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An Effective Methodology for Cloud-Based Priority Generation System using an ANFIS-CNN Classification Architecture

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Abstract

The cloud architecture improves the memory capacity and optimizes bandwidth across the entire network architecture, facilitating the transmission and the reception of large amounts of multimedia data. The cloud system requires workflow computation and a scheduling algorithm to enhance the network performance. Therefore, this algorithm generates the priority of each multimedia data stream for effective transmission over the wireless network. In this research, a priority (PR) generation system is proposed for the efficient transmission of large multimedia videos over wireless networks through cloud architecture. This proposed system involves preprocessing video frames, computing features, and classifying them using the ANFIS-CNN classifier. This classifier is the integration of an adaptive neuro-fuzzy inference system (ANFIS) and the Convolutional Neural Network (CNN) classifier. The ANFIS-CNN based priority generation algorithm has been tested on two independent cloud platforms: Microsoft Azure and Amazon EC2. Experiment results from these cloud platforms have been compared with other existing algorithms for the priority generation process.

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1. Introduction

The advanced wireless and mobile phone technologies on the internet require the transfer of large amount of data, such as multimedia videos, audio, and files, to the network continuously. This requires larger network bandwidth to transfer and receive all this multimedia data without degrading the network performance. Though the existing system provides sufficient network performance, its high memory requirements gradually degrade the performance of transferring and receiving multimedia data [1-4]. The cloud environment enhances the memory capacity and optimizes bandwidth across the entire networking architecture, addressing the bandwidth limitation of the existing system. The cloud system employs three types of services: Public cloud, Private cloud and Hybrid cloud. Each cloud service type is differentiated by its utilization and access through the remote virtual machines. The public cloud uses a shared memory area accessible to all users through the same communication medium [5-6]. The private cloud provides separate memory for each individual user, with access requiring authentication through the user's name, passwords, and activation token. The features of both public and private cloud are combined to produce the Hybrid cloud, which allows the users to access memory in both public and private environments [7]. Figure 1 shows the cloud system architecture, including the number of modules.

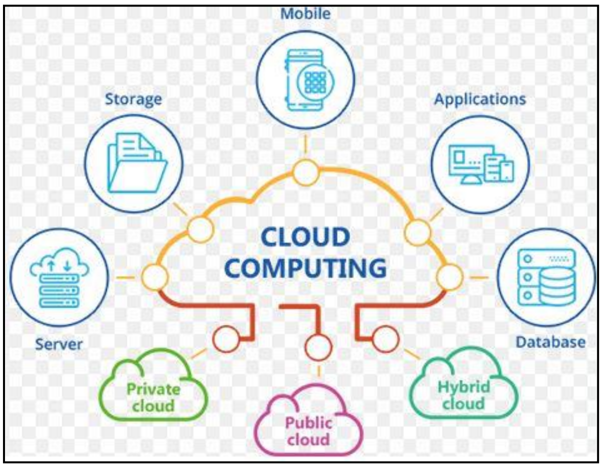


Figure 1. Cloud System Architecture

The cloud system requires workflow computation and a scheduling algorithm to enhance network performance. Consequently, the priority of each multimedia data stream is generated by this algorithm for the effective transmission of multimedia data over the wireless network system. In this study, a priority generation method for multimedia video files, combining the machine learning (ANFIS) and deep learning (CNN) algorithm, has been proposed.

This research has been structured into several sections: Section 2 elaborates on conventional priority generation methods; Subsection 3 presents the proposed priority generation system based on the ANFIS-CNN classification algorithm; Subsection 4 provides the experimental results of the ANFIS-CNN classification algorithm; and Subsection 5 concludes the research.

