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Research Article

Performance Analysis of Priority Generation System for Multimedia Video using ANFIS Classifier

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Abstract:

The priority-based multimedia video transmission over the cloud system uses different bandwidth functioned multimedia video information which has been sent or transmitted to the cloud system through the priority selection system. This priority selection system uses machine learning algorithm for selecting the highest priority of the multimedia video and passes the multimedia video having the high priority to the cloud system. The proposed Workflow Computations and Scheduling (WCS) system using machine learning algorithm has consisted of three stages as preprocessing, feature computations with Principal Component Analysis (PCA) and Adaptive Neuro Fuzzy Inference System (ANFIS) classifier. The preprocessing stage of the proposed system is used to separate the frames from each multimedia video and the RGB frame has been converted into grey scale frame in this stage. The features are estimated from each grey scale frame and these features are scrutinized using PCA. The final scrutinized features are fed into ANFIS classifier to generate the priority results. The performance of the proposed WCS system has been analyzed in Amazon EC2 cloud environment with respect to Make Span (MS) and Execution Cost (EC).

1. Introduction

The internet medium at present day is having large volume of information in the form of multimedia data, video, audio and graphics. This type of multimedia information occupies more bandwidth over the public internet medium which slows down the entire operation of the communication network [1,2]. Moreover, it requires larger memory area with high level of multimedia data protection. In order to reduce the over burden of the large multimedia information playing on the public internet medium, there is a need for implementing cloud structure on the public internet medium. By implementing cloud system or structure on the internet medium, the handling and processing of the multimedia information over the public internet is simplified. In addition to this, priority of the multimedia information flow is also important to reduce the congestion over the same communication medium with limited bandwidth and memory resources [3,4]. The priority of the multimedia video has been chosen based on the contents and its impact. The selection of priority is done by implementing artificial intelligence techniques on the multimedia video information. The artificial intelligence techniques use either machine learning algorithm or deep learning algorithm for generating the priority sequences for the multimedia video information. The machine learning techniques based priority selection methods used Support Vector Machine (SVM) with different polynomial kernels and Artificial Neural Networks (ANN). The existing machine learning based priority selection methods has overfitting problem with the input multimedia video information and also they consumed more priority generation time period due to its inbuilt kernel functions. These limitations of the machine learning techniques reduce the functional efficiency of the priority selection system over the cloud system [5-10]. Hence, the over fitting problem of the existing machine learning algorithm can be mitigated using fuzzy incorporating neural network which generates the ANFIS structure for the efficient generation of priority sequences for the multimedia video information. The ANFIS classifier has been operated by a unique kernel structure which further enhanced by the fuzzy rules. Hence, this research work uses ANFIS classification structure based priority selection method for the cloud system.

Figure 1 is the priority based multimedia video transmission over the cloud system, where the different bandwidth functioned multimedia video information has been sent or transmitted to the cloud system through the priority selection system. This priority selection system uses machine learning algorithm for selecting the highest priority of the multimedia video and passes the multimedia video having the high priority to the cloud system.

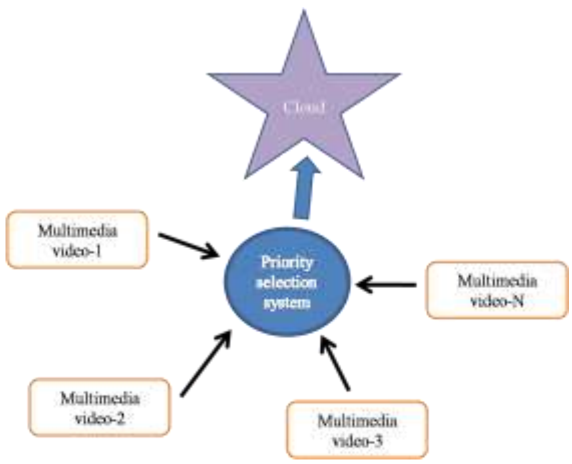


Figure 1 *Priority based multimedia video transmission over the cloud system*

This paper has been split into several functional and descriptive modules, where the existing priority based multimedia video selection methods are elaborated in module 2, the proposed ANFIS based multimedia video priority selection method has been proposed in module 3, the experimental results of the priority selection method with respect to various cloud systems or environments have been illustrated in module 4 and finally module 5 details about the summary of this research paper in detail with its limitations.

