Recent Advances and Trends in Multimodal Deep Learning: A Review

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Deep Learning has implemented a wide range of applications and has become increasingly popular in recent years. The goal of multimodal deep learning is to create models that can process and link information using various modalities. Despite the extensive development made for unimodal learning, it still cannot cover all the aspects of human learning. Multimodal learning helps to understand and analyze better when various senses are engaged in the processing of information. This paper focuses on multiple types of modalities, i.e., image, video, text, audio, body gestures, facial expressions, and physiological signals. Detailed analysis of past and current baseline approaches and an in-depth study of recent advancements in multimodal deep learning applications has been provided. A fine-grained taxonomy of various multimodal deep learning applications is proposed, elaborating on different applications in more depth. Architectures and datasets used in these applications are also discussed, along with their evaluation metrics. Last, main issues are highlighted separately for each domain along with their possible future research directions.

 $CCS\ Concepts: \bullet\ Computing\ methodologies \rightarrow Machine\ learning; \bullet\ Information\ systems \rightarrow Multimedia\ and\ multimodal\ retrieval.$

Additional Key Words and Phrases: Deep Learning, Multimedia, Multimodal learning, datasets, Neural Networks, Survey

1 Introduction:

Machine learning (ML) has become increasingly popular in recent studies. It has been implemented in a vast application range such as image recognition, multimedia concept retrieval, social network analysis, video recommendation, text mining, etc. Deep Learning (DL) is widely used in these applications [117]. The exponential growth, incredible developments, and data availability in computing technologies have contributed to the rise of DL research. DL success has been a motivating factor for solving even more complex ML problems. Additionally, DL's principal advantage is its representation in hierarchical form, i.e., it can learn effectively through a general-purpose learning process. Various new DL approaches have been developed and have shown impressive outcomes across multiple applications such as visual data processing, Natural Language Processing (NLP), voice and audio processing, and many other widely-known applications. Multimodal Deep learning (MMDL) has recently attracted significant research intentions due to the development of DL. A list of abbreviations is presented in the Table 1.

Our experience of things around us is multimodal; we see things, hear, touch, smell, and taste. Multiple aspects of the object are captured to transmit information in different media forms like image, text, video, graph, sound, etc. Modality specifies a representation format in which a particular type of information is stored. Therefore, various media forms mentioned above relate to modalities, and the representation of these multiple modalities together can be defined as multimodal [47]. Extensive development has been made in terms of uni-modal. Still, it is insufficient to model the complete aspects of humans. Uni-modal works better where progress of the method is required in only one mode. Multimodal learning suggests we understand and analyze better when a variety of senses are engaged in the processing of information. This paper focuses on various types of modalities, i.e., image,

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video, text, audio, body gestures, facial expressions, and physiological signals from the MMDL perspective. The main goal of MMDL is to construct a model that can process information from different modalities and relate it.

Table 1. List of Abbreviations

Abbreviation	Explanation	Abbreviation	Explanation
AFDBN	Adaptive Fractional Deep Belief Network	AI	Artificial Intelligence
AMT	Amazon Mechanical Turk	ANN	Artificial Neural Network
ASKMS	Adaptive Shape Kernel Based Mean Shift	ATTS	Articulatory Text To Speech
AUC	Area Under Curve	AVSR	Audio-Visual Speech Recognition
BiLSTM	Bidirectional Long Short-Term Memory	BNDBM	Batch Normalized Deep Boltzmann Machine
BRNN	Bidirectional Recurrent Neural Network	C3D	Three Dimensional Convolutional Neural Networks
CALO-MA	CALO Meeting Assistant	CDBN	Competitive Deep Belief Network
CHIL		CLEVR	1 * *
CILL	Computers in the Human Interaction Loop	CLEVK	Compositional Language and Elementary Visual Reasoning diagnostics
CMN	Commonitional Madulon Naturals	CNN	Convolutional Neural Network
COH	Compositional Modular Network	CRF	Conditional Random Field
	Color Oriented Histogram Cascade Recurrent Neural Network	CssCDBM	
CRNN	Cascade Recurrent Neural Network	CSSCDBM	Contractive slab and spike Convolutional Deep Boltzmann Machine
CTTS	Concatenative Text To Speech	CV	Computer Vision
DAQUAR	DAtaset for QUestion Answering on Real-world images	DBM	Deep Boltzmann Machine
DBN	Deep Belief Network	DDBN	Discriminative Deep Belief Network
DL	Deep Learning	DLTTS	Deep Learning Text To Speech
DNN	Deep Neural Network	DRL	Deep Reinforcement Learning
E2E	End-to-End	EDR	Equal Detected Rate
EER	Equal Error Rate	EOH	Edge Oriented Histogram
F3RBM	Fuzzy Removing Redundancy Restricted Boltzmann Ma-	FDBN	Fuzzy Deep Belief Network
1 SKBWI	chine	IDDIN	Tuzzy beep benefivetwork
FRBM	Fuzzy Restricted Boltzmann Machine	FTTS	Formant Text To Speech
FVQA	Fact-based Visual Question Answering	GBRBM	Gaussian-Bernoulli Restricted Boltzmann Machine
GLU	Gated Linear Unit	GMM	Gaussian Mixture Model
GRU	Gated Recurrent Unit	HMM	Hidden Markov Model
HRL	Hierarchical Reinforcement Learning	IEMOCAP	Interactive Emotional Dyadic Motion Capture
KB	Knowledge Bases	LSTM	Long Short-Term Memory
MAE	Mean Absolute Error	mAP	mean Average Precision
MCB	Multimodal Compact Bilinear	MCD	Mel Cepstral Distortion
MDP	Markov Decision Process	MFCC	Mel Frequency Cepstral Coefficients
ML	Machine Learning	MMAM	Multimodal Attention-Based Models
MMDL	Multimodal Deep Learning	MMED	Multimodal Event Detection
MMER	Multimodal Emotion Recognition	MMEKBM	Multimodal External Knowledge Bases Models
MMIEM	Multimodal Joint-Embedding Models	MOS	Mean Opinion Score
MS-COCO	Microsoft-Common Objects in Context	msDBM	Mean supervised Deep Boltzmann Machine
MSR-VTT	Microsoft Research-Video to Text	MSVD	Microsoft Video Description
MuSE	Multimodal Stressed Emotion	M-VAD	Montreal-Video Annotation Dataset
NLP	Natural Language Processing	NMI	Normalized Mutual Information
NN	Neural Networks	NRBM	Normalized Restricted Boltzmann Machine
PoS	Part of Speech	PPLX	Perplexity metric
PTTS	Parametric Text to Speech	RBM	Restricted Boltzmann Machine
RBS	Rule Based System	RECOLA	REmote COLlaborative and Affective
RF TF	Random-Forest Tag-Propagation	RGB-D	Red Green Blue-Depth
RF_IF RNN	Recurrent Neural Network	RossDBM	Robust spike-and-slab Deep Boltzmann Machine
SEMAINE	Sustained Emotionally coloured Machinehuman Interaction	SGRU	Stacked Gated Recurrent Unit
SEMAINE	using Nonverbal Expression	SGRU	Stacked Gated Recurrent Unit
SiGRU	Simplified GRU	SML	Stochastic Maximum Likelihood
SMT	Statistical Machine Translation	SRE	Semantic Relation Extractor
SST	Single-Stream Temporal	STFT	Short-Time Fourier Transform
SVO	Subject, Object, Verb	TDIUC	Task Directed Image Understanding Challenge
TTS	Text To Speech	V2C	Video-to-Commonsense
VAE	Variational Auto-Encoders	VCTK	Voice Cloning Toolkit
VDR	Visual Dependency Representation	VOA	Visual Question-Answering
* DI	visual Dependency representation	I VQA	A 120rdi Ancerion-vineweimik

The future of Artificial Intelligence (AI) has been revolutionized by DL. It has addressed several complex problems that have existed for many years within the AI community. For MMDL, various deep architectures with

different learning frameworks are rapidly designed. Machines are developed to perform similarly to humans or even better in other application areas such as self-driving cars, image processing, medical diagnosis and predictive forecasting etc [129]. The recent advances and trends of MMDL are from Audio-visual speech recognition (AVSR) [173], multimodal emotion recognition [26], image and video captioning [58, 89], Visual Question-Answering (VQA) [161], to multimedia retrieval [134] and so on.

1.1 Contribution and Relevance to other surveys:

Recently, numerous surveys (such as, C. Zhang et al. [174] 2020, Y. Bisk et al. [16] 2020, J. Gao et al. [40] 2020, A. Mogadala et al. [101] 2019, SF Zhang et al. [176] 2019, W Guo et al. [47] 2019, T Baltrušaitis et al. [12] 2018, Y Li et al. [83] 2018, and D Ramachandram et al. [119] 2017 are already published relating to the topic of multimodal learning. These review articles are analyzed and discussed further in the section 1.1.1. Our contributions to this article are described in section 1.1.2. A summarized list of these review articles is presented in Table 2.

- 1.1.1 Analysis of baseline surveys: C. Zhang et al. [174] discussed natural language and vision modalities in NLP and Computer Vision (CV). Y. Bisk et al. [16] reviewed work based on NLP contextual foundations. The fundamentals of MMDL fusion methods and their challenges are discussed by Gao et al. [40]. Mogadala et al. [101] mentioned ten different groups of approaches based on language and vision tasks. Datasets, evaluation metrics used in these approaches, and their results are also discussed. SF Zhang et al. [176], W Guo et al. [47], and Y Li et al. [83] explained different algorithms and applications of multimodal representation learning, its recent trends and challenges. T Baltrušaitis et al. [12] described various frameworks based on five core challenges, i.e., representation, translation, alignment, fusion and co-learning of multimodal machine learning. D Ramachandram et al. [119] examined recent developments in deep multimodal learning and limitations and obstacles in this active area of study; also regularization strategies and methods to optimize the structure of multimodal fusion are highlighted.
- 1.1.2 Our contributions: All these literature surveys provide a review on only a specific domain of multimodal learning. Some authors only discussed methods and applications of representation learning and some on fusion learning. Others discussed representation and fusion learning methods together using few modalities like vision or text. As mentioned earlier, Mogadala et al. [101] explained different models of MMDL using image, video and text modalities. However, we have taken one step further; along with these modalities, this paper provides a technical review of various models using audio, body gestures, facial expressions and physiological signals modalities. Our primary focus is distinctive in that we seek to survey the literature from up-to-date deep learning concepts using more modalities. The main contributions of our article are listed below:
 - A novel fine-grained taxonomy of various Multimodal Deep Learning applications is proposed, which elaborates different groups of applications in more depth.
 - Various models using the image, video, text, audio, body gestures, facial expressions and physiological signals modalities are discussed together.
 - Recent advancements of MMDL in image description is discussed in section 3.1.1, 3.1.2 and 3.1.3.
 - In video description and VQA tasks, up-to-date literature is discussed in section 3.2.1, 3.2.2, 3.2.3 and 3.3.1, 3.3.2, 3.3.3 respectively.
 - In Section 3.4.1 and 3.5.1, the contribution of deep learning frameworks about speech synthesis and emotion recognition is explained in detail.
 - Main issues are highlighted separately for each application group, along with their possible future research directions.

Table 2. List of related literature surveys

No.	Title	Pub.	Year
1	Multimodal Intelligence: Representation Learning, Information Fusion, and Applications [174]	IEEE	2020
2	Experience Grounds Language [16]	arXiv	2020
3	A Survey on Deep Learning for Multimodal Data Fusion [40]	NC(MIT)	2020
4	Trends in integration of vision and language research: A survey of tasks, datasets, and methods [101]	arXiv	2019
5	Multimodal Representation Learning: Advances, Trends and Challenges [176]	IEEE	2019
6	Deep multimodal representation learning: A survey [47]	IEEE	2019
7	Multimodal Machine Learning: A Survey and Taxonomy [12]	IEEE	2018
8	A Survey of Multi-View Representation Learning [83]	IEEE	2018
9	Deep Multimodal Learning: A survey on recent advances and trends [119]	IEEE	2017

1.2 Structure of Survey:

The rest of the article is structured as follows. Some background of MMDL is discussed in section 2. Section 3 presents various MMDL application groups. Architectures used in MMDL are discussed in section 4. Dataset and evaluation metrics are discussed in sections 5 and 6, respectively. In section 7, we provided a brief discussion and propose future research directions in this active area. Finally, section 8 concludes the survey paper.