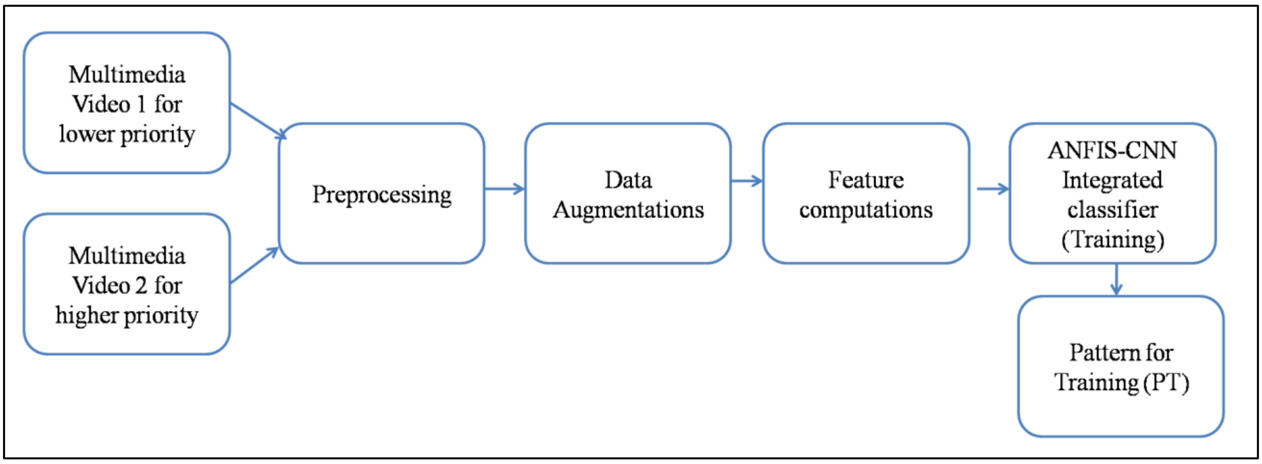
2. Literature Survey

Babuli Sahu et al. (2023) proposed a multi-objective classification algorithm for generating the priority results for each multimedia video in the cloud system. This work used the Cuckoo Search Algorithm (CSA) for optimizing and prioritizing the features of the multimedia video. This proposed CSA based workflow computation methodology has been tested on various cloud platforms to check the efficiency of the developed system for PR generation sequences. The authors obtained a response time of 16.6 ms for make span (MS) and 21.8 ms for execution time (ET) with 100 tasks on the Microsoft Azure cloud platform. For 5,000 tasks, the response times were 55.9 ms for MS and 58.9 ms for ET on the same platform [8]. Singh et al. (2020) used an energy-efficient cloud optimization algorithm to enhance the performance of the cloud-based systems. The work proposed in this study has been validated using various optimization algorithms to assess the effectiveness of the system. The authors obtained 21.8 ms MS and 29.8 ms ET for 100 tasks on the Microsoft Azure cloud platform and 61.8 ms MS and 67.7 ms ET for 5000 tasks on the Microsoft Azure cloud platform. [9]. Gao et al. (2019) developed a workflow computation and scheduling algorithm for generating the priority sequences for each multimedia video in a cloud system. This research proposed a hybrid workflow algorithm that combined the non-linear and linear algorithms for generating the priority sequences for each processed multimedia video. The authors obtained 25.6ms MS and 31.7ms ET for 100 tasks on Microsoft Azure cloud platform and obtained 67.9ms MS and 71.9ms ET for 5000 on Microsoft Azure cloud platform [10].

