A Novel Framework for Video Retrieval Algorithm Evaluations and Methods for Effective Context-Aware Video Content Retrial Method on Cloud

T. Naga Raja, V. V. Venkata Ramana, and A. Damodaram

Abstract In recent time, multiple research outcomes have demonstrated diversified approaches for content management and showcased better outcomes. However, the parallel research outcomes are highly criticized for higher time complexity, reduction of the key contents, and finally, the lesser accurate indexing of the contents. Majority of the recent work outcomes have demonstrated the reduction of keywords based on language recommendations rather the context recommendations. This leads to non-context-aware reduction and further leads to incorrect extraction of keywords. Thus, the demand from recent research is to identify the keywords based on the context. Also, based on the previous claim, the proposed works must identify the actual frames if the keyword identification is based on the context. Thus, based on the recommendations by popular research outcomes, a framework is to be proposed to compare the existing video content retrieval methods and propose a novel process to identify the keyframes from the video contents using contextual mining and consider the optimal storage architecture for the proposed process input metadata and results for cloud-based storage service providers. The final outcome of this work is reduced complexity of the framework, compared with the parallel research outcomes, and higher accuracy for video content retrieval with reduction of the size for the searchable contents. The proposed work demonstrated nearly 15% improvements for content retrieval process and 86% improvements for time complexity over the parallel research outcomes for making the video content management and delivery mechanisms better and faster.

Keywords Segmented noise removal · Adaptive threshold · Video summarization · Cluster knowledge discovery · Quartic polynomial randomization · Similarity region extractor

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1 Introduction

The content management in recent years has gained a lot of attention due to the fact that the communication over the internet has increased to a greater extend. The recent works show for various domains multiple practices have started for making the content delivery online. Some of the business cases like for corporate practices, the meeting and the discussions are happening over the internet to increase the reachability and effective time utilization. Many of the medical practices are also using online content managements as the treatments over the internet via video conferences are getting high popularity for making knowledge sharing over various regions of the world. Also, in the field of education, many of the universities have showcased a higher rate of learning via online contents as the learners can learn at their own pace with greater engagements. So, the adaptability of the online contents, especially the video-based contents, is the demand of the recent research and practices.

Nonetheless, preserving the video quality is always a task for various reasons. In this work, the challenges are precisely identified based on the parallel research outcomes and further, the proposed solutions as a complete framework on cloud systems are also elaborated with significant improvements over recent and parallel research outcomes.

The later sections of this research are furnished as such a way that in Section 2, the parallel outcomes are discussed; in Section 3, the problems and research scope based on the earlier research outcomes are identified; in Section 4, the proposed frameworks and the sequence of the deployed algorithms are discussed; in Section 5 the results are analyzed; in Section 6, the real-time deployment of the proposed framework is analyzed on cloud; in Section 7, the comparative analysis is carried out; and, at the end, conclusion and future research directions of this research are discussed and on Section 8.

2 Literature Review

The parallel research outcomes will help in understanding the fundamental improvements in this domain of research and, at the same time, the gaps in the research can also be identified.

The work by Feng et al. [1] has recently demonstrated the applicability of the video data processing for a higher volume of the data. The work has clearly showcased the benefits of contextual video data processing for learning specific content retrieval. The personalized video searching, and retrieval process is definitely the demand for the current research.

The video content retrieval is not only the challenge of the present research context. Rather, the security or the sharing of the video contents are also to be considered with equal importance. The work by Yang et al. [2] has showcased the need for the time-dependent video content security approaches for a higher volume of the video data. This work also demonstrates the time-dependent query processing using the historical query results for making the query processing faster.

Further, the information, specifically the video information retrieval process is complex for the cloud- or cluster-based architectures. Thus, the information of the video content distribution is one of the keyfactors to be identified for context-based searching from distributed data sources. The work by Yang et al. [3] has listed the benefits and the challenges of the cloud-based content retrieval processes.

Many of the parallel research works have demonstrated similar outcomes focusing on the content retrieval processes. The majority of the works have showcased better outcomes for the static multimedia contents such as images. The work by Wang et al. [4] has established a process for managing, storing, and retrieval actions on the video data. The CHCF framework is widely accepted by the research community.

During the retrieval of the video or image or multimedia contents, the enhancements of the contents during the searching process is also important. Thus, the noise reduction processes come into the place for many of the parallel research works. The similar outcome by Song et al. [5] for content retrieval processes have confirmed this ideology.

The video content retrieval process is used for various purposes from security to education to entertainments. The distinguished work by Gao et al. [6] has demonstrated the use of video content retrieval methods for the identification of human or other objects from the video. The similar measures can be applied for identification or retrieval of the video contents, where the video contents are the search string or search input.

