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A comprehensive survey of deep learning in the field of medical imaging and medical natural language processing: Challenges and research directions

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ABSTRACT

The extensive growth of data in the health domain has increased the utility of Deep Learning in health. Deep learning is a highly advanced successor of artificial neural networks, having powerful computing ability. Due to the availability of fast data storage and hardware parallelism its popularity grows in the last five years. This in article presents a comprehensive literature review of research deploying deep learning medical imaging and medical NLP including tasks, pipelines, and challenges. In this work, we have presented an extensive survey of deep learning architecture deployed in the fields of medical imaging and medical natural language processing. This paper helps in identifying suitable combination of Deep learning, Natural language processing and medical imaging to enhance diagnosis. We have highlighted the major challenges in deploying deep learning in medical imaging and medical natural language processing. All the results are presented in pictorial form. This survey is very helpful for novices working in the area of health informatics.

Contents

1. Introduction

In this era of artificial intelligence (AI), deep learning (DL) techniques are dominating among all the available AI techniques in health domain due to their effective solutions, implicit feature engineering ability, word embedding integration ability (Ru et al., 2019, 2018), and ability to deal with complex and unstructured

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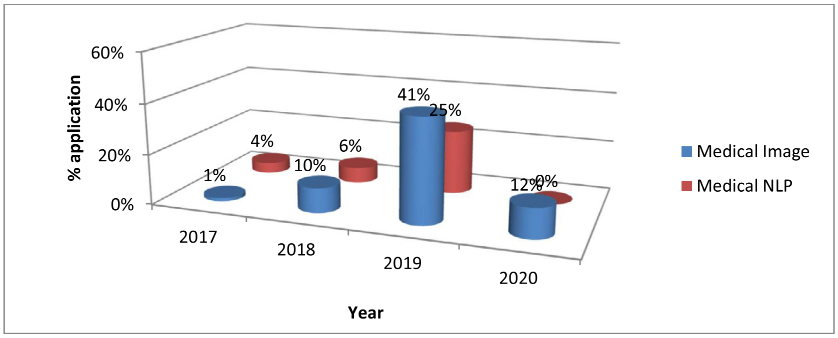

Fig. 1. Comparative view of number papers published in MI and Medical NLP deploying DL.

data. Meanwhile, the availability of unprecedented volumes of data related to health such as digital text in electronic health records (EHRs), clinical text on social media, text in electronic medical reports and medical images are also highly responsible for growing the popularity of DL in the health domain. The popularity of DL in the health domain is also observed from the number of literature reported during 2017–2020 as shown in Fig. 1. In 2019 the percentage of publication is 4 times than of 2018. However, growth is higher in medical imaging (MI) as compared to medical natural language processing (NLP).

This scenario motivated us to study the variant of DL deployed in the health domain.

Presently large numbers of medical images are available. These images are usually accompanied by radiology reports and thus natural language processing has great potential in image analysis (Shin et al., 2017). In addition, image annotation and labelling are very time consuming and required expert knowledge. Image annotation and labelling can be automated by involving human annotation. Natural language processing has great potential in this area and the relationship between NLP and MI will lead the medical diagnosis far step away.

The objective of this work is to identify the relationship among DL techniques, MI, and medical NLP, via a methodical review of the literature.

The major contribution of this paper is to identify: the suitable combination of MI processing pipelines, DL architectures, NLP tasks and finally report the challenges faced during the Combining of DL, MI, and medical NLP. This survey is very helpful for novices working in the area of health informatics.

To find the solution to these questions and to draw deep insights, we consider 211 articles from a Scopus database, published between 2017 and April 2020. The keyword used for searching is deep learning, health informatics, medical imaging, text mining, medical text and natural language processing. Paper based on medical tutorials and securities in medical system are removed from the selected paper. The important observations that we obtained from the study includes:

- Publications on DL in MI are approximately double as compared to medical NLP.
- Depending upon the type of training data and combination strategy the DL techniques are classified into two categories. Further the former is divided into supervised, unsupervised, and semi-supervised and the latter is divided into integrated, hybrid, ensemble, embedded, Joint, and transfer learning as shown in Fig. 2.
- The majority of this literature in MI deploys DL for segmentation, automatic feature extraction, and classification whereas in medical NLP for information extraction.
- There is a growing acceptance of DL as the baseline for medical imaging and NLP research in the medical community.

The rest of the paper is structured as follows. Section 2 describes related work on deep learning in MI and medical NLP. Section 3

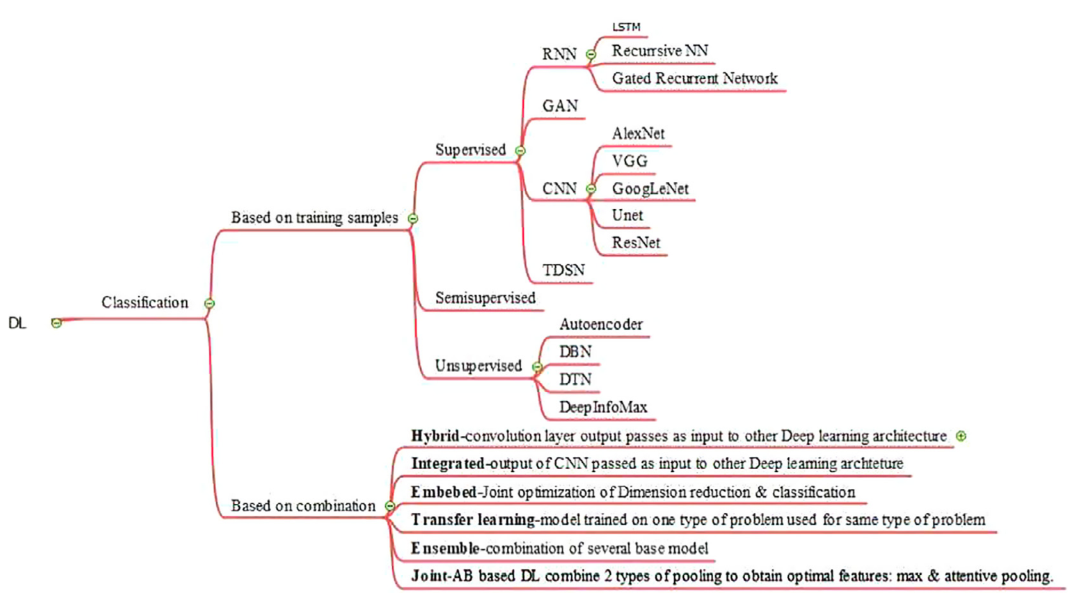

Fig. 2. Breakdown of Deep learning methods that are commonly used for health domain.

explains the numerous DL architectures deployed in MI and medical NLP. Section 4 discusses various DL applications. Section 5, describes results findings and discussion related to challenges, limitations faced by researchers. Section 6 finally concludes the presented work with future possibilities related to DL.