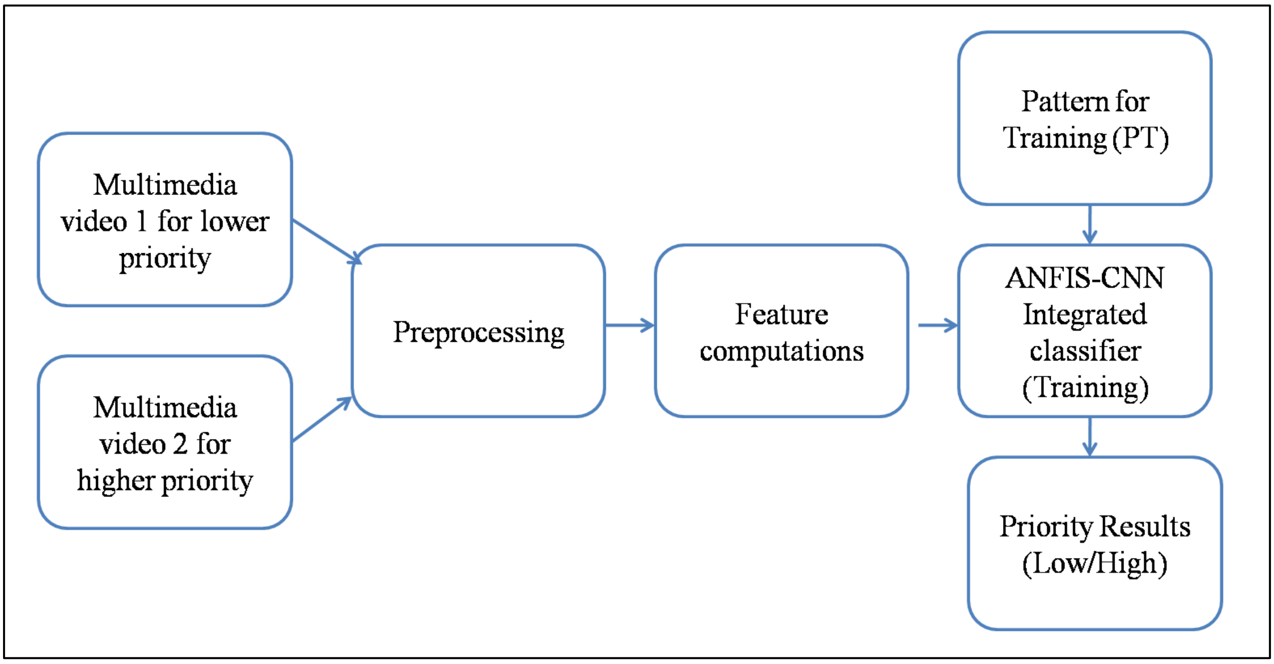
Jain et al. (2019) used a provocation enhanced algorithm for workflow computation and scheduling processes in cloud systems. The entire cloud model has been divided into several sub modules and each module has been used by different virtual machine to enhance bandwidth of the processed multimedia video frames over the larger cloud environment. The authors obtained 51.7ms MS and 56.9ms ET for 100 tasks on Microsoft Azure cloud platform and 78.3ms MS and 79.9ms ET for 5000 tasks on Microsoft Azure cloud platform [11]. Wu et al. (2017) developed a cost optimization algorithm for resource constrained cloud systems using a cloud workflow scheduling algorithm. In this work, the optimization was entirely based on the workflow determinations of each multimedia video, and based on this process, the priority sequence was generated by the proposed system. The authors obtained 71.2ms MS and 70.8ms ET for 100 tasks on Microsoft Azure cloud platform and 81.3ms MS and 84.7ms ET for 5000 tasks on Microsoft Azure cloud platform [12].

3. Proposed Method

Figure 2 (a) is the video frame training pattern generation in ANFIS-CNN Integration classifier during training stage and Figure 2(b) is the video frame priority generation in ANFIS-CNN Integration classifier during testing stage.



(a)



(b)

Figure 2. (a) Video Frame Training Pattern Generation in ANFIS-CNN Integration Classifier during Training Stage (b) Video Frame Priority Generation in ANFIS-CNN Integration Classifier during Testing Stage

In this research, a priority (PR) generation system is proposed for the effective transmission of the large multimedia video over wireless networks through cloud architecture. The proposed system includes of preprocessing video frames, Feature computations and the classifications through the proposed ANFIS-CNN classifier. This classifier is the integration of the ANFIS classifier and the Convolutional Neural Network (CNN) classifier. This proposed ANFIS_CNN based priority generation algorithm has been tested on two independent cloud platforms. The experimental results from these cloud platforms are compared with other existing algorithms for the priority generation process.