2. Literature survey

Chiang et al. [11] proposed a novel cloud system management algorithm using load balancing approach. The performance of the task scheduling and management was done through the load matching and balancing approach. The authors modified the conventional load balancing algorithm for task scheduling process. The main limitation of this method was that it did not support large number of tasks at the same time which degraded the functional efficiency of the cloud system. The authors obtained 96.1% of functional efficiency for the work flow computation process using the load balancing algorithm. An ANFIS classification structure was projected by Kumarganesh et al. [6] in order to classify cancers from groundwork pictures, and they were successful in achieving 97.63% segmentation accuracy. To identify cancers in simple images, Kumarganesh et al. [12] suggested using an adaptable fuzzy inference system (ANFIS) classification approach, which they found to have a 96.6% classification accuracy. Naela Rizvi et al. [13] developed an effective work flow computational and scheduling algorithm for the public and private clouds systems using genetic algorithm. The existing static genetic algorithm was modified into dynamic genetic algorithm by modifying the number of internal hyper parameters of the algorithm for cloud services system. This modified genetic algorithm has been influenced by the functional fuzzy rules which were constructed for the task work flows and scheduling in this work. This proposed task scheduling methodology has been tested on various active cloud systems with respect to different number of tasks in nature. The authors obtained 167.79 ms of make span and also obtained 276.3 ms of execution time period for the public cloud system. The authors obtained 178.3 ms of make span and also obtained 281.3 ms of execution time period for the private cloud system.

Imene et al. [10] performed task generation and scheduling work using genetic algorithm based work flow computational environment. This proposed based used fuzzy logic incorporated genetic algorithm and varies the functional behaviour of each mutation and crossover process. Due to this optimization procedure between the different tasks, the work flow computational efficiency has been improved. The authors obtained 94.5% of functional efficiency for the work flow computation process using the fuzzy incorporating genetic algorithm.

Neha Garg et al. [14] proposed energy aware work flow computation and scheduling algorithm for cloud systems. This energy aware algorithm for high number of tasks was tested in both public and private clouds. The authors obtained 276.1 ms of make span and also obtained 329.1 ms of execution time period for the public cloud system. The authors obtained 387.3 ms of make span and also obtained 392.1 ms of execution time period for the private cloud system. Tharani et al. [15] used hybrid classification structure for the effective management of the tasks in cloud environment. The authors combined the machine learning algorithm with the deep learning algorithm for the effective improvement of the task work flow computations and scheduling process. Jia et al. [16] used Whale Optimization Algorithm (WOA) for the effective task work flow computation and scheduling process. Concurrent multipath transfer (CMT) was developed by S. Kumarganesh et al. [17] for radiocommunication heterogeneous networks for video streaming applications, and frame-level delay performance can be improved for higher video quality.

This proposed hybrid structures were tested on different cloud environment system for estimating the performance efficiency. The authors obtained 167.3 ms of make span and also obtained 198.5 ms of execution time period for the public cloud system. The authors obtained 156.3 ms of make span and also obtained 193.9 ms of execution time period for the private cloud system. The performance efficiency of this WOA was compared with the performance efficiency of the other similar task optimization algorithms in this paper with respect to various set of clouds.

3. Proposed methodologies

The proposed WCS system using machine learning algorithm has consisted of three stages as preprocessing, feature computations with PCA and ANFIS classifier. The preprocessing stage of the proposed system is used to separate the frames from each multimedia video and the RGB frame has been converted into grey scale frame in this stage. The features are estimated from each grey scale frame and these features are scrutinized using PCA. The final scrutinized features are fed into ANFIS classifier to generate the priority results. The entire flow of the priority generation system is illustrated in figure 2.

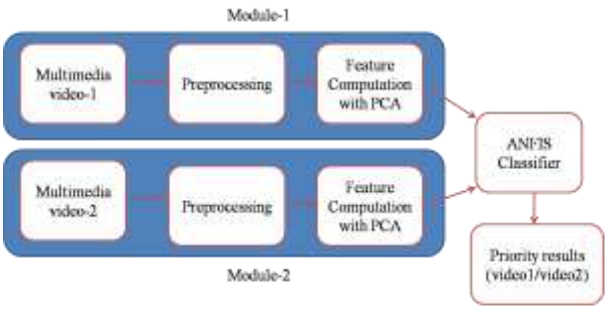


Figure 2 *Proposed Workflow Computations and Scheduling (WCS) using Machine learning Algorithm*

Feature computations

The feature values are computed from the multimedia frames of the multimedia video which are used to compute the priority values. In this paper, the following features have been computed from each frame of the multimedia video and they are stored in a two-dimensional vector matrix for further scrutinizing process.