2. Related work

Deep learning (DL) in a MI and medical NLP is an active area of research in the last five years and has thus spawned numerous other review articles. Kakra et al. (2019) have reviewed the complete layer-wise architecture of convolution networks. They highlighted the barriers of DL such as high computational cost and high training time on CPUs. Ravi et al. (2017) have studied the application of DL in MI, translational bioinformatics, and health informatics. They highlighted various barriers in developing effective DL models for health data such as black box architecture, the small size of data, over-fitting, generalization error, optimization of a large number of hyper-parameters, small changes in input data may cause a very high change in output. Ranschaert et al. (2019) discussed the use of AI and their applications in the MI. Das et al. (2020) described the computational algorithms applied to histopathological images. They discussed two image processing pipeline: handcrafted feature-based pipeline, which mainly includes pre-processing step, segmentation, features extraction, feature selection, and classification and learned feature-based pipeline, which includes extraction of high-level abstractions by utilizing DL techniques. Cao et al. (2018) studied various DL techniques including their optimization method and application in MI. Tsang et al. (2020) and Valliani et al. (2019) studied various machine learning (ML) techniques deployed in the diagnosis of the degenerative disorder. Valliani et al. (2019) highlighted the barriers of medical records which hamper the deployment of DL such as incorrect and small size data, nuanced language, acronyms, inaccurate temporal representation, and siloed existence, lack of homogeneity, lack of interpretability and lack of explainability. Akay and Hess (2019), Jang and Cho (2019), Wlodarczak (2019), and Liu et al. (2020) reviewed the computer-assisted system, AI, ML and DL techniques in radiology, pathology, drug discovery, lung nodules, molecular shuttles, obstetrics, and gynecology. Diao et al. (2018) reviewed the ML techniques in pathogenic variation and clinical genomics. They observed that ML techniques improved the understanding of pathogenic variation and the barrier of ML techniques may limit their emerging role in clinical genomics. Xiao et al. (2018) and Shickel et al. (2018) identified challenges such as lack of universal benchmarks (Xiao et al., 2018), lack of data and label, lack of model interpretability and lack of model transparency (Shickel et al., 2018) in deploying DL for EHRs. Faust et al. (Faust et al., 2018, 2019) studied the usage of DL techniques for the analysis of physiological signals. They highlighted the barriers in deploying DL such as the biased nature of medical records and societal heterogeneity. The study of (Faust et al., 2019) has turned the research direction in DL from information extraction to systemic improvements. Luo et al. (2018) studied the numerous techniques and methodologies used for endoscopic navigation. Zhou et al. (2019) studied the use of DL to clinical information extraction systems. They reported transfer learning is a good solution for problems such as a limited amount of data, expert knowledge in medical text analysis, and recognition. Prosperi et al. (2018) studied the technical and societal barriers such as biased medical records, age, gender, and race, etc. in developing DL based model in the health domain. They addressed these factors as risk factors in-place of biological factors. Pattanaik et al. (2020) have proposed deep residual neural network (MM-ResNet) for Malaria detection. Hafiz et. al. (Hafiz et al., 2020) have developed deep convolutional neural network (CNN) for calculation of nutritional information of soft drinks. Haryanto et al. (2017) have applied CNN architecture of deep learning with different number of layers for diagnosis of cancer. Haryanto et al. (2019) have enhanced medical image processing dataset for detection of cancer using Mean-shift-filter technique. Haryanto et al. (2019) have classified the status of cancer using histopathology images and observed that Theano is fast compared to tensorflow.

3. Deep learning architecture

The section describes categorization of DL architecture as shown in Fig. 2.DL architecture can be divided into three categories: Supervised, unsupervised, semi-supervised. Supervised DL models are recurrent neural networks (RNNs), long short-term memory (LSTM), gated recurrent unit (GRU), convolutional neural networks (CNNs), and generative adversarial network (GAN). Unsupervised deep learning models are deep belief networks (DBN), Deep Transfer Network (DTN), Tensor Deep Stack Networks (TDSN), and autoencoders (AE).

CNN: CNN contains multiple layers which are arranged in a hierarchical fashion. Each layer learns specific features of the image (Vizcarra et al., 2019). It consists of convolutional layers, pooling layers, dropout layers, and an output layer. Some of the popular CNN architectures used in medicine domain are:

AlexNet: It consists of 5 convolution and 3 dense layers, max pooling, dropout, data augmentation, ReLU activations after every convolutional and fully-connected layer, SGD with momentum (Krizhevsky et al., 2017). It is used for object recognition.

VGG (Visual Geometry Group): It consists of 13 convolution layers (in VGG16) & 16 convolution layers (in VGG19), 3 dense layers, pooling, and three ReLU units, very small receptive fields (Simonyan and Zisserman, 2014). It is used for large scale object recognition.

GoogLeNet. It consisted of 22 layers deep CNN and 4 million parameters. It contains more filters per layer and stacked convolutional layers (Zhou et al., 2016). It used batch normalization, image distortions, and RMSprop.

ResNet (Residual Neural Network): It contains gated units or gated recurrent units and has a strong similarity to recent successful elements applied in RNNs. It is able to train 152 layers NN (He et al., 2015). It has lower complexity than VGGNet.

UNet: It consists of three units: contraction, bottleneck, and expansion. The contraction section is made of many contraction blocks. Each block is arranged in a hierarchal fashion. In which the max-pooling layer is arranged after two convolution layers. Each block is followed by kernels, whose number is increasing in multiple of 2. It helps in learning the complex structures. The bottommost layer mediates between the contraction layer and the expansion layer. It consists of two CNN layers followed by the up convolution layer. It performs segmentation and classification in a single step (Nowling et al., 2019).

RNN: Recurrent neural networks and its one-directional and bi-directional variants, such as long short-term memory (LSTM) and gated recurrent units (GRU), recursive Neural Networks (recursive NN), Bidirectional RNNs (BiRNN).The one-dimensional RNN learns from the past to predict the future. Though, the Bidirectional RNN learns from the future to fix the past. The RNN is very efficient to capture long term dependencies.

GAN: It is used to generate synthetic training data from original data using latent distribution (Hsieh et al., 2020). It composed of two networks, a generator, which deployed to generate synthetic data from noise and a discriminator, which differentiates the real and synthetic instances of data. Together these two adversarial networks improve the quality of generated data.

AEs: They are composed of an encoder and decoder. AEs discover meaningful representations of data by mapping lower-dimensional inputs to outputs. They utilize the latent representation of input to reconstruct output. They learn only those features of data that are necessary to reconstruct the input. Such algorithms are utilized to learn features that can be subsequently utilized in conjunction with deep learning techniques.

DBN: It consists of two networks, The Belief Networks and Restricted Boltzmann Machines which stacked each other. Belief network is an acyclic graph composed of layers of stochastic binary units with weighted connections. Boltzmann Machine is a stochastic RNN with stochastic binary units and undirected edges between units. It is suitable for large-scale problems (Algarsamy and Kathavarayan, 2018).

DTN: It composed of two layers: feature extraction layer, which learns a shared feature subspace in which the marginal distributions of the source and the target samples are drawn close and a discrimination layer, which match conditional distributions by classifier transduction (Zhang et al., 2015).Its computational complexity O(n). It is suitable for large-scale problems.

TDSN: It contains two parallel hidden representations which are combined using a bilinear mapping (Hutchinson et al., 2012). This arrangement provides a better generalization as compared to single module architecture. It deduces the biases of the generalizer (s) with respect to the learning set. It works effectively and better than a cross-validation strategy when used with multiple generalizers as compared to individual generalizers.

Deep InfoMax (DIM): It maximizes the mutual information between an input and the output of a highly flexible convolutional encoder (Hjelm, 2018)by training another neural network that maximizes a lower bound on a divergence between the product of marginal of the encoder input and output. The estimates obtained by another network can be used to maximize the mutual information of the features in the encoder with the input. The memory requirement of DIM is less because it only requires encoder not decoder.

