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Deep understanding of 3-D multimedia information retrieval on social media: implications and challenges

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Abstract
With the recent penetration and proliferation of social networks into our lives, human choices and preferences have become more socially accessible. This easy accessibility of private data in different formats has opened many new initiatives. The big explosion of multimedia data on the web has enabled social networks to gauge user likes, dislikes, and needs. This has imposed high demands on multimedia information retrieval (MIR) techniques. This manuscript illustrates the MIR concept in terms of its application to social media. It further positions the current research in the field of 3D MIR. Further it highlights the challenges in 3-D MIR on social media and finally translates them into significant research directions.

Keywords Multimedia information retrieval (MIR) · 3D multimedia information retrieval (3D MIR) · Social media · Multimedia data · Deep learning

1 Introduction

Advancements in technology are fast penetrating into our lives, digitizing our personalities in smart ways. Social networks (Twitter, Facebook, Snapchat, Instagram, etc.) today are proficient enough to learn our likes, dislikes, needs and preferences. The core idea behind this intelligence of social networks is an underlying neural network that accumulates data and utilizes it for other processes such as analysis and prediction [1–8]. However, the intriguing question here is how do social networks manage to look into our private, less comprehensible, and concealed selves. The technique behind this novel intelligence of social networks is what is technically called deep learning [9]. The science of deep learning simply explained divides ideas as layers of definitions [10]. Hence, smaller concepts collectively abstract to larger ones and so on. Hence, with enough input information, a sufficiently layered neural net can learn quite deeply similar to the human brain [11–13].

Many varied deep learning technologies have been successfully applied onto social networks [3], [14–16]. This deep intelligence has been successfully applied to an almost infinite collection of consumer data accumulated by the world's largest social networks for varied useful tasks [16–19]. Table I below highlights the significant applications of deepnet onto popular and large social networks.

Table 1 above is by no means a complete essence of successful deep learning applications to gauge social network data. However, it gives a strong view of the fact that deep learning frameworks have been successfully applied for effective usage of multimedia big data available from social networks for different business domains [34].

The flow of this manuscript is as follows: Sect. 2 elaborates on how Deep Multimedia Information Retrieval Techniques are being applied for managing the biggest big data available on social networks. Section 3 summarizes the techniques available for 3D-multimedia information. Section 4 highlights the challenges for MIR techniques while giving significant future research directions.

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Table 1 Significant deep learning applications to social networks

S.no.	Application	Description	Key research domain
1.	Social network search based on semantic analysis and learning [1]	Summarizes semantics of a complete social network search framework	Deep semantic learning of social networks
2.	Attributed social network embedding [20]	Summarizes a generic social network embedding (SNE) outline that learns representations for social actors while preserving attribute and structural proximity	Social network embedding
3.	Personality prediction system from Facebook users [2]	Summarizes a prediction system to automatically forecast a user's personality through Facebook user information. successfully applies deep learning architectures	Personality prediction
4.	Deep learning for network analysis [21]	Discusses advances in application of deep learning frameworks for identification of patterns, characteristics, and anomalies in networks	Network anomaly detection
5.	Age-group classification in social networks using deep learning [4]	Applies deep convolutional networks to extract user age from the social network data and apply it for useful sentiment analysis	Age-group classification
6.	Ontology-based deep learning for human behavior prediction with explanations in health social networks [6]	Proposes ORBM^{+} to achieve human behavior prophecy through undirected and nodes-attributed graphs. The method is based on the illustrious deep learning-restricted Boltzmann machine concept	Behavior prediction
7.	Detecting spammers on social networks [7]	Increasing popularity and usage of social networks has also exposed significant incidences of spammers leading to user inconvenience. Proposes a SVM-based spammer detection algorithm for detecting spammers on Sina Weibo data	Spammer detection
8.	Cloud-based big data analytics framework for face recognition in social networks using machine learning [8]	Proposes a big data, cloud computing, machine learning and social networks based approach for performing face tagging for social networks running on big data	Face recognition
9.	Learning deep architectures for AI [10]	Summarizes the principles related to learning algorithms for deep architectures to construct deeper models such as deep belief networks for application to different domains	Deep model design
10.	Fusing social networks with deep learning for volunteerism tendency prediction [22]	Summarizes a framework for multiple social network learning that fuses social networks through deep learning with consistency regularization and source confidence for predicting user penchant for volunteerism	Volunteerism tendency prediction
11.	Applications of online deep learning for crisis response using social media [23]	Applies stochastic gradient descent-based deep neural networks for classification of informal tweets to topical classes especially during disaster circumstances	Crisis response
12.	Link prediction based on common neighbors for dynamic social networks [24]	Novel approach for link prediction using dynamic topology of a social network. Utilizes time-varied weight, change measure of common neighbor and relationship between common neighbors for edge prediction	Link prediction
13.	Data crawler for Sina Weibo based on Python [25]	Proposes a data crawler based upon keyword matching and parallelization technology to extract fan information of different Weibo users from Weibo data in real time	Data crawler
14.	Online social network image classification and application based on deep learning [26]	Proposes image classification on data obtained from the Sina blog by combining text and content features from deep learning architectures	Image classification

