

# **REVIEW OF VISUAL DATA DESCRIPTION**

#### Supriya Pradeep Kurlekar

Phd Student, Dept of Electronics Engineering in Shivaji University Kolhapur, India

# Dr. Manasi R. Dixit

Professor, Department of Electronics and Telecommunication Engineering, KIT's College of Engineering, Kolhapur, State: Maharashtra, India

#### Abstract

Nowadays due to vast number of camera equipped devices, large amount of data in terms of image and video are getting generated which brings lot of information which can address many real world problems [16]. Deep learning based Visual data description is one of the most popular research field of Research. Image understanding is associated with objects identification, location and for captioning we need to detect interrelation of objects. Describing video in natural language automatically is very challenging task. It includes understanding of many entities like background scene, human interaction, and other sequential events. Video/image captioning is having huge scope for development in human –robot interaction, virtual assistance, visually impaired people assistance, surveillance, and many more. Captioning can do a lot for those who can't hear. Social media is one of the biggest platform used by more than half billion people for video watching. One great advantage of having caption of your content is that it enables a video or image to be found by search engines including Google, through Search Engine optimization.

### I Introduction

Obtaining meaningful information from video is crucial task. Availability of standardized data sets and deep neural network algorithms contributed in significant improvement of video caption generation. Videos may include number of activities, entities, inter related events. Dense Video caption generation has become most challenging task in recent years. It requires many sentences for meaningful captioning. Consequently, dense video captioning task [2] has been introduced and getting more popular recently. The complexity of the defined task is more in conceptual manner compared to simple video captioning as individual events detection becomes necessary for video processing. On Also, due to complexity of the video sequences while generating captions, up to two events are considered in most of the methods [1, 10]. Also, type of event is the main attribute considered while designing and testing the network oriented evaluation methods.

In most of video classification systems object contents are simple and video sequences are used to classify the objects. When scenes in the video are more complex, the computer based algorithms require more computations which is challenging task. The task of captioning of video sequence is one such challenging. Beyond object recognition the challenge shows the requirement of natural language processing requirements in which semantically meaningful information of objects is taken into consideration which establishes relationship among multiple objects. Also, meaningful and informative with fluent caption generation is the main objective. When relationship establishment is concerned, the complex scene give rise to more complex issues along with text data relationship problems. During development of such models have challenge of establishing relationship between text data in the description and objects in complex scenes while generating natural language descriptions.

The important description to video linked relationship problem is relation between events, objects and activities. On the other hand, the words in description are the contextual information. Prime most tasks in "visual to text" conversion are Fine grained natural descriptions, Intermediate representation learning, Recounting of visual contents and Benchmark Datasets with rich text [16].

The content collection and documentary formation has become easy task due to advancement in such digital content distribution and video recorders. The video data is long sequence which consumes time during users perspective of understanding the content which is the main problem during content sharing. With saving of time maximum information conveyance to the users from such video data is the need of time. The most demanding domain video captioning shows huge scope for the research. Many methods that involve deep learning approach show better success while achieving these targets which also make use of natural language processing methods [11]. We propose machine learning based method for describing video sequence in text description by combining the visual content recognition and natural language processing.

#### II Literature Review

W. Xu, J. Yu, Z. Miao, et.al [1] Proposed deep reinforcement polishing network consisting of network model for word denoising and network for grammar checking, adequate evaluations have been done to improve performance of video captioning. The long term reward based technique is used for long video sequences with deep reinforcement learning strategy. This also minimizes the gap between visual content information and text data in language domain with revising of words and grammar errors.

D. Yasin, A. Sohail and I. Siddiqi,et.al [2] In this paper, objects appearing in the scenes are considered by authors along with word embedding which finds similar words from the description text. The collection of various video is done for experimentation in which FaceNet is used to identify individuals and combination of CNN and RNN models is used. The valuation of performance is also shown which shows satisfactory results.

MasoomehNabati, Alireza Behrad, et.al [3] have designed parallel processing based boosted architecture using Long Short –Term Memory networks. The iterative training of LSTM is important step towards parallel processing implementation. Which acts as an AdaBoost algorithm during the training phase. The experimental testing is done on public datasets along with comparative analysis with other algorithms. Authors show future scope of the work by dictating the architecture of model which can be trained on small videos in batch processing approach.