Combined DL models: DL models can be combined in five different ways: hybrid model – in this model, the output of convolution layer is directly passed as input to other DL architecture such as residual attention network, recurrent convolutional neural network (RCNN) and inception recurrent residual convolutional neural network (IRRCNN) model (Alom et al., 2019); Integrated model – in this model, the output of one DL model is passed as input to other DL model; Embedded model – in this model, the dimension reduction model and classification model are jointly optimized for example enhanced joint hybrid CNN-BiLSTM (EJH-CNN-BiLSTM); Ensemble – in this model, the output of several base models are combined; and Transfer learning (TL) – in this model, DL model trained on one type of problem is used for the same type of problem. Popular CNN models which are used as TL models are VGG (e.g. VGG16 or VGG19), GoogLeNet (e.g. InceptionV3), Inception Network (Inception-v4), Residual neural Network (e.g. ResNet50), AlexNet. Joint AB based DL combines two types of pooling to obtain optimal features: max pooling, and attentive pooling.

4. Applications

The section summarizes 211 literatures obtained from Scopus database that deploy DL in the field of MI and medical NLP. Tables 1 and 2 contain the summary of the DL applications in MI and medical NLP respectively. Tables 1 and 2 are organized on the basis of deployment of DL in chronological order. The last column in the Tables 1 and 2 shows the purpose or field of study.

5. Result and discussion

5.1. Comparative analysis

This section present the comparative analysis of 211 articles obtained from Scopus database and published between 2017 and April 2020. The summary of application which includes data set used, architecture, performance measure and field of study is given in Tables 1 and 2.

The Comparative analysis of various DL architectures deployed in MI and medical NLP are shown in Fig. 3. It is observed from Fig. 3, that CNN architecture is equally suitable for processing of MI as well as NLP due to its efficiency. Another, DL architecture BiLSTM, a variant of LSTM is widely used in medical NLP too.

GRU, Joint, and ensemble architectures are deployed only in medical NLP and integrated technique was utilized more in medical NLP as compared to MI. Most of the joint models have an attention layer with DL or conditional random field with DL. LSTM-CNN hybrid architecture is mostly deployed in medical NLP. Embedded DL is deployed only in ML. The variant of CNN such as AlexNet, VGG, Inspection, ResNet, and U-Net are deployed only in MI. Other than the above CNN variants GAN, DTN, DBN, DIM is also not deployed in medical NLP. TDSN is the DL architecture that is not deployed in either MI or medical NLP. But it is utilized in NLP. Therefore, it can be utilized in medical NLP too.

The comparative view of embedding techniques deployed in medical NLP is shown in Fig. 4. From Fig. 4, it is observed that the word embedding technique is the highest used technique among others.

From Figs. 3 and 4 it is observed that the most suitable combination for DL, image and medical NLP is CNN with word embedding. Other suitable architectures are encoder-decoder with word embedding and encoder with word embedding can perform well in NLP based medical image analysis.

5.2. Challenges in medical imaging

Various types of images are considered for analysis among which CT, MRI, X-ray, Ultra sound, PET, Wave images, Biopsy, Mammogram and spectrographs are popular. Image analysis pipeline is very important too in MI as it is responsible for reducing time, error, cost, and complexity. In general the pipeline consists of following task: feature extraction, dimension reduction, Augmentation, segmentation, clustering or classification. Many authors has proposed new pipeline to make MI an effective and accurate (Zhang et al., 2018; Vizcarra et al., 2019; He et al., 2019; Zhu et al., 2019; Wang et al., 2019; Cheimariotis et al., 2020). Deep learning in MI suffers many issues. We summarize some of the potential issues associated with deep learning. Image type, processing phase and challenges encountered in our study, from the MI are shown in Fig. 5.

Low resolution images and reconstruction overhead: Low-resolution images have attracted researcher's attention in the health domain because of their easy acquisition method and small computational cost (Chen et al., 2019) but their classification is a challenging task due to their noisy representation and limited information (Zhn et al., 2020). Researchers deployed conventional linear interpolation methods to generate high-resolution images from low-resolution images but these methods suffer from artifacts such as aliasing, blur, and halo around the edges (Siu and Hung, 2012). The reconstruction overhead is high too (Umehara et al., 2018; Hoppe et al., 2019). The super-resolution convolutional neural network is the preferred method for reconstruction (Umehara et al., 2018).

Table 1
DL based application for image processing.

Author	Image; Dataset	Techniques	Performances	Purpose/Finding
Cha et al. (2017)	CT	CNN	Not mentioned	Identify the feasibility of pre- & post-treatment CT for bladder cancer
Korfiatis et al. (2017)	MRI	ResNet50	Acc: 94.9%	Reduced the pre-processing computational overhead in molecular biomarkers prediction
Aghdam et al. (2018)	rs-fMRI & sMRI	DBN depth 3	Acc: 65.56%; Sen: 84%; Spe:32.96%;F1 score: 74.76%	Exploit the abstract high-level features to classify autism spectrum disorders
Zhang, et al. (2018)	Colonoscopic images extracted from videos	Regression-based CNN	Pre: 88.6%,Recall: 71.6%	New pipeline phases: spatial features learning, object detection with ResYOLO, refining the detection results via Efficient Convolution Operators for detection of Polyp during colonoscopy
Hoseini et al, (2018)	MRI; BRATS 2016 dataset	DCNN	Not mentioned	Efficiently deal with heterogeneous features of brain tumors
Gruetzemacher et al. (2018)	LIDC-IDRI dataset	3D U-Net & 3D **ResNet**	DR:89.29% (Test);FP perscan: 1.789	DL was deployed for candidate generation &FP reduction. Showed good generalization on unseen data for detection of pulmonary nodules
Umehar et al. (2018)	Chest CT	SRCNN	Not mentioned	Construct high resolution image from low resolution
Burdick et al. (2018)	Skin Lesion	TL: CNN	Not mentioned	Enlarge segmentation border to classify skin lesion
Mohamed et al. (2018)	Breast mammogram	CNN	Not mentioned	Reduce variability in mediolateral oblique & cranial caudal view interpretation while assessing BI-RADS based breast dataset
Mutasa et al. (2018)	Radiographs of Bone age	Hybrid: residualconnections & inception CNN	Acc: 0.64–0.66 (validation) & 0.49–0.56 (test)	Overcome the hard-coded features limitation by customizing CNN model
Brown et al. (2018)	retinal photographs (RP)	DCNN	AUROC: 0.94Sen:93%Spe: 94%	Automate method to analyse RP do reduce the variability in human interpretation
Fernandes et al. (2018)		Embedded DL model: Deep auto-encoders	AUC = 0.6875	Jointly optimize the dimension reduction & classification method using loss function
Lee & Kim, (2018)	X-ray images	DL tool Caffe,	Mean AD:18.9 months &CCC: 0.78.	Reduce time and cost overhead in bone age estimation process
Wang, et al. (2018)	MammogramImageNet dataset	DCNN	AUC: 0.813	Ensemble of hybrid DL model & SVM for breast lesion detection
Brown, , et al. (2018)	retinal images	U-NetGoogLeNet	Not mentioned	Deal with variations in acquisition & image quality
Heidari et al. (2018)	Mammographic	CNN	Not mentioned	Deployed a local preserving projection based feature regeneration method to predict short-Term breast cancer risk.
Tóth et al, (2018)	CT	CNN	Acc: 93.4%	Resolve the issue of contentious labeling
Choi & Kim, (2018)	physiological & video signal; DEAP dataset	LSTM	Acc: 74%-78%	Classify emotionNo explicit feature extraction
Kim et al. (2019)	NIH ChestX-ray14 database	DCNN	Acc: 98–99.6%AUCs:0.997 to 1;	Classification; chest radiograph
Hassan, et al. (2019)	Real-timesurgical videos	Hybrid CNN-encoder network	Pixel acc: 97%	Telementoring System
Aghdam, et al, (2019)	Functional MRI ; (ABIDE I & II datasets;	TL	Acc: 0.7–0.727, Sen: 0.67–0.712, Spe: 0.73–0.74	Reduce time overhead in diagnosis of Autism Spectrum Disorders
Kaplan & Zhu, (2019)	PET Image	estimator n -adversarial discriminator network	Not mentioned	Reduced cost of PET Image estimation
Alkadi et al. (2019)	T2 MRI;I2CVB dataset	deep convolutional encoder-decoder	AUC: 0.995,Acc: 0.894,Recall: 0.928	A novel 3D sliding window approach to preserve 2D domain complexity while exploiting 3D information in detection of prostate cancer
Kuzmak et al, (2019)	DR surveillance retinal fundus Photographs;	i-ROP	Not mentioned	New DL model for diabetic retinopathy(DR) Detection
Ha et al. (2019)	Breast MRI Tumor Dataset	CNN	Acc:87%-88%Sen:84%-70%. Spe:90% 98%.	Prediction of neoadjuvant chemotherapy treatment response prior to initiation of chemotherapy
Alnujaim & Kim, (2019)	Spectrograms	GAN	Not mentioned	Augment human motion micro-Doppler data
Vizcarra et al. (2019)	BreAst CancerHistology; BACH dataset	CNN	Acc: 92%	Develop new classification pipeline by fusing shallow and a deep learner for diagnosis of breast cancer
Choudharyet al. (2019)	Histopathology images	TriNet-P	Not mentioned	New DL model for stain normalization
Abdelhafiz et al. (2019)	Mammography(MG) images	Hybrid: Residual - UNet	Superior performance	New hybrid DL model for mass segmentation & classification in MG of breast
Hosseini & Guo, (2019)	EEG signals images;	DCNN	Acc: 91.78%Sen: 92.84%Spe: 90.73%	First study to detect mind wandering by DL
He et al. (2019)	pathwayfigures in the biomedical from PubMed	Not mention	Not mentioned	Developed new pathway curation pipeline