Let $F(i,j)$ be the frame in multimedia video with respect the pixel coordinates i and j.

$$Mean\ (M) = \frac{\sum F(i,j)}{M*N} \quad (1)$$

Where, M and N are the rows and columns count in each frame of the multimedia video.

$$Mean\ Metric\ Index\ (MMI) = \frac{\sum F(i,j) - Min\ \{F(i,j)\}}{M*N} \quad (2)$$

$$Mean\ Max\ Index\ (MAI) = \frac{\sum F(i,j) - Max\ \{F(i,j)\}}{M*N} \quad (3)$$

$$Frame\ Contrast\ Index\ (FCI) = \sum_i \sum_j (i-j)^2 * F(i,j) \quad (4)$$

$$Frame\ Energy\ Index\ (FEI) = \sum_i \sum_j F(i,j)^2 \quad (5)$$

$$Frame\ Dissimilarity\ Index\ (FDI) = \sum_i \sum_j M * |i-j| \quad (6)$$

These features are computed for each frame of the multimedia video and they are stored in a two-dimensional feature matrix whose column and row are denoted by M and N respectively. In the similar way, these features are computed for all the frames in the multimedia video and the final two-dimensional feature matrix is fed into the PCA algorithm for reducing the size of the computed feature matrix.

PCA

The orthogonal transform has been used in PCA algorithm for converting the correlating coefficient values into uncorrelating coefficient variables. This algorithm is based on the linear shifting optimization technique which reduces the size of input pattern data. It is in the category of unsupervised algorithm. The algorithm receives the computed feature two dimensional matrix and produces the dimensionality reduces feature matrix. This PCA algorithm is explained in the following steps.

Step 1:

The standardization process is carried out for all the computed input features which satisfy the following criteria.

(i) Mean of each input feature should be zero;
(ii) Standard deviation of each input feature should be 1.

The standardization factor of all computed input variables has been determined using the following equation with the above criteria.

$$z = \frac{x-\mu}{\sigma} \quad (7)$$

Where, μ and σ are the mean and standard deviation of the computed features and they are given in the following vector formats.

$$\mu = \{\mu 1, \mu 2 \ldots . \mu M\} \quad (8)$$

$$\sigma = \{\sigma 1, \sigma 2 \ldots . \sigma M\} \quad (9)$$

Step 2:

To find the covariance between two variables which represent the covariance bond between them.

The covariance can be found using the following equation.

$$Covariance(p1, p2) = \frac{\sum_{i=1}^{N}(p1, p1i)(p2, p2i)}{N-1} \quad (10)$$

Where, N is the total number of computed features in two dimensional feature matrix.

The covariance factor is positive if p1 and p2 has the positive values in same direction and the covariance factor is negative if p1 and p2 has the negative values in opposite direction.

Step 3:

Find the Eigen values and Eigen vectors of each computed correlation variables.

Step 4:

Find the principal components of computed Eigen values and Eigen vectors.

Step 5:

Choose the optimum principal components among the all computed principal components.

ANFIS Classifications

Classification module is important for the priority selection in the proposed system. It performs the priority video selection based on the input parameters which are computed from the input multimedia video sequences. There are numerous conventional classification architectures available for priority based video selection process and used by many researchers in the past decades. Many researches in the priority based multimedia video selection process used existing AI technique and SVM. These methods consumed more priority selection time and hence it is not used in the proposed priority selection methods. Instead, ANFIS classification architecture has been used in this paper with minimum priority selection time period and optimize the priority selection output for multimedia video information transmission process. The ANFIS classification structure for priority selection is depicted in figure 3, where it is designed with five internal layers with two input patterns 'a' and 'b' along with the unique output pattern y as the priority state. The PCA based optimized values are fed into the input membership parameters P1, P2 and S2, S2 in membership layer. The output of this layer has been integrated with fuzification layer where the sugeno fuzzy model has been adopted. The fuzzified outputs from this layer are normalized by the nodes in the normalization layer which produces the normalized pattern output. This pattern is again defuzzified by the defuzzification layer and these defuzzified output patterns are summed up into unique pattern y, as illustrated in figure 3.