The proposed priority generation for multimedia video in cloud system environment has following internal modules.

- Preprocessing Video Frames;
- Feature Computations;
- Classifications through ANFIS-CNN classifier;

3.1 Preprocessing

This process is performed before classification of the multimedia video for PR generation in the proposed system. In general, the multimedia video contains a large number of RGB color frames, with each pixel in this frame consisting of 24 bits, representing the pixel's resolution. Consequently, the processing time for each frame is high, and thus, it cannot be directly applied to the next module of the proposed system. Therefore, each RGB frame is converted into the YCbCr color space, which reduces the processing time for subsequent stages. This conversion process is commonly used in all image and video processing system.

The conversion of RGB frame into YcbCr frame has been illustrated by the following equations.

$$Y = 16 + (65.48\,R + 128.5\,G + 24.9\,B) \quad (1)$$

$$Cb = 128 + (-37.7\,R - 74.2\,G + 112\,B) \quad (2)$$

$$Cr = 128 + (112\,R - 93.7\,G - 18.2\,B) \quad (3)$$

This process produces a luminance component and chrominance component from each RGB frame in the multimedia video sequences.

3.2 Feature computations

In this work, features are computed from each luminance and chrominance frame in each multimedia video. These features are individually computed for each converted frame and it can be computed for both lower priority and higher priority video sequences. The features which are used in this research work are given in the following equations.

$$\boldsymbol{Luminance\ Frame\ Energy\ Feature\ (LFEF) = \sum_{i=1}^{M}\sum_{j=1}^{N} {Y_i}^2} \quad (\mathbf{4})$$

Where, M and N represents the row and column of each frame in multimedia video sequences.

$$\boldsymbol{Chrominance\ Blue\ Component\ Feature\ (CBCF) = \sum_{i=1}^{M}\sum_{j=1}^{N} {Cb_i}^2} \quad (5)$$

$$\boldsymbol{Chrominance\ Red\ Component\ Feature\ (CRCF) = \sum_{i=1}^{M}\sum_{j=1}^{N} {Cr_i}^2} \quad (6)$$

$$\boldsymbol{Index\ Metric\ Feature\ (IMF)} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} Y_i^{\,2}}{M*N} \quad (7)$$

$$\boldsymbol{Index\ Metric\ Average\ Feature\ (IMAF)} = \frac{1}{M*N}\frac{\sum_{i=1}^{M}\sum_{j=1}^{N} Y_i^{\,2}}{(CRCF*CBCF)} \quad (8)$$

The computed luminance and chrominance features are stored in a two-dimensional matrix and this matrix has been used for the generation of PR sequence.

3.3 ANFIS-CNN classifier for PR generation

The researchers in this field used machine learning algorithms mostly for generating the priority sequences for the multimedia videos in cloud system for error free and congestion free network environment. Though this machine learning based priority generation system produces priority correctly for the multimedia videos, the time consumption for the priority generation for video sequences is high and it is not suitable for high traffic congestion networks. This requires to improve the network bandwidth and to reduce the network congestion based on the priority of the video sequences. To obtain this research goal for uninterrupted network services over the cloud system, this proposed study integrates the machine learning algorithm (ANFIS) and deep learning algorithm (CNN) for improving the service background for the cloud system. Hence, the machine learning algorithm ANFIS has been used for feature selection and further the selected features have been classified using the CNN architecture. This integration of both ANFIS and CNN algorithms produces ANFIS-CNN classification architecture for generating the priority sequences in cloud system.