2 Background:

A lot of ML approaches have been developed over the past decade to deal with multimodal data. Multimodal applications came into existence in the 1970s and were categorized into four eras [102]. Description of these eras is explained in section 2.1. In this paper, we concentrate mainly on deep learning era for multimodal applications.

2.1 Eras of multimodal learning:

Prior research on multimodal learning can be categorized into four eras, listed below.

- "Behavioral Era (BE)": The BE starts from the 1970s to the late 1980s. During this era, AA Lazarus [76] proposed Multimodal behavior therapy based on seven different personality dimensions using inter-related modalities. RM Mulligan & ML Shaw [103] presents multimodal signal detection, wherein the signal detection task, the pooling of information is examined from other modalities, i.e., auditory and visual stimuli.
- "Computational Era (CE)": The CE starts from the late 1980s to 2000. During this era, ED Petajan [115] proposed an "Automatic Lipreading to Enhance Speech Recognition." BP. Yuhas et al. [173] increase the performance of automatic speech recognition system even in noisy environments by using neural networks (NN). Hidden Markov Model (HMM) [70] has become so popular in speech recognition because of the inherent statistical framework, the ease and accessibility of training algorithms to estimate model parameters from finite speech data sets.
- "Interaction Era (IE)": The IE starts from 2000 to 2010. During this era, one of the first milestones is the AMI Meeting Corpus [23] (a multimodal dataset) with over 100 hours of meeting recordings, all thoroughly annotated and transcribed. AMI seeks to create a repository of meetings and to evaluate conversations. CHIL project motive [148] uses ML methods to extract nonverbal human behaviors automatically. CALO Meeting Assistant (CALO-MA) [145] real-time meeting recognition system takes the speech models. CALO-MA architecture includes real-time and offline speech transcription, action item recognition, question-answer pair identification, decision extraction, and summarization.

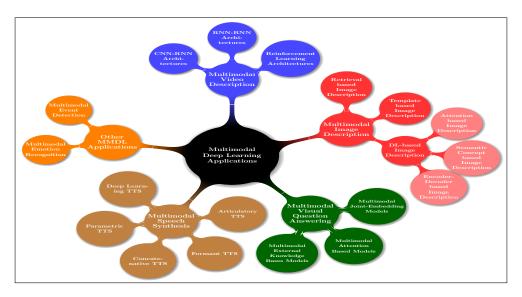


Fig. 1. Taxonomy diagram of Multimodal Deep Learning Applications.

• "Deep Learning Era (DLE)": The DLE starts in 2010 to date. This deep learning era is the main focus of our review paper. We comprehensively discuss different groups of applications in section 3, MMDL architectures in section 4, datasets in section 5 and evaluation metrics in section 6 proposed during this era.

3 MMDL Applications:

During the DLE, various applications are designed by using multimodal deep learning techniques. In this article, these applications are grouped with relevance and dominance across multiple research areas. The taxonomy diagram of these applications is presented in the Figure 1.

3.1 Multimodal Image Description:

Image Description is mostly used to generate a textual description of visual contents provided through input image. During the deep learning era, two different fields are merged to perform image descriptions, i.e., CV and NLP. In this process, two main kinds of modalities are used, i.e., image and text. The image description's general structure diagram is shown in Figure 2. Image description frameworks are categorized into Retrieval-based, Templatebased, and DL-based image descriptions. Retrieval and Template based image descriptions are one of the earliest techniques for describing visual contents from images. In this article, DL-based image description techniques are explained in detail, which are further categorized into encoder-decoder-based, semantic concept-based, and attention-based image descriptions.

3.1.1 Encoder-Decoder based Image Description (EDID): EDID plays a vital role in image captioning tasks using DL architectures. CNN architectures are used mainly as encoder parts to extract and encode data from images, and RNN architectures are used as decoder part to decode and generate captions. J. Wu & H.hu [159] proposed a Cascade Recurrent Neural Network (CRNN) for image description. For the learning of visual language interactions, a cascade network is adopted by CRNN from the forward and backward directions. In this approach, two embedding layers are constructed for dense word expression, and Stacked GRU (SGRU) is designed for mappings of the image to its corresponding language model. R. Hu et al. [60] proposed an end-to-end (E2E) Compositional

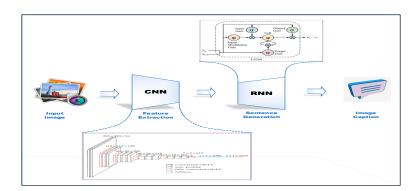


Fig. 2. General structure diagram of Image Description Model.

Modular Network (CMN) model that learns image region localization and language representation jointly. In this model, Referential expressions are observed based on subject-entity, object-entity and a relationship. L. Guo et al. [46] proposed a multi-style image captioning framework using CNN, GAN, LSTM and GRU architectures. In this framework, five different captioning styles are introduced for the image: romantic, negative, positive, factual and humorous styles. X. He et al. [54] proposed an image caption generation framework with the guidance of Part of Speech (PoS). In the word generation part, PoS tags are fed into LSTM as guidance to generate more effective image captions. Y. Feng et al. [37] proposed an unsupervised image captioning framework. In this model first attempt is made to do captioning of the image without any labeled image-sentence pairs. For this purpose, about two million sentences are crawled to facilitate unsupervised scenario of captioning.

- 3.1.2 Semantic Concept-based Image Description (SCID): A collection of semantic concepts extracted from the image are selectively addressed by SCID approaches. These concepts are extracted at the encoding stage along with other features of an image, then merged into hidden states of language models, and output is used to generate descriptions of images based on semantic concepts. W. Wang et al. [154] proposed an attribute-based image caption generation framework. Visual features are extracted by using salient semantic attributes and are pass as input to LSTM's encoder. These semantic attributes can extract more semantic related data in images to enhance the generated caption's accuracy. P. Cao et al. [22] proposed a semantic-based model for image description. In this model, semantic attention-based guidance is used for LSTM architecture to produce a description of an image. L. Cheng et al. [29] proposed a multi-stage visual semantic attention mechanism based image description model. In this approach, top-down and bottom-up attention modules are combined to control the visual and semantic level information for producing fine-grained descriptions of the image.
- 3.1.3 Attention-based Image Description (AID): AID plays a vital role because it helps the image description process by focusing on distinct regions of the image according to their context. In recent years, various techniques have been proposed to better describe an image by applying an attention mechanism. Some of these attention mechanism based image descriptions techniques are; L. Li et al. [80] proposed a new framework for describing images by using local and global attention mechanisms. Selective object-level features are combined with image-level features according to the context using local and global attention mechanisms. Therefore, more appropriate descriptions of images are generated. P. Anderson et al. [7] proposed bottom-up and top-down attention based framework for image description to encourage deeper image understanding and reasoning. M. Liu et al. proposed a dual attention mechanism-based framework to describe an image for Chinese [86] and English [87] languages. The textual attention mechanism is used to improve the data credibility, and the visual attention mechanism is used to a deep understanding of image features by integrating various image labels for English and Chinese description

Table 3. Comparative analysis of Image Description models. Where, EDID = Encoder-Decoder based Image Description, SCID = Semantic Concept-based Image Description, and AID = Attention-based Image Description.

	Paper	Year	Architecture	Multimedia	Dataset	Evaluation Metrics
	J. Wu et al. [159]	2017	CNN/VGG16-InceptionV3, Stacked GRU	Image, Text	MS-COCO	BLEU, CIDEr, METEOR
	R. Hu et al. [60]	2017	Faster RCNN/VGG16, RNN/BLSTM	Image, Text	Visual Genome, Google-Ref	Top-1 precision (P@1) metric
EDID	L. Guo et al. [46]	2019	Deep CNN, GAN, RNN/LSTM, GRU	Image, Text	FlickrStyle10K, SentiCap, MS-COCO	BLEU, CIDEr, METEOR, PPLX
	X. He et al [54]	2019	CNN/VGG16, RNN/LSTM	Image, Text	Flickr30k, MS-COCO	BLEU, CIDEr, METEOR
	Y. Feng et al. [37]	2019	CNN/InceptionV4, RNN/LSTM	Image, Text	MS-COCO	BLEU, ROUGE, CIDER, METEOR, SPICE
	W. Wang et al. [154]	2018	CNN/VGG16, RNN/LSTM	Image,Text	MS-COCO	BLEU, CIDEr, METEOR
SCID	P. Cao et al. [22]	2019	CNN/VGG16, RNN/BLSTM	Image, Text	Flickr8k, MS-COCO	BLEU, CIDEr, METEOR
	L. Cheng et al. [29]	2020	Faster-RCNN, RNN/LSTM	Image, Text	MS-COCO	BLEU, SPICE, METEOR, CIDEr,
						ROUGE
	L. Li et al. [80]	2017	CNN/VGG16-Faster RCNN,	Image, Text	Flickr8K, Flickr30K, MS-COCO	METEOR, ROUGE $_L$, CIDEr,
			RNN/LSTM			BLEU
	P. Anderson et al. [7]	2018	Faster RCNN/ResNet101,	Image, Text	Visual Genome Dataset, MS-COCO,	BLEU, METEOR, CIDEr, SPICE,
			RNN/LSTM, GRU		VQA v2.0	ROUGE
	M. Liu et al. [86]	2020	CNN/InceptionV4, RNN/LSTM	Image, Text	Flickr8k-CN, Flickr8k-CN, AIC-ICC	BLEU, ROUGE, CIDEr, METEOR
AID	M. Liu et al. [87]	2020	CNN/InceptionV4, RNN/LSTM	Image, Text	AIC-ICC	BLEU, ROUGE, CIDEr, METEOR
	B. Wang et al. [150]	2020	CNN/InceptionV4, RNN/LSTM	Image, Text	Flickr8K, Flickr8k-CN	BLEU, ROUGE, CIDEr, METEOR
	Y. Wei et al. [158]	2020	GAN, RNN/LSTM	Image, Text	MS-COCO	BLEU, METEOR, CIDEr, SPICE,
						ROUGE
	LU Jiasen et al. [68]	2020	CNN/ResNet, RNN/LSTM	Image, Text	Flickr30K, MS-COCO	BLEU, ROUGE, CIDEr, METEOR

generation. B. Wang et al. [150] proposed an E2E-DL approach for image description using a semantic attention mechanism. In this approach, features are extracted from specific image regions using an attention mechanism for producing corresponding descriptions. This approach can transform English language knowledge representations into the Chinese language to get cross-lingual image description. Y. Wei et al. [158] proposed an image description framework by using multi attention mechanism to extract local and non-local feature representations. LU Jiasen et al. [68] proposed an adaptive attention mechanism based image description model. Attention mechanism merges visual features extracted from the image by CNN architecture and linguistic features by LSTM architecture.

During the deep learning era (2010 to date), many authors contributed a lot by proposing various techniques to describe the visual contents of an image in the domain of image description. Different image description approaches described in section 3.1.1, 3.1.2, and 3.1.3 are analyzed comparatively according to architectures, multimedia, publication year, datasets, and evaluation metrics in Table 3. The architectures used in these proposed techniques are explained briefly in section 4. Similarly, datasets and evaluation metrics are discussed in sections 5 and 6, respectively.

3.2 Multimodal Video Description:

Like image Description, video description is used to generate a textual description of visual contents provided through input video. It has various applications in video subtitling, visually impaired videos, video surveillance, sign language video description, and human-robot interaction. Advancements in this field open up many opportunities in various application domains. During this process, mainly two types of modalities are used, i.e., video stream and text. The general structure diagram of the video description is shown in Figures 3 (a) & (b) and 4.