(continued on next page)

Table 1 (*continued*)

Author	Image; Dataset	Techniques	Performances	Purpose/Finding
Luckett et al. (2019)	EEG signals	Nonlinear phase space analysis,deep CNN	RMSE:14.1 minAdjusted R-squared:0.95	Scalp sEEG feature are extracted via time delay embedding & phase-space reconstruction
Eslami & Saeed, (2019)	fMRI	Hybrid DL;augment data via SMOTE	Acc: 80%	New hybrid DL model :Auto-ASD-Network
Hoppe et al. (2019)	MRF	RNN	Not mentioned	Reduced the reconstruction time
Pezeshk et al. (2019)	Chest CT;LIDC dataset.	Integrated FCNN – CNN	Sen: 91%	Reduce processing time & augment training samples by different thresholds for detection of pulmonary nodules
Gupta et al. (2019)	retinal images	i-ROP	Not mentioned	To obtain Retinopathy of prematurity (ROP) vascular severity score regression
Taylor et al. (2019)	retinal images	i-ROP	Not mentioned	To obtain quantitative ROP severity score
Zhou et al. (2019)	ChestX-ray8	TL	AUC: 0.87	Identify the cardiomegaly
Zhang et al. (2019)	footsteps	VGG16	Acc: 82–89%	First study to deploy DL for diagnosis of huntington disease;
Alom et al. (2019)	Histopathological Images;BreakHis and breast cancer (BC)dataset	IRRCNN model hybrid ofInception-v4, ResNet, RCNN.	Superior performance	New hybrid DL model for classification of breast cancer;
Mojab et al. (2019)	fundus image	InterGD	Not mentioned	New model InterGD - deal interpretability & inadequate label problem
Wang et al. (2019)	Dermatology Image	TL: InceptionResNetV2 architecture	Not mentioned	Resolve the issue of assembling a cohort of specific images
Yoon et al. (2019)	ECG signal;	CNN	AUROC: 0.93; F1-score:0.80; sen:0.88; spe:0.89; PPV:0.74; NPV:0.96	First study to deploy DL to automate noise screening in ECG
Xie et al. (2019)	physiologicalsignals	Hybrid: FCN - U-Net	Improved result	First study to deploy DL to detect sequence human mental workload &introduce novel loss function
Dai et al, (2019)	skin cancer image	CNN	Save bandwidth	Resolve the latency and privacy issue
Tuncer et al, (2019)	Pulse Transition Time (PTT) signal	AlexNet & VGG-16	Satisfactory results	Eliminate the tiring & biased step of parameter examination
Chien et al. (2019)	360-degree thermal video and RGB images of foot	CNN	successfully detect	Used thermal imaging to detect plantar fasciitis
Guo et al. (2019)	cervical image	RetinaNet;TL (VGG, Inception)	Acc: 94%	Resolving the issue of smart phone based low quality image screening for the diagnosis of cervical cancer
Shrivastava et al. (2019)	histopathological images	ResNet50	Acc: 90%	Wide range of available syndromes & pathologies make the celiac disease classification task very expensive in term of time and expert
Zhu et al. (2019)	whole-slide imaging	stacked convolutional autoencoder	Higher accuracy	Develops new pipeline: feature extraction, dimension reduction, classification which reduced time cost and error
Ravichandran et al. (2019)	cardiac CTCA scans	U-Net models(3D inception u-net)	Segmentation DSC: 0.81	Develop a method for automating CTCA Segmentation
Nguyen et al. (2019)	heart aorta CT dataset;	U-NetStochastic	CVDS: 4% betterPerformance: 2% better	Automate CT scan segmentation using novel loss function
Malmsten et al. (2019)	TLM images	CNN	Acc: 93% (human) &100% (mouse)	Automate cell stage prediction to reduce time and expert's biasness
Giordano et al. (2019)	Video Capsule Endoscopy (VCE)images	CNN	Accurate diagnosis	Automated lesion identification to reduce time
Nowling et al. (2019)	MRI	U-Net	AUC: 97.7%	Segmentation and classification in single step.
Tan et al. (2019)	colon CT	CNN	AUC: 0.93	Used co-occurrence matrix for texture indicator
Wang et al. (2019)	Ultrasound images	U-net	Not mentioned	Propose a distance based loss to reduce the noise and enhance the localization map
Chen et al. (2019)	ECG	Integrated CNN & LSTM	Promising results	First study to classify 12 lead ECG using DL
Fedorov et al. (2019)	ADNI database	DIM	Not mentioned	First study to use DIM for prediction of Alzheimer's
Bruzelius et al, (2019)	Satellite images	TensorBox	PPV: 86.47%Sen: 79.49%	Objects detection in satellite images to use in health service
Wang et al., (2019)	CT	deep stacked sparse auto-encoder	Higher accuracy	Used deep contextualFeatures; Reduced model complexity
Nam et al, (2019)	EMG: waveform images	Inception v4	Acc: 93.8%,Pre: 99.5%, recall: 90.8%	TensorFlow-Slim & Python were used to image recognition
Suganya & Rajaram, (2019)	ultrasound	CNN	Acc:100%Sen:98%	Deployed correlation based feature selection to categorization of liver cirrhosis
Zhang et al, (2019)	Breast MRI	DL: not mention	Best DC	segment breast tumor
Espanha et al. (2019)	Brain images	DL: not mention	Not mentioned	Extend XNAT for segmentation of brain tumor

Table 1 (*continued*)