Chohan, Murk & Khan, et.al [4] provided study of image captioning methods which makes use of encoder-decoder models and also attention mechanism. A combinational analysis is shown. Authors have found different mechanisms for scene understanding. Author have listed various fields like medical, industry, agriculture where captioning method of images can be used to automate their tasks.

J. Mun, L. Yang, Z. Ren, et.al [9] have given a method pf video captioning which focuses on temporal features of the video sequence. The coherent feature matching is the main attribute

considered while generating a story from the sequence. The event oriented sequence of video and using such sequence for training of the neural network for captioning purpose is the main approach in reinforcement learning. The rewards are of two type which are at bottom event and episode levels. Authors used performance evaluation tool. The tool is from 2018 "ActivityNet Captions challenge", which is evaluated in terms of event describing ability and locating such events in the videos. Supervised learning based experimental analysis is performed and have achieved the state-of-the- art accuracy on the activity net captions data set in terms of METEOR.

T. Fujii, Y. Sei, et.al [10] proposed a method that updates the model by adding new data vector in trained captioning model. They employed data processing methods and trend the same data with the simplest encoder decoder model and calculated the metrics. The document vectorization is done for variable length to fixed length conversion of feature vectors. The hidden layers are trained by combined vectors of images and sentences. A supervised learning approach is used for training and evaluation. Zhang, X.; Wang, X,Tang et.al [12] addressed the challenge in high level and low level semantic features and methods of bridging the gap between them. The application of remote sensing images is considered. The attribute attention based model is developed for caption generation of remote sensing images. The global information is attributed with the use of embedding layer for high level feature extraction of remote sensing images.

Dong-Jim Kim Jinsoo Choi, et.al [13] have introduced relational captioning, proposed a network with multi-task triple-stream. The model network consists of three recurrent units. The joint POS features are used for caption generation. Authors have discussed about Loss functions, triple stream LSTMs, region proposal networks and relational captioning dataset. Authors have done holistic image captioning comparison, suggested that their work can be used in applications of video summarization with natural language processing.

J. Dong, X. Li and C. G. M. Snoek, et.al [14] this paper focuses on choice of sentences that can well describe the scenery in image or video sequence. The visual features are extracted and paired with text features in which firstly text data is converted into vectors using Word2VisualVec (W2VV). The model can extract visual features from text data. The experimental analysis shows that this method can find the most likely caption for given image. Authors have suggested use W2VV with sentence vectorization as multi scale level. The features are predicted using ResNet for training. C. I. Orozco, M. E. Buemi et.al [15] Proposed neural network architecture for encoder and decoder. First CNN for feature extraction and then LSTM has been used to automatically generate the description of the video. They have used Microsoft Video Description Corpos data set for training and testing. Authors commented that automatic generation of video description is currently a topic of interest in computer vision due to applications such as web indexation, video description for people with visual disabilities. Sheng Li, Zhiqiang Tao, et.al [16] performed literature classification with the use of visual to text description link methods. The latest deep learning methods are considered. Authors have discussed and presented the strategies of quantitative evaluations for selected methods that make use of public datasets. In captioning methods according to authors, accuracy of visual information describing is related to mostly natural language processing for better outcomes. Authors have discussed scope for future work in generating natural and diverse descriptions, deep reinforcement learning, and unified framework in captioning applications. The visual

understanding and reasoning also large scale benchmarks and evaluations are important aspects.

R.shetty, HamedTavakoli, Jorma Laaksonen et.al [17] discussed various methods that convert visual domain information into language domain. Author discussed overall visual captioning framework consisting of visual feature extraction, CNN features, video features, scene type features and object type and location features. Author also proposed Language model and deeper model with contextual features. Author shared limitations of proposed model that it could count the objects that are prone to repeated words which is better than numeric analysis in some of the captions.

Bai, Shuang & An, Shan. et.al [18] Authors introduced a comparative approach for object relation transfer using geometric attention model on spatial features. MS\_COCO dataset is used for quantitative and qualitative performance evaluation with the use of geometric attention for image captioning, which shows significant improvements.