Figure 3 shows the proposed ANFIS-CNN classifier architecture for PR generation results for multimedia videos in cloud system. The computed features are integrated into input port of the ANFIS architecture, as illustrated in the following equations.

$$\{\boldsymbol{A1, A2}\} = \{\boldsymbol{Low\ priority\ features\ from\ the\ multimedia\ video}\} \quad (\boldsymbol{9})$$

$$\{\boldsymbol{B1, B2}\} = \{\boldsymbol{High\ priority\ features\ from\ the\ multimedia\ video}\} \quad (\boldsymbol{10})$$

The nodes in the first layer of the ANFIS are represented as A1, A2, B1 and B2 as shown in Figure 3. During the training phase, known priority video sequences are trained by the ANFIS architecture which is illustrated in Figure 3. During the test phase, unknown features from the test multimedia video is fed into the proposed architecture to select the optimal set of features. These features are then directly fed into the CNN architecture to generate the PR sequence for the test multimedia video.

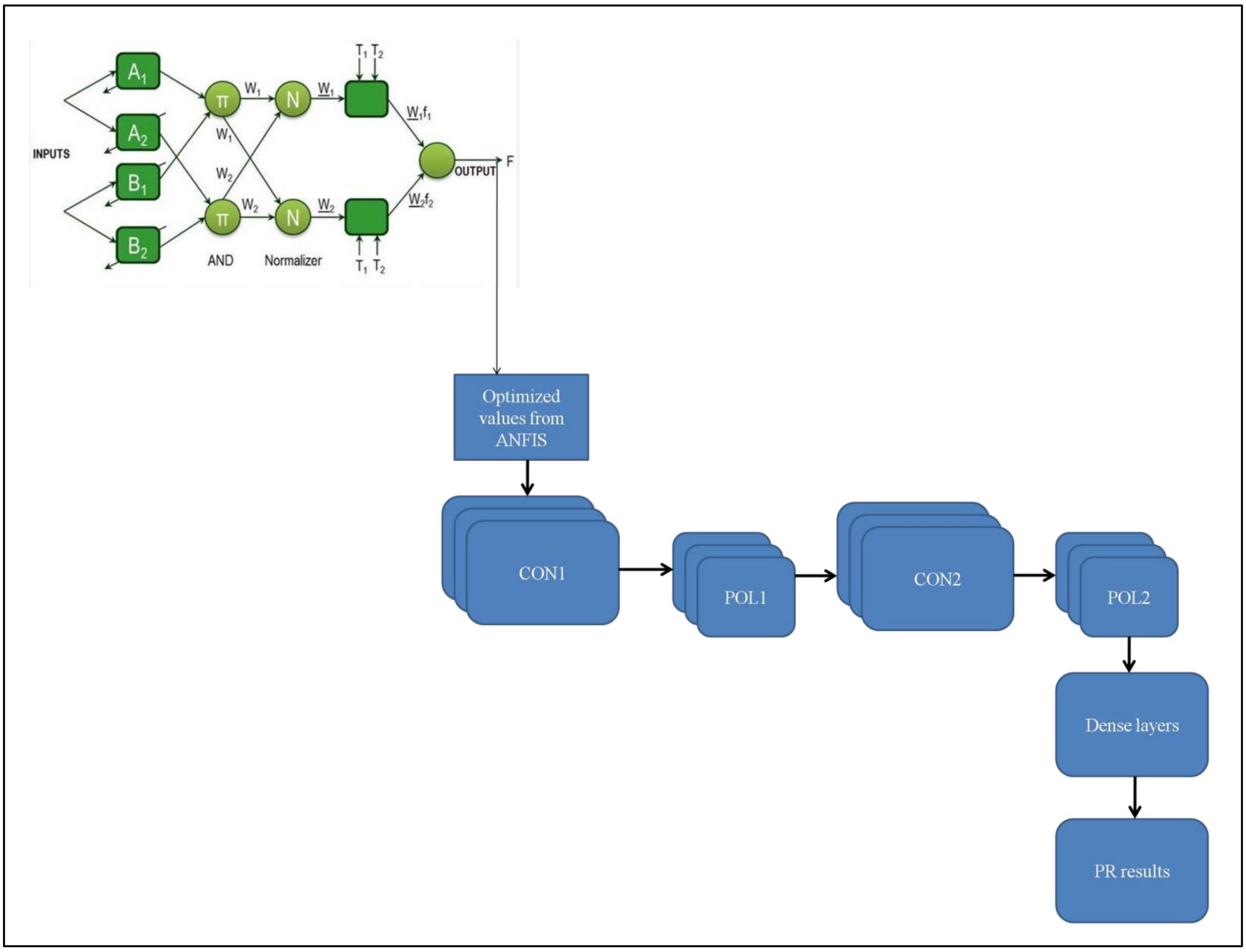


Figure 3. Proposed ANFIS-CNN Classifier Architecture for PR Generation Results for Multimedia Videos in Cloud System

The CNN system consists of two Convolutional module (CON1 and CON2) and two pooling modules (POL1 and POL2) with dense layers to generate the PR sequence for the test multimedia video. In this study, the CON1 consists of 32 filter kernels and CON2 consists of 64 filter kernels, as specified in the following equations.

$$\boldsymbol{CON1} = \{\boldsymbol{32\ filters, 5 * 5}\} \quad (\boldsymbol{11})$$

$$\boldsymbol{CON2} = \{\boldsymbol{64\ filters, 7 * 7}\} \quad (\boldsymbol{12})$$

The dense layer which is used in this CNN architecture has been illustrated by the following equation.

$$\{Dense\} = \{4096, 2048, 2048\} \quad (13)$$

The neurons count in each internal dense layer has been illustrated in the above equations where, the 4096 neurons are assigned in first layering, 2048 neurons are assigned in second layering and 2048 neurons are assigned in third layer. The final neurons in the final dense layer produce the PR sequence.