During the deep learning era, many authors contribute to video description by using various methods. At the start of this DL era, some classical and statistical video description approaches are proposed based on Subject, Object, Verb (SVO) tuple methods [2]. These SVO tuple-based methods laid the foundation for the description of

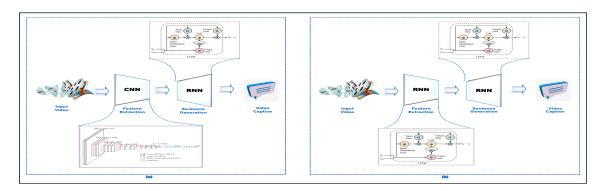


Fig. 3. General structure diagram of Video Description Model. (a) is general structure diagram of CNN-RNN architecture video description and (b) is general structure diagram of RNN-RNN architecture combination for video description.

the video's visual contents. Deep learning approaches can solve open domain description problems of videos. Here, DL approaches for the description of visual contents from videos are discussed in detail. There are two video description stages in deep learning techniques, i.e., visual feature extraction and text generation. In the visual feature extraction phase, various architectures are practiced like CNN, RNN, or LSTM. For the text generation phase, RNN, BRNN, LSTM, or GRU architectures are used. In this research, the video description approach is categorized based on the following architectural combinations for visual feature extraction and text generation. These approaches are comparatively analyzed according to architectures, multimedia, publication year, datasets, and evaluation metrics in Table 4.

- CNN-RNN Architectures: Most broadly used architecture combination in the domain of video description is CNN-RNN. Figure 3(a) presents the general view of the video description process by using CNN-RNN architectures. Where at the visual extraction (encoder) stage variants of CNN architectures are used and at the sentence generation (decoder) stage variants of RNN architectures are used. During deep learning era, several authors proposed techniques for describing videos that are based on this encoder, decoder combination. R Krishna et al. [73] proposed a video description technique using action/event detection by applying a dense captioning mechanism. This is the first framework to detect and describe several events, but it didn't significantly improve video captioning. B. Wang et al. [149] proposed a reconstruction network for video description using an encoderdecoder reconstructor architecture, which utilizes both forward flow (from video to sentence) and backward flow (from sentence to video). W. Pei et al. [114] proposed an attention mechanism based encoder-decoder framework for video description. An additional memory based decoder is used to enhance the quality of video description. N Aafaq et al. [1] proposed video captioning and capitalized on Spatio-temporal dynamics of videos to extract high-level semantics using 2D and 3D CNNs hierarchically, and GRU is used for the text generation part. S. Liu et al. [88] proposed SibNet; a sibling convolutional network for video description. Two architectures are used simultaneously to encode video, i.e., the content-branch to encode visual features and the semantic-branch to encode semantic features. Features of these two branches are fed together to RNN architecture by using a soft attention mechanism.
- 3.2.2 RNN-RNN Architectures: During the DL era, RNN-RNN is also a popular architectural combination because many authors contribute a lot by proposing various methods using this combination. Authors extract the visual content of the video by using RNN architectures instead of CNN. Figure 3(b) presents the general view of the video description process by using RNN-RNN architectures. Both visual extraction (encoder) and sentence generation (decoder) stage variants of RNN architectures are used. H. Yu et al. [169] proposed a hierarchical based two RNN

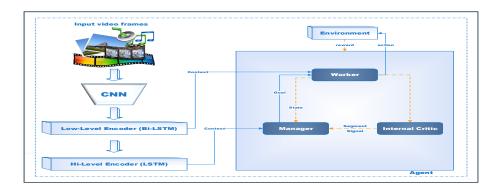


Fig. 4. General structure diagram of Video Description Deep Reinforcement Learning Architectures.

architecture with attention mechanism for video description task. This approach is used for both sentence and paragraph generation for video. M. Rahman Et al. [118] proposed a video captioning framework that modifies the generated context using spatial hard pull and stacked attention mechanisms. This approach illustrates that mounting an attention layer for a multi-layer encoder will result in a more semantically correct description. Z. Fang et al. [36] proposed a framework to generate commonsense captions of the input video. Commonsense description seeks to identify and describe the latent aspects of video like effects, attributes, and intentions. A new dataset, "Video-to-Commonsense (V2C)," is also proposed for this framework.

Deep Reinforcement Learning (DRL) architectures: DRL is a learning mechanism where machines can learn intelligently from actions like human beings can learn from their experiences. In it, an agent is penalized or rewarded based on actions that bring the model closer to the target outcome. DRL outperforms in many ML areas and has become more popular since 2013 after the Google Deep Mind platform. The main contributions of authors using DRL architectures are; X. Wang et al. [155] proposed a hierarchical based reinforcement learning (HRL) model for describing a video. In this framework, a high-level manager module designed sub-goals and low-level worker module recognize actions to fulfill these goals. ResNet-152 extracts visual features from a video at the encoding stage, and these features are processed subsequently by low-level BLSTM [128] and high-level LSTM [56]. And at the decoding stage, HRL is used to generate the language description. Y. Chen et al. [28] proposed a framework based on RL for choosing informative frames from an input video. Fewer frames are required to generate video description in this approach. To minimize the computation, on average 6~8 key/informative frames are selected to represent the complete video. L. Li & B. Gong [79] proposed an E2E multitask RL framework for video description. In this framework, CNN and LSTM architectures are trained simultaneously for the first time. The proposed method combines RL with attribute prediction during the training process, which results in improved video description generation compared to existing baseline methods. J. Mun et al. [104] proposed a framework where an event sequence generation network is used to monitor the series of events for generated captions from the video. This framework is trained in a supervised manner, while RL further enhances the model for better context modeling. W. Zhang et al. [177] proposed a reconstruction network for a description of visual contents, which operates on both forward flow (from video to sentence) and backward flow (from sentence to video). Encoder-Decoder utilizes the forward flow for text description, and reconstructor (local and global) utilizes backward flow. W. Xu et al. [165] proposed a polishing network that utilizes the RL technique to refine the generated captions. This framework consists of word denoising and grammar checking networks for fine-tuning generated sentences. RL's policy-gradient algorithm policy optimizes the parameter of these networks. R. Wei et al. [157] proposed a framework for better exploration of RL events to generate more accurate and detailed video

R. Wei et al. [157]

	D	37	A 1. 14 4	3414	Detect	Paralantian Matrice
	Paper	Year	Architecture	Multimedia	Dataset	Evaluation Metrics
	R. Krishna et al. [73]	2017	CNN/C3D, RNN/LSTM	Video, Text	ActivityNet Captions	BLEU, CIDEr, METEOR
CNN	B. Wang et al. [149]	2018	CNN/InceptionV4,	Video, Text	MSVD, MSR-VTT,	BLEU, $ROUGE_L$, METEOR, CIDEr.
			RNN/LSTM			
to	W. Pei et al. [114]	2019	CNN/ResNet101/ResNeXt101,	Video, Text	MSVD, MSR-VTT	BLEU, $ROUGE_L$, METEOR, CIDEr.
			RNN/GRU			
RNN	N. Aafaq et al. [1]	2019	CNN/IRV2, 3DCNN/C3D,	Video, Text	MSVD, MSR-VTT	BLEU, ROUGE, CIDEr, METEOR
			RNN/GRU			
	S. Liu et al. [88]	2020	CNN/GoogLeNet/Inception,	Video, Text	MSVD, MSR-VTT	BLEU, ROUGE, CIDEr, METEOR
			RNN/LSTM			
	H. Yu et al. [169]	2016	RNN, RNN/GRU	Video, Text	YouTubeClips, TACoS-MultiLevel	BLEU, CIDEr, METEOR
RNN					• •	
to	Z. Fang et al. [36]	2020	CNN/ResNet-LSTM,	Video, Text	V2C, MSR-VTT	BLEU, METEOR, $ROUGE_L$
			RNN/LSTM			
RNN	Md Rahman [118]	2020	CNN/VGG16-LSTM,	Video, Text	MSVD	BLEU
			RNN/LSTM			
	X. Wang et al. [155]	2018	CNN/ResNet,	Video, Text	MSR-VTT, Charades	BLEU, $ROUGE_L$, METEOR, CIDEr.
			RNN/BLSTM/LSTM, HRL	,	•	2,
	Y. Chen et al. [28]	2018	RNN/LSTM, RNN/GRU	Video, Text	MSVD, MSR-VTT	BLEU, $ROUGE_L$, METEOR, CIDEr.
	L. Li et al. [79]	2019	CNN/Inception-Resnet-V2,	Video, Text	MSVD, MSR-VTT	BLEU, $ROUGE_L$, METEOR, CIDEr.
			RNN/LSTM			
DRL	J. Mun et al. [104]	2019	SST, C3D, RNN/GRU/LSTM	Video, Text	ActivityNet Captions	METEOR, BLEU, CIDEr
	W. Zhang et al. [177]	2019	CNN/InceptionV4,	Video, Text	MSVD, MSR-VTT, ActivityNet	BLEU, $ROUGE_L$, METEOR, CIDEr.
			RNN/LSTM		Captions	
	W. Xu et al. [165]	2020	MDP, RNN/LSTM	Video, Text	MSVD, MSR-VTT	BLEU, $ROUGE_L$, METEOR, CIDEr

Table 4. Comparative analysis of Video description models.

captions. The LSTM model is applied on video frames in a sliding window manner to leverage the local temporal information, and the temporal attention mechanism selects the most relevant sliding window to generate the most appropriate words.

Video, Text

MSVD, MSR-VTT, Charades

BLEU, METEOR, CIDEr

3.3 Multimodal Visual Question Answering:

2020

VQA is an emerging technique that has piqued the interest of both the CV and NLP groups. It is a field of research about creating an AI System capable of answering natural language questions. It is a multimodal architectural system where a machine provides the answer in few words or short phrases by combining CV and NLP communities. Extracted features from input image/video and question are processed and combined to answer the question about the image as presented in Figure 5. CNN architectures are used to extract the image/video features while RNN architectures are used to extract the question features.

VQA is more complex as compared to other vision and language functions like text-to-image retrieval, video captioning, image captioning, etc. because;

(1) Questions asked in VQA are not specific or predetermined.

3D CNN/ResNet, RNN/LSTM

- (2) Visual information in VQA is at a high degree of dimensionality. Usually, VQA required a more thorough and detailed understanding of an image/video.
- (3) VQA solves several CV subtasks.

Search and reasoning over image content is the significant difference in VQA. It is a multi-disciplinary AI area to process problems that belong to several sub-tasks of CV, NLP, and Knowledge Representation & Reasoning like, object detection and recognition, attribute and scene classification, commonsense and knowledge-base reasoning, counting, activity recognition, or spatial relationships among objects. During the deep learning era, many authors contribute to the field of VQA by using various methods. These methods are grouped and presented into three groups, i.e., multimodal joint-embedding Models, multimodal attention-based models, and multimodal external knowledge-based models. Various methods of these models are comparatively analyzed in Table 5.

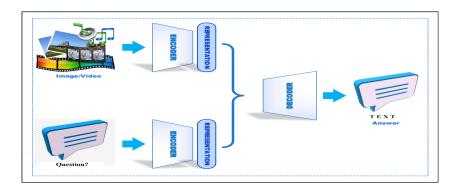


Fig. 5. General structure diagram of VQA System

3.3.1 Multimodal Joint-Embedding Models (MMJEM): MMJEM join and learn representations of multiple modalities in a common feature space. This rationale is improved further in VQA by performing more reasoning over modalities than image/video description. H. Ben-Younes et al. [15] proposed a MUTAN framework for VQA. A tensor-based tucker decomposition model is used with a low-rank matrix constraint to parameterize the bi-linear relations between visual and text interpretations. MT Desta et al. [34] proposed a framework that merges the visual features and language with abstract reasoning. High-level abstract facts extracted from an image optimize the reasoning process. R. Cadene et al. [21] proposed an E2E reasoning network for VQA. This research's main contribution is introducing the MuRel cell, which produces an interaction between question and corresponding image regions by vector representation, and region relations are modeled with pairwise combinations. This MuRel network works finer than attention maps. B. Patro et al. [113] proposed a joint answer and textual explanation generation model. A collaborative correlated (encoder, generator, and correlated) module is used to ensure that answer and its generated explanation is correct and coherent. S. Lobry et al. [90] proposed a VQA framework for remote sensing data, which can be useful for land cover classification tasks. OpenStreetMap data is used for this framework, which can be further subcategorized into low and high-resolution datasets. For the remote sensing domain, these sub-datasets queries the data needed to generate the question and answers. Z. Fang et al. [36] proposed an open-ended VQA framework for videos using commonsense reasoning in the language part, where questions are asked about effects, intents, and attributes.