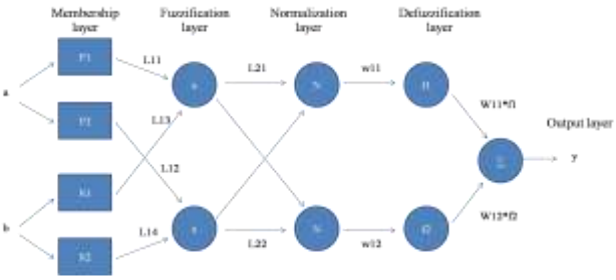


Figure 3 *ANFIS classification structure for priority selection*

In layer-1 of this ANFIS architecture, the following modelling rules are adopted with the input variables.

Input Model rule-1:

If (a==p1) && if (b==s1) then

{f1=p1a+q1b+k1};

Input Model rule-2:

If (a==p2) && if (b==s2) then

{f2=p2a+q2b+k2}

The functions of nodes in layer-1 of this architecture are given by the following equations.

$$L1, i = \mu_{pi}(a); \text{ for i=1 and 2}$$

$$L1, j = \mu_{qj}(b); \text{ for j=1 and 2}$$

$$\mu(x) = \frac{1}{1+\left|\frac{x-ci}{ai}\right|^{2b}} \quad (11)$$

Where as, {a,b,c} are the aligned functional parameters in the given fuzzy set.

Layer-2:

In this layer, all the internal nodes are fixed and labelled with different identifier. The nodes in this layer perform the multiplication function where the outputs of all the nodes are the product (or) multiplication of all the input parameters as given the following equations.

$$L21 = L11 * L13$$

$$L22 = L12 * L14$$

This layer also functioned by fuzzy AND operation and the nodes output are passed to next layer in sequential order.

Layer-3:

The nodes in this layer are also fixed and having static behaviour with all the nodes. The firing strength of each node are computed using the output functions from the previous layer. The nodes functioning in this layer is given in the following equations.

$$w11 = \frac{w1}{w1+w2} \quad (12)$$

$$w21 = \frac{w2}{w1+w2} \quad (13)$$

All the nodes in this layer are normalized by firing strength factors of all nodes.

Layer-4:

The nodes in this layer are adaptive and its functions are based on the normalizing strength of the previous layer. Its output function is given by,

$$L4 = wi * fi$$

Whereas, fi=pia+qib+ki;

Therefore, the functional output of this layer is given as,

$$L4 = wi * (\text{pia} + \text{qib} + \text{ki})$$

Layer-5:

It performs the summation operation which sums up all the output functions of the previous layer and it is given by,

$$y = \frac{\sum wi * fi}{\sum wi}$$

The final summed up unique value from this architecture has a factor value which produces the priority for the multimedia videos.

4. Results and Discussions

The proposed ANFIS based priority selection system has been evaluated using MATLAB R2022 [9-17] simulation software with Core i9 processor and 1TB hard disk drive with 16 GB RAM memory. The cloud system used in this paper is Amazon EC2. The performance of the proposed priority generation system for multimedia video [18] has been analyzed in terms of Make Span (MS) and Execution Cost (EC). Both performance estimation parameters for priority generation system are measured in milli seconds (ms). Table 1 is the estimation of MS and EC computational parameters on the proposed WCS system [19] using ANFIS classifier incorporating PCA.

Table 1 *Estimation of MS and EC on the proposed WCS system*

Running Module	**Methods combinations**	**Frames count in multimedia video**	**MS (ms)**	**EC (ms)**
Module 1	ANFIS	1000	78.3	109.3
	PCA		69.2	89.3
	PCA + ANFIS		**55.4**	**77.9**
Module 2	ANFIS	10000	156.9	198.3
	PCA		143.2	163.9
	PCA + ANFIS		**112.8**	**151.2**
Module 3	ANFIS	50000	382.2	403.4
	PCA		302.1	204.5
	PCA + ANFIS		**167.3**	**178.3**
Module 4	ANFIS	100000	456.3	536.2
	PCA		378.9	453.2
	PCA + ANFIS		**205.6**	**302.5**

The module 1 contains 1000 frames, module 2 contains 10000 frames, module 3 contains 50000 frames and module 4 contains 100000 frames. The proposed WCS system using ANFIS classifier attains 55.4 ms MS and 77.9 ms EC for module 1, attains 112.8 ms MS and 151.2 ms EC for module 2, attains 167.3 ms MS and 178.3 ms EC for module 3 and attains 205.6 ms MS and 302.5 ms EC for module 4. Table 2 is the systematic comparative study of the proposed WCS system [20] with respect to four different modules in terms of MS and EC.