The hyper parameters of this proposed ANFIS-CNN architecture include a population size of 500,100 epochs, and Adam optimizer with SoftMax technique. The Figure.4 below shows the model summary of the CNN used.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 220, 220, 32)	2,432
max_pooling2d (MaxPooling2D)	(None, 110, 110, 32)	0
conv2d_1 (Conv2D)	(None, 104, 104, 64)	100,416
max_pooling2d_1 (MaxPooling2D)	(None, 52, 52, 64)	0
flatten (Flatten)	(None, 173056)	0
dense (Dense)	(None, 4096)	708,841,472
dense_1 (Dense)	(None, 2048)	8,390,656
dense_2 (Dense)	(None, 2048)	4,196,352
dense_3 (Dense)	(None, 10)	20,490

Total params: 721,551,818 (2.69 GB)
Trainable params: 721,551,818 (2.69 GB)
Non-trainable params: 0 (0.00 B)

Figure 4. Model Summary

4. Results and Discussion

In this work, the priority generation for multimedia videos within a cloud system has been simulated in MATLAB. The proposed PR generation algorithm was tested on two different cloud systems. The training process was conducted using existing video sequences available in MATLAB. The experimental results of the proposed PR generation system were evaluated with respect to two key parameters MakeSpan (MS) and Execution Time (ET).

The performance of the proposed priority generation system was evaluated using two independent cloud platforms: Microsoft Azure and Amazon EC2. Microsoft Azure cloud service platform has been developed and maintained by the Microsoft, a provides a comprehensive suite of cloud services for management and access through various web services globally. It operates through a network of data centers, offering real-time platform support for diverse applications. Amazon EC2, developed and maintained by Amazon Web

Services (AWS), was also utilized for testing. This platform enables management and access through web services across the globe, supported by an extensive network of data centers, and is designed for a wide range of real-time computing needs.

Table 1 is the estimation of MS and ET of the proposed system on EC2 cloud system.