Eleftherios Daskalakis, Maria Tzelepi, et.al [19] proposed captioning model that makes use of contextual information from image features. The CNN based features are extracted from which similarity trajectory is estimated. The framework from authors shows better performance over MS-COCO image captioning dataset and method have also topped the MSR-VTT video to text challenge leader board.

Su, Jiaqi.et.al [20] discussed review of various methods of video captioning. The papers are addressed in the literature with video captioning datasets used by various authors and evaluation metrics that are commonly used. Author have discussed benchmark datasets like TACoS, MSVD, M-VAD, MPII Movie Description Corpus (MPII-MD), MSR Video-to-text and ActivityNet Captions. Author have suggested different methods as Template-based Captioning, Joint Embedding, Encoder-Decoder, Attention Mechanism and Hierarchical Neural Encoder. Author have also identified several possible future directions.

X. He and L. Deng, et.al [21] addressed the video captioning field, also analyzed the key contributions and their progress. Also, the applicability and demands in the field in research and industry deployment is discussed. Future breakthroughs are addressed. The integration of encoder-decoder models in captioning applications are discussed. They also discussed about major deep learning methods in image captioning applications.

Sujin Lee, Incheol Kim, et.al [22] Have proposed method with attention models SeFLA (Semantic Feature Learning and Attention-Based Caption generation). The use of semantic text captions for effective video captioning with respect to events is considered. The attention model used focuses on feature sets with respect to the events in the video sequence with respect to time stamp that generates effectively correct captions based on the features of video. Authors have developed model consists of three parts mainly, feature extraction using pre trained ResNet and C3D, Dynamic semantic network and static semantic network. Authors conducted experiments with the two datasets MSVD (Microsoft Video Description) and MSR-VTT (Microsoft Research Video-to-text) and demonstrated evaluation of the proposed model.

Rafael A. Rivera-Soto, et.al [25] explored sequence to sequence models that are mainly used in applications of neural machine translation. Authors modified RESNET-50 and VGG-16 CNN in conjunction with the LSTM recurrent neural network model. Performance evaluation is done by authors on the Microsoft dataset and evaluated performance using the METEOR metrics. Authors investigated a simple mean pool model along with sequence to sequence models that are commonly used in video captioning applications. They compared performance and validated experimentally. The instability is analyzed for a single layer encoder-decoder network while performing the task of generating video captions.

Bo Luo, XiaoouTang, et.al [30] proposed a method that segments text from video using temporal feature vectors. Authors have defined few buffers and flags. The captions text is coarsely segmented for generative abstract sequence. The analysis in terms of statistical methods is performed which identifies the (dis)appearance of captions and pairing of text in between adjacent images. The indexing key frames are collected from video which provides video summary which are high quality frames that are sent for optical character recognition.

Author,	Title	Methods	Outcome	Drawback
Journal,				
Year.				
W. Xu et al,	Deep	CNN for Video	Improved score for	Entire sentence of
IEEE	Reinforceme	feature extraction,	understandable	description is
Transaction	nt Polishing	RNN based word	captions with more	considered for word
on	Network for	denoising and	grammatically	denoising and
Multimedia,	Video	grammar checking	correct captions.	grammar
2021.	Captioning	network.		corrections which
				can be replaced with
				part of speech based
				approach for further
				better results.
MasoomehN	Video	Video to frames,	Key frame	Number of images
abati et al,	captioning	fixed length frame	extraction method	to process definition
Computer	using boosted	count approach,	improves caption	linkage defines the
Vision and	and parallel	ResNet101,	linking with that of	accuracy which may
Image	Long Short-	encoder decoder	actual needed	change with respect
Understandin	Term	model	process, improved	to process
g,	Memory		results of captioning	application. The
ELSEVIER,	networks		about process.	change in
2020.				application changes
				the results.
R. Shetty et	Image and	Neural Network	MSVD dataset	Comparative study
al, IEEE	Video	architecture	based evaluation	with other methods
transactions	Captioning	Encoder-Decoder.	shows better	is not presented.
on	with	CNN 3D extracts	performance.	Simplistic model is
Multimedia,	Augmented	the features of the		capable of
2018.	Neural	input video.		generating caption
	Architectures	MSVD dataset.		only on limited
				dataset.