From this analysis, the value of MS and EC are higher in Module 1 when compared with other modules. Figure 4 is the graphical representation of systematic comparative study of the proposed WCS system.

Table 2 *Systematic comparative study of the proposed WCS system*

Running Module	MS (ms)	EC (ms)
Module 1	55.4	77.9
Module 2	112.8	151.2
Module 3	167.3	178.3
Module 4	205.6	302.5

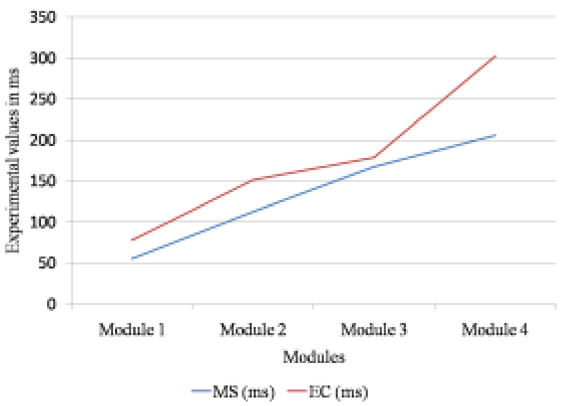


Figure 4 *Graphical representation of systematic comparative study of the proposed WCS system*

Table 3 is the performance estimation of the proposed WCS system with respect to various classifiers environments on Module 1. In this work, the performance of the ANFIS based priority generation system has been compared with Support Vector Machine (SVM), Radial neural networks, Adaboost classifier and Fuzzy C Means (FCM) classifiers in terms of MS and EC. Figure 5 is the graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 1.

Table 3 *Performance estimation of the proposed WCS system with respect to various classifiers environments on Module 1*

Classifiers environment	MS (ms)	EC (ms)
ANFIS	55.4	77.9
SVM	103.2	94.3
Radial Neural Networks	176.4	107.2
Adaboost classifier	189.6	205.3
FCM	207.3	287.9

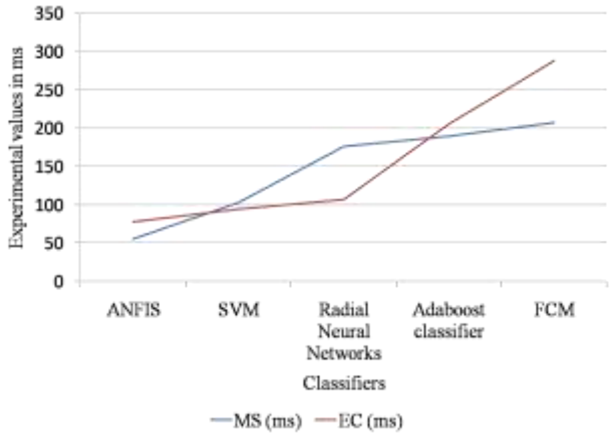


Figure 5 *Graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 1*

Table 4 is the performance estimation of the proposed WCS system with respect to various classifiers environments on Module 2. In this work, the performance of the ANFIS based priority generation system has been compared with SVM, Radial neural networks, Adaboost classifier and FCM classifiers in terms of MS and EC. From this extensive analysis, the proposed ANFIS based priority generation system has higher performance than the other classification algorithms. Figure 6 is the graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 2. Table 5 is the performance estimation of the proposed WCS system with respect to various classifiers environments on Module 3. From this extensive analysis, the proposed ANFIS based priority generation system has higher performance than the other classification algorithms. Figure 7 is the graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 3. Table 6 is the performance estimation of the proposed WCS system with respect to various classifiers environments on Module 4.

Table 4 *Performance estimation of the proposed WCS system with respect to various classifiers environments on Module 2*

Classifiers environment	MS (ms)	EC (ms)
ANFIS	112.8	151.2
SVM	145.3	156.9
Radial Neural Networks	189.2	203.6
Adaboost classifier	297.4	302.8
FCM	312.7	376.3