Author	Image; Dataset	Techniques	Performances	Purpose/Finding
Shahin et al. (2019)	Blood smear image	TL: CNN	Acc: 96%	Classify small limited dataset
Yu et al. (2019)	ophthalmic image	Mask R-CNN framework	Not mentioned	Identify and analyse object in ophthalmic photography
Crosby et al. (2019)	thoracic radiographs	CNN	AUC: 0.97 ± 0.005	Classify the thoracic radiographs containing imprinted labels.
Liu et al. (2019)	4D-curvature images computed CT image	encoder-decoder CNN model	median DC: 0.8 for low & 0.89 for high resolution	Developed a new model SegNet, which work on advance pipeline: data normalization, datatransformation, extrapolation & data augmentation
Kudva et al. (2019)	cervix images	TL : AlexNet & VGG-16 net	Acc: 91.46%.	Classify cervical cancer
Gonçalves et al. (2019)	EyePACSdataset	Inception-V3	Acc: 89%	Resolve the issue of delay, preciseness & decentralized in diagnosis of diabetic retinopathy
Dadsetan & Wu (2019)	digital mammogram images	CNN	–	A new DL model for prediction of breast Cancer
Guan & Loew, (2019)	mammographic images	Integrated: GAN-TL (VGG-16)	Acc: 98.85%	Detection of breast cancer by augmenting more training images
Kim et al. (2019)	fundus images; MESSIDOR dataset	Integrated: FCN - U-Net	JI: 0.94,Sen: 0.98,Spe: 0.99 &Acc: 0.99.	Diagnosis of glaucomaAutomate the optic disc segmentation
Tachibana et al., (2019)	CT colonography	Hybrid GAN – 3D convolutional kernels	Not mentioned	New electronic cleansing method to reduce time and artefact
Khened et al. (2019)	Brain Magnetic Resonance; TCIA dataset	CNN	Acc: 90%	Prediction of molecular markers
Andrearczyk et al. (2019)	CT ;phantom images	hand-crafted & deep features	Not mentioned	New features standardization method to deal heterogeneity of health data
Arefan et al. (2019)	mammogram images;	3-channel CNN	Not mentioned	Multi-space model for diagnosis of breast tumors
Moriyama et al. (2019)	oral images	MapReduce-DL model	Acc: 91.7%	Resolve the difficulty of feature extraction from small RIO & tooth identification among heterogeneous teeth
Lüneburg et al. (2019)	Drivelineexit site images.	U-net	DSC: 0.95	Develop health monitoring system for wound infection identification from images that contain less information
Azehoun-Pazou et al. (2019)	linea nigraimages	DL: not mention	Not mentioned	Android mobile application for prostate hypertrophy monitoring
Dutta et al, (2019)	CT Spine datasets (Spineweb repository)	Integrated: Conditional GAN - U-Net	Pre: 97%,Sen: 96% &F1 (Dice): 96%	Simultaneously optimize 7 hyper-parameters of DL model for of vertebral bone image segmentation
Uemura et al. (2019)	CT imaging; radiomic image	conditional GAN	Not mentioned	Developed new model based on 4D curvature prognostic biomarker
Gupta et al. (2020)	Liver CT; CCTA dataset	TL	AUOC: for grayscale: 0.78 & color:0.88 for APV;For grayscale: 0.93 & color: 0.91 for MPV	Increase the performance of DL by formatting small volumetric images from 3D to 2D using Aggregate (APV) & Mosaic (MPV) method
Ranjbar et al. (2020)	brain tumor MRI	CNN	Acc: 99%	Resolve the issue of annotation of MRI due to non-standard labelling by deploying DL
Wang et al. (2019)	ECG	Integrated: CNN - bidirectionalRNN	Acc: 87.69%	Hybrid CNN-BRNN model, in which BRNN fused the features of leads to build deeper features
Jeyaraj& Nadar, (2019)	ECG	Deep CNN	Acc: 96.3%,Sen: 93.5%,Pre: 97.5%.	Resolve the issue of deploying DL in IoT based ECG pattern detection
Cho et al. (2019)	Vedio frameimages	CNN	Acc: 96.7%	First study to apply CNN on Horn-Schunk-algorithm images for identification of cecum
Karim et al. (2019)	Signal images	deep sparse autoencoders	Not mentioned	Develop a novel hybrid energy spectral density - deep sparse autoencoders model for diagnosis of Cardiac Arrhythmias in less computational time
Rehman et al. (2020)	CT scan;CSI 2004	Full U-Net	DS: 96.4 ± 0.8% without fracturedDS: 92.8 ± 1.9% with fractured cases	Integrated region-based level set & DL framework for vertebral bone segmentation; to deal low-contrast & noise in image
Chen et al. (2020)	Wireless Signal	DTN	Acc: 98%	Classification of human motion; Passive radio sensing technology used in health care
Bargshady et al. (2020)	facial images;UNBC-McMaster Shoulder Pain Archive Database	hybrid CNN-BiLSTM;	Good accuracy	New Hybrid DL model for detection of Pain intensity
Kim et al. (2020)	Spine CT;hierarchical data format file	U-Net	DC:90.4%,Pre: 96.81%,F1-score: 91.64%.	Web-based DL approach for diagnosis spine pain
Hsieh et al. (2020)	Head and Neck CT image	GAN	Reduces the false positive rate	Generating synthetic images
Sharma & Mehra, (2020)	Histopathological images;BreakHis dataset	TL models(VGG16, VGG19, and ResNet50),	Acc:Patch & Patient based: 91–94%	Multi-Classification; of breast cancer
Chen et al. (2020)	X-ray images	CNN	Success rate 97.56%.	Augmentation by flipping images at various angles for tooth treatment
Su & Fan, (2020)	abdominal CT of liver and spleen	Multi-channel U-net	Structure similarity index: 0.9731;DSC : 0.9508	Automatic segmentation model to deal the ambiguous boundaries, heterogeneous appearances and highly varied shapes of images

(*continued on next page*)

Table 1 (*continued*)

Author	Image; Dataset	Techniques	Performances	Purpose/Finding
Cheimariotis et. al., (2020)	IVOCT	AlexNet	Acc :Training: 100% validation:86%	New processing pipeline : transform images to binary code, detection, split, transformation, labelling & classification
Panganiban, et al. (2020)	graph images Physionet.org Database;	Inception V3 model	Acc: 96.8%.	New algorithm for automaticdetection of AF exclude pre-processing step of detection of peak
Panganiban et al. (2020)	Biosensors signalsMIT-BIH ECG database	Integrated: LSTM-CNN	Acc: 99.05% Lossrate:4.96%	Combination of wireless transmission & DL to collect, transmit & analyse signal
Chen et al. (2020)	Wireless signals	DTN	Not mentioned	Monitor human respiration;Novel method to disentangle the chaotic bursts in congested radio environments
Chen et al, (2020)	–	Cascade Adaboost with CNN	Not mentioned	Automatically delineate the breast calcifications

Note: Positive predictive value: PPV; negative predictive value: NPV; precision(pre); Dice score coefficient (DSC); Jaccard index (JI); multi-channel U-net network CNN, Transfer learning (TL), joint bidirectional LSTM/ bidirectional LSTM (BiLSTM), residual attention U-Net model (RUNet), and the Recurrent Convolutional Neural Network (RCNN), Dice coefficient(DC), Root mean squared error (RMSE): Fully Convolutional Network (FCN)**;** cross-validation Dice scores: (CVDS); Accuracy: (Acc) Sensitivity : (Sen); Precision: (Pre); Detection rate: (DR); false positives: (FP); super-resolution CNN: (SRCNN); Specificity: (Spe); concordance correlation coefficient: (CCC); absolute difference : (AD);

Ambiguous boundaries, heterogeneous appearance & varied shape: The complexity of image segmentation is increased and effectiveness of feature extraction is reduced due to ambiguity in the separation between neighbouring regions, heterogeneous appearance & different shapes of objects in images.