Table 1 (continued)

S.no.	Application	Description	Key research domain
15.	Text normalization algorithm on twitter in complaint category [27]	Normalization algorithm for unstructured Twitter complaint text in Indonesian language	Language processing
16.	Enhancing deep learning sentiment analysis with ensemble techniques in social applications [3]	Integrates deep learning techniques with traditional surface-based approaches for sentiment analysis to propose a sentiment classifier that surpasses the existing surface classifiers	Sentiment analysis
17.	Deep learning model for sentiment analysis in arab social media [19]	Automated deep learning-based information processing system in arabic language domain	Sentiment analysis
18.	Deep learning model for sentiment analysis on Thai Twitter data [18]	Automated deep learning-based sentiment classifier for thai twitter data	Sentiment analysis
19.	Deep learning Twitter sentiment analysis [28]	Analysis of efficacy of deep learning models for Twitter sentiment analysis	Sentiment analysis
20.	Ontology-based deep learning for human behavior prediction in health social networks [14]	Proposes ontology-based restricted Boltzmann machine (ORBM) framework for human conduct calculation in health social networks	Health informatics
21.	Information assimilation framework for event detection in multimedia surveillance systems [29]	Proposes multimedia information assimilation framework based on hierarchical probabilistic integration to sense atomic events	Information assimilation
22.	Real-time speaker tracking particle filter sensor fusion [30]	Applies sensor fusion for real-time speaker identification and tracking	Object detection
23.	Content-based image retrieval—approaches and trends of the new age [31]	Recent advances in image reclamation and automated image annotation discussed	Image retrieval
24.	Content-based 3D object retrieval [32]	Two novel approaches for benchmarking 3D object retrieval systems	3D object retrieval
25.	Companies applying deep learning [33]	Affectiva: applies deep networks for real-time analysis of emotions from video or images Gridspace: applies deep networks for sophisticated speech recognition systems for speaker identification Ditto Labs: deep learning network based detection system for identification of brands and logos from social media data Nervana: applies deep framework named neon to allow users create their own cloud-based deep data Deep genomics: applies deep networks to predict natural and therapeutic genetic variations in cellular processes Deep instinct: applies deep learning to identify, predict and prevent advanced, persistent cyber threats in real time	Industry

2 Deep MIR on social networks

As per records there are already more than 1.8 billion Facebook users of which around 800 million spend close to 40 min per day on the social network each day [1]. From these big numbers it is not difficult to analyze that the amount of multimedia data available on Facebook alone shall be somewhere between some significant tera, peta or exabyte numbers growing each day. Multimedia data from all social networks combined alone are rightly termed as the biggest available big data of present times [34].

To effectively handle this vast multimedia data, multimedia information retrieval (MIR) techniques have become a necessity. To understand and appreciate the need of MIR systems we first need to clarify the meaning of few common terms being used in this manuscript. First, multimedia data implies one or more primary data types such as audio, video, images, text, graphics, animation, etc. [35]. Multimedia information retrieval implies the mechanism of searching for and locating multimedia documents [36] to develop multimedia search engines. An important challenge for MIR is the fact that the input query here itself might be multimedia. However, considerable research has been performed in development of effective MIR systems to allow optimum usage of vast multimedia data on the web [37]. With the growth of available multimedia data on social networks different MIR techniques have also been applied for effective management of this social multimedia data.