i v Comparative Analysis	IV	Com	par	ative	Ana	lysis
--------------------------	----	-----	-----	-------	-----	-------

Dong-Jin	Dense	A multi-task triple-	MTTSNet, which	Natural language
Kim et al,	Relational	stream network	facilitates	processing is not
IEEE	Captioning:	(MTTSNet),	POS aware	considered.
transactions,	Triple-	consists of three	relational	
2019.	Stream	recurrent units for	captioning	
	Networks for	the respective POS	the effectiveness of	
	Relationship-	and jointly	the framework	
	Based	performs POS	over scene graph	
	Captioning	prediction and	generation and the	
		captioning.	traditional	
			captioning	
			Frameworks.	
W. Xu et al,	Deep	CNN model for	Object oriented	Text outcome in
Transactions	Reinforceme	feature extraction,	features and	terms of
on	nt Polishing	object oriented	respective text	meaningfulness and
Multimedia,	Network for	feature location,	linkage accuracy	grammar is not
2021.	Video	bigram and trigram	improved.	considered.
	Captioning	oriented text		
		feature linking.		
L. Pang et al	Deep	CNN for feature	Finding matching	Text generation is
IEEE	Multimodal	extraction, video	video from dataset	another aspect and
Transactions	Learning for	retrieval		this paper only
on	Affective			focuses on video to
Multimedia,	Analysis and			video matching
2015	Retrieval			which shows feature
				types extraction
				with respect to
				objects in video.
W. Zhang et	Reconstruct	Reconstruction	the RecNet is fine-	The text data
al, IEEE	and	network (RecNet)	tuned by CIDEr	features and
Transactions	Represent	encoder-decoder-	optimization via	language quality in
on Pattern	Video	reconstructor	reinforcement	terms of
Analysis and	Contents for	architecture, video	learning, which	meaningfulness and
Machine	Captioning	semantic features.	significantly boosts	grammar is not
Intelligence,	via		the captioning	considered.
2020.	Reinforceme		performance.	
	nt Learning			
T. Wang et	Event-	Dense video	Quantitative and	Natural language
al, <i>IEEE</i>	Centric	captioning aims to	qualitative	processing steps not
Transactions	Hierarchical	localize and	evaluations on the	followed.
on Circuits	Representati	describe multiple	ActivityNet	
and Systems	on for Dense	events in	Captions and	
for Video		untrimmed videos,	YouCook2 datasets	

Technology,	Video	temporal-linguistic	demonstrate that the	
2021.	Captioning	non-maximum	method improves	
		suppression (TL-	the quality of	
		NMS) to	generated captions	
		distinguish		
		redundancy in both		
		localization and		
		captioning stages		
L. Gao et al,	Hierarchical	Hierarchical	The Cross-modality	Shows better results
IEEE	Representati	Representation	Matching Task	on standard public
Transactions	on Network	Network with	enables the learning	datasets whereas
on Image	with	Auxiliary Tasks	of hierarchical	limited application
Processing,	Auxiliary	(HRNAT), for	representation of	approach is defined.
2021.	Tasks for	learning multi-	videos, guided by	Change application
	Video	level	the three-level	video may reduce
	Captioning	representations and	representation of	the performance.
	and Video	obtaining syntax-	languages.	
	Question	aware video		
	Answering.	captions.		
Y. Zheng et	Stacked	video captioning	It adopts additional	Only limited set of
al, IEEE	Multimodal	framework, named	visual and textual	datasets considered
Transactions	Attention	Stacked	historical	for performance
on Circuits	Network for	Multimodal	information during	valuation.
and Systems	Context-	Attention Network	caption generation	
for Video	Aware Video	(SMAN), the	as context features,	
Technology,	Captioning.	Reinforcement	employs a stacked	
2021		Learning method	architecture to	
			process different	
<b>X</b> 7 <b>X</b> 7	<b>T</b> 7' 1	A 1 * 1	features gradually.	<b>T</b> 1 1 1
Y. Yang et	Video	Adversarial	The discriminator	Typical object
al., IEEE	Captioning	learning and long	acts as an	oriented
Iransactions	by	short-term memory	adversary toward	performance is
on Image	Adversarial	(LSIM).	the generator, and	better and gets
Processing,	LSIM	generative	with its controlling	degraded as objects
2018.		adversariai	mechanism, it neips	in image increase.
		network (GAN)	the generator to	
		arcmtecture	accurate more	
B. Zhao et al.	CAM-RNN:	a co-attention	During the	Limited set of
in IEEE	Co-Attention	model based	generation	databases are used
Transactions	Model Based	recurrent neural	procedure, the	to evaluate the
on Image	RNN for	network (CAM-	visual attention	performance.
		RNN) is proposed,	module is able to	^

