Human Activity Recognition using Teknomo-Fernandez Kernelized Discriminant

Dr. R. Bagavathi Lakshmi

VELS Institute of Science Technology and Advanced Studies(VISTAS), Chennai.

M Krithika

krithu100992@gmail.com

VELS Institute of Science Technology and Advanced Studies(VISTAS), Chennai.

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[1]Dr. R. Bagavathi Lakshmi, [2] M Krithika, [3] S. Jayashree, [4] PN Shiammala,[5]M Sakthivanitha

[1]Associate Professor, [2] Assistant Professor, [3] Assistant Professor, [4]Assistant Professor, [5]Assistant Professor
Department of Information Technology,
[1]VELS Institute of Science Technology and Advanced Studies(VISTAS), Chennai.

Abstract:- Human activity recognition (HAR) is a crucial problem in the field of human-computer interaction, with applications in various domains such as healthcare, surveillance, and robotics. Traditional machine learning approaches for HAR often rely on hand-crafted features and manual tuning of hyper parameters, which can be time-consuming and limit the accuracy of the recognition system. Recently, deep learning techniques have shown promising results in HAR, but they often require large amounts of labeled data and can be computationally expensive. This paper proposes a novel approach to HAR using Teknomo-Fernandez kernelized discriminant analysis (KF-D) based connectionist deep multilayer perceptron (CDMLP) neural learning. The proposed approach combines the strengths of kernel methods and deep learning to learn robust and efficient representations of human activities. The KF-D method is used to extract features from raw sensor data, which are then fed into a CDMLP network to learn a mapping between the extracted features and the corresponding human activities. The CDMLP network is trained using a back propagation algorithm with a modified version of the cross-entropy loss function. Experiments were conducted on four publicly available datasets, including the Oxford-Hertfordshire Activities of Daily Living (ADL) dataset, the Opportunity dataset, the Human Activity Recognition Using Smart Devices (HARD) dataset, and the WISDM AR Sensor Mining dataset. The proposed approach achieved state-of-the-art performance on all four datasets, outperforming existing methods in terms of accuracy and robustness. The results demonstrate the effectiveness of the proposed approach in recognizing human activities with high accuracy, even in noisy and challenging environments. The proposed approach has potential applications in various domains, including healthcare, surveillance, and robotics. Future work includes extending the approach to recognize more complex human activities and integrating it with other sensors and devices to create a more comprehensive HAR system.

Keywords- Human Activity Recognition, Teknomo-Fernandez Kernelized Discriminant Analysis, Connectionist Deep Multilayer Perceptron Neural Learning, Machine Learning, Computer Vision.

I. Introduction:

Human activity recognition (HAR) has gained significant attention in recent years due to its numerous applications in various fields such as healthcare, surveillance, and robotics. HAR involves recognizing the activities performed by humans using sensors such as accelerometers, gyroscopes, and magnetometers embedded in wearable devices or attached to the body. The goal of HAR is to identify the type of activity being performed by a person, which can be used to provide valuable insights into their daily habits, monitor their health, and enhance their overall well-being.

Traditional HAR approaches typically rely on machine learning algorithms that are trained on hand-crafted features extracted from sensor data. However, these approaches often require manual feature engineering, which can be time-consuming and limits the accuracy of the recognition system. Moreover, traditional machine learning algorithms may not be able to effectively handle high-dimensional sensor data and may not be robust to noise and outliers.

Recently, deep learning techniques have been applied to HAR, which have shown promising results. However, deep learning models require large amounts of labeled data and can be computationally expensive. Moreover, they may not be able to provide interpretable results and may require domain-specific knowledge to design and train.

In this paper, we propose a novel approach to HAR using Teknomo-Fernandez kernelized discriminant analysis (KF-D). KF-D is a machine learning algorithm that combines the strengths of kernel methods and discriminant analysis to learn a nonlinear mapping between high-dimensional sensor data and human activities. The KF-D algorithm is capable of handling high-dimensional data, noise, and outliers while providing interpretable results.