Hard to construct high resolution images from low resolution: The construction of high resolution image from a single low-resolution image is a big challenge due to the degradations that occurs during the acquisition of low resolution image such as: occurrence of aliasing due to the larger spatial sampling periods, blurred continuous scene due to physical dimensions of the low resolution sensor, blurring due to motion of sensor which varies from image to image and lastly the noise occurred due to the acquisition method. These issues must be addressed in the high resolution image.

Lack of sufficiently large and labeled image datasets: A successful deep learning model requires an extremely large amount of training data that are clearly labelled. Most of the medical images are unlabelled and manual annotation of the images is very time consuming and require expert knowledge. Standardized, organized, and concise labeling is advocated by researchers (Wang et al., 2019), but it suffers with over-labeling with superfluous details which is time consuming and thus leads to impede clinical flow.

High model complexity, un- interpretable & hyper parameter optimization: The deep learning architecture is a kind of black box architecture. It is not easy to interpret why it provides good results (Ravì et al., 2017). The deep learning model requires extremely large data to train, and in the absence of large data, it suffers the over-fitting problem and thus increases the model complexity. The problem of over-fitting can be removed by adding dropout. To develop a successful deep learning model, it is required to optimize a large number of hyper-parameters such as the size and the number of filter, depth, learning rate, activation function, number of the hidden layers, etc. It is a hit and trial process. This is a lengthy process that requires significant training resources and human expertise (Ravì et al., 2017).

Large variation in pipeline phases: The major challenge in developing a deep learning model in MI is that there is no standard phases lie in the image analysis. This is due various region such as-the images are captured from many region (Sharma and Mehra, 2020), various types of learner are fused in a phase (Vizcarra et al., 2019), various types of images (He et al., 2019), expensive, laborious and error-prone manual examination of tissue (Zhu et al., 2019), small sample size regime, algorithm are computationally complex and suffered with low sensitive problem (Zhang et al., 2018).

Computationally expensive 3D image segmentation: 2D CNN showed remarkable results for 2D images but for volumetric images such as CT and MRI, the CNN is required to extend to 3D, which is a time consuming task (Hamidian et al., 2019). Segmentation of 3D images is very challenging due to variations in object shape and blurred boundaries (Yu et al., 2017). Although, this problem can be solved with the interpolation method. But this method suffers from blurred images. The CNN architecture deployed for this purpose (Wu et al., 2015; Qi et al., 2016) are either computationally expensive or does not exploits the 3D spatial contextual information of the input.

Network latency and privacy issue: An extensive large amount of data is required to train a deep learning model. Due to the storage and processing of such large data mobile health applications are deployed on the cloud (Ruiz-Zafra et al., 2013; Gatsios et al., 2015; Paolo, 2014; Pan et al., 2015; Ahsan et al., 2013). But the cloud-based application suffers the issue of latency, privacy, cost, connectivity, and customization (Dai et al., 2019).

5.3. Challenges in medical NLP

The task, medical text, and embedding method are crucial in medical NLP. The type of text which are used generally for medical NLP are tweet, EMR, RCT article, free text, biomedical text, reviews on WebMD patient, pathology reports, adverse medical event, and adverse medical reports. Generally, three types of embedding are performed on the medical text: concept, word, and sense. Concept embedding mapped medical entities to the clinical phenotype. It associates a vector to each phenotype such as med2vec (Choi et al., 2016). Word embedding is an unsupervised method to capture the relationships between words. It associates a vector representation with each word (Joopudi et al., 2018; Hu et al., 2018; Munkhdalai et al., 2018; Gao et al., 2018; Yokota et al., 2018; Xie et al., 2018; Alawad et al., 2019). Words with similar semantic contexts have the same representation such as Word2Vec (Kang et al., 2019; Kim and Meystre, 2019; Li et al., 2019; Ge and Moh, 2017). Sense/Context embedding maps the context with its correct term given in a set of candidates. In the medical text, each ambiguous word takes many instances, and in turn, it takes many senses. It is performed UMLS (Pesaranghader et al., 2019; Yao and LuoY, 2019; Jiang et al., 2019) ELMo and Flair. Sense embedding maps the context with the correct sense given in a set of ambiguous words. In the medical text, each ambiguous word takes many instances, and in turn, it takes many senses. Each sense is attached to the UMLS concept, which is closest to its meaning. Position embedding maps target entities with their position information (Li et al., 2019; Liu et al., 2019). Various tasks, which are performed

Table 2
DL based application for medical NLP.