3.3.2 Multimodal Attention-based Models (MMAM): During the encoding stage, a general encoder-decoder can feed some noisy and unnecessary information at the prediction phase. MMAM are designed to improve the general baseline models to overcome this problem. The attention mechanism's main objective is to use local features of image/video and allow the system to assign priorities to the extracted features from different regions. In an image, the attention portion identified salient regions, and then the language generation part is more focused on those regions for further processing. This concept is also used in VQA to enhance model's performance by focusing on a specific part of an image according to the asked question. The attention step does some additional processing in the reasoning part by focusing on a particular part of the image/video before further language computations.

During the DL era, various approaches are proposed for VQA tasks based on attention mechanisms, like P. Wang et al. [153] proposed a VQA framework based on a co-attention mechanism. In this framework, the co-attention mechanism can process facts, images, and questions with higher order. Z. Yu et al. [172] proposed a factorized bi-linear pooling method with co-attention learning for the VQA task. Bilinear pooling methods outperform the conventional linear approaches, but the practical applicability is limited due to their high computational

Table 5. (Comparative and	lysis of Visual Ques	stion Answering models.

	Paper	Year	Architecture	Multimedia	Dataset	Evaluation Metrics
	H. Ben-Younes et al. [15]	2017	CNN/ResNet152, RNN/GRU	Image, Text	VQA	Accuracy
	MT. Desta et al. [34]	2018	Faster RCNN/Resnet101, RNN/LSTM,	Image, Text	CLEVR	Accuracy
			RNN/GRU			
MMJEM	R. Cadene et al. [21]	2019	Faster RCNN, GRU	Image, Text	VQA v2.0, VQA-CP v2, TDIUC	Accuracy
	B. Patro et al. [113]	2020	CNN, RNN/LSTM	Image, Text	VQA-X	BLEU, SPICE, CIDERr,
						METEOR, $ROUGE_L$
	S. Lobry et al. [90]	2020	CNN/ResNet152, RNN	Image, Text	OpenStreetMap (LR,HR)	Accuracy
	Z. Fang et al. [36]	2020	CNN/ResNet-LSTM, RNN/LSTM	Video, Text	V2C-QA	TopK
	P. Wang et al. [153]	2017	CNN/VGG19-ResNet100, RNN/LSTM	Image, Text	Visual Genome QA, VQA-real	WUPS, Accuracy
	Z. Yu et al. [172]	2017	CNN/ResNet152, RNN/LSTM	Image, Text	VQA MS-COCO	Accuracy
MMAM	P. Anderson et al. [7]	2018	Faster R-CNN, RNN/GRU	Image, Text	Visual Genome, VQA v2.0	Accuracy
	Z. Yu et al. [171]	2019	Faster R-CNN/ResNet101, RNN/LSTM	Image, Text	VQA v2.0	Accuracy
	L. Li et al. [78]	2019	Faster R-CNN/ResNet101, RNN/LSTM	Image, Text	VQA v2.0, VQA-CP v2	Accuracy
	Y. Xi et al. [161]	2020	CNN, RNN/LSTM	Image, Text	DQAUAR, COCO-QA	Accuracy, WUPS
	W. Guo et al. [48]	2020	Faster R-CNN, RNN/LSTM	Image, Text	VQA v2.0	Accuracy
	P. Wang et al. [152]	2018	Faster R-CNN/VGG16, RNN/LSTM	Image, Text	MS-COCO, FVQA	Accuracy TopK, WUPS
MMEKM	M. Narasimhan et al. [106]	2018	CNN/Faster RCNN/VGG16, RNN/LSTM	Image, Text	FVQA	Accuracy TopK
	K. Marino et al. [95]	2019	CNN/ResNet, RNN/GRU	Image, Text	OK-VQA	Recall TopK
	J. Yu et al. [170]	2020	Faster-RCNN, RNN/LSTM	Image, Text	FVQA, Visual7W+KB, OK-VQA	Accuracy TopK
	K. Basu et al. [14]	2020	YOLO, SRE	Image, Text	CLEVR	Accuracy

complexities and high dimensional representations. P. Anderson et al. [7] proposed bottom-up and top-down attention based framework for VQA. This attention mechanism enables the model to calculate feature based on objects or salient image regions. Z. Yu et al. [171] proposed a deep modular co-attention network for the VQA task. Each modular co-attention layer consists of question guided self-attention mechanism of images using the modular composition of both image and question attention units. L. Li et al. [78] proposed a relation aware graph attention mechanism for VQA. This framework encodes the extracted visual features of an image into a graph, and to learn question-adaptive relationship representations, a graph attention mechanism modeled inter-object relations. W. Guo et al. [48] proposed a re-attention based mechanism for VQA. The attention module correlates the pair of object-words and produces the attention maps for question and image with each other's guidance.

3.3.3 Multimodal External Knowledge Bases Models (MMEKM): Traditional multimodal joint embedding and attention-based models only learn from the information that is present in training sets. Existing datasets do not cover all events/activities of the real world. Therefore, MMEKM is vital to coping with real-world scenarios. Performance of VQA task is more increasing by linking knowledge bases (KB) databases to VQA task. Freebase [17], DBPedia [11], WordNet [99], ConceptNet [85], and WebChild [141] are extensively used KB. A robust VQA framework requires access to broad information content from KB. It has been effectively integrated into the VQA task by embedding the various entities and relations.

During the DL era, various external KB methods are proposed for VQA tasks. P. Wang et al. [152] proposed another framework for the VQA task names "Fact-based VQA (FVQA)" that uses data-driven approaches and LSTM architecture to map image/question queries. FVQA framework used DBPedia, ConceptNet, and WebChild KB. M. Narasimhan & AG. Schwing [106] proposed a framework for the VQA task using external knowledge resources that contain a set of facts. This framework can answer both fact-based and visual-based questions. K. Marino et al. [95] proposed an outside knowledge dataset for VQA, which contains more than 14,000 questions. This dataset contains several categories like sports, science and technology, history, etc. This dataset requires external resources to answer, instead of only understanding the question and image features. K. Basu et al. [14] proposed a commonsense based VQA framework. In this framework, the image's visual contents are extracted and understood by the YOLO framework and represented in the answer set program. Semantic relations features and additional commonsense knowledge answer the complex questions for natural language reasoning. J. Yu

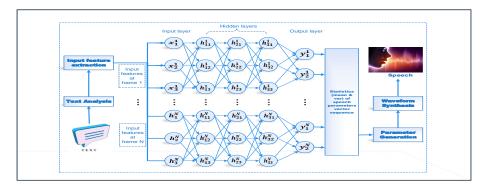


Fig. 6. General structure diagram of Deep Learning Text To Speech framework using DNN architecture.

et al. [170] proposed a framework in which visual contents of an image is extracted and processed in multiple perspectives of knowledge graph like semantic, visual, and factual perspectives.

Multimodal Speech synthesis:

The most important aspect of human behavior is communication (write/speak). Humans can communicate using natural language by text and speech, representing the written and vocalized form of natural language, respectively. The latest research in language and speech processing helps systems talk like a human being. Speech synthesis is the complicated process of generating natural language spoken by a machine. Natural language text modality is converted into its respective spoken waveform modality in real-time by the Text To Speech (TTS) system. Various applications are introduced in the real world using speech synthesis, like human-computer interactive systems, screen readers, telecommunication and multimedia applications, talking toys games, etc. The main research objective of TTS systems these days is to produce a sound like a human's. Therefore, various aspects are used for the evaluation of the TTS system's quality, such as naturalness (quality with the perspective of generated speech timing structure, rendering emotions and pronunciation), intelligibility (in a sentence, quality of each word being produced), synthetic speech preferences (choice of a listener in term of voice and signal quality for better TTS system) and human perception factors like comprehensibility (understanding quality of received messages). Articulatory TTS, Concatenative TTS, Formant TTS, Parametric TTS, and Deep Learning TTS are the main categories of the speech synthesis process. This section discusses recent research trends and advancements of Deep Learning TTS.

Deep Learning TTS (DLTTS): In DLTTS frameworks, DNN architectures model the relationship between text and their acoustic realizations. The main advantage of DLTTS is the development of its extensive features without human prepossessing. Also, the naturalness and intelligibility of speech are improved using these systems. Text to speech synthesis process is explained in the general structure diagram of Deep Learning Text To Speech frameworks using DNN architectures, shown in the Figure 6. Comparative analysis of these approaches is shown in Table 6.

Y. Wang et al. [156] proposed "Tacotron," a sequence 2 sequence TTS framework that synthesizes speech from text and audio pairs. Encoder embeds the text that extracts its sequential representations. The attention-based decoder process these representations, and after that, post-processing architecture generates the synthesized waveforms. In an another research, "Deep Voice" model using DNN architecture are proposed by SO Arik et al. [10] synthesizes audio from characters. This model consists of five significant blocks for the production of synthesized speech from text. The computational speed is increased compared to existing baseline models because

Table 6.	Comparatively	analysis of	speech synthesis	(DLTTS) models.

Paper	Year	Architecture	Multimedia	Dataset	Evaluation Metrics
Y. Wang et al. [156]	2017	Bidirectional-GRU/RNN	Text, Audio	North American English	MOS
SO Arik et al. [10]	2017	GRU/RNN	Text, Audio	Internal English speech database, Blizzard	MOS
A. Gibiansky et al. [42]	2017	GRU/RNN	Text, Audio	Internal English speech database	MOS
W. Ping et al. [116]	2017	Griffin-Lim, WORLD,	Text, Audio	Internal English speech database, VCTK,	MOS
		WaveNet vocoder		LibriSpeech	
A. Oord et al. [109]	2018	CNN	Audio	North American English, Japanese	MOS
SO Arik et al. [9]	2018	Griffin-Lim vocoder	Text, Audio	LibriSpeech, VCTK	Accuracy, EER, MOS
Y. Taigman et al. [139]	2018	GMM	Text, Audio	Lj speech, Blizzard, VCTK	MOS, MCD, TopK
J. Shen et al. [130]	2018	STFT, BiLSTM	Text, Audio	Internal US English	MOS
I. Elias et al. [35]	2020	GLU, VAE, LSTM	Text, Audio	Proprietary speech	MOS

the model can train without human involvement. A. Gibiansky et al. [42] proposed a Deep Voice-2 architecture. This framework is designed to improve existing state-of-the-art methods, i.e., Tacotron and Deep Voice-1, by extending multi-speaker TTS through low-dimension trainable speaker embedding. In third version of Deep Voice, W. Ping et al. [116] proposed a neural TTS system based on the fully convolutional model with an attention mechanism. This model performs parallel computations by adapting Griffin-Lim spectrogram inversion, WORLD, and WaveNet vocoder speech synthesis. "Parallel WaveNet" an advanced version of WaveNet proposed by A. Oord et al. [109] using the probability density distribution method to train networks. A teacher and a student WaveNet are used parallelly in this model. SO Arik et al. [9] proposed a neural voice cloning system that learns human voice from fewer samples. For that purpose, two techniques, i.e., speaker adaptation and encoding, are used together. Y. Taigman et al. [139] proposed a VoiceLoop framework for a TTS system. This model can deal with un-constrained voice samples without the need for linguistic characteristics or aligned phonemes. This framework transformed the text into speech from voices using a short-shifting memory buffer. J. Shen et al. [130] proposed "Tacotron2. It is neural TTS architecture used to synthesize speech directly from the text. A recurrent based sequence to sequence feature prediction network can map characters to spectrogram, and then these spectrogram are used to synthesize waveforms by using a modified version of WaveNet vocoder. Parallel Tacotron is another brilliant invention in recent times for neural TTS approach proposed by I. Elias et al. [35]. During inference and training processes, this approach is highly parallelizable to achieve optimum synthesis on modern hardware. One to many mapping nature of VAE enhance the performance of TTS and also improves its naturalness.

3.5 Other MMDL applications:

3.5.1 Multimodal Emotion Recognition (MMER): Emotions of human is one of the approach for expressing feelings. MMER is enormously vital for enhancing the interaction experience between humans and computers. The task of ML is to empower computers to learn and identify new inputs from training datasets, hence it can be used efficiently to detect, process, respond, understand and recognize emotions of human through computers training. Thus, the primary purpose of affective computing is to provide machines/systems emotional intelligence ability. It has several research areas such as learning, health, education, communication, gaming, personalized user interface, virtual reality and information retrieval. Multimodal emotion recognition framework can be developed on an AI/ML based prototypes designed to extract and process emotion information from various modalities like speech, text, image, video, facial expression, body gesture, body posture, and physiological signals. The general structure diagram of multiplicative multimodal emotion recognition using facial, textual, and speech cues are shown in Figure 7.