Yet another direction of the research community is extending their expertise for making the complete video content retrieval process with lower time complexity. The demand is eventually propagating throughout all the aspects of the content retrieval processes, where the searching device, the device generating the search string, is limited in terms of resources and processing capabilities. The work by Liu et al. [7] has showcased the process of video content retrieval from mobility devices with novel indexing methods. The identified problem from these works is discussed in the next section of the work.

3 Problem Identification

In this segment of the research, after a thorough analysis of the recent and parallel results are examined for identifying the bottlenecks of the parallel research outcomes and propose the research objectives as shown in Table 1.

Henceforth, the final research objectives are furnished here:

1. **Objective-1**: Apply a novel solution for the reduction of the keyframes with the reduction of the time complexity and improvement of the content retrieval accuracy.

Table 1 Identification of the research objectives

Research outcome	Proposed methodology	Identified bottlenecks	Research objectives
Kan Yang et al. [2]	Time slot-based content retrieval process	• The reduction of the informative content is grossly missing • Reduction of the keyframes or the important content can lead to the reduction in time for content retrieval	Objective-1
Xiaodan Song et al. [5]	Context-awareness during the video information retrieval	• The reduction in the frames can improve the complexity of the framework	Objective-1
Yinan Feng et al. [1]	A context-based online big data-oriented personalized video retrieval system	• Information about the cluster information is not considered • The lack of cluster information leads to the lack of information on data replication and contextual parameters	Objective-2
Hanli Wang et al. [4]	Distributed video information retrieval	• The video content is replicated for distributed systems. However, no approach is taken for generating cluster information	Objective-2
Guangyu Gao et al. [6]	Segmentation of the objects and detection for retrieval	• The threshold-based similarity measures can generate better performance measures	Objective-2
Wu Liu et al. [7]	Mobile instant content retrieval	• This direction of the search is also the need for further researches • The complexity of the framework or the retrieval time can be reduced further	Objective-2 & Further research directions

(continued)

Table 1 (continued)

Research outcome	Proposed methodology	Identified bottlenecks	Research objectives
Zhen Yang et al. [3]	The content retrieval process from cloud-based video library with data encryption	• The content retrieval process for video contents is significantly higher • During the encryption process, no optimization is proposed	Objective-3

2. **Objective-2**: Apply a novel solution for the improvement of content retrieval process on cloud-based or distributed online contents with the knowledge of data distributions over clusters.
3. **Objective-3**: Apply a novel solution for providing data encryption and decryption for data at rest and data on go for the complete framework with the reduction in time complexity and improved accuracy for content retrieval.

Based on the identified problems and the proposed solutions, the conceptual framework is formulated in the next portion of this work.

4 Proposed Framework

Based on the identification of the problems, research gaps and outcomes from the earlier research works, in this section, the proposed framework is elaborated (see Fig. 1).

The proposed algorithms are the outcomes from the works of the same authors and are summarized here.

Firstly, the Segmented Noise Removal Processing using Deep Segmentation Algorithm is displayed here [8].

Algorithm - 1: ***Segmented Noise Removal Processing using Deep Segmentation*** *Algorithm (SNRP-DS)*
Step - 1.*Accept all the video content as V[]* Step - 2.*For each V[i]* a. *Accept the video signal in analog form as f(t):V[i]* b. *For each time interval t/Δt,* i. *Calculate the signal variance as Amp(t/Δt) = (f(t/Δt):V[i]* ii. *Revise the variance difference, AmpDiff(t/Δt) = (|Amp(t/Δt) - Amp(t+1/Δt)|)/(t/Δt)* iii. *Report the overall signal variance, Amp[]* c. *Reduce the noise, V[i] - Amp[]* Step - 3.*Report the noise removed video content as V'[]*

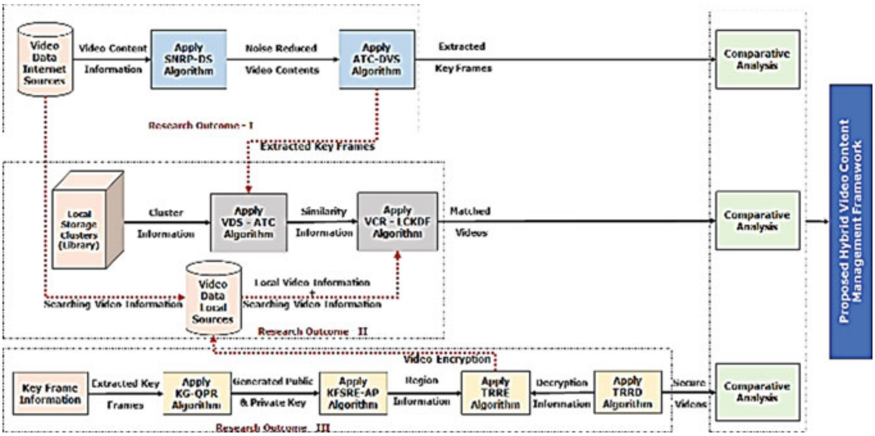

Fig. 1 Proposed framework for video content retrieval and management

Secondly, the Adaptive Threshold Calculation for Distributed Video Storage Algorithm is displayed here [8, 11].