Author	Source of Text	Techniques	Accuracy	Purpose/finding
Liu et al. (2017)	clinical text	WE- skipgram;LSTM	micro-average F1-scores: 85.81% (concept extraction), 92.29% (event detection), & 94.37% (de-dentification)	Entity recognition
Cocos et al. (2017)	Twitter posts	WE- skipgram;RNN	F-score:0.755	ADR detection
Choi et al. (2017)	HER	WE- skipgram;GRU	AUC: 0.88 18-month window	Temporal relation
Zhu et al. (2017)	HER	CE;CNN	Not mentioned	Temporal matching
Hughes et al. (2017)	clinical text	CE;Deep CNN	Not mentioned	Classify at sentence level
Deng et al. (2017)	Clinical text	CE- CBOW;DL type not mentioned	less match rate 0.43	Code generation,semantic representation generated
Lee et al. (2018)	EHRs	No embedding;Hybrid: attention-based RNN & conditional deep generative model	Not mentioned	Prediction from historical EHRs
Sun et al. (2018)	EHR inputs	No embedding;LSTM	Not mentioned	Identify attack;Reduce vulnerability
Chen et al. (2018)	Present illness history; EMR	WE-word2vecCNN	Not mentioned	Relation extraction
Chu et al. (2018)	EMR	CWE;Joint: neural attention network-DL	Not mentioned	Adverse medical event detection
Joopudi et al. (2018)	Clinical text	WE-word2vec;CNN	Acc: 0.97 (micro average) & 0.929 (macro average)	Abbreviation disambiguation
Hu et al. (2018)	Chinese medical text	WE-word2vec;LSTM	–	Relation extraction
Munkhdalai et al. (2018)	HER	WE- skipgram;Joint: LSTM withattention layer	F1-score: 65.72%	Relation extraction
Gao et al. (2018)	cancer pathology reports	WE: (Word2Vec & GloVe)Integrated: LSTMs/GRU- LSTMs/GRU	mean micro F-scores: 0.852 & macro F-scores: 0.708	Information extraction
Yokota et al. (2018)	Japanese incident reports	WE- skipgram;DL not mentioned	Pre: 0.62,Recall: 0.53,F-score: 0.57	Fail to remove ambiguity in medical terms
Xie et al. (2018)	social media clinical text	WE;Bi-LSTM	Pre: 94.10%, Recall:91.80%,F-measure: 92.94%	Mining adverse event;Hard to interpret consumer vocabulary in social media
Alawad et al. (2019)	cancer pathology reports	Embedding not mentioned;TL- CNN	Improved macro F-score in 6.90% and 17.22%	Text information extraction
Pesaranghader et al. (2019)	biomedical text; MSH WSD dataset	SE (UMLS);BiLSTM;	Macro acc: 96.82% f	Predict ambiguous term.
Liu et al. (2019)	Chinese clinical notes	WE: (Context embedding); Integrated: LSTM-CNN	F1-score:75.97% (TRC)Acc:71.96% (TI)	Temporal relation classification (TRC) & temporal indexing (TI)
Wang et al, (2019)	patient safety incident reports	WE;CNN	Incident F- scores >85%, Severity F- scores by11.9%-45.1%	Identify the type & severity
Wang et al. (2019)	EHR data	Embedding not mentionedCNN	Sen: 0.837, spec: 0.867, PPV: 0.532	Prediction; advancedcolorectal cancer
Yao et al. (2019)	TCM records	WE- skipgram;Bidirectional Encoder	Acc: 89.39% ± 0.35%, Macro F1 score 88.64% ± 0.40% & Micro F1 score 89.39% ± 0.35%.	No explicit feature engineering task;Use unlabeled clinical corpus
Shi et al. (2019)	Clinical text	WE- skipgram;joint DLBiLSTM-CRF (ER)BiLSTM (ERE)	F1-score:74.46% (ER) & 50.21% (ERE)	Pipeline: entity recognition (ER), entity relation extraction (ERE); Cumulative error to next phase
Weissenbacher et al. (2019)	Tweet	WE (Glove);Ensemble: 3 layer DL model with GRU	F1-score: 93.7%	New tool to deal with spelling error & ambiguity
Rong et al. (2019)	Tweet	WE- (Glove & HF);CNN, LSTM & GRU	Acc: 87.9%	Handled non-standard expressions
Ben Abacha & Demner-Fushman, (2019)	Clinical-QE data Question Answer	WE- (Glove);RNN	Acc: 98.6%	Recognizing Question Entailment
Wei et al. (2019)	Biomedical text	WE- skipgram;Integrated: CNN-LSTM	F1-scores: 91.94% (micro-averaged) & 85.42% (macro-averaged)	New disambiguation method
Richter-Pechanski et al. (2019)	German medical reports (GMR)	DCWE via ELMo;BiLSTM	Identification: 93%F1-score: 96%	Lack of de-identifiedGMR medical corporaInvestigate de-identification & entity recognition task
Yang et al. (2019)	EMR	DCWE via ELMo;joined DL-attention-based BiLSTM-CRF	Not mentioned	New phase of pipeline entity discovery added
Santiso et al. (2019)	Spanish EHRs	WE-(lemmas);Joint: AB-LSTM	f-measure of 73.3	High lexical variability reduced by lemma
Obeid et al. (2019)	illness notes	WE- (word2vec);CNN	Acc: 95%	Perform de-identification
Hu et al. (2019)	twitter-sphere	WE- skipgram;Ensemble: word level CNN & character-level CNN models	Acc: 87%	Deal with imbalance data
Tao et al. (2019)	free-text narratives	WE;DL not mentioned	Not mentioned	New augmentation method based on pseudo-data generation

(continued on next page)

Table 2 (*continued*)

Author	Source of Text	Techniques	Accuracy	Purpose/finding
Kang & Meystre (2019)	Randomized controlled trial (RCT) articles	WE-(word2vec);Join LSTM-CRF	F1 score mean 0.66	Eliminate the laborious feature engineering task;Extract statements
Kim & Meystre, (2019)	HER	WE-(word2vec);Ensemble: BLSTM-CNN-CRF	Mean Acc: of 77.5%	Give precise extraction
Sun et al. (2019)	Clinical notes	Embedding not mention;CNN	AUCs above 0.83	Structured & unstructured data
Knoll et al. (2019)	Medical records in English	DCWE;Integrated: CNN-Bi-LSTM	Not mentioned	sentence boundary disambiguation
Sarker et al. (2019)	Twitter	WE- skipgram;DCNN	Acc: of 70.4%	Resolve context less tweets & data imbalance issue
Lee et al. (2019)	HER	DCWE;GRU	Not mentioned	Investigate de-identification
Huang et al. (2019)	MIMIC-III clinical notes	Embedding not mentionSingle RNN & CNN	F1-score: 0.6957Acc: 0.8967	Map clinical notes to codes
Du et al. (2019)	Biomedical texts	DCWE;Integrated DL: ML-Net	Not specified	prediction of optimal label set
Li et al. (2019)	MIMIC-II & MIMIC-III clinical notes	WE- skipgram;CNN	micro F-measure: 0.335 on MIMICII& 0.408 on MIMIC-III dataset	Map clinical notes to codes based on global features
Ru et al. (2018)	reviews on WebMD patient	WE- (word2vec);LSTM	Not mentioned	Mine social media for over drug usage
Bai & Vucetic, (2019)	MIMIC-III data clinical note	WE- skipgram;CNN	AUC: 0.96	Generating codes
Qiu et al. (2019)	Louisiana Tumor Registry	WE- skipgram;Joint: convolutional attention-based auto-encoder	micro F-scores between 0.012 & 0.064	Annotation of pathology reports
Yoon et al. (2019)	Cancer pathologyReports	WE- skipgram;Joint: CNN & convolutional attention network	F1-score: 0.915(mean of micro) & 0.902 (mean of macro) for CNN	Bayesian optimization for hyper-parameter optimization
Alawad et al. (2020)	cancer registries, unstructured text	WE- skipgram;CNN	Not mentioned	Good Computation efficiency
Xu et al. (2019)	EHR's clinical notes	WE- skipgram;Joint: document-level attention- BiLSTM-CRF	NCBI: Pre:0.883, Recall: 0.89, F1:0.886; BioCreativeCDR: Pre: 0.891, Recall:0.875, F1:0.883	Minimize the tagging inconsistency impact;Entity recognition
Yao et al. (2019)	clinical notes	SE: (UMLS)CNN	Not mentioned	rule-based features and knowledge-guided deep learning models
Lee et al. (2019)	EMR text-Radiology reports	WE: skipgram;Hybrid: LSTM encoder-LSTM decoder	Pre: 0.967, Recall: 0.967, Acc:0.982,F1 :score: 0.967	Performed disease annotation
Li et al. (2019)	clinical text	PE & WE: word2vec;PE;Integrated: Bi-LSTM - CNN	Pre: 75.69%Recall: 73.03%F-score: 74.34%	Extract clinical entities relation
Liu et al. (2019)	Chinese clinical notes	PE & WE;Integrated:LSTM-CNN	F1-score: 75.97% (temporalrelation classification) Acc: 71.96% (temporal indexing)	New pipeline: extract temporal expressions (TE), generates representation for TE,learns the context information & generate a word representationsequence, extracts features & produce representation then classifies
Ru et al. (2019)	patient forum of WebMD	WE: (word2vec)Integrated: CNN-LSTM-convolutional LSTM (CLSTM)	Not mentioned	Use contextual information
Danilov et al. (2019)	HER	WE;GRU	Mean absolute error: 2.8 days	Demonstrate the utility of medical text in decision support technologies
Zhang et al., (2019)	EMR	WE- skipgram;Joint: attention layer-GRU-CNN	Pre: 92.95,Recall: 89.65,F1: 91.27	New pipeline:Medical dictionary level entity representation followed by classification
Jiang et al.,(2019)	Clinical text	Combined embedding: CWE- (ELMo & Flair)& SE: UMLSJoint: biLSTM-CRF	F-1 score: 87.44%	Integrated embedding is deployed
Afzal et al.,(2019)	biomedical literature	Embedding not mentioned;ensemble DL	Acc: 90.97%	Pipeline: question generation, evidence quality recognition, ranking & summarization of evidence

Note: conditional random field: (CRF); Embedded Language Models (ELMo); Sense embedding: (SE); deep contextualized word embedding (DCWE); Concept embedding (CE); contextualized word embedding (CWE); electronic medical record (EMR); electronic health record (EHR); Accuracy (Acc); Precision: (Pre); area under curve (AUC); Sensitivity: (Sen); Specificity : (Spec); Positive predictive value: (PPV); Unified modelling language system (UMLS); word embedding: (WE);

on medical text such as de-identification, attribute recognition/ discovery, relation extraction, segmentation, temporal indexing extraction, temporal relation extraction, AME and ADR detection, and annotation. DL in MI suffers many issues. We have summarized some of the potential issues associated with DL.