Table 1. Estimation of MS and ET of the Proposed System on EC2 Cloud System

Running Phases	Methods	Frames count in Multimedia Video	MS (ms)	ET (ms)
Phase 1	ANFIS	100	10.5	12.8
	CNN		15.6	17.1
	ANFIS-CNN classifier		**7.31**	**10.1**
Phase 2	ANFIS	500	15.9	17.8
	CNN		21.7	24.5
	ANFIS-CNN classifier		**10.6**	**12.7**
Phase 3	ANFIS	1000	21.8	29.6
	CNN		29.8	33.7
	ANFIS-CNN classifier		**16.7**	**21.8**
Phase 4	ANFIS	5000	31.7	49.1
	CNN		37.6	45.3
	ANFIS-CNN classifier		**25.6**	**34.7**

Table 2 is the Priority generation (PR) results in Phase 1, with respect to MS and ET on EC2 cloud system

Table 2. Priority Generation (PR) Results -Phase 1

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	7.31	10.1
ANFIS	10.5	12.8
CNN	15.6	17.1
KNN	25.1	23.4

AdaBoost	27.6	31.9

Table 3 is the Priority generation (PR) results in Phase 2, with respect to MS and ET on EC2 cloud system.

Table 3. Priority Generation (PR) Results - Phase 2

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	**10.6**	**12.7**
ANFIS	15.9	17.8
CNN	21.7	24.5
KNN	32.9	38.9
AdaBoost	42.0	43.7

Table 4 is the Priority generation (PR) results in Phase 3, with respect to MS and ET on EC2 cloud system

Table 4. Priority Generation (PR) Results-Phase 3

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	**16.7**	**21.8**
ANFIS	21.8	29.6
CNN	29.8	33.7
KNN	48.3	51.3
AdaBoost	51.9	61.3

Table 5 is the Priority generation (PR) results in Phase 4, with respect to MS and ET on EC2 cloud system.

Table 5. Priority Generation (PR) Results -Phase 4

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	**25.6**	**34.7**
ANFIS	31.7	49.1
CNN	37.6	45.3
KNN	67.3	70.3
AdaBoost	71.9	77.8

Table 6 is the comparative analysis of proposed PR generation system on EC2 cloud system.

The proposed PR generation system obtained 7.31ms MS and 10.1ms ET for 100 tasks on EC2 cloud platform and obtained 25.6ms MS and 34.7ms ET for 5000 tasks on EC2 cloud platform.

Table 6. Comparative Analysis of Proposed PR Generation System on EC2 Cloud System

Classification Algorithms	**Number of Tasks**	**Computational Parameters**	
		MS (ms)	**ET (ms)**
ANFIS-CNN **classifier (in this work)**	100	**7.31**	**10.1**
Babuli Sahu et al. (2023)		10.76	15.3
Singh et al. (2020)		15.98	17.6
Gao et al. (2019)		16.1	18.7
ANFIS-CNN **classifier (in this work)**	500	**10.6**	**12.7**
Babuli Sahu et al. (2023)		16.7	15.9
Singh et al. (2020)		19.0	17.3
Gao et al. (2019)		21.8	18.1
ANFIS-CNN **classifier (in this work)**	1000	**16.7**	**21.8**
Babuli Sahu et al. (2023)		31.9	39.3
Singh et al. (2020)		39.8	44.4
Gao et al. (2019)		44.3	47.1
ANFIS-CNN **classifier (in this work)**	5000	**25.6**	**34.7**
Babuli Sahu et al. (2023)		45.6	52.3
Singh et al. (2020)		51.9	61.8
Gao et al. (2019)		59.3	67.9

Table 7 is the estimation of MS and ET of the proposed system on Microsoft Azure cloud system.

Table 7. Estimation of MS and ET on the Proposed System on Microsoft Azure Cloud System

Running Phases	Methods	Frames count in Multimedia Video	MS (ms)	ET (ms)
Phase 1	ANFIS	100	15.1	19.7
	CNN		21.9	29.4
	ANFIS-CNN classifier		**11.7**	**16.2**
Phase 2	ANFIS	500	21.9	34.5
	CNN		31.8	45.6
	ANFIS-CNN classifier		**18.3**	**22.9**
Phase 3	ANFIS	1000	34.7	45.4
	CNN		39.9	42.9
	ANFIS-CNN classifier		**29.3**	**31.8**
Phase 4	ANFIS	5000	48.9	56.7
	CNN		67.3	71.2
	ANFIS-CNN classifier		**41.2**	**45.9**

Table 8 is the Priority generation (PR) results in Phase 1, with respect to MS and ET on Microsoft Azure cloud system.