*Algorithm - 2: **Adaptive Threshold Calculation for Distributed Video Storage** Algorithm (ATC-DVS)*

Step - 1. *Input the list of storage instances as S[]*
Step - 2. *At each level for every instance S[i]*

a. *Accept the list of noise reduced video content set as V'[]*
 i. *For each V'[i]*
  1. *Extract the video meta data as*
   a. *Frames Per Second, FPS*
   b. *Scan System, SS*
   c. *Aspect Ratio, AR*
   d. *Augmented Aspect Ratio, AAR*
   e. *Channel information, C*
  2. *Calculate the key frame extraction threshold as f(FPS, SS, AR, AAR, C)*
  3. *Scan V'[i] for each frame V'F[t]*
  4. *If f(V'F[t])>=f(V'[i]) and V'F[t](AAR)> V'[i](AAR)*
  5. *Then,*
   a. *V'[i]_KeyFrame[j] = V'F[t]*
  6. *Else,*
   a. *Discard V'F[t]*
 ii. *Report the total key frames for V'[i]*

b. *Calculate the overall threshold as, f(S[i] V'[i])*
c. *If f(S[i] V'F[t]))< f(S[i] V'[i])*
d. *Then,*
 i. *Discard the key frames in V'[i]_KeyFrame[j]*
e. *Else,*
 i. *Report the final key frames for V'[i]*

Thirdly, the Video Data Summarization with Adjustable Threshold Correction is displayed here [9].

Algorithm - 3: ***Video Data Summarization with Adjustable Threshold Correction*** *Algorithm (VDS - ATC)*
Step - 1. Consider Set of Clusters as C[]
Step - 2. Consider set of Video data as V[]
Step - 3. For each V[i]
a. Split video data into frames as F[]
b. For each C[j], Find similarity as S for V[i] and C[j]V[j]
c. Calculate F[k] = S
d. Update F[k](t+1) = F[k](t) ±(S/Δ S)
e. Find V[j+1] = C[j]V[j] Union C[j+1]V[j]
f. Update collaborative cluster as C'[{V[i]}] for V[i]
Step - 4. Report C'[]

Fourthly, the Video Content Retrieval using Local Cluster Knowledge Discovery Factors is displayed here [9].

Algorithm - 4: ***Video Content Retrieval using Local Cluster Knowledge Discovery Factors*** *Algorithm (VCR - LCKDF)*
Step - 1. Consider Set of Clusters as C[]
Step - 2. Consider the searching video as V
Step - 3. For each C[i]
Calculate the KDF[i] = Selection of V[j] for V
Step - 4. Find the match based on KDF[] and C'[]
Step - 5. Report the final V[j] as match for V

Fifthly, the "Key Generation Based on Quartic Polynomial Randomization Algorithm" is displayed here [10].

Algorithm - 5: ***Key Generation Based on Quartic Polynomial Randomization*** *Algorithm (KG-QPR)*

Step - 1. Initialize the Quartic Polynomial function as f(X) with N order
Step - 2. Select two prime numbers based on f(X) as A and B with randomization of Order N
Step - 3. Calculate R as R = A product B
Step - 4. For each N as i
- *a. Calculate α(i) = [A{f(X^N)-1}] XOR [B{f(X^N)-1}] as polynomial component*
- *b. Calculate β(i) = α(i) XNOR [A{f(X^N)-1}] XNOR [B{f(X^N)-1}] as public component*

Step - 5. Generate the public key as PK = {α[] XOR β[]}
Step - 6. Generate the private key for similar regions as PSRK = {α[1..N/2] XNOR β[1..N/2]}
Step - 7. Generate the private key for dissimilar regions as PDRK = {α[N/2..N] XNOR β[N/2..N]}
Step - 8. Report final keys as PK, PSRK and PDRK

Sixthly, the Keyframe Similarity Region Extractor using Adaptive Progression Algorithm is displayed here [10].