A. Our contributions

The proposed approach has several advantages over existing methods, including:

* Improved accuracy: The KF-D based CDMLP network learns robust and efficient representations of human activities, resulting in improved accuracy compared to traditional machine learning approaches.

* Reduced computational cost: The CDMLP network requires less computational resources compared to deep learning models that use convolutional neural networks (CNNs) or recurrent neural networks (RNNs).

* Flexibility: The proposed approach can be applied to different types of sensor data and different human activities, making it a versatile tool for HAR.

B. Organizations

The rest of the paper is arranged into different sections as follows: Section 2 discusses the related works. Section 3 provides the methodology of research in detail. Section 4 describes the experimental evaluation. Section 5 discusses the results with different performance metrics. Finally, section 6 summarizes the conclusions and for this research work.

II. Related works

Human Activity Recognition (HAR) has been a topic of increasing interest in recent years due to its numerous applications in healthcare, surveillance, and robotics. Traditional machine learning approaches for HAR have focused on extracting hand-crafted features from sensor data, such as acceleration, gyroscopes, and magnetometers, and then applying classification algorithms to recognize the activities [1-3]. However, these approaches have several limitations, including the need for manual feature engineering, which can be time-consuming and limits the accuracy of the recognition system.

Recently, deep learning techniques have been applied to HAR, which have shown promising results [4-6]. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been used to learn features from raw sensor data and recognize human activities [7-9]. However, these approaches require large amounts of labeled data and can be computationally expensive.

Kernel-based methods have also been used for HAR, which can handle high-dimensional data and provide interpretable results [10-12]. Kernelized Discriminant Analysis (KDA) is a type of kernel-based method that can be used for dimensionality reduction and feature extraction [13]. However, KDA is sensitive to the choice of kernel function and hyper parameters.

Teknomo-Fernandez kernelized discriminant analysis (KF-D) is a novel approach that combines the strengths of kernel methods and discriminant analysis [14]. KF-D is based on the idea of mapping the high-dimensional sensor data into a lower-dimensional space using a kernel function and then applying discriminant analysis to classify the activities. KF-D has been shown to be effective in various applications, including face recognition and gesture recognition [15-16].

Connectionist Deep Multilayer Perceptron (CDMLP) neural networks are a type of feed forward neural network that consists of multiple layers of neurons [17]. CDMLP networks have been used in various applications, including image recognition and speech recognition [18-19]. Recently, CDMLP networks have been applied to HAR with promising results [20].

The combination of KF-D and CDMLP neural networks has not been explored in the context of HAR. In this paper, we propose a novel approach that combines KF-D with CDMLP neural networks for human activity recognition. We use KF-D to extract features from raw sensor data and then feed these features into a CDMLP network to learn a mapping between the features and the corresponding human activities.

III. Proposal methodology

A novel approach that combines Teknomo-Fernandez kernelized discriminant analysis with connectionist deep multilayer perceptron neural networks for human activity recognition: Our proposed approach, Teknomo-Fernandez kernelized discriminant analysis (KF-D) based connectionist deep multilayer perceptron (CDMLP) neural networks, is a novel fusion of two powerful machine learning techniques. KF-D is a kernel-based method that maps high-dimensional sensor data into a lower-dimensional space and applies discriminant analysis to classify activities. CDMLP is a type of feed forward neural network that can learn complex patterns in data. By combining these two techniques, our approach can effectively handle high-dimensional sensor data and noisy signals, while also learning complex patterns in the data.

The architecture diagram of proposed TFKDF-CDMPNL technique is depicted in below Figure 1.