Processing,	Video	where the CAM is	adaptively attend to	
2019.	Captioning	utilized to encode	the salient regions	
		the visual and text	in each frame and	
		features, and the	the frames most	
		RNN works as the	correlated with the	
		decoder to generate	caption.	
		the video caption.	1	
M. Qi et al,	Sports Video	hierarchical	A new dataset	Only sports
IEEE	Captioning	recurrent neural	called sports video	captioning strategy
Transactions	via Attentive	network-based	captioning dataset-	is considered and
on Circuits	Motion	framework with an	volleyball for	when application is
and Systems	Representati	attention	evaluation.	changed the
for Video	on and Group	mechanism for		performance
Technology,	Relationship	sports video		decreases.
2020.	Modeling	captioning, in		
		which a motion		
		representation		
		module is proposed		
		to capture		
		individual pose		
		attribute and		
		dynamical		
		trajectory cluster		
		information with		
		extra professional		
		sports knowledge		
L. Li et al,	Adaptive	An adaptive spatial	The proposed	Process oriented
IEEE	Spatial	location module	adaptive spatial	video change
Transactions	Location	for the video	location method not	decreases the
on Circuits	with	captioning task	only makes our	performance.
and Systems	Balanced	which dynamically	model focus on	
for Video	Loss for	predicts an	local object	
Technology,	Video	important position	information, but	
2020.	Captioning	of each video	also reduces time	
		frame in the	and memory	
		procedure of	consumption	
		generating the	brought by the	
		description	temporal	
		sentence.	redundancy in	
			extensive video	
			frames and	
			improves the	
			accuracy of	

			generated	
			description.	
A. Wu et al,	Convolutiona	CNN-based	long-term	Limited datasets are
IEEE	1	encoder-decoder	dependencies could	used for
Transactions	Reconstructi	framework for	be captured by a	performance
on Circuits	on-to-	video captioning.	shorter path along	evaluation.
and Systems	Sequence for	Particularly, we	the hierarchical	
for Video	Video	first append inter-	structure, the	
Technology,	Captioning	frame differences	decoder could	
2020.		to each CNN-	alleviate the loss of	
		extracted frame	long-term	
		feature to get a	information	
		more		
		discriminative		
		representation		

# V References:-

[1] W. Xu, J. Yu, Z. Miao, L. Wan, Y. Tian and Q. Ji, "Deep Reinforcement Polishing Network for Video Captioning," in IEEE Transactions on Multimedia, vol. 23, pp. 1772-1784, 2021, doi: 10.1109/TMM.2020.3002669.

[2] D. Yasin, A. Sohail and I. Siddiqi, "Semantic Video Retrieval using Deep Learning Techniques," 2020 17th International Bhurban Conference on Applied Sciences and Technology (IBCAST), Islamabad, Pakistan, 2020, pp. 338-343, doi: 10.1109/IBCAST47879.2020.9044601.

[3] MasoomehNabati, Alireza Behrad, Video captioning using boosted and parallel Long Short-Term Memory networks, Computer Vision and Image Understanding, Volume 190, 2020, 102840, ISSN 1077-3142,

[4] Chohan, Murk & Khan, Adil & Mahar, Muhammad &Katper, Saif& Ghafoor, Abdul & Khan, Mehmood. (2020). Image Captioning using Deep Learning: A Systematic Literature Review. International Journal of Advanced Computer Science and Applications. 11. 10.14569/IJACSA.2020.0110537.