Algorithm - 6: ***Key Frame Similarity Region Extractor using Adaptive Progression*** *Algorithm (KFSRE-AP)*

Step - 1. Accept the set of Key Frames as KF[]
Step - 2. For each KF[] as j
- *a. Calculate region similarity as KF[j], KF[j+1] as RS[i]*

Step - 3. Calculate mean RS[] as RMS
Step - 4. For each KF[] as n
- *a. If region_similarity(KF[n], KF[n+1])> RMS*
- *b. Then, Mark regions as SR[]*
- *c. Else, Mark regions as DR[]*
- *d. Report SR[] and DR[] for each KF[n]*

Seventhly, the Time Restricted Region Encryption Algorithm is displayed here [10].

Algorithm - 7: ***Time Restricted Region Encryption*** *Algorithm (TRRE)*

Step - 1. Accept PK, PSRK and PDRK
Step - 2. Accept SR[] and DR[]
Step - 3. Accept KF[]
Step - 4. For each KF[] as m
- *a. Apply PK and PSRK for SR[m] for encryption*
- *b. Apply PK and PDRK for DR[m] for encryption*

Step - 5. Merge KF[] into video data V[]

Finally, the Time Restricted Region Decryption Algorithm is displayed here [10].

*Algorithm - 8: **Time Restricted Region Decryption** Algorithm (TRRD)*
Step - 1. Accept PK, PSRK and PDRK
Step - 2. Accept V[] and extract KF[]
Step - 3. Extract SR[] and DR[] from KF[]
Step - 4. For each KF[] as m
a. Apply PK and PSRK for SR[m]
b. Apply PK and PDRK for DR[m]
Step - 5. Merge KF[] into video data V[]

The proposed framework is deployed on the cloud infrastructure and the deployment environment is elaborated in the next section of this work.

5 Results and Discussions

After the identification of the problems and the detailed discussion on the framework, the results obtained from the proposed framework is discussed (Table 2).

The first outcome from the framework is nearly 96.83% accuracy for content retrieval process with mean of 95.71%, which also demonstrates the normal distribution of the accuracy for various datasets and various test runs (see Fig. 2).

The second outcome from the framework is nearly 97.93% accuracy for content retrieval process with mean of 97.15%, which also demonstrates the normal distribution of the accuracy for various datasets and various test runs (see Fig. 3).

The final outcome from the framework is nearly 99.93% accuracy for content retrieval process with mean of 99.41%, which also demonstrates the normal distribution of the accuracy for various datasets and various test runs (see Fig. 4).

Moreover, the incremental growth of the accuracy is also visible in the results and visualized graphically here (see Fig. 5).

Secondly, the time complexity analysis is carried out (Table 3).

It is natural to the observer that the time complexity is reducing progressively over the complete framework for three phases as nearly 9.54 s for the first phase, 7.93 s for the second phase, and, finally, 7.12 s in the final phase of the framework. The results are visualized graphically here (see Fig. 6).

Finally, with the detailed analysis of the obtained results, in the next section of the work, the comparative analysis is carried out.

Table 2 Accuracy analysis

Dataset	Test Run	Accuracy of SNRP-DS & ATC-DVS (%) [8]	Accuracy of VDS-ATC & VCR-LCKDF (%) [9]	Accuracy of KG-QPR & KFSRE-AP & TRRE & TRRD (%) [10]
BBC Motion Gallery Set-1	Test Run-1	94.68	96.98	99.12
BBC Motion Gallery Set-1	Test Run-2	96.55	96.64	99.18
BBC Motion Gallery Set-1	Test Run-3	94.49	97.72	99.30
BBC Motion Gallery Set-2	Test Run-4	96.11	97.38	99.21
BBC Motion Gallery Set-2	Test Run-5	94.04	97.93	99.70
BBC Motion Gallery Set-2	Test Run-6	95.65	97.78	99.05
BBC Motion Gallery Set-3	Test Run-7	95.98	96.80	99.74
BBC Motion Gallery Set-3	Test Run-8	96.83	96.63	99.64
BBC Motion Gallery Set-3	Test Run-9	95.83	96.62	99.93
TRECVID Set-1	Test Run-10	94.64	97.33	99.37
TRECVID Set-1	Test Run-11	96.15	96.61	99.26
TRECVID Set-1	Test Run-12	94.84	97.81	99.02
TRECVID Set-2	Test Run-13	96.80	96.91	99.78
TRECVID Set-2	Test Run-14	96.67	96.91	99.31
TRECVID Set-2	Test Run-15	96.42	97.18	99.52