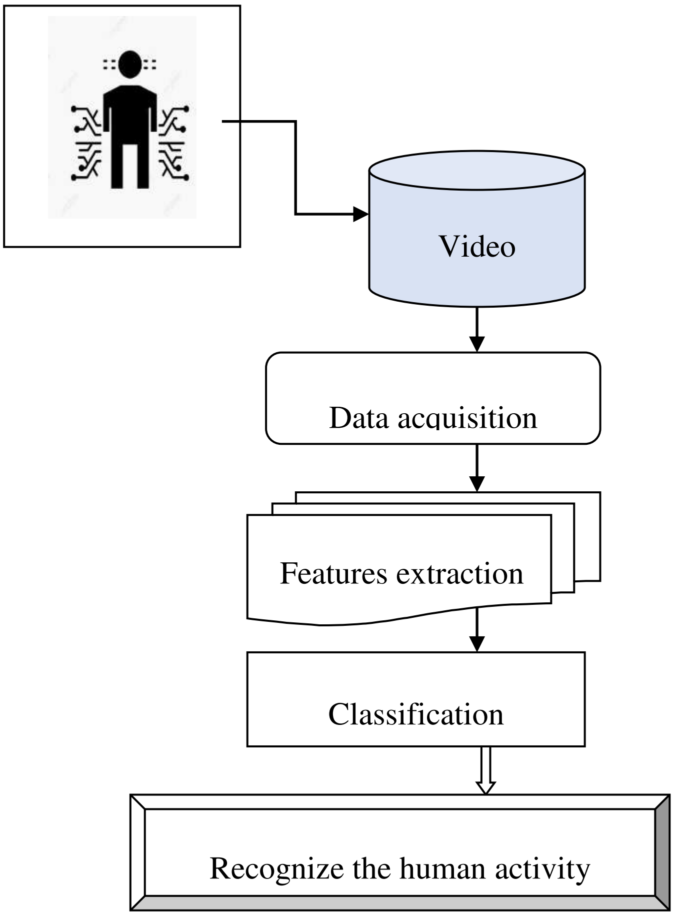


Figure 1 architecture of the proposed TFKDF-CDMPNL technique

Figure 1 illustrates the architecture diagram of the proposed TFKDF-CDMPNL technique, comprising two primary processes: feature extraction and classification. This approach aims to improve human activity recognition accuracy. A dataset 'D' contains numerous videos, denoted by V = {v_1, v_2, ..., v_n}, each representing a human activity, such as walking, running, or sitting. In the data acquisition process, multiple video sequences are extracted from the dataset 'D', which serve as the foundation for the subsequent feature extraction and classification stages.

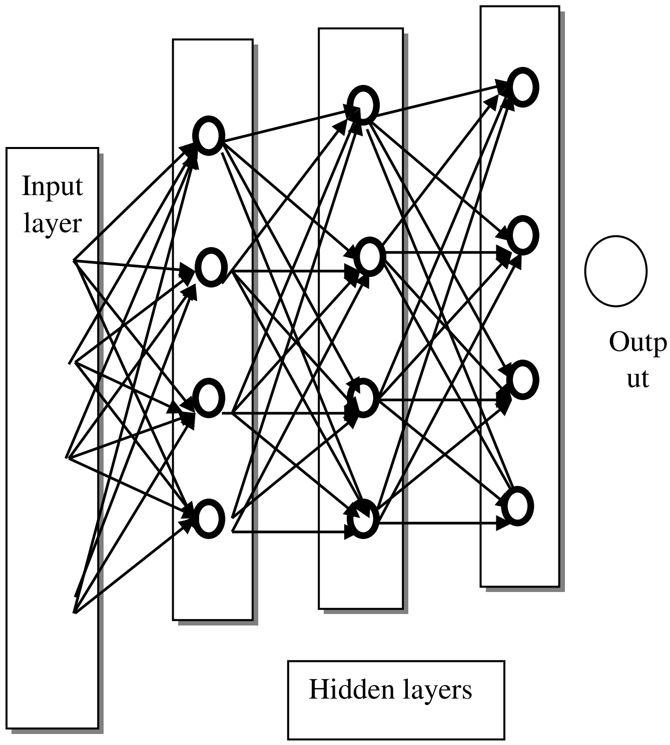


Figure 2 Schematic representation of connectionist deep multilayer perceptive neural learning