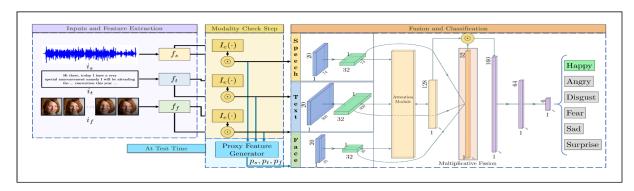


Fig. 7. General structure diagram of Multimodal Emotion Recognition using Facial, Textual, and Speech Cues [100].

During the DL era, various authors contribute to emotion recognition by using different architecture and multiple modalities. Like, Y. Huang et al. [63] proposed a fusion method for emotion recognition using two modalities, i.e., facial expression and electroencephalogram (EEG) signals. A NN classifier detects happiness, neutral, sadness, and fear states of emotions. D. Nguyen et al. [108] proposed another approach for emotion recognition by using audio and video streams. In this method, a combination of C3D and DBN architectures is used to model Spatio-temporal information and representation of video audio streams. S. Tripathi et al. [144] proposed a multimodal emotion recognition framework using various modalities like, text, speech, face expression, and hands movement on the IEMOCAP dataset. The fusion of modalities is performed only at the final layer to improve emotion recognition performance. D. Hazarika et al. [52] proposed an emotion recognition framework from video conversations. This method can generate self and interpersonal affective summaries from conversations by using contextual information extracted from videos. They also proposed another framework for detecting emotions using the attention mechanism [51]. In this framework, audio and textual modalities are used for the detection of emotions. M. Jaiswal et al. [67] analyzes the change of emotional expressions under various stress levels of an individual. The performance of this task is affected by the degree of lexical or acoustic features. L. Chong et al. [31] proposed a new online-chatting system called "EmoChat" to automatically recognize the user's emotions and attach identified emotion automatically and the sent message within a short period. During the chatting user can know each other's emotions in this network. M. Li et al. [81] proposed a multi-step deep system for reliable detection of emotions by using collected data that contains invalid data as well. Neural networks are used to filter this invalid data from videos and physiological signals by using continuity and semantic compatibility. H. Lai et al. [75] proposed a model for emotion recognition in interactive conversations. In this model, different RNN architectures with variable contextual window sizes differentiate various aspects of contexts in conversations to improve the accuracy. RH Huan et al. [61] proposed a model using attention mechanism. In this method, for better use of visual, textual and audio features for video emotion detection, bidirectional GRU is cascaded with an attention mechanism. The attention function is used to work with various contextual states of multiple modalities in real-time. Y Cimtay et al. [33] proposed a hybrid fusion method for emotion recognition using three modalities, i.e., facial expression, galvanic skin response (GSR) and EEG signals. This model can identify the actual emotion state when it is prominent or concealed because of natural deceptive face behavior.

In this section, recent existing methods for emotion recognition and analysis using multimodal DL are presented. Comparative analysis of these techniques is shown in Table 7. This literature review on emotion detection is based on text, audio, video, physiological signals, facial expressions and body gestures modalities. It is clearly shown from an empirical study that automatic emotion analysis is feasible and can be very beneficial in increasing

Table 7. Comparative analysis of MMER and MMED models.

	Paper Year Architecture Multimedia		Dataset	Evaluation Metrics		
	Y. Huang et al. [63]	2017	SVM	Physiological signals,	Manual offline data collec-	Weighted Accuracy
				facial expression	tion	
	D. Nguyen et al. [108]	2017	C3D, DBN	Video, Audio	eNTERFACE Audio-visual	Weighted Accuracy
	D. Nguyen et al. [107]	2018	C3D, MCB, DBN	Video, Audio	eNTERFACE Audio-visual,	Weighted Accuracy
	0.001		Lance Dinistrative		FABO	*** . 1 . 1 .
	S. Tripathi et al. [144]	2018	MFCC, RNN/LSTM	Audio, Text, Facial ex-	IEMOCAP	Weighted Accuracy
	D. Hazarika et al. [52]	2018	CNN, 3D-CNN, RNN/GRU	pressions, Body gesture Text, Audio, Video	IEMOCAP, SEMAINE	Weighted Accuracy, F1-Score,
	D. Hazarika et al. [32]	2016	CININ, 3D-CININ, KININ/GRU	Text, Audio, Video	IEMOCAF, SEMAINE	MAE
	D. Hazarika et al. [51]	2018	CNN, OpenSMILE, MFCC	Text, Audio	IEMOCAP	Weighted Accuracy, F1-Score,
	D. Habarita et al. [61]	2010	erit, opensimiz, in ee	Tent, Tudio	TENTO CT II	Recall
MMER	M. Jaiswal et al. [67]	2019	GRU	Physiological signals,	MuSE, IEMOCAP, MSP-	Weighted Accuracy
				Text	Improv	
	L. Chong et al. [31]	2019	TextCNN, Mini-Xception, HMM	Text, Facial expression	FER2013	Weighted Accuracy
	M. Li et al. [81]	2020	C3D, DBN, SVM-RBF	Video, Physiological sig-	RECOLA	Weighted Accuracy, F1-Score,
				nals		Recall
	H. Lai et al. [75]	2020	CNN, 3D-CNN, RNN/GRU	Text, Audio, Video	IEMOCAP, AVEC	Accuracy, F1-Score
	RH Huan et al. [61]	2020	RNN/GRU	Video, Text, Audio	CMU-MOSI, POM	MAE, Accuracy, F1-Score, Pre-
	V Cimtum et al [00]	2020	CNINI/I	Facial expressions.	THINED & DEAD	cision, Recall
	Y Cimtay et al. [33]	2020	CNN/InceptionResnetV2	Facial expressions, Physiological signals	LUMED-2, DEAP	Weighted Accuracy
	1.53			, ,		
	Y. Gwon et al. [50]	2016	MFCC, CNN	Audio, Video	TRECVID MED Brand-Social-Net	mAP, Accuracy
MMED	Y. Gao et al. [41] S. Huang et al. [62]	2017 2018	CNN, HMM CRBM, CDBN, SVM	Image, Text Video	UCSD. Avenue	Recall, precision, F1-Score AUC, EER, EDR, Accuracy
WINED	P. Koutras et al. [72]	2018	CNN, C3D	Audio, Video	COGNIMUSE	AUC, EER, EDR, Accuracy AUC
	Z. Yang et al. [167]	2018	CNN/VGGNet-AlexNet	Image, Text	MED, SED	NMI, F1-Score
	2. rang et al. [107]	2019	CIVIN/ VOGINCI-AIEXINCI	mage, rext	MED, SED	INIVII, I I-SCOIC

the accuracy of the system response and enabling the subject's emotional state to be anticipated more rapidly. Cognitive assessment and their physical response are also analyzed along with primary emotional states.

3.5.2 Multimodal Event Detection: Due to the popularity of media sharing on the internet, users can easily share their events, activities, and ideas anytime. The aim of multimodal event detection (MMED) systems is to find actions and events from multiple modalities like images, videos, audio, text, etc. According to statistics, Million of tweets are posted per day, and similarly, YouTube users post more than 30,000 hours of videos per hour. Hence, in many CV applications, automatic event and action detection mechanisms are required from this large volume of user-generated videos. Finding events and actions from this extensive collection of data is a complex and challenging task. It has various applications in the real-world like disease surveillance, governance, commerce, etc and also helps internet users to understand and captures happenings around the world. Summary of various MMED methods are presented in Table 7.

Researchers have contributed a lot during the DL era and proposed many methods for event and action detection using multiple modalities. Like, Y. Gwon et al. [50] proposed a multimodal sparse coding scheme for the learning of multiple modalities features representation. In this approach, these feature representations are used to detect events from audio and video media. Y. Gao et al. [41] proposed a method for event classification via social tracking and deep learning in microblogs. Images and text media are fed to a multi-instance deep network to classify events in this framework. S. Huang et al. [62] proposed an unsupervised method for the detection of anomaly events from crowded scenes using DL architectures. In this model, visual, motion map and energy features are extracted from video frames. A multimodal fusion network utilized these features for the detection of anomaly events by using the SVM model. In another research to detect salient events from videos, P. Koutras et al. [72] employed CNN architecture using audio and video modalities. In this framework, a CNN architecture based on C3D nets is used to detect events from a visual stream, and a 2D-CNN architecture is used to detect events from the audio stream. Experimental results show the improvement of the proposed method performance over

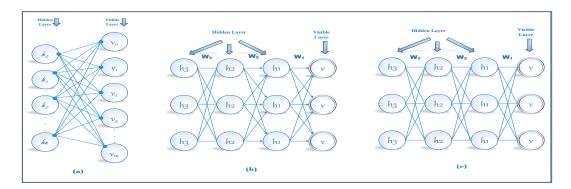


Fig. 8. Structure diagrams of Probabilistic Graphical models: (a) Restricted Boltzmann Machine (RBM), (b) Deep Belief Network (DBN); Partially directed connections between layers and (c) Deep Boltzmann Machine (DBM); Fully undirected connections between layers

the baseline methods for salient event detection. Z. Yang et al. [167] proposed a framework for event detection from multiple data domains like social and news media to detect real-world events. A unified multi-view data representation is built for image and text modalities from social and news domains in this framework. Class wise residual units are formulated to identify the multimedia events.

4 MMDL Architectures:

Multimodal processing, learning and sense have a range of deep learning models. Deep learning is a hierarchical computation model, learns the multilevel abstract representation of the data based on the Artificial Neural Networks (ANN). Hierarchical representation of DL can learn automatically for each modality rather than manually designing particular features of modalities. In this section, a brief explanation of different architectures is presented, which is used in various applications mentioned in section 3. These architectures are categorized into probabilistic graphical models, ANN and miscellaneous architectures groups.

4.1 Probabilistic graphical models:

In MMDL architectures, probabilistic graphical models includes Restricted Boltzmann machine (RBM) [133], Deep Belief Networks (DBN) [55], Deep Boltzmann Machines (DBM) [127], and Variational Auto-Encoders [59]. Restricted Boltzmann Machines (RBM) The most popular sub-class of the Boltzmann Machine [5] is RBM. RBM is a stochastic and generative model with two layers; one is the stochastic visible layer $v \in \{0, 1\}^D$, and the other is a stochastic hidden layer $h \in \{0,1\}^F$ that can learn the distribution of training data. It is an undirected graphical modal whose connections are restricted so that it must form a bipartite graph by its neurons. The structure diagram of RBM is shown in Figure 8(a). RBM can be broadly extended to its respective variants when considering visible sparse count or real-valued data like, replicated softmax RBM [112], Fuzzy RBM (FRBM) [24], Fuzzy Removing Redundancy RBM (F3RBM) [91], Gaussian-Bernoulli RBM (GBRBM) [140], and Normalized RBM (NRBM) [3]. Deep Belief Networks (DBN) is another probabilistic graphic model that offers a joint probability distribution over the observable labels and data [55]. It is a graphical generative model that learns how to extract a deep hierarchical representation of the training data. DBN is composed by stacking multiple RBMs and train them in an unsupervised greedy manner by using a contrastive divergence procedure. Initially, DBN employs an efficient layer-by-layer greedy learning strategy to initialize deep networks and tunes all weights with the desired output in parallel. At the top layers, it has undirected connections, and at the lower layers, it has directed connections. The structure diagram of DBN is shown in Figure 8(b). DBN has been widely used in various fields to

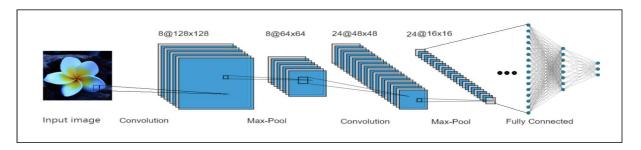


Fig. 9. General Diagram of Convolutional Neural Network architecture.

address representation learning, semantic hashing and data dimension reduction. DBN can be broadly extended to its respective variants like Fuzzy Deep Belief Network (FDBN) [178], Discriminative Deep Belief Networks (DDBN) [92], Competitive Deep Belief Networks (CDBN) [166], and Adaptive Fractional Deep Belief Network (AFDBN) [94].