6 Cloud-Based Deployment Models

One of the primary objectives of this research is to deploy the complete working framework on the cloud environment. Thus, this work selects the Amazon Web Services (AWS) cloud environment for the deployment of the work. The AWS framework provides multiple benefits for video content management and sharing. One the

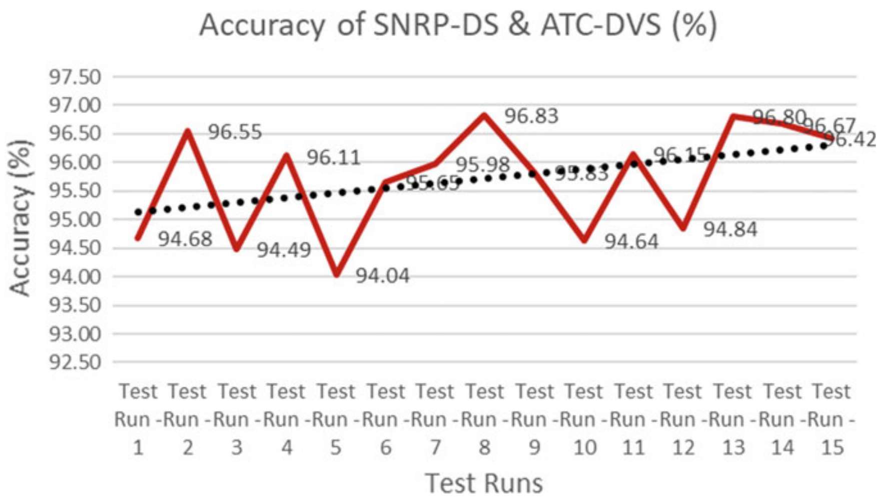

Fig. 2 Accuracy of SNRP-DS & ATC-DVS (%)

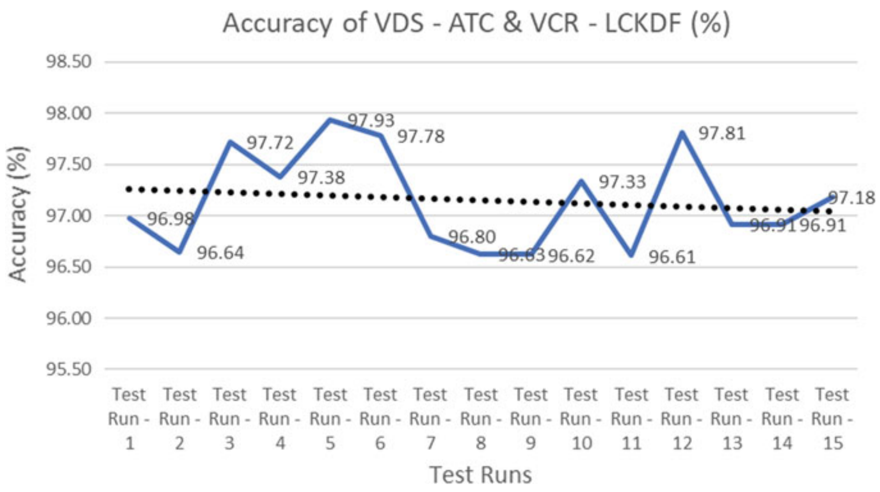

Fig. 3 Accuracy of VDS-ATC & VCR-LCKDF (%)

key components, which is used by the proposed framework, is the content management pipelines. The pipeline is one of the components which enables processing of the video data based on the sequences of the algorithms. The first two algorithms are deployed on the same component and the visualization is furnished here (see Fig. 7).

Further, the content management and retrieval algorithms can further be deployed on the jobs on AWS. The job component of the AWS enables multiple algorithms sequences to be applied on the video contents adaptively based on the pre-set

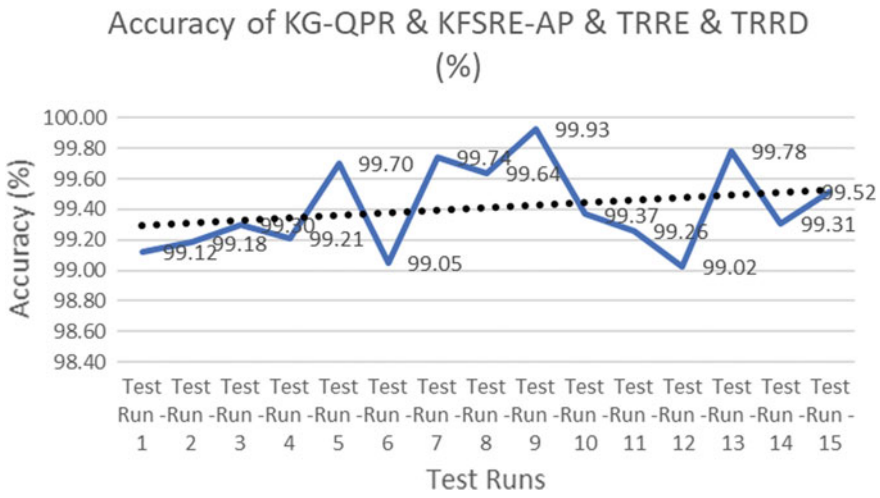

Fig. 4 Accuracy of KG-QPR & KFSRE-AP & TRRE & TRRD (%)