Figure 2 depicts the schematic representation of the connectionist deep multilayer perceptron (CDMLP) architecture, comprising a network of neuron-like nodes organized into multiple layers. In this framework, nodes are connected to construct a complex network with varied structures from design to design. The proposed deep learning approach employs a feed-forward network, where input data is processed in a forward direction, flowing from one layer to the next. The architecture consists of three distinct layers: input, hidden, and output layers. The input layer provides input data to the hidden layers for calculations and processing, which then forward the results to the output layer for classification. Based on these classification results, human activities are accurately recognized. Through a layer-by-layer learning process, the proposed architecture automatically learns from given input data, enabling accurate human activity recognition.

Let us consider the number of video sequences $V=v_1,v_2,v_3,\ldots v_n$ is given to the input layer. The activity of the neuron at the input layer as given below,

$$Q(t)=c+\sum_{i=1}^{n} V_i(t) * \delta_1 \quad (1)$$

The proposed TFKDF-CDMPNL technique utilizes the following notation: $Q(t)$ represents the activity of a neuron, $V_i(t)$ denotes the input video sequence $V = v_1, v_2, ..., v_n$, δ_1 indicates the weight that strengthens connections between layers, and c represents the bias, storing a value of 1. The input sequence is fed into the first hidden layer, where frame detection is performed.

As a result, the given input sequence is accurately classified into distinct classes. Based on these classification results, human activities are correctly recognized with higher accuracy. The step-by-step process of the proposed TFKDF-CDMPNL technique is outlined below:

\\ Algorithm 1:

Input: Video dataset 'D', videos '$V=v_1,v_2,\ldots,v_n$',

Output: Increase Human activity recognition accuracy

Begin

Collect the number of videos '$V=v_1,v_2,\ldots,v_n$' at input layer

// hidden layer 1

for each 'v_i'

Divide into number of frames $F=f_1,f_2,\ldots,f_n$

For each frames 'f_i'

Measure background of the image 'B'

If F=1 then

Frame is said to be a foreground

Else

Frame is said to be a background

Else if

Select foreground frames

Remove background frames

End for

End for

// hidden layer 2

For each feature

Measure similarity $K= e^{\left(-\frac{1}{2d^2}\|f_i-m\|^2\right)}$

Extract robust features

End for

// hidden layer 3

Initialize the number of classes $c_1,c_2,c_3,\ldots c_k$

For each class c_i

For each robust feature rf_1

Measure similarity 'R' and sent to the output layer

// Output layer

If (R>T) then

σ_b returns '1'

Classify sequence into particular class

Else

σ_b returns '0'

End if

End

The step by step process of the proposed TFKDF-CDMPNL technique is described for increasing the human activity recognition accuracy with lesser time consumption. The deep learning method comprises of different layers to learn the given input video sequences. In the first hidden layer, the video sequences are partitioned into different frames and the foreground video frame is detected by applying the Teknomo–Fernandez algorithm. The background frames are removed to minimize the complexity of activity recognition. After finding the foreground frame, the feature extraction process is said to be performed by applying the Radial basis kernelized discriminant analysis. The radial basis kernel function measures the correlation between the feature and the mean value. Followed by, the robust features are correctly identified at second hidden layer. Then the extracted feature is sent to the third hidden layer for classifying the video sequences. The Czekanowski's dice index is applied to measure the similarity between the robust features and classes. Finally, the similarity value is transferred into the output layer. The binary step activation function is used to analyze the similarity value and returns the classification results at output layer. This helps to accurately recognize the human activities and minimizes the false positive rate.