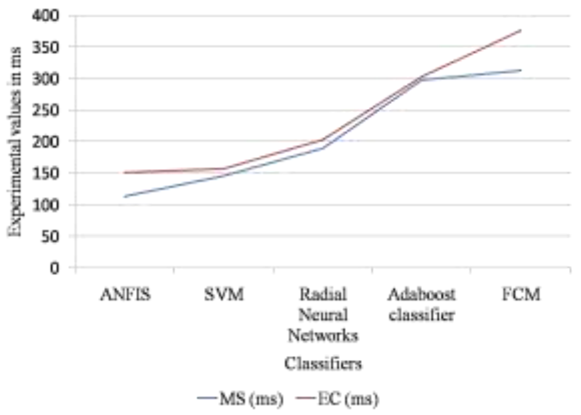


Figure 6 *Graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 2*

Table 5 *Performance estimation of the proposed WCS system with respect to various classifiers environments on Module 3*

Classifiers environment	MS (ms)	EC (ms)
ANFIS	167.3	178.3
SVM	204.3	267.3
Radial Neural Networks	289.3	302.8
Adaboost classifier	302.6	383.2
FCM	327.9	387.6

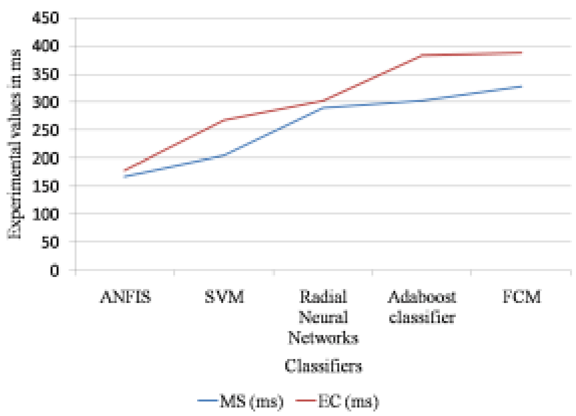


Figure 7 *Graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 3*

From this extensive analysis, the proposed ANFIS based priority generation system has higher performance than the other classification algorithms. Figure 8 is the graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 4. Table 7 is the computational comparisons of proposed WCS system with other state of the art methods.

Table 6 *Performance estimation of the proposed WCS system with respect to various classifiers environments on Module 4*

Classifiers environment	MS (ms)	EC (ms)
ANFIS	205.6	302.5
SVM	278.3	378.2
Radial Neural Networks	309.5	402.3
Adaboost classifier	367.3	445.6
FCM	405.2	487.3

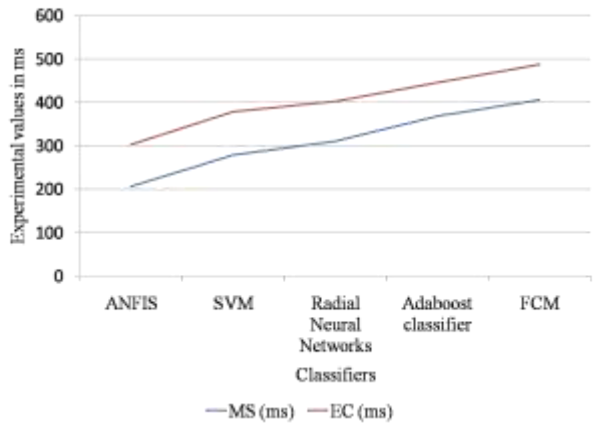
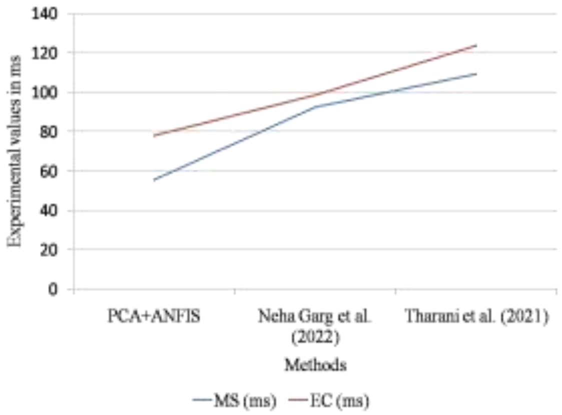


Figure 8 *Graphical performance estimation of the proposed WCS system with respect to various classifiers environments on Module 4*