Deep Boltzmann Machines (DBM) is another probabilistic graphic model; RBM is used as the building block for DBM model. The main difference of DBM model with DBN is that connections between all layers are undirected. It is a completely generative model that can extract features from data with some missing modalities. The right selection of interactions between hidden and visible layers can result in a more tractable version of DBM. It can capture several layers of complex input data representations and are suitable for unsupervised learning because they can be trained on unlabeled data. Nevertheless, it can also be tuned in a supervised manner for a specific task. In DBM, all the layers' parameters can be optimized jointly by following the approximate gradient of lower bound variation. This is especially helpful in cases where heterogeneous data learning models from different modalities. The structure diagram of DBM is shown in Figure 8(c), it can be broadly extended to its respective variants like robust spike-and-slab deep Boltzmann machine (RossDBM) [175], Batch Normalized Deep Boltzmann Machines (BNDBM) [147], Contractive Slab and Spike Convolutional Deep Boltzmann Machine (CssCDBM) [162], and Mean Supervised Deep Boltzmann Machine (msDBM) [105]. And Variational Auto-Encoders (VAE) [59] are directed probabilistic graphical models, a DL approach for latent representations learning. VAE is one of the most famous techniques for complex distributions in unsupervised learning approaches. It provides a probabilistic way of defining latent space observations and ensures that latent space contains good properties to enable the generative process. VAE is also considered a high-resolution network because it is used to design complex models with large datasets. It shows promising progress in producing complex data like faces, handwritten digits, segmentation, the future prediction from static images and speech synthesis, etc.

4.2 Artificial Neural Network (ANN):

A biological neuron's computational powers inspire an ANN. These NNs are the origin of AI and solve complex problems by efficiently utilizing its self-learning capabilities. It is used in various activities, including CV, speech recognition, social network filtering, medical diagnosis, machine translation, video games, etc. According to the utilization of ANN architectures in various applications discussed in section 3, three basic ANN categories have been briefly explained in this article, i.e., CNN, RNN, and YOLO architectures. **Convolutional Neural Network (CNN)** architecture is a DL algorithm composed of input, hidden, and output layers to solve complex patterns. These hidden layers consist of convolutional, pooling and fully connected layers. Convolutional layers contain distinct filters, which depict input data in fewer dimensional slices to generate feature maps. Then pooling layer performs the sub-sampling on these feature maps by reducing their dimensionality. Pre-processing required for CNN architecture is much less in contrast to other classification algorithms. CNN was introduced in 1989 when

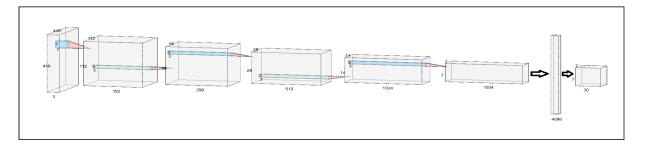


Fig. 10. General Diagram of You Only Look Once architecture.

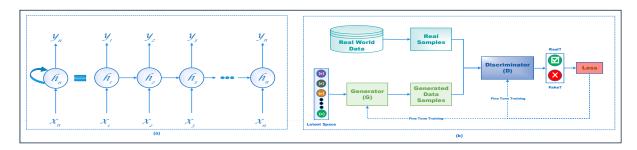


Fig. 11. General Diagram of (a) Recurrent Neural Network architecture and (b) Generative Adversarial Network architecture.

LeCuN's work on the processing of grid-like time series and image data [77]. CNN is used in various application areas like image segmentation, image classification, video processing, object detection, Speech recognition, NLP, recommender system, anomaly detection, medical image analysis, drug discovery, media recreation etc. A general Diagram of Convolutional Neural Network architecture is shown in Figure 9. Variants of CNN architectures used in different models discussed in section 3 are VGGNet [132], GoogLeNet [137], ResNet [53], Inception [138], Inception-ResNet-V2 [136], ResNeXt101 [163], Xception [30], Faster R-CNN [124], Deep CNN , C3D [143], and TextCNN [43] architectures.

Recurrent Neural Network (RNN) architecture is used to enhance NN's capabilities, which can get inputs from fixed-length data to process variable-length sequences. RNN architecture can process one element at a time, and the output of hidden nodes is used as additional input for the next element. It can address speech synthesis, time series and NLP problems. A general diagram of Recurrent Neural Network architecture is shown in Figure 11(a). RNN architecture is further extended to variants of memory units, including LSTM [56] and GRU [32]. Variants of RNN architectures used in different models discussed in section 3 are Bidirectional RNN (BRNN) [128], LSTM [56], Bidirectional LSTM (BiLSTM) [13], GRU [32], and Stacked GRU (SGRU) [159]. J. Redmon et al. proposed a You Only Look Once (YOLO) architecture, which is efficiently used for real time object detection [121]. YOLO architecture is repurposed as a regression problem instead of a classification problem in this research. A single neural network is used in YOLO model to predict various object's bounding boxes and for the association of class probabilities. Object detection problem is more complex than classification problem because more objects are detected instead of one at a time, and the location of these objects is also detected. YOLO algorithm applies a clever CNN architecture to an entire image and then splits them into various regions. Then probabilities and bounding boxes of each region are predicted. The general architecture diagram of You Only Look Once is presented in Figure 10.

		Flickr8k		Flickr8k-CN		
	Images	Caption/image	Total Captions	Images	Caption/image	Total Captions
Training	6000	5	30,000	6000	5	30,000
Validation	1000	5	5000	1000	5	5000
Test	1000	5	5000	1000	5	5000
Total	8000	5	40,000	8000	5	40,000
		Flickr30k			FlickrStyle1	0k
Training	29,783	5	1,48,915	7000	7	49,000
Validation	1000	5	5000	2000	7	14,000
Test	1000	5	5000	1000	10	10,000
Total	31.783	5	158.915	10.000	-	73.000

Table 8. Dataset splits of Flickr group.

4.3 Miscellaneous Architectures:

Miscellaneous architectures like Support Vector Machine, Generative Adversarial Network and Hidden Markov model are used in the various model presented in section 3. Support Vector Machine (SVM) is a traditional supervised learning approach of ML and is used to solve big data classification issues to help multi-domain applications [135]. SVM is characterized as a statistical learning algorithm to solve linear and non-linear regression or classification problems. The algorithm of SVM creates a hyperplane or line between data to separate it into classes. Its attempt to create a possibly wide separation between two classes that is helpful to make decisions. In this article, SVM and its variant SVM-RBF architectures are used in various models of retrieval-based and templatebased image description tasks, emotion recognition tasks and event detection tasks. Generative Adversarial **Network (GAN)** is a hybrid architecture consisting of two primary components, i.e., generator and discriminator networks. These networks can be in the form of NN like ANN, CNN, RNN, LSTM etc. And discriminator network contains fully connected layers along with the classifier [44]. GAN architecture consists of two NN compete to minimize the difference between actual input data and generated data. The discriminator network takes the real data and data generated from the generator network and attempts to identify whether data is real or fake. A general diagram of the Generative Adversarial Network is shown in Figure 11(b). The generator network can produce new output data after training completion, i.e., not distinct from actual data. In this article, GAN and its variant WaveGAN architectures are used in various models of encoder-decoder based and attention-based image description tasks and speech synthesis tasks. Hidden Markov Model (HMM) is a statistical model used first time in speech recognition tasks and biological sequences analysis [38]. These models are used to collect confidential information from sequential patterns. In HMM architecture, the modeling method is considered an unknown parametric Markov process, and the goal is to decide hidden parameters from given parameters. Many ML techniques are focused on successfully implementing HMMs in speech recognition, computational biology, character recognition, mobile communication techniques, bio-informatics, time series surveillance data, etc. In this article, HMM architectures are used in various template-based image descriptions, video descriptions, emotion detection and event detection tasks.

MMDL Datasets:

A wide variety of datasets are available for multimodal deep learning applications. These datasets are a major driving force for accelerated development in the research area of various MMDL applications. In this review, the datasets used in multiple applications discussed in section 3 are briefly described below.

Datasets used for Image Description:

In this literature, various datasets are used for image description task which are explained herewith, Flickr was first created in 2004 by Ludicorp. It is an American online community for hosting images and video services.

Table 9. MS-COCO dataset statistics

MS-COCO						MS-COCO Caption		
	Images	Categories	Label Instances	Captions/Image	Images	Categories	Label Instances	Captions/Image
Training	164,000	91	2,500,000	5	166,000	80	1,500,000	5
Validation	82,000	91	2,500,000	5	82,000	80	1,500,000	5
Test	82,000	91	2,500,000	5	82,000	80	1,500,000	5
Total	328,000	91	2,500,000	5	330,000	80	1,500,000	5

Table 10. SentiCap dataset statistics

	Dataset Splits	Number of Images	Number of Sentences	Number of Sentiments
Positive Subset	Training Testing	998 673	2,873 2,019	3 3
Negative Subset	Training Testing	997 503	2,468 1,509	3 3

Billions of High resolution as well as professional images, are available publicly in online community. Different versions of Flicker datasets are available for research i.e. Flickr-8k[57], Flickr-8kCN [82], Flicker-30k [168], and FlickrStyle10k [39]. A brief description of these datasets is given below, and their dataset splits are summarized in Table 8. PASCAL dataset: PASCAL Visual Object Classes (PASCAL-VOC) challenges from 2005 to 2012 provides datasets for object class recognition. Later, C. Rashtchian et al. [120] proposed a UIUC PASCAL sentence dataset used for image classification, object detection and object segmentation tasks. This dataset contains 1000 images, five human written descriptions in English language are generated for each image.

Another dataset for image description task is SBU Captioned Photo, that contains one million filtered images from Flickr with associated descriptions in the form of text. V. Ordonez et al. [110] made the first attempt to prepare a large dataset for the image description task. The analysis shows some issues with SBU Captioned Photo dataset's utility, like captions containing irrelevant information (name, location of objects) compared to image content or brief descriptions for each image. And Microsoft-Common Objects in Context (MS-COCO) dataset contains 328,000 images used for object recognition, captioning, and segmentation. [84]. MS-COCO dataset is categorized into 91 common objects categories, 82 out of 91 categories include more than 5000 label instances resulting in 2,500,000 label instances. This dataset contains more label instances as per category, and each image contains five descriptions. The dataset is split into a training set containing 164,000 images paired with five captions per image. And Validation and test sets comprise 82,000 images, each with five captions per image. MS-COCO Captions [27] and MS-COCO QA [123] are other variants of this dataset, whose statistics are summarized in Table 9.

SentiCap [97] dataset characterizes images with emotions by producing captions automatically with negative or positive sentiments. It is a subset of the MS-COCO dataset based on COCO images labeled with three negative and three positive sentiments. The positive subset includes 998 images with 2,873 sentences for training and 673 images with 2,019 sentences for testing; similarly, the negative subset contains 997 images with 2,468 sentences for training and 503 images with 1,509 sentences for testing. Statistics and splits of the SentiCap dataset are shown in Table 10.

5.2 Datasets used for VQA task:

In this section, datasets used for VQA task are discussed, like Visual Question Answering (VQA) dataset is the most frequently used dataset for the Visual Question Answering task. There are various variants of the VQA dataset like VQA v1.0 [8], VQA v2.0 [160], VQA-CP [6], VQA-X [64], Ok-VQA [95], and FVQA [151]. VQA v1.0 also named as VQA-real dataset is split into two parts; 1st part contains 123,287 training-validation images and 81,434

VQA v1.0 dataset							
	Dataset Splits	Number of Images	Questions/ Image	Answers/ Question	Questions Annotations	Answers Annotations	Complementary Pairs Annotations
VQA-Real Images	Training	82,783	3	10	248,349	2,483,490	-
	Validation	40,504	3	10	121,512	1,215,120	-
	Testing	81,434	3	10	244,302	-	-
VQA-Abstract Scenes	Training	20,000	3	10	60,000	600,000	-
	Validation	10,000	3	10	30,000	300,000	-
	Testing	20,000	3	10	60,000	-	-
				VQA v2.0 data	set		
VQA-Balanced Real Images	Training	82,783	-	10	443,757	4,437,570	200,394
	Validation	40,504	-	10	214,354	2,143,540	95,144
	Testing	81,434	-	10	447,793	-	-
VQA-Balanced	Training	20,629	-	10	22,055	220,550	-
Abstract Scenes	Validation	10,696	-	10	11,328	113,280	-

Table 11. VQA V1.0 and V2.0 dataset statistics

Table 12. Statistics of different Visual Question Answering datasets.