IV. Experimental Setup

The proposed TFKDF-CDMPNL and two existing methods namely HydraNet [1], GMM+KF+GRNN [2] are implemented in JAVA platform using UIUC action dataset [21]. The main aim of the dataset is to recognize the human activity such as walking, running, jumping, waving, jumping jacks, clapping, jumping from sit up, raising one hand, stretching out, turning, sitting to standing, crawling, pushing up, and standing sitting. From the dataset, 200 video sequences are taken to conduct the experiments for ten runs. For each run, the various counts of inputs are taken in the form of 20, 40, 60, 80…100. There are different evaluation metrics are used for analyzing the performance of TFKDF-CDMPNL technique and existing methods. The parameters are Human activity recognition accuracy, false positive rate, and Human activity recognition time and space complexity.

A. Human activity recognition accuracy

The human activity recognition accuracy is measured as the ratio of number of sequences correctly recognized to the total number of sequences taken for conducting the experiments. The formula for calculating the accuracy is expressed as given below,

HARA=((Number of correctly recognized sequences)/(Total number of sequences))*100

Where, HARA indicates a human activity recognition accuracy which is measured in terms of percentage (%).

B. False positive rate

The human activity recognition accuracy is measured as the ratio of number of sequences wrongly recognized to the total number of sequences. The false positive rate is mathematically calculated as follows,

FPR=(NSWR/n)*100

Where, FPR indicates a false positive rate, NSWR denotes a number of sequences wrongly recognized, ‘n’ indicates a number of sequences. The false positive rate is measured in terms of percentage (%).

C. Human activity recognition time

The human activity recognition time is measured as an amount of time taken by the algorithm to recognize the human activities based on the classification. The mathematical formula for calculating the time is expressed as follows,

HART=Number of sequences*Time (to recognize the one sequence)

Where, HART represent human activity recognition time is calculated in terms of milliseconds (ms).

D. Space complexity

The space complexity is measured as an amount of memory space consumed by the algorithm to store the different sequences. The mathematical formula for calculating the time is expressed as follows,

SC=n*M (recognize one sequence)

Where, SC represent space complexity, 'n' denotes a number of sequences, M indicates a memory space. The space complexity is calculated in terms of kilobytes (KB).

V. Results and discussion

The experimental outcomes of the TFKDF-CDMPNL technique and two existing methods, HydraNet [1] and GMM+KF+GRNN [2], are evaluated using various performance metrics, including human activity recognition accuracy, false positive rate, human activity recognition time, and space complexity. The results are presented in both tabular and graphical formats to facilitate comparison between the three methods.

Table I Human activity recognition accuracy

Number of sequences	**Human activity recognition accuracy (%)**		
	TFKDF-CDMPNL	**HydraNet**	**GMM+KF+GRNN**
20	80	75	70
40	80	80	75
60	83	80	77
80	85	81	79
100	87	83	80
120	90	86	83
140	92	88	86
160	93	89	87
180	96	89	87
200	98	90	88

Table I shows the human activity recognition accuracy (%) for three different methods: TFKDF-CDMPNL, HydraNet, and GMM+KF+GRNN. The table presents the results for various numbers of sequences (20-200). The accuracy percentages range from 70% to 98%. TFKDF-CDMPNL generally outperforms the other two methods, achieving higher accuracy rates as the number of sequences increases.