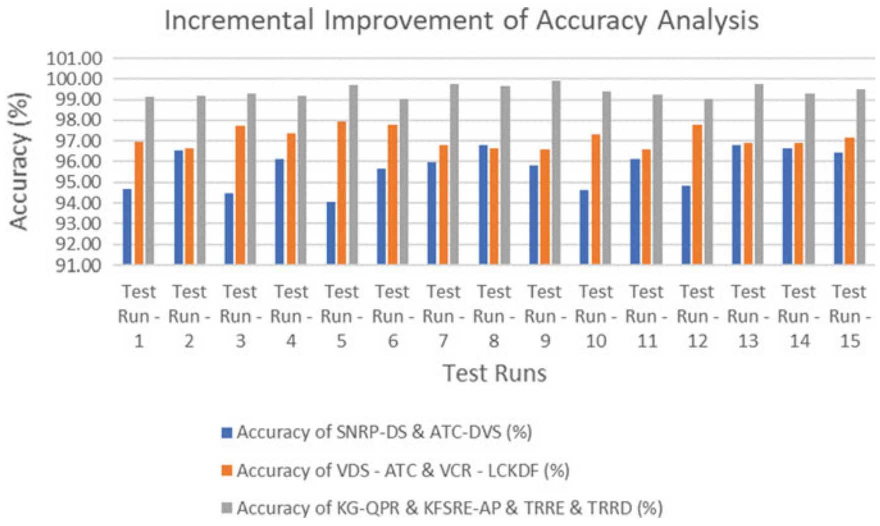

Fig. 5 Incremental improvement of accuracy analysis

sequences. The next two algorithms are deployed on the AWS and the deployment scenario is furnished here (see Fig. 8).

Further, the complete framework is again managed from the AWS EC2 instances and the deployment scenario is furnished here (see Fig. 9).

Furthermore, in the next section of this work, the comparative analysis is carried out.

Table 3 Time complexity analysis

Dataset	Test Run	Accuracy of SNRP-DS & ATC-DVS (Sec) [8]	Accuracy of VDS-ATC & VCR-LCKDF (Sec) [9]	Accuracy of KG-QPR & KFSRE-AP & TRRE & TRRD (Sec) [10]
BBC Motion Gallery Set-1	Test Run-1	9.07	7.80	7.44
BBC Motion Gallery Set-1	Test Run-2	9.80	8.24	7.70
BBC Motion Gallery Set-1	Test Run-3	9.16	7.44	6.71
BBC Motion Gallery Set-2	Test Run-4	9.56	7.49	6.03
BBC Motion Gallery Set-2	Test Run-5	9.61	8.07	7.94
BBC Motion Gallery Set-2	Test Run-6	9.10	7.99	6.45
BBC Motion Gallery Set-3	Test Run-7	9.79	8.28	7.92
BBC Motion Gallery Set-3	Test Run-8	9.58	7.16	7.15
BBC Motion Gallery Set-3	Test Run-9	9.87	8.30	7.04
TRECVID Set-1	Test Run-10	9.59	7.80	7.10
TRECVID Set-1	Test Run-11	9.94	8.89	7.58
TRECVID Set-1	Test Run-12	9.84	7.21	6.98
TRECVID Set-2	Test Run-13	9.13	7.92	6.28
TRECVID Set-2	Test Run-14	9.83	8.26	7.66
TRECVID Set-2	Test Run-15	9.22	8.13	6.77

7 Comparative Studies

For any research outcome, to be identified as the best, it is important to perform the comparative study of parallel research findings. Henceforth, the proposed framework is contrasted with the parallel major research findings in this portion of the study (Table 4).

In terms of retrieval accuracy, time complexity, overall framework complexity with additional features, it is observed that the proposed method outperforming. The improvements for content retrieval accuracy is nearly 15% and the improvement over time complexity is nearly 85%.

The accuracy improvements are visualized graphically here (see Fig. 10).