It may be noted here that though social media has penetrated into our lives in a big way, majority of the multimedia data here is unstructured [38]. Conventional MIR systems are limited in their ability to identify and extract unusual information [39]. Majority of this deals with feature extraction/retrieval from this data [34]. To optimize performance of these techniques recent efforts have shifted towards application of deep learning-based techniques. In the recent times, deep learning has made its mark in a number of varied domains. It has also successfully affected MIR techniques applied to social networks for effective information gathering and dissemination [1]. Many varied Deep Learning techniques have also given hopeful results in large-scale multimedia processing and reclamation [34]. As deep learning systems are capable of learning features in a hierarchy, thus they can prove useful in reducing the semantic gap in multimedia data on social networks.

Conventional multimedia computing was restricted in capturing multifaceted multimedia content such as text, images, audio, and video as it was restricted to specific domain knowledge [34]. Deep Learning enables automatic representation learning to model the multi-modal data. Many significant deep learning-based MIR systems are being successfully applied to social networks. Table II below lists some important deep learning-based MIR systems successfully being applied to social network multimedia data.

Table 2 above elaborates how deep learning has empowered MIR systems to effectively be applied for revolutionary advances in varied domains such as speech recognition [52], image analysis [53], information retrieval [36, 54], recommendation [48], and natural language processing [22], etc. However, this successful application of deep frameworks does not imply the end of road has been achieved. Table 2 also highlights the various unanswered research challenges and future research directions that are still open in almost every domain.

3 3-D MIR on social networks

The previous sections successfully documented the successful materialization of deep learning-based MIR systems into varied domains of computing. Recent trends have now shifted from single mode information retrieval to 3-D multimedia information retrieval (3D MIR) based systems. 3D multimedia is an amalgamation of 3D models, images, motion data, movies, etc [55]. Single-dimensional data retrieval as well as 2-D retrieval mechanisms cannot be directly generalized to 3-D retrieval mechanisms [56]. Hence, deep research is now directed towards designing 3D MIR systems that can accurately recover 3D multimedia data analogous to user query component structure in real time. This 3D multimedia data have big potential to represent complex information [32, 56–61]. Successful application of 3D-content-based searching from large 3D object repositories has been performed in numerous domains such as CAD/CAM [62], biomedical, virtual reality, military, entertainment, etc. Table 3 below elaborates some significant work in the same.

Table 3 above enlists certain significant implementations of 3D MIR systems. However, it is important to note that 3-D MIR is the most challenging MIR system as it involves mapping similarity-based searching among 3D multimedia data [72]. Certain individual challenges of each application have been outlined in Table 3 above. However, Sect. 4 elaborates the significant challenges faced by 3-D MIR techniques.

4 Challenges for 3-D MIR techniques

Deep Learning algorithms are powerful enough to enable MIR systems understand the multimedia data at different semantic levels and extract user choice of data from the same. Quite significant work has been done on applying deep MIR technologies to diverse real world usage of big data generated through social networks. However, despite