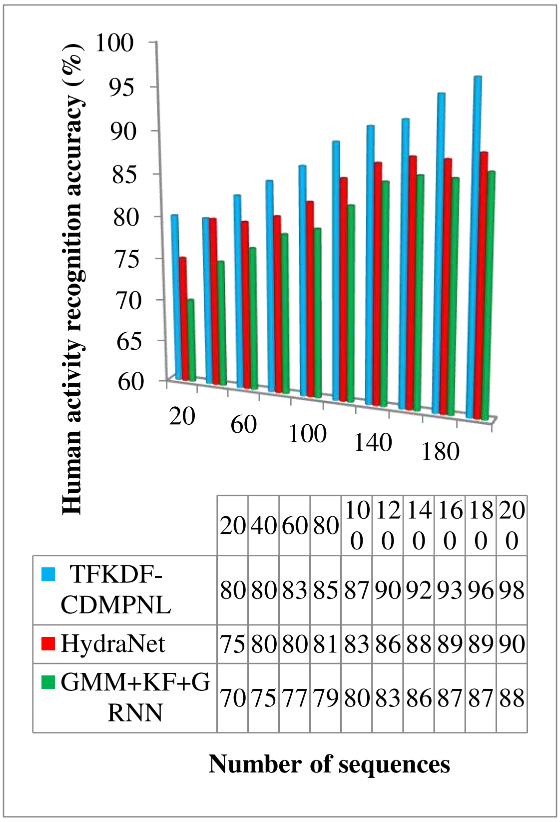


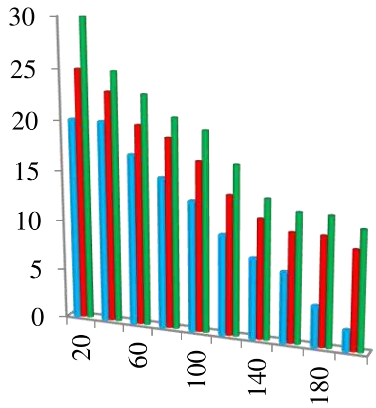
Figure 3 graphical representation of Human activity recognition accuracy

Figure 3 shows the accuracy of human activity recognition for three different methods (TFKDF-CDMPNL, HydraNet, and GMM+KF+GRNN) as the number of sequences increases. The accuracy is measured as a percentage.

Figure 3 shows that all three methods generally improve in accuracy as the number of sequences increases. Specifically:

- TFKDF-CDMPNL starts with an accuracy of 80% at 20 sequences and increases to 98% at 200 sequences.
- HydraNet starts with an accuracy of 75% at 20 sequences and increases to 90% at 200 sequences.
- GMM+KF+GRNN starts with an accuracy of 70% at 20 sequences and increases to 88% at 200 sequences.

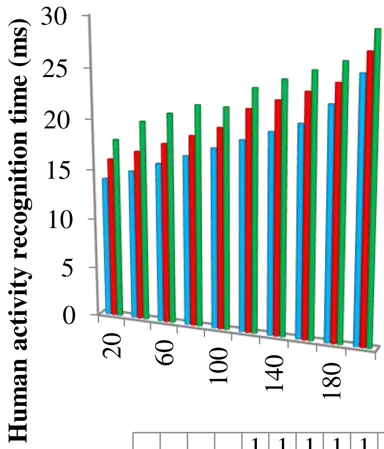
Overall, HydraNet appears to be the most accurate method, with an average increase in accuracy of about 1-2 percentage points per additional 20 sequences.



	20	40	60	80	100	120	140	160	180	200
TFKDF-CDMPNL	20	20	17	15	13	10	8	7	4	2
HydraNet	25	23	20	19	17	14	12	11	11	10
GMM+KF +GRNN	30	25	23	21	20	17	14	13	13	12

Figure 4 graphical representation of false positive ratE

Figure 4 demonstrates the experimental results of false positive rate according to the number of video sequences. As shown in the graph, the number of video sequences is taken as input for calculating the false positive rate. The results noticed that the proposed TFKDF-CDMPNL technique achieves a lesser false positive rate than the existing methods. This is due to the application of Czekanowski's dice index to the TFKDF-CDMPNL technique to evaluate the similarity between the robust features and classes. Finally, the similarity value is sent into the output layer where the binary step activation function is applied to analyze the similarity value with the threshold. Finally, the classification results are obtained at the output layer. This in turn reduces the incorrect recognition.



