thomas and D.J. Cook, "Simple and Complex Activity Recognition through Smart Phones," Proc. 2012 Eighth International Conference on Intelligent Environments, IEEE, Guanajuato, Mexico, pp. 214-221, 2012.

[16] H. Akhter and V.K. Panchal, "A Recommender System using Machine Learning Algorithms," Global Sci-Tech, 11(2), pp. 93-97, 2019.

[17] L. Fan, Z. Wang and H. Wang , "Human Activity Recognition Model based on Decision Tree,", in Proc. 2013 International Conference on Advanced Cloud and Big Data, IEEE, Nanjing, China, pp. 64-68, 2013.

[18] P. Siirtola and J. Röning, "Ready-to-Use Activity Recognition for Smartphones," in Proc. 2013 IEEE Symposium on Computational Intelligence and Data Mining (CIDM), IEEE, Singapore, pp. 59-64, 2013.

[19] S. Chernbumroong, S. Cang and H. Yu, "A Practical Multi-Sensor Activity Recognition System for Home-based Care," Decision Support Systems, 66, pp. 61-70, 2014.

[20] L. Zheng, Y. Cai, Z. Lin, W. Tang, H. Zheng, H. Shi, B.Liao and J. Wang, "A Novel Activity Recognition Approach Based on Mobile Phone,", Multimedia and Ubiquitous Engineering pp 59–65, 2014.

[21] H. Xu, J. Li, H. Yuan, Q. Liu, S.Fan, T. Li and X. Sun, "Human Activity Recognition based on Gramian Angular Field and Deep Convolutional Neural Network," IEEE Access, 8, pp. 199393-199405, 2020.

[22] K. Chen, L. Yao, D. Zhang, X. Wang, X. Chang and F. Nie, "A Semi-supervised Recurrent Convolutional Attention Model for Human Activity Recognition," IEEE Transactions on Neural Networks and Learning Systems, 31(5), pp. 1747-1756, 2019.

[23] S. Seto, W. Zhang and Y. Zhou, "Multivariate Time Series Classification using Dynamic Time Warping

Template Selection for Human Activity Recognition," in Proc. 2015 IEEE Symposium Series on Computational Intelligence, IEEE, Cape Town, South Africa, pp. 1399-1406, 2015.

[24] D. Anguita, , A. Ghio, , L. Oneto, , P.X. Parra , and O.J.L Reyes , "A Public Domain Dataset for Human Activity Recognition using Smartphones,"in Proc. 21th International European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, Louvain-la-Neuve, Bruges, Belgium, pp. 437-442, 2013.

Authors Profile

Neha Bansal obtained her B.Tech degree from IDEAL INSTITUTE OF TECHNOLOGY, Ghaziabad in 2009 and Master degree in Information and Communication Technology from GLA University, Mathura, India in 2014. She is currently pursuing Ph.D. from GLA University, Mathura, India. Her areas of interest include Human Activity Recognition using Artificial Intelligence and other latest trends in technology. She has more than 14 years of experience in teaching and research in the area of Image Processing.

Dr. Atul Bansal is currently Professor (ECE) and Controller of Examinations at GLA University, Mathura. He did his Masters from IIT Delhi in 2002 and Ph.D. from Thapar University, Patiala in 2015. Dr. Bansal has more than Twenty years of research and teaching experience. He has published 60+ research papers in reviewed international journals of repute, national and international conferences to his credit. 04 Students have been awarded Ph.D. under his guidance and 03 are pursuing Ph.D. Dr. Bansal is a Senior Member of IEEE, Life Member of Metrology Society of India. His current area of research includes Image Processing, Biomedical Imaging, and Biomedical Signal Processing.

Dr. Manish Gupta working as an Associate Professor in Electronics and Communication Engineering Department, GLA University Mathura. He received his BE degree in electronics engineering from Jiwaji University, Gwalior, India in 2000 and M Tech degree in digital communication from UPTU, Lucknow India in 2006. He received PhD in electronics engineering from RTU, Kota, India in 2016. His area of interest is signal and image processing. He have published more than 60 research paper in reputed Journal and Conferences. He also serves as the reviewer for various international conferences.