[5] Himanshu Sharma ; Manmohan Agrahari ; Sujeet Kumar Singh ; MohdFiroj ; Ravi Kumar Mishra,"Image Captioning: A Comprehensive Survey",IEEE Xplore: 07 May 2020 Conference Location: Mathura, Uttar Pradesh, India. : 10.1109/PARC49193.2020.236619

[6] Yiyu Wang, Jungang Xu, Yingfei Sun, Ben He, (2019), "Image Captioning based on Deep Learning Methods: A Survey', arXiv:1905.08110v1

[7] Haoran Wang, Yue Zhang, Xiaosheng Yu, "An Overview of Image Caption Generation Methods", Computational Intelligence and Neuroscience, vol. 2020, Article ID 3062706, 13 pages, 2020. https://doi.org/10.1155/2020/3062706

[8] Liu, L., Ouyang, W., Wang, X. et al. Deep Learning for Generic Object Detection: A Survey. Int J Comput Vis 128, 261–318 (2020). https://doi.org/10.1007/s11263-019-01247-4

[9] J. Mun, L. Yang, Z. Ren, N. Xu and B. Han, "Streamlined Dense Video Captioning," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, 2019, pp. 6581-6590, doi: 10.1109/CVPR.2019.00675.

[10] T. Fujii, Y. Sei, Y. Tahara, R. OriharaAnd A. Ohsuga, ""Never fry carrots without cutting." Cooking Recipe Generation from Videos Using Deep Learning Considering Previous Process," 2019 IEEE International Conference on Big Data, Cloud Computing, Data Science & Engineering (BCD), Honolulu, HI, USA, 2019, pp. 124-129, doi: 10.1109/BCD.2019.8885222.

[11] A. Dilawari and M. U. G. Khan, "ASoVS: Abstractive Summarization of Video Sequences," in IEEE Access, vol. 7, pp. 29253-29263, 2019, doi: 10.1109/ACCESS.2019.2902507.

[12] Zhang, X.; Wang, X.; Tang, X.; Zhou, H.; Li, C. "Description Generation for Remote Sensing Images Using Attribute Attention Mechanism". Remote Sens. 2019, 11, 612 DOI:10.3390/RS11060612

[13] .Dong-Jim kim and Jinsoo Choi and Tae-Hyun Oh and In So Kweon, (2019), "Dense Relational Captioning: Triple-Stream Networks for Relationship-Based Captioning", arXiv, cs.CV.

[14] J. Dong, X. Li and C. G. M. Snoek, "Predicting Visual Features From Text for Image and Video Caption Retrieval," in IEEE Transactions on Multimedia, vol. 20, no. 12, pp. 3377-3388, Dec. 2018, doi: 10.1109/TMM.2018.2832602.

[15] C. I. Orozco, M. E. Buemi and J. J. Berlles, "Video to Text Study using an Encoder-Decoder Networks Approach," 2018 37th International Conference of the Chilean Computer Science Society (SCCC), Santiago, Chile, 2018, pp. 1-5, doi: 10.1109/SCCC.2018.8705254.

[16] Sheng Li,Zhiqiang Tao "Visual to Text :Survey of image and video captioning" IEEE2019 DOI 10.1109/TETCI.2019.282755

[17] R. Shetty, H. R. Tavakoli and J. Laaksonen, "Image and Video Captioning with Augmented Neural Architectures," in IEEE MultiMedia, vol. 25, no. 2, pp. 34-46, Apr.-Jun. 2018, doi: 10.1109/MMUL.2018.112135923.

[18] Bai, Shuang & An, Shan. (2018). A Survey on Automatic Image Caption Generation. Neurocomputing. 311. 10.1016/j.neucom.2018.05.080.

[19] Eleftherios Daskalakis, Maria Tzelepi, Anastasios Tefas, Learning deep spatiotemporal features for video captioning, Pattern Recognition Letters, Volume 116, 2018, Pages 143-149, ISSN 0167-8655.

[20] Su, Jiaqi. "Study of Video Captioning Problem." (2018).

[21] P. Anderson et al., "Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 6077-6086, doi:10.1109/CVPR.2018.00636.

[22] Sujin Lee, Incheol Kim, "Multimodal Feature Learning for Video Captioning", Mathematical Problems in Engineering, vol. 2018, Article ID 3125879, 8 pages, 2018. https://doi.org/10.1155/2018/3125879X.