Dataset Name	Number of Images	Number of Questions	Questions Type	Unique Answers
DAQUAR	1,449	16,590	3	968
COCO-QA	123,287	117,684	4	430
Visual7W	47,300	327,939	7	25,553
Visual Genome	108,000	1,773,358	6	207,675
TDIUC	167,437	1,654,167	12	1,618

testing images from MS-COCO [8]. Second part contains 50,000 abstract scenes which are used for high-level reasoning in VQA task. Ten answers for each question from different annotators is gathered in this version. VQA v2.0 [160] is proposed to remove the limitation of inherent bias in version 1.0 by adding another image with a different answer for the same question. Therefore, the VQA v2.0 dataset size is double as compared to version 1.0. VQA v2.0 dataset contains additional complimentary images to cope with the referred above limitation and hence contains approximately 443,000 (Question, Image) pairs for training, 214,000 pairs for validation, and 453,000 pairs for testing. Statistics of VQA v1.0 and 2.0 are summarized in Table 11.

DAtaset for QUestion Answering on Real-world images (DAQUAR) [93] was the first significant dataset for the VQA task. DAQUAR dataset contains 6,795 QA pairs for the training set and 5,673 QA pairs for the testing set on 1,449 images from the NYU-DepthV2 dataset. Visual7W [179] is another dataset used for the VQA task that contains object localization and dense annotations in an image. Visual7W dataset consists of seven questions (what, when, where, why, who, which, and how.) The questions in Visual7W are much richer, and their answers are also longer than the VQA dataset. It consists of 327,939 QA pairs on 47,300 images from the COCO dataset. Visual Genome dataset is a huge structured knowledge presentation of visual perceptions and a complete collection of question-answers and descriptions [74]. Dense annotations of attributes, relationships, and objects within each image are collected in this dataset. This dataset contains approximately 108,000 images.

Compositional Language and Elementary Visual Reasoning diagnostics (CLEVR) dataset [69] is used to solve complex reasoning. It performs extensive diagnostic for better understanding of reasoning capabilities. It contains 100,000 images, out of which 70,000, 15,000, and 15,000 images are used for training, testing, and validation sets, respectively. Task Directed Image Understanding Challenge (TDIUC) dataset [71] contains 167,437 Images from Visual Genome and MS-COCO datasets. TDIUC dataset contains 1,654,167 QA pairs derived from three different sources, which are organized into 12 separate categories. Statistics of other VQA datasets are summarized in Table 12.

Dataset Name Number of Total Videos Number of Number of sen-Number of Length Classes clips tences Words (Hours) TACoS-MultiLevel [126] 185 14,105 52,593 2.000 27.1 1,970 MSVD [25] 218 1 970 70.028 607 339 53 M-VAD [142] 92 48,986 55,904 519.933 84.6 MSR-VTT [164] 20 7,180 10,000 200,000 1,856,523 41.2 Charades [131] 157 9,848 27,847 82.01 1.348.000 ActivityNet Captions [73] 20,000 100,000 849.0

Table 13. Statistics of video description method datasets.

5.3 Datasets used for Video Description:

In this section, dataset used for video description task are explained briefly, like TACoS-MultiLevel dataset [126] is also annotated on TAcos Corpus [122] through AMT workers. TACoS-MultiLevel dataset contains 185 long indoor videos, and approximately every video is six minutes long. These videos contain various actors, small interacting objects, and activities about cooking scenarios. Multiple AMT workers annotate the video sequence intervals by pairing them with a short sentence. Statistics of the various dataset used for video description task is summarized in Table 13. And Microsoft Video Description (MSVD) dataset [25] corpus contains a different crowd-sourced description of small video clips in the form of text. MSVD dataset contains 1,970 clips from YouTube annotated in the format of sentences by AMT workers. Approximately, 10-25 seconds duration video clip is used to illustrate activity in this dataset, and it also supports multilingual descriptions like in the form of English, Chinese, German, etc. Similarly Montreal-Video Annotation Dataset (M-VAD) [142] consists of 48,986 video clips from ninety-two different movies based on descriptive video service. M-VAD dataset contains 92 filtered and 92 unfiltered movies. On Average, each video clip is spanned over 6.2 seconds and the entire running time for the whole dataset is approximately 84.6 hours. It contains 510,933 words, 48,986 paragraphs and 55,904 sentences. The dataset is split into 38,949 clips for training, 4,888 clips for validation, and 5,149 clips for testing.

Microsoft Research-Video to Text(MSR-VTT) dataset [164] consists of a broader range of open domain videos used for videos' description task. MSR-VTT contains approximately a total of 7,180 videos, which are sub-divided into 10,000 video clips. Twenty different categories are organized to group these clips. The dataset is split into a training, validation, and testing set containing 6,513, 497 and 2,990 videos. Twenty captions are annotated for each video by AMT workers. Charades dataset [131] includes 9,848 videos of various daily life indoor activities. Different 267 AMT workers are deployed to captures these activities in the form of videos from three continents. The recordings are captured based on a given script that contains descriptions of actions and objects to be recorded. Recording of these videos is accomplished through 15 different indoor scenarios. In this dataset, 157 action classes and 46 objects are used for the description of scenes. It provides 27,847 descriptions for all captured indoor scenes. ActivityNet Captions dataset [73] includes 100,000 dense descriptions in natural language for approximately 20,000 videos from ActivityNet [20]. The total period for these videos is about 849 hours. In this article, ActivityNet dataset is used in video description task. And Video-to-Commonsense (V2C) dataset [36] consists of approximately nine thousand human agents videos implementing different actions from MSR-VTT dataset. Three kinds of commonsense descriptions are used to annotate these videos by recruiting two sets of AMT workers. 6,819 videos are used for the training set, and 2,906 are used for the testing set. Approximately 121,65 commonsense captions are generated for these videos. Extension of this dataset named V2C-QA is also proposed to deal with the VQA task in the perspective of commonsense knowledge.

Table 14. Statistics of different emotion detection databases.

Dataset Name	Language	Number of subjects	Number of samples	Emotion states
eNTERFACE [96]	English	42 (34-male, 8-female)	1166 video sequences	6
FABO [45]	English	23 (11-male, 12-female)	Camera recording of 1 hour/subject	10
IEMOCAP [18]	English	10 (5-male, 5-female)	12 hours	5
MSP-Improve [19]	English	12 (6-male, 6-female)	18 hours	4
MuSE [66]	English	28 (19-male, 9-female)	10 hours	2
SEMAINE [98]	English	150 (57-male,93-female)	959 conversations	5
RECOLA [125]	French	46 (19-male, 27-female)	7 hours	5

5.4 Datasets used for Speech Synthesis:

Datasets used for speech synthesis task are explained briefly herewith, like **North American English** dataset [156] are built using a single speaker speech database. The duration of speech data in this dataset is around 24.6 hours. Professional female speakers are used to speak this speech data. This dataset is used for the speech synthesis process. **Voice Cloning Toolkit (VCTK)** dataset [146] contains read speech data from 109 native English speakers with different accents. Speakers read approximately 400 sentences chosen from the newspaper. The cumulative length of these audios is about 44 hours, with a sample rate of 48-kHz. Standard train and test splits are not provided in this dataset. **LibriSpeech** corpus [111] contains English read speech from audiobooks that are derived through the LibriVox project. Around 2484 male and female speakers are engaged to create this corpus. The cumulative length of these audios is approximately 1000 hours with a sample rate of 16-kHz.

Lj Speech dataset [65] is a publicly available speech dataset; it contains 13,100 small audio clips. These clips are recorded by a single speaker, who read passages from 7 different books. The duration of each clip is different, can vary from 1 to 10 seconds. The cumulative period of these clips is around 24 hours. And **Proprietary Speech** [35] dataset is used for the speech synthesis process. The cumulative duration of speech data in this dataset is around 405 hours. It includes a total of 347,872 utterances varying in three different English accents from 45 speakers. Out of these 45 speakers, 32 speakers have a US English accent, 8 have a British English accent, and 5 have an Australian English accent.

5.5 Datasets used for Emotion Recognition:

In this section, datasets used for emotion recognition task are explained briefly. eNTERFACE audio-visual database [96] contains 1,166 video sequences. Out of these sequences, 902 covers male video recordings, and 264 covers female recordings. Six different emotion categories are expressed in this database, i.e., happiness, anger, fear, disgust, surprise, and sadness. Statistics of different datasets used for emotion detection task is summarized in Table 14. Hatice Gunes and Massimo Piccardi produced the Bimodal Face and Body Gesture Database (FABO) database [45] at the University of Technology, Sydney. This database creates bimodal face and body expressions for the automated study of human affective activities. Various volunteers gathered visual data in a laboratory environment by directing and requesting the participants with the perspective of desired actions/movements. Ten different emotion categories are expressed in this database, i.e., neutral, happiness, anger, fear, disgust, surprise, sadness, uncertainty, anxiety, and boredom. Interactive Emotional Dyadic Motion Capture (IEMOCAP) [18] is a multi-speaker and multimodal database. The cumulative duration of audio-visual data in this dataset is around 12 hours. Various videos, face motions, speech, text transcriptions are included in this bunch of data. Multiple annotators are used to annotating this dataset into categorical labels like happiness, frustration, anger, sadness, neutrality, and dimensional labels like activation, valence, and dominance.

MSP-Improve [19] database was compiled to record naturalistic emotions from improvised circumstances. Six sessions are recorded from 12 actors, and 652 target sentences are collected containing lexical data. The duration of each session is around three hours. Data is split into 2,785 natural interactions, 4,381 improvised turns,

Table 15. Overview of Evaluation metrics used in MMDL Applications.

Evaluation Metrics	Supporting Datasets	MMDL Application Group
BLEU [2, 7, 22, 28, 29, 36, 37, 46, 54, 68, 73, 79, 80,	Pascal Sentence, Flickr8k, Flickr30k, FlickrStyle10k, MS-COCO, MS-COCO	Image Description, Video Description, VOA
86–88, 104, 113, 114, 118, 150, 154, 155, 155, 157–	Caption, SentiCap, Visual Genome, VQA2.0, TACoS-MultiLevel, ActivityNet	image Description, video Description, v Q11
159, 165, 169, 177]	Captions, MSVD, MSR-VTT, V2C, Charades, VQA-X	
ROUGE [2, 7, 28, 29, 36, 37, 68, 79, 80, 86–88, 113,	Pascal Sentence, Flickr8k, Flickr8k-CN, Flickr30k, MS-COCO, Visual	Image Description , Video Description, VQA
114, 149, 150, 155, 158, 165, 177]	Genome, VQA2.0, MSVD, MSR-VTT, V2C, Charades, VQA-X	image Bescription, viaco Bescription, vgri
PPLX [46]	MS-COCO, Pascal Sentence, Flickr8k, FlickrStyle10k, SentiCap	Image Description, Video Description
METEOR [1, 7, 22, 28, 29, 36, 37, 46, 54, 68, 73, 79,	MS-COCO, Pascal Sentence, Flickr8k, Flickr30k, FlickrStyle10k, SentiCap,	Image Description, Video Description, VQA
80, 86–88, 104, 113, 114, 149, 150, 154, 155, 157, 158,	Visual Genome, VQA2.0, MSVD, M-VAD, ActivityNet Captions, MSR-VTT,	
165, 169, 177]	TACoS-MultiLevel, V2C, Charades, VQA-X	
CIDEr [1, 7, 22, 28, 29, 37, 46, 54, 68, 73, 79, 80, 86–	MS-COCO, Flickr8k, Flickr8k-CN, Flickr30k, FlickrStyle10k, SentiCap, Vi-	Image Description, Video Description, VOA
88, 104, 113, 149, 150, 154, 155, 157–159, 165, 169,	sual Genome, VQA2.0, ActivityNet Captions, MSVD, MSR-VTT, TACoS-	8 1 , 2
177]	MultiLevel, Charades, VQA-X	
SPICE [7, 37, 113, 158]	MS-COCO, Visual Genome, VQA2.0, VQA-X	Image Description, VQA
WUPS [123, 152, 153, 161]	DAQUAR, COCO-QA, VQA, FVQA, Visual Genome	VQA
Accuracy [9, 14, 15, 21, 31, 33, 34, 48, 50, 52, 61–63,	DAQUAR, COCO-QA, VQA, VQA2.0, VQA-CP, FVQA, OK-VQA, Visual	VQA, Speech Synthesis, Emotion Recogni-
67, 78, 81, 90, 106–108, 144, 152, 153, 161, 170, 172]	Genome, Visual7W, CLEVR, TDIUC, LibriSpeech, VCTK, eNTERFACE,	tion, Event Detection
	FABO, IEMOCAP, SEMAINE, MuSE, MSP-Improve, RECOLA, MED	
TopK [36, 60, 106, 139, 152, 170]	Visual Genome, V2C-QA, FVQA, OK-VQA	Image Captioning, VQA
MOS [9, 10, 35, 42, 109, 116, 130, 139, 156]	North American English, MagnaTagATune, VCTK, LibriSpeech, LJ Speech	Speech Synthesis
EER [9, 62]	LibriSpeech, VCTK, UCSD	Speech Synthesis, Event Detection
MCD [139]	LJ Speech, VCTK	Speech Synthesis
F1-Score [41, 51, 52, 61, 75, 81, 167]	IEMOCAP, SEMAINE, RECOLA, MED	Emotion Recognition, Event Detection
MAE [51]	IEMOCAP, SEMAINE	Emotion Recognition
Unweighted Average Recall [81]	IEMOCAP, RECOLA	Emotion Recognition
mAP [50]	TRECVID, MED	Event Detection
AUC [62, 72]	UCSD, Avenue, COGNIMUSE	Event Detection
EDR [62]	UCSD, Avenue	Event Detection