Table 2 Deep learning-based significant MIR systems

S.no.	Application	Description	Deep learning framework implemented	Challenge
1	Deep learning and music adversaries [40], [41]	Proposes deep learning system application to image–object recognition. It exploits system constraints to locate minimal changes of the input image to enable system misclassify the same with high confidence	Convolutional neural network architectures	High recorded throughput of these systems does not ensure that they are trained to perfectly resolve high-level problems
2	A deep learning-based radiomics model for prediction of survival in glioblastoma multiforme [42]	Investigates if deep features from MR images can generate radiomics signature for prediction of overall survival in patients suffering from glioblastoma multiforme	Deep feature extraction through transfer learning	Generalization of the radiomics model questionable and requires a more large-scale multicenter analysis. Further the radiomics–genomics correlation needs to be evaluated
3	VulDeePecker: a deep learning-based system for vulnerability detection [43]	Vulnerability deep pecker applies code gadgets for program transformation to vectors to enable automatic detection of software vulnerabilities	Bidirectional long short-term memory (LSTM) neural network	Detection of vulnerabilities in executables is still unanswered. Further, proposed VulDeePecker design is only limited to vulnerabilities in library/API function calls in C/C++ programs and is not generic
4	Feature learning for chord recognition: the deep chroma extractor [44]	Proposes learned chroma feature extractor	Three-layered deep neural network with 512 rectifier units each	DNN ensemble usage could result in better results
5	Query by singing/humming system based on deep learning [45]	Proposes a deep learning-based query by singing/humming system for proficient indexing and recovery of desired music from a huge music database	Two-layered deep belief network with top layer composed of undirected binary chart and lower layer a directed sigmoid belief network	More accurate deep framework-based pitch extractor still requires work
6	Cardiac arrhythmia detection using deep learning [46]	Proposes efficient automatic cardiac arrhythmia detection method based upon transferred deep learning	AlexNet-feature extraction; back-propagation neural network: classifier	Realization of a viable computer-aided diagnostic system well recognized in clinical practice to aid clinicians and patients alike
7	Deep learning-based automated segmentation of macular edema in optical coherence tomography [47]	Proposes a convolutional neural network (CNN) that identifies intraretinal fluid (IRF) on OCT	Convolutional neural network	Generalizable studies missing
8	Deep content-based music recommendation [48]	Proposes a model for suggestion, and forecast of latent factors from music audio when they cannot be retrieved from conventional data	Deep convolutional neural networks	Generic model missing
9	Metric learning-based data augmentation for environmental sound classification [49]	Proposes a framework for data augmentation through metric learning. The idea is to first discover a metric from the original training data, and then use it to filter out augmented data samples that are far from original ones in the same class	Convolutional neural network	Generative model for augmentation schemes

Table 2 (continued)

S.no.	Application	Description	Deep learning framework implemented	Challenge
10	Geometric deep learning [50]	Proposes a unified framework allowing to generalize CNN architectures to non-Euclidean realms (graphs and manifolds) and learn local, stationary, and compositional task-specific features Adv: deformable 3D shape analysis applications, the key advantage of our approach is that it is intrinsic and thus deformation invariant by construction	Convolutional neural network on spatial domain model	Application of proposed model to computational social sciences
11	Graph-based classification of omni-directional images [51]	Proposes image classification task by taking into account the specific geometry of omni-directional cameras with graph-based representations	Graph convolutional network	Extension of proposed framework to generic geometries of the camera lenses

its successful applications to varied business domains many significant open challenges and research areas still require optimal solutions. Simply put the core issues with multimedia data on social networks are optimizing storage, processing, indexing and searching of this data. 3D multimedia data storage, processing, indexing as well as searching is even more challenging as it deals with multimodal data. Simply put, 3D information is not effortless to recover [56]. This section lists some significant open challenges for 3D MIR techniques [73–75]:

i. Effective acquirement and representation of available spatio-temporal data in social networks [1]: acquiring social network data involves cleaning and filtration of data followed by feature extraction and effective storage and management. As the storage space required for such big data is immense, computation cost involved rises exponentially. To apply cost-friendly techniques for effective as well as optimal storage, representation and management of spatio-temporal multimedia data from social networks are important concerns.
ii. Scalable and efficient storage and processing framework [34]: 3D multimedia information recovery demands a scalable and proficient storage and processing framework for the enormous amount of data. This challenge demands architectures more robust and capable than the conventional database management systems. MapReduce Framework has established itself as the real, practical yardstick for batch processing of big data. The Hadoop distributed file system (HDFS) is one significant technology implementing the MapReduce framework in an efficient mechanism. Here, data in a Hadoop cluster are stored in blocks and disseminated all through the cluster. Further the map and reduce functions are run on smaller subsets of a larger dataset. Some significant work has been carried out recently on the indexing, searching, and analysis of multimedia big data using MapReduce framework. Table 4 below highlights some of the notable works:

As we can observe from Table 4 above to Map Reduce Framework has proven itself as the framework of choice for big data processing and storage. However, there are still unresolved issues and challenges that still require research effort [82, 83].

iii. Multi-modal study and recovery algorithms [15]: evaluating the synergy between the varied media including text and context information is a significant challenge for MIR systems. Success has been noted on single nodal media as well as limited multimedia data. However, the same when applied to 3D multimedia

Table 3 Significant 3D MIR systems

S.no.	3D-MIR system	Description	Challenge
1.	Automatic Alzheimer's disease recognition from MRI data using deep learning method [53]	Proposes an automatic deep learning-based AD recognition algorithm that uses 3D brain MRI	Data processing is costly and requires more efficient capability
2.	3D multimedia data search system based on stochastic ARG matching method [55]	Treats 3D multimedia data through a MIR framework designed on stochastic attribute relational graph	High calculation cost of ARG matching can be reduced by parallel processing, further the proposed system needs to be generalized to support various file types
3.	Real-time facial segmentation and performance capture from RGB input [63]	Proposes real-time 3D facial routine confine through overt semantic segmentation in the RGB input	Limited application to only facial recognition; should be generalized to other body parts
4	Multimodal location based services semantic 3D city data as virtual and augmented reality [64]	Proposes novel mobile service for investigating urban frameworks at diverse level of details (LoDs) through popular standards such as CityGML. Facilitates researchers and city planners to discover energy datasets through virtual globes, virtual reality and augmented reality	Should be generalized with different data sources such as the internet of things (IoT) simulation to provide real-time data
5	Deep shape-aware descriptor for nonrigid 3D object retrieval [15], [50], [65]	Proposes 3D shape recovery through a multi-level facet learning method	High computation time for training the model attributes can be warded off by use of GPU. SA-BoF also requires testing on 3D large-scale shape benchmarks
6	On-the-fly learning for visual search of large-scale image and video datasets [66]	Proposes to enable run-time visual search of large-scale video datasets for semantic entities through a text query	Developing varied available competencies for visual search rather than conventional text-based search
7	3-D content-based retrieval [32] [56]	Automated 3-D object retrieval systems based on similarity measures	Choice of an effective and optimum predefined similarity algorithm to enable automatic similarity assessment between 3-D object pairs
8	3D model search engines [67], [68]	Propose shape-based search techniques for effectively searching 3D data on the web	Though speedy, however, high computational costs involved
9	Princeton shape benchmark [69]	Freely accessible collection of 3D models, software tools, and software for 3D shape matching	High storage and computational costs involved; most shape matching algorithms do not perform generically well on all objects
10	Comparison framework for 3D object classification methods [70]	Proposes structure to evaluate effectiveness of diverse query-to-class membership measures	Can be generalized to definition of classifiers based on model prototypes. Reduction of search space for object recovery can also be computed
11	Stratified point sampling of 3D models [71]	Procedure to generate a stratified sampling of 3D models applicable across many domains	Effectiveness and computation costs may vary across domains

data becomes more challenging due to the inherent complexities of the media involved.

iv. Bridging the semantic gap [75, 82]: this implies effectively mapping the low-level multimedia features to high-level user terms or queries. Enabling meaningful semantic search directed at detection of concepts in media with multifaceted backgrounds is an important challenge. In 3D-multimedia data this becomes even more rigorous as the variety of underlying data increases.

v. Absence of Benchmarked standardized datasets for testing algorithms [75, 84]: varied media-related standardized databases on which diverse groups can test their algorithms are required. For text retrieval, it is uncomplicated to acquire big compilation of old newspaper texts as the copyright owners do not consider the same to be of much value; however, image, video, and speech library owners value their collections and, therefore, are more guarded in sharing their data. While not exactly a research challenge, accessing big 3D-multimedia compilations for extensive assessment benchmarking is a realistic and significant issue to be addressed. Competitions and events such as TRECVID [75] are aimed at making such task-related data accessible.