Table 8. Priority Generation (PR) Results-Phase 1

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	**11.7**	**16.2**
ANFIS	15.1	19.7
CNN	21.9	29.4
KNN	34.8	33.9
Adaboost	38.2	42.9

Table 9 is the Priority generation (PR) results in Phase 2, with respect to MS and ET on Microsoft Azure cloud system.

Table 9. Priority Generation (PR) Results - Phase 2

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	**18.3**	**22.9**
ANFIS	21.9	34.5
CNN	31.8	45.6
KNN	45.6	51.2
Adaboost	49.0	55.4

Table 10 is the Priority generation (PR) results in Phase 3, with respect to MS and ET on Microsoft Azure cloud system.

Table 10. Priority Generation (PR) Results - Phase 3

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	**29.3**	**31.8**
ANFIS	34.7	45.4
CNN	39.9	42.9
KNN	45.7	56.8
Adaboost	67.4	71.3

Table 11 is the Priority generation (PR) results in Phase 4, with respect to MS and ET on Microsoft Azure cloud system.

Table 11. Priority Generation (PR) Results- Phase 4

Classifiers	MS (ms)	ET (ms)
ANFIS-CNN	**41.2**	**45.9**
ANFIS	48.9	56.7
CNN	67.3	71.2
KNN	77.6	81.3
Adaboost	81.2	88.9

Table 12 is the comparative analysis of proposed PR generation system on Microsoft Azure cloud system.

The proposed PR generation system obtained 11.7ms MS and 16.2ms ET for 100 tasks on Microsoft Azure cloud platform and obtained 41.2ms MS and 45.9ms ET for 5000 tasks on Microsoft Azure cloud platform.

Table 12. Comparative Analysis of Proposed PR Generation System on Microsoft Azure Cloud System

Classification Algorithms	Number of Tasks	Computational Parameters	
		MS (ms)	ET (ms)
ANFIS-CNN classifier (in this work)	100	**11.7**	**16.2**
Babuli Sahu et al. (2023)		16.6	21.8
Singh et al. (2020)		21.8	29.8
Gao et al. (2019)		25.6	31.7
ANFIS-CNN classifier (in this work)	500	**18.3**	**22.9**
Babuli Sahu et al. (2023)		25.7	29.8
Singh et al. (2020)		31.8	33.4
Gao et al. (2019)		34.8	37.9
ANFIS-CNN classifier (in this work)	1000	**29.3**	**31.8**
Babuli Sahu et al. (2023)		41.3	45.6
Singh et al. (2020)		49.8	51.9
Gao et al. (2019)		55.6	61.9
ANFIS-CNN classifier (in this work)	5000	**41.2**	**45.9**
Babuli Sahu et al. (2023)		55.9	58.9
Singh et al. (2020)		61.8	67.7
Gao et al. (2019)		67.9	71.9

5. Conclusion

To obtain the research goal for uninterrupted network services over the cloud system, this research integrates the machine learning algorithm and deep learning to enhance the cloud service platforms. Specifically, the ANFIS machine learning algorithm is used for feature selection, while the selected features are classified using a CNN architecture. This integration of ANFIS and CNN produces the ANFIS-CNN classification architecture for generating priority sequences within the cloud system. The proposed PR generation system obtained 7.31ms MS and 10.1ms ET for 100 tasks on EC2 cloud platform and obtained 25.6ms MS and 34.7ms ET for 5000 tasks on EC2 cloud platform. The proposed PR generation system obtained 11.7ms MS and 16.2ms ET for 100 tasks on Microsoft Azure cloud platform and obtained 41.2ms MS and 45.9ms ET for 5000 tasks on Microsoft Azure cloud platform.

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