and 620 read sentences for 8,438 utterances in total. **Multimodal Stressed Emotion (MuSE)** [66] database recognizes the interaction between emotion and stress in naturally spoken communication. This dataset contains 55 different recordings from 28 contestants. Each contestant was recorded for stressed and not-stressed sessions. The cumulative duration of this dataset is approximately 10 hours from 2,648 utterances. **Sustained Emotionally coloured Machinehuman Interaction using Nonverbal Expression (SEMAINE)** [98] has built a substantial audio-visual database to create Sensitive Artificial Listener agents that involve a person in a prolonged emotional conversation. Five high-resolution cameras and four microphones are used synchronously for high-quality recording. One hundred fifty contestants from eight different countries record 959 conversations in total. **REmote COLlaborative and Affective (RECOLA)** database [125] consists of spontaneous and natural emotions in continuous domain. Video, audio, electrocardiogram, and electro-dermal activity modalities are used in this database. The cumulative duration of the recording is around 9.5 hours from 46 French-speaking contestants.

6 MMDL Evaluation Metrics:

Evaluation metrics determine the performance of machine learning or statistical models. For any project, evaluation of algorithms and ML models are essential. There are several kinds of evaluation metrics available to validate the frameworks. To test the model, single as well as multiple evaluation metrics are used. Because the performance of architecture may vary to different evaluation metrics, it may show better results using one metric but shows different results using other metrics. Therefore, evaluating the performance of a model with the perspective of many evaluation metrics gives a broader view. Overview of Various Evaluation metrics used in this article is summarized and presented with its relevant dataset and MMDL application group in Table 15.

7 Discussion and Future Direction:

Issues and limitations or various applications mentioned in section 3 are highlighted below. Their's possible future research directions are also proposed separately.

7.0.1 Multimodal Image Description: In recent years, the image description domain improves a lot, but there is still some space available for improvement in some areas. Some methods did not detect prominent attributes, objects and, to some extent does not generate related or multiple captions. Here, some issues and their possible future directions are mentioned below to make some advancement in the image description.

- The produced captions' accuracy depends mostly on grammatically correct captions, which depends on a
 powerful language generation model. Image captioning approaches strongly depend on the quality and
 quantity of the training data. Therefore, another key challenge in the future will be to create large-scale
 image description datasets with accurate and detailed text descriptions in an appropriate manner.
- Exiting models demonstrate their output on datasets comprising a collection of images from the same domain. Therefore, implement and test image description models on open-source datasets will be another significant research perspective in the future.
- Too much work has been done on supervised learning approaches, and training requires a vast volume of labeled data. Consequently, reinforcement and unsupervised learning approaches have less amount of work done and have a lot of space for improvement in the future.
- More advanced attention-based image captioning mechanism or captioning based on regions/multi-region
 is also a research direction in the future.

7.0.2 Multimodal Video Description: The performance of the video description process is enhanced with the advancement of DL techniques. Even though the present video description method's performance is already far underneath the human description process, this accuracy rate is decreasing steadily, and still, there is sufficient space available for enhancement in this area. Here, some issues and their possible future directions are mentioned below to make some advancement in the video description.

- It is expected in the future that humans would be capable of interacting with robots as humans can interact with each other. Video dialogue is a promising area to cope with this circumstance similarly to audio dialogue (like, Hello Google, Siri, ECHO, and Alexa). In visual Dialogue, the system needs to be trained to communicate with humans or robots in a conversation/dialogue manner by ignoring conversational statements' correctness and wrongness.
- In CV, most research has focused on descriptions of visual contents without extraction of audio/speech features from the video. Existing approaches extract features from visual frames or clips for a description of the video. Therefore, extraction of these audio features may be more beneficial for the improvement of this description process. Audio features, like the sound of water splash, cat, dog, car, guitar, etc., provide occasional/eventual information when no visual clue is available for their existence in the video.
- Existing approaches have performed end-to-end training, resultantly more and more data is utilized to
 improve the accuracy of the model. But extensive dataset still does not cover the occurrences of real-world
 events. To improve system performance in the future, learning from data itself is a better choice and
 achieves its optimum computational power.
- In the video description process, mostly humans describe the visual content based on extensive prior knowledge. They do not all the time rely solely on visual contents; some additional background knowledge is applied by the domain expertise as well. Augmentation of video description approaches with some existing external knowledge would be an attractive and promising technique in this research area. This technique shows some better performance in VQA. Most likely, this would dominate some accuracy improvement in this domain as well.

- Video description can be used in combination with machine translation for auto video subtitling. This combination is very beneficial for entertainment and other areas as well. So this combination needs to be focused on making the video subtitling process easier and cost-effective in the future.
- 7.0.3 Multimodal Visual Question Answering: In recent years, the VOA task has gained tremendous attention and accelerated the development process by the contribution of various authors in this specific domain. VQA is especially enticing because it comprises a complete AI task that considers free-form, open-ended answers to questions by extracting features from an image/video and the question asked. The accuracy of VQA research still goes beyond answering the visual-based questions as compared to human equivalent accuracy. Some issues and their possible future directions for the VQA task are mentioned below.
 - So far, the image/video feature extraction part is almost fixed to a model like, most of the time ImageNet Challenge model is used. In this model, image features are extracted by the split of frames into uniform boxes that works well for object detection, but VQA needs features by tracking all objects using semantic segmentation. Therefore, some more visual feature extraction mechanisms for VOA tasks need to be explored in the future.
 - Goal-oriented datasets for VQA research need to be designed in feature to support real-time applications like instructing users to play the game, helping visually impaired peoples, support for data extraction from colossal data pool and robot interaction, etc. So far, VizWiz [49] and VQA-MED [4] are two publicly available goal-oriented datasets for VOA research. Therefore, in the future, more goal-oriented datasets need to be built for mentioned above applications.
 - Most baseline VQA methods have been tested using traditional accuracy measure that is adequate for the multiple-choice format. In the future, the assessment or evaluation method for open-ended frameworks for VQA tasks is examined to improve these models' accuracy.
- 7.0.4 Multimodal Speech synthesis: The DLTTS models use distributed representations and complete context information to substitute the clustering phase of the decision tree in HMM models. Therefore, to produce a better quality of speech synthesis process compared to the traditional method, several hidden layers are used to map context features to high dimensional acoustic features by DLTTS methods. More hidden layers inevitably raise the number of system parameters to achieve better performance. As a result, space and time complexity for system training is also increased. Therefore for network training, a large amount of computational resources and corpora is required. Besides these achievements, there is still room available for DLTTS models in terms of quality improvement in intelligibility and speech's naturalness. Therefore, some issues and their feature research directions are discussed below.
 - DLTTS approaches usually require a huge amount of high-quality (text, speech) pairs for training, which is time-consuming and an expensive process. Therefore in the future, data efficiency for E2E DLTTS models training is improved by the publicly availability of unpaired text and speech recordings on a large scale.
 - Little progress is made in front-end text analysis to extract valuable context or linguistic features to minimize the gap between the text-speech synthesis process. Therefore it is a good direction in the future to utilize specific context or linguistic information for E2E DLTTS systems.
 - Parallelization will be an essential aspect for DLTTS systems to improve system efficiency because most DNN architecture needs many calculations. Some frameworks proposed in recent years also use parallel networks for training or inference and achieve some good results, but there is still room available to achieve optimum results in the future.
 - As for DLTTS application concerns, the use of speech synthesis for other real-world applications like voice conversion or translation, cross-lingual speech conversion, audio-video speech synthesis, etc., are good future research directions.

7.0.5 Multimodal Emotion Recognition: Analysis of automatic emotions requires some advanced modeling and recognition techniques along with AI systems. For more advanced emotion recognition systems future research based on AI based automated systems constitutes more scientific progress in this area. Some future directions of listed issues of multimodal emotion recognition are mentioned below.

- Existing baseline approaches are successful, but further experience, knowledge, and tools regarding the analysis and measurement of automatic non-invasive emotions are required.
- Humans use more modalities to recognize emotions and are compatible with signal processing; machines are expected to behave similarly. But the performance of automated systems is limited with a restricted set of data. Therefore, to overcome this limitation, new multimodal recordings with a more representative collection of subjects are needed to be considered in the future.
- The preprocessing complexity of physiological signals in emotion detection is a big challenge. In physiological signals, detection of emotion states through electrocardiogram, electromyography, and skin temperature is still emerging. Hence, to determine the potency of these techniques a detailed research can be carried out in the future.

7.0.6 Multimodal Event Detection: Due to the exponential increase in web data, multimodal event detection has attracted significant research attention in recent years. MMED seeks to determine a collection of real-world events in a large set of social media data. Subspace learning is an efficient approach to handle the issue of heterogeneity for the learning of features from multimodal data. On the other hand, E2E learning models are more versatile because they are structured to obtain heterogeneous data correlations directly. MMED from social data is still challenging and needs to be improved in some open issues in the future.

- The "curse of dimensionality" issue is raised with the concatenation of various feature vectors of multiple modalities. Some considerable advancement has been made in curse of dimensionality issue, but existing techniques still require some improvement in terms of achieving better learning accuracy for social platforms. Like, GAN or some RNN architectures' extensions are valuable to improve feature learning accuracy of multimodal social data.
- Textual data also coincide with audio and video media. Therefore, MMED is improved if this textual information is considered jointly with these media.
- Current research primarily focuses on the identification of events from a single social platform. A comprehensive understanding of social data events is obtained by synthesizing the information from multiple social platforms. Hence, event detection methods can be implemented simultaneously to examine social data from multiple platforms using a transfer learning strategy.

8 Conclusion:

In this survey, we discussed the recent advancements and trends in multimodal deep learning. Various DL models are categorized into different application groups and explained thoroughly using multiple media. This article focuses on an up-to-date review of numerous applications using various modalities like image, audio, video, text, body gesture, facial expression, and physiological signals compared to previous related surveys. A novel fine-grained taxonomy of various multimodal DL applications is proposed. Additionally, a brief discussion on architectures, datasets, and evaluation metrics used in these MMDL applications is provided. Finally, open research problems are also mentioned separately for each group of applications, and possible research directions for the future are listed in detail. We expected that our proposed taxonomy and research directions would promote future studies in multimodal deep learning and helps in a better understanding of unresolved issues in this particular area.

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