[23] X. He and L. Deng, "Deep Learning for Image-to-Text Generation: A Technical Overview," in IEEE Signal Processing Magazine, vol. 34, no. 6, pp. 109-116, Nov. 2017, doi: 10.1109/MSP.2017.2741510.

[24] L. Pang, S. Zhu and C. Ngo, "Deep Multimodal Learning for Affective Analysis and Retrieval," in IEEE Transactions on Multimedia, vol. 17, no. 11, pp. 2008-2020, Nov. 2015, doi: 10.1109/TMM.2015.2482228.

[25] Rafael A. Rivera-Soto, Juanita Ord'o nez, "Sequence to Sequence Models for Generating Video Captions",cs231n.stanford.edu > reports > pdfs

[26] SimaoHerdade, Armin Kappeler, Kofi Boakye, Joao Soares, Image Captioning: Transforming Objects into Words, arXiv:1906.05963v2

[27] Omid Mohamad Nezami, Mark Dras, Stephen Wan, Cecile Paris, "Image Captioning using Facial Expression and Attention", arXiv:1908.02923v3.

[28] G. Kulkarni, V. Premraj, V. Ordonez et al., "Babytalk: understanding and generating simple image descriptions," IEEETransactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 12, pp. 2891–2903, 2013.

[29] S. Li, G. Kulkarni, T. L. Berg, and Y. Choi, "Composing simple image descriptions using web-scale N-grams," in Proceeding of Fifteenth Conference on Computational Natural Language Learning, pp. 220–228, Association for Computational Linguistics, Portland, OR, USA, June 2011.

[30] Bo Luo, XiaTang, JianzhuangLiu"Video Caption detection and extraction using temporal information" 0-7803-7750-8/03/1%7 .00 02003 IEEE2003.

[31] W. Zhang, B. Wang, L. Ma and W. Liu, "Reconstruct and Represent Video Contents for Captioning via Reinforcement Learning," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 12, pp. 3088-3101, 1 Dec. 2020, doi: 10.1109/TPAMI.2019.2920899.

[32] T. Wang, H. Zheng, M. Yu, Q. Tian and H. Hu, "Event-Centric Hierarchical Representation for Dense Video Captioning," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 31, no. 5, pp. 1890-1900, May 2021, doi: 10.1109/TCSVT.2020.3014606.

[33] L. Gao, Y. Lei, P. Zeng, J. Song, M. Wang and H. T. Shen, "Hierarchical Representation Network with Auxiliary Tasks for Video Captioning and Video Question Answering," in IEEE Transactions on Image Processing, 2021, doi: 10.1109/TIP.2021.3120867.

[34] Y. Zheng, Y. Zhang, R. Feng, T. Zhang and W. Fan, "Stacked Multimodal Attention Network for Context-Aware Video Captioning," in IEEE Transactions on Circuits and Systems for Video Technology, doi: 10.1109/TCSVT.2021.3058626.

[35] Y. Yang et al., "Video Captioning by Adversarial LSTM," in IEEE Transactions on Image Processing, vol. 27, no. 11, pp. 5600-5611, Nov. 2018, doi: 10.1109/TIP.2018.2855422.
[36] B. Zhao, X. Li and X. Lu, "CAM-RNN: Co-Attention Model Based RNN for Video Captioning," in IEEE Transactions on Image Processing, vol. 28, no. 11, pp. 5552-5565, Nov. 2019, doi: 10.1109/TIP.2019.2916757.

[37] M. Qi, Y. Wang, A. Li and J. Luo, "Sports Video Captioning via Attentive Motion Representation and Group Relationship Modeling," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 8, pp. 2617-2633, Aug. 2020, doi: 10.1109/TCSVT.2019.2921655.

[38] L. Li, Y. Zhang, S. Tang, L. Xie, X. Li and Q. Tian, "Adaptive Spatial Location with Balanced Loss for Video Captioning," in IEEE Transactions on Circuits and Systems for Video Technology, doi: 10.1109/TCSVT.2020.3045735.

[39] A. Wu, Y. Han, Y. Yang, Q. Hu and F. Wu, "Convolutional Reconstruction-to-Sequence for Video Captioning," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 11, pp. 4299-4308, Nov. 2020, doi: 10.1109/TCSVT.2019.2956593.