Lack of de-identification of medical corpora: Medical records contain a lot of personal and private information about patients. The process of identifying and removing this information is called de-identification. The traditional de-identification methods such as: rule-base, which is based on rare information in a medical text and machine learning, which is based on information not in dictionary and other method, which based on dictionary look-ups, regular expressions, and heuristics are not suitable for medical text that contain not tokenized words, irregular terms and large abbreviation (Richter-Pechanski et al., 2019; Obeid et al., 2019; Lee et al., 2019). This makes the de-identification process very challenging for researchers.

Hard to generate ICD code from medical record: ICD codes are alphanumeric codes, which are developed by WHO for standard reporting of mortality and morbidity statistics. ICD-10 is required

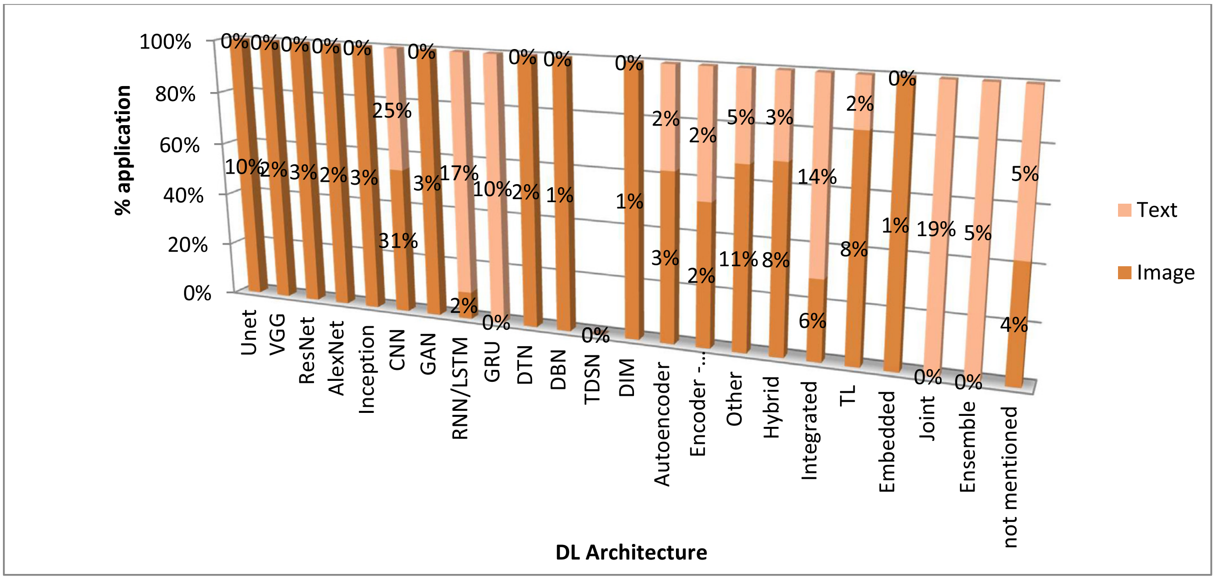

Fig. 3. Comparative view of DL techniques deployed in medical image and medical NLP.

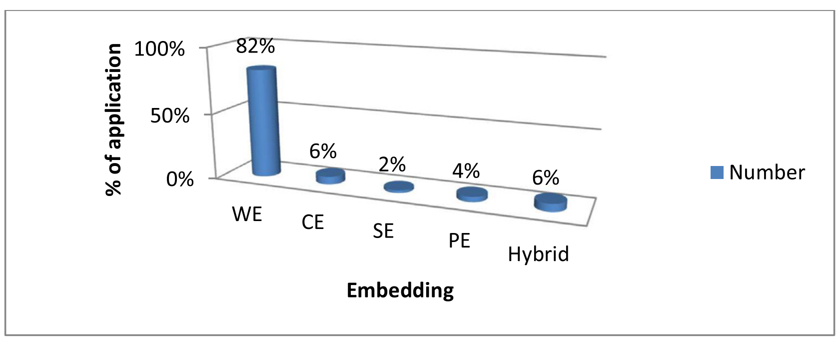

Fig. 4. Comparative analysis of embedding techniques deployed in medical NLP.

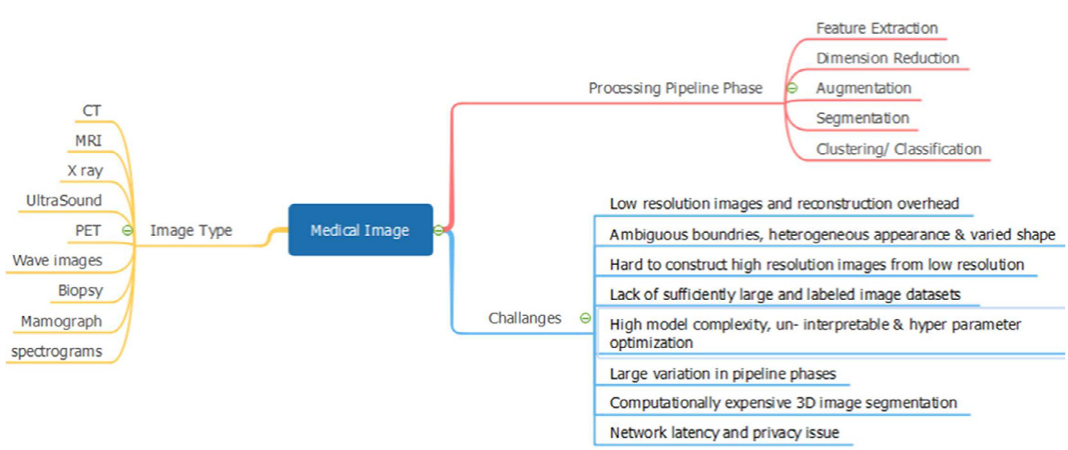

Fig. 5. Image type, processing phase and challenges encountered in our study, from the MI.

for claiming insurance; ICD-9 code is required for billing or creating valid report of patents (Huang et al., 2019). The availability of large amount of medical data make manually code generation task tedious and it required expert's knowledge too. Although the concept, rule-based, and machine learning-based classification methods are available for automatic code generation however, they are limited due to handcrafted rules and limited vocabulary in a concept library (Deng et al., 2017; Huang et al., 2019; Li et al., 2019; Bai and Vucetic, 2019). The lack of a baseline model to reliably assess different algorithms on benchmark datasets (Deng et al., 2017; Huang et al., 2019; Li et al., 2019; Bai and Vucetic, 2019), makes the code generation task a challenge for researchers.

Lack of key annotation of medical text: To make efficient use of medical text, it is required to convert them to outcome labels that contain specific information (Lee et al., 2019). However, manual categorization of medical text with key annotations is a laborious