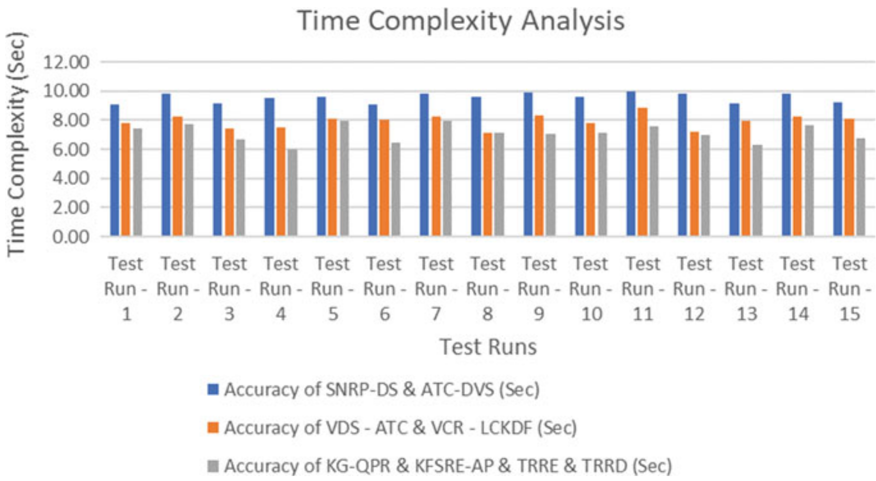

Fig. 6 Time complexity analysis

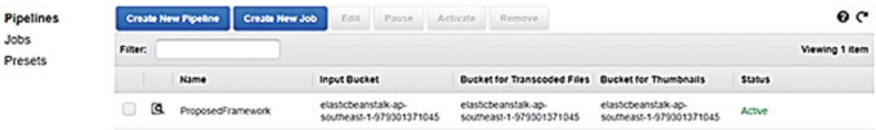

Fig. 7 Deployment on AWS pipelines

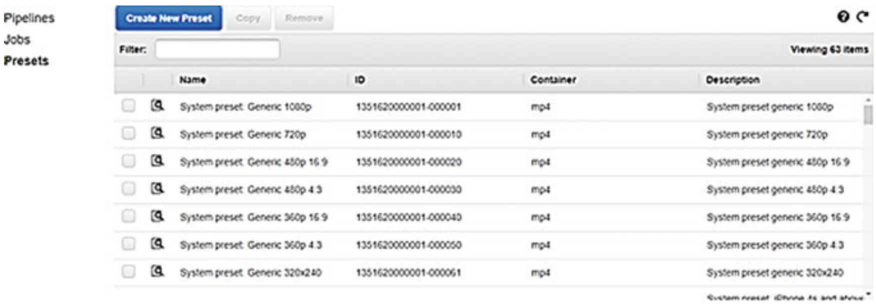

Fig. 8 Deployment on AWS jobs and pre-sets

The improvements over time complexity are also visualized graphically as (see Fig. 11).

Henceforth, in the next section of the work, the final research conclusion is presented.

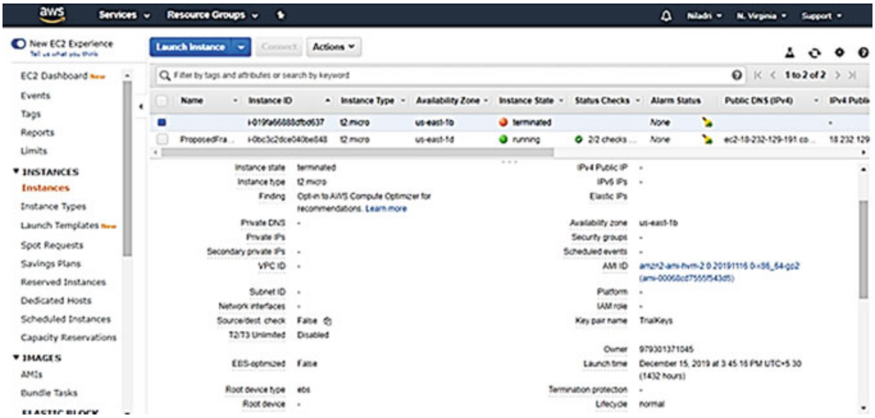

Fig. 9 Deployment on AWS EC2 instances

Table 4 Comparative analysis

Research outcome	Retrieval accuracy (%)	Time complexity (Sec)	Framework complexity	Applicable to distributed data
Kan Yang et al. [2]	79.98	51.36	$O(n * n^m)$	No
Xiaodan Song et al. [5]	71.96	86.31	$O(n^3)$	No
Yinan Feng et al. [1]	77.47	92.35	$O(n * m)$	Yes
Hanli Wang et al. [4]	85.49	42.62	$O(n^2)$	No
Guangyu Gao et al. [6]	87.86	80.59	$O(n * m)$	Yes
Wu Liu et al. [7]	75.82	78.10	$O(n^m)$	Yes
Zhen Yang et al. [3]	79.45	74.82	$O(n^2)$	No
Proposed Method, 2019	99.93	6.03	$O(\log n)$	Yes