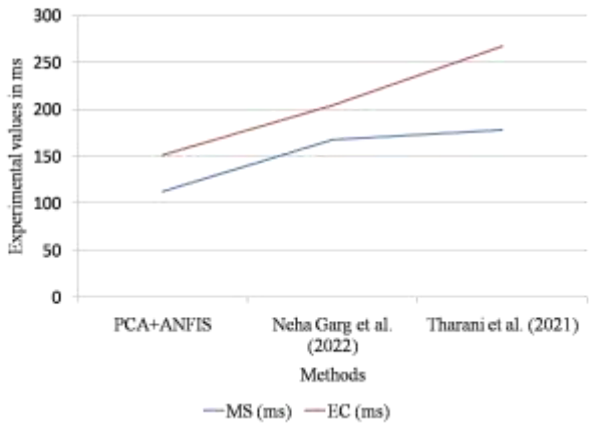
Table 7 *Computational comparisons of proposed WCS system with other state of the art methods*

Classification Algorithms	**Number of tasks**	**Computational parameters**	
		MS (ms)	**EC (ms)**
PCA+ANFIS (Proposed work)	1000	55.4	77.9
[14]		92.3	98.5
[15]		109.3	123.8
PCA+ANFIS (Proposed work)	10000	112.8	151.2
[14]		167.6	204.5
[15]		178.0	267.3
PCA+ANFIS (Proposed work)	50000	167.3	178.3
[14]		204.5	276.9
[15]		278.9	298.4
PCA+ANFIS (Proposed work)	100000	205.6	302.5
[14]		289.3	356.9
[15]		298.7	389.3

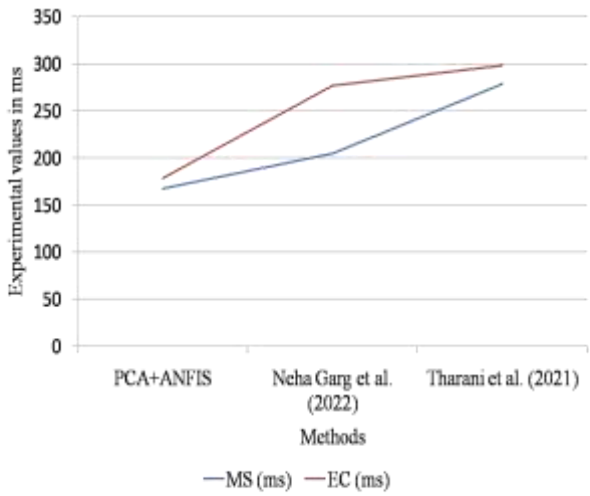
Figure 9 shows the performance comparisons of proposed WCS system with other state of the art methods (a) 1000 tasks (b) 10000 tasks (c) 50000 tasks (d) 100000 tasks.



(a)



(b)



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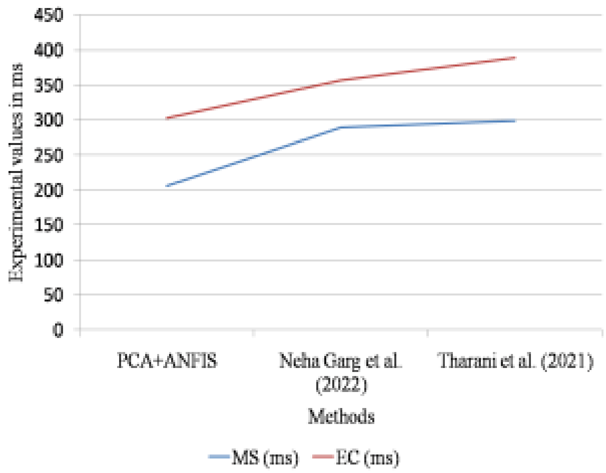

(d)

Figure 9 *Performance comparisons of proposed WCS system with other state of the art methods (a) 1000 tasks (b) 10000 tasks (c) 50000 tasks (d) 100000 tasks*

6. Conclusions

The proposed WCS system using machine learning algorithm has consisted of three stages as preprocessing, feature computations with PCA and ANFIS classifier. The performance of the proposed priority generation system for multimedia video has been analyzed in terms of MS and EC. The module 1 contains 1000 frames, module 2 contains 10000 frames, module 3 contains 50000 frames and module 4 contains 100000 frames. The proposed WCS system using ANFIS classifier attains 55.4 ms MS and 77.9 ms EC for module 1, attains 112.8 ms MS and 151.2 ms EC for module 2, attains 167.3 ms MS and 178.3 ms EC for module 3 and attains 205.6 ms MS and 302.5 ms EC for module 4. Though the experimental results using ANFIS classifier obtains higher results, they are not enough for handling larger multimedia files at the same time. This limitation has been overcome by proposing deep learning methodologies for priority generation is considered as future scope of this research work.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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