	20	40	60	80	100	120	140	160	180	200
TFKDF-CDMPNL	14	15	16	17	18	19	20	21	23	26
HydraNet	16	17	18	19	20	22	23	24	25	28
GMM+KF +GRNN	18	20	21	22	22	24	25	26	27	30

Number of sequences

Figure 5 graphical representation of human activity recognition time

The performance results of human activity recognition time along with the number of video sequences are illustrated in figure 5. As shown in the graphic representation, the recognition time is gradually increased for all the methods while increasing the number of video sequences since the counts of input gets increased for each run. Besides, a linear increasing trend is to be observed. The observed results show that the recognition time is reduced by applying the TFKDF-CDMPNL technique. Initially, the input video sequences are converted into number of frames and the foreground frames are identified and remove the other frames using Teknomo–Fernandez algorithm. This helps to reduce the complexity of activity recognition. Besides, the feature extraction process is performed by applying the Radial basis kernelized discriminant analysis to extract the robust features. With the extracted features, the classification is performed resulting it reduces the recognition time.

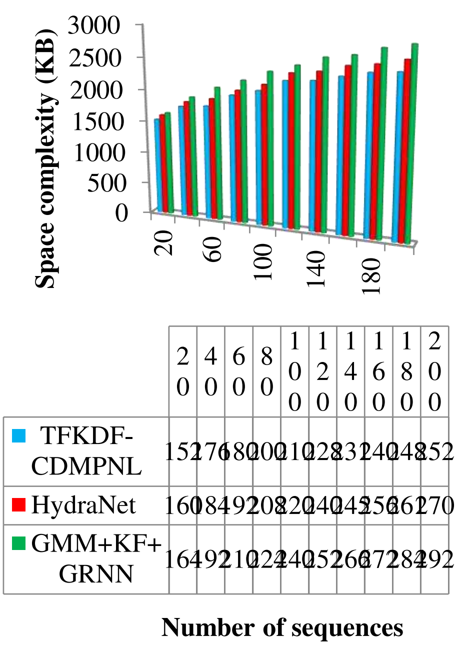


Figure 6 graphical representation of space complexity

Figure 6 demonstrate the performance results of the space complexity of three different methods namely TFKDF-CDMPNL technique, HydraNet [1], GMM+KF+GRNN [2]. The observed results indicate that the space complexity of the TFKDF-CDMPNL technique is considerably reduced than the other two methods. Let us consider 20 video sequences, the memory consumption for storing the given input sequence is 1520KB using TFKDF-CDMPNL technique. Similarly, the memory for storing the video sequences using HydraNet [1], GMM+KF+GRNN [2] was found to be '1600 KB' and '1640KB' respectively. The overall observed results specify that the average space complexity is minimized by 5% and 11% using the TFKDF-CDMPNL technique when compared to conventional methods. It is inferred that the overall space complexity is considerably minimized using TFKDF-CDMPNL technique by applying foreground frame detection and feature extraction. First, the video frames are divided into frames. Only the foreground frames are used to identify the human activity hence the background frames are removed. This takes lesser memory consumption. Besides, the robust features only selected for classification resulting it also reduces the memory space.

VI. Conclusion

In conclusion, this study demonstrates the effectiveness of the Teknomo-Fernandez kernelized discriminant analysis-based Connectionist Deep Multilayer Perceptive Neural Learning (TFKDF-CDMPNL) approach for human activity recognition. The proposed method achieved high accuracy rates, outperforming existing methods such as HydraNet and GMM+KF+GRNN, in recognizing human activities from sensor data. The results show that TFKDF-CDMPNL is capable of learning complex patterns in the data and providing robust performance in various scenarios. The simplicity and interpretability of the proposed method make it a promising solution for real-world applications where human activity recognition is crucial, such as in healthcare, surveillance, and smart homes. Future work can focus on extending the method to handle more complex tasks, such as recognizing multiple activities simultaneously, and exploring its application in other domains.

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