8 Conclusion

The motivating factor for online video-based content management is wide adaptations and popularity. This catalyzed the growth in the recent research trends for making the video content management and revivals better and faster and more secure for cloud. However, the bottlenecks identified by many other researchers and this work as well are the setbacks for the growth of more adaptation of the video content delivery and management over cloud. Henceforth, this work designed a three-phase solution of the

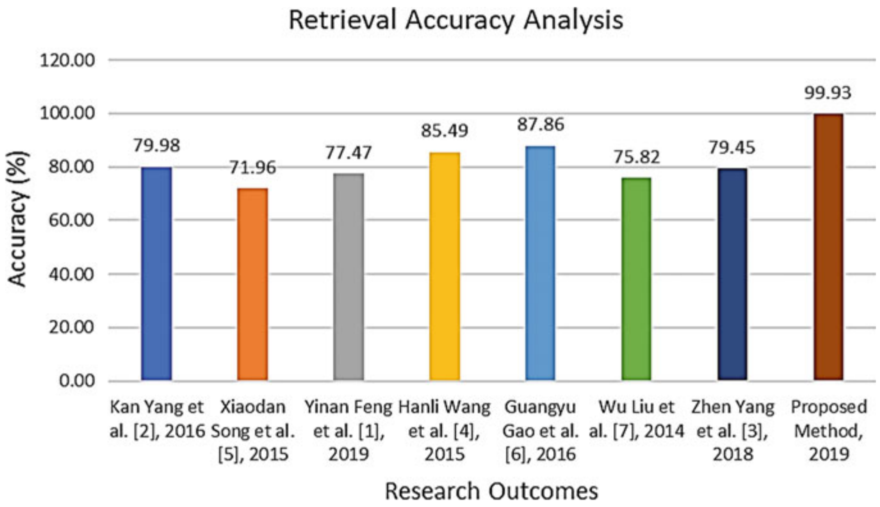

Fig. 10 Content retrieval accuracy analysis

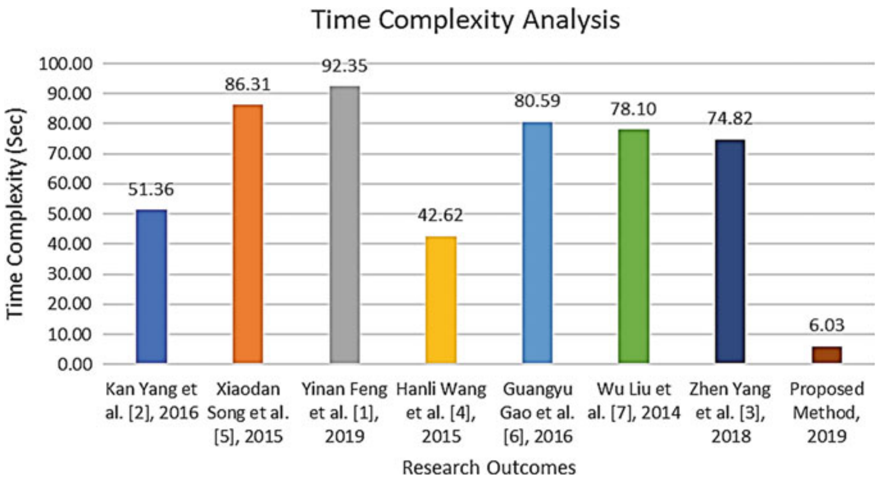

Fig. 11 Time complexity analysis

complete problem as in the first phase, designed a novel solution for the reduction of the keyframes with reduction of the time complexity and improvement of the content retrieval accuracy of 96.83%, in the second phase, designed a novel solution for improvement of content retrieval process on cloud-based or distributed online contents with the knowledge of data distributions over clusters with an accuracy of 97.83%, and, in the final phase, designed a novel solution for providing data encryption and decryption for data at rest and data on go for the complete framework with a reduction in time complexity and improved accuracy for content retrieval with an accuracy of retrieval 99.93%. Considering the final outcome and the comparative improvements over the other parallel research outcomes, this work is to be considered as one of the benchmarked work in this domain of research for making the video content management on cloud a faster, secure, and better area.

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