vi. Implementation of efficient similarity search algorithms [85–89]: similarity matching of 3D shapes is a challenging task as they require modes for effective representation of the skeletal and topological structure of the data involved [85]. Establishing accurate correspondence between parts of a 3D object is a difficult task. Hence, searching and matching different 3D objects in a data set requires selection and implementation of efficient similarity search algorithms at different levels of matching. Varied techniques have successfully been applied on 2D multimedia data. However, these techniques cannot be directly applied to 3D data. When dealing with 3D data, different techniques have been successfully applied to different types of data [62, 87–90]. However, a generic efficient similarity search algorithm for all types of 3D data is still a distant dream. Further issues such as sensitivity of noise, surface undulations need to be appropriately handled on 3D data [58, 70, 91–94].

vii. Ability to perform partial matching [95, 96]: 3D multimedia data may not require to be matched completely. For many real world applications such as 3D scene searching partial matching of 3D multimedia data may also serve the purpose [95, 96]. Hence, partial matching between 3D objects can also prove to be useful if done appropriately. However, the implemented approaches for such matching still suffers from a number of limitations such as noise, low resolution, etc.

Table 4 Significant works on multimedia big data

S.no.	Work	Description	Challenge
1	Indexing and searching 100 M images with map reduce [76]	Proves greater scalabilty in indexing large volume of images by applying MapReduce framework through Hadoop	Inputting the data under consideration into the grid/cloud through restricted bandwidth is a realistic hitch
2	Implementation and performance evaluation of a hybrid-distributed system for storing and processing images from the web [77]	Proposes design and implementation of a hybrid-distributed architecture realized through Hadoop distributed file system for processing images crawled from the web	Testing if the architecture is plausible with video content
3	Mars: a MapReduce framework on graphic processors [78]	Binds GPU power for MapReduce. Abstracts the programming complexity of GPU through the interface of MapReduce	Integrating Mars into existing MapReduce implementations
4	A multimedia parallel processing approach on GPU MapReduce framework [79]	Proposes a parallel processing technique for multiple multimedia processing programs	Cannot support dynamic multimedia processing programs
5	Large-scale multimedia data mining using MapReduce framework [80]	Explores MapReduce for large-scale data mining	Successful on image categorization and video-event recognition, however, implementation on multimodal data to be tested
6	Towards fast multimedia feature extraction: Hadoop or storm [81]	Evaluates Apache Hadoop and Apache storm for multiprocessor task distribution	Apache Hadoop was found to be inappropriate for cases where data were externally stored. Suggests integration of both frameworks for a more generically viable scenario

viii. Lack of a sustainable 3D file format: currently, there exists no generic as well as widespread 3D file format. All popular 3D tools have their own proprietary formats. Hence, what is required is a fundamental file format that congregates characteristics of all 3D representations into a customizable as well as extensible encoding [97, 98].

ix. The absence of canonical 3D representations: 3D data have no canonical representation. Hence, 3D representations are generally layered across surfaces, volumes, and structures. As a result there are no representation-independent, stable 3D markup, retrieval or query techniques available [58, 82, 99].

The above listed are a few main challenges that need to be addressed significantly to enable effective and smooth knowledge transfer from social networks to commercial user realistically plausible [74, 100, 101].

5 Conclusion and future directions

Multimedia information retrieval technology for big data on social networks has made momentous progress in recent times. The rapid improvements in this technology have largely concentrated on development of deep learning MIR systems that have resulted in groundbreaking improvements in the accuracy of storage, processing, indexing and searching of user desired multimedia data from social networks.

However, despite tremendous effort directed at evolving and establishing deep techniques for effective multimedia, multimodal information retrieval from popular social networks there still remain significant challenges that should be addressed before we can claim fully optimal, generic and effective commercially viable multimedia information retrieval. This manuscript has analyzed 3D MIR techniques and their applications and has tried to highlight the challenges still faced by these systems. From our reasoning we can foresee that 3D multimedia data are gaining momentum and shall soon result into a huge 3D online data set in the near future. To use this large set of 3D documents though there shall be multiple specialized tools but notion of generalized treatment of 3D documents is still far from reality. Though 3D shall soon have penetrated significantly into our lives making the technology scalable and manageable at the large scale of its growth shall remain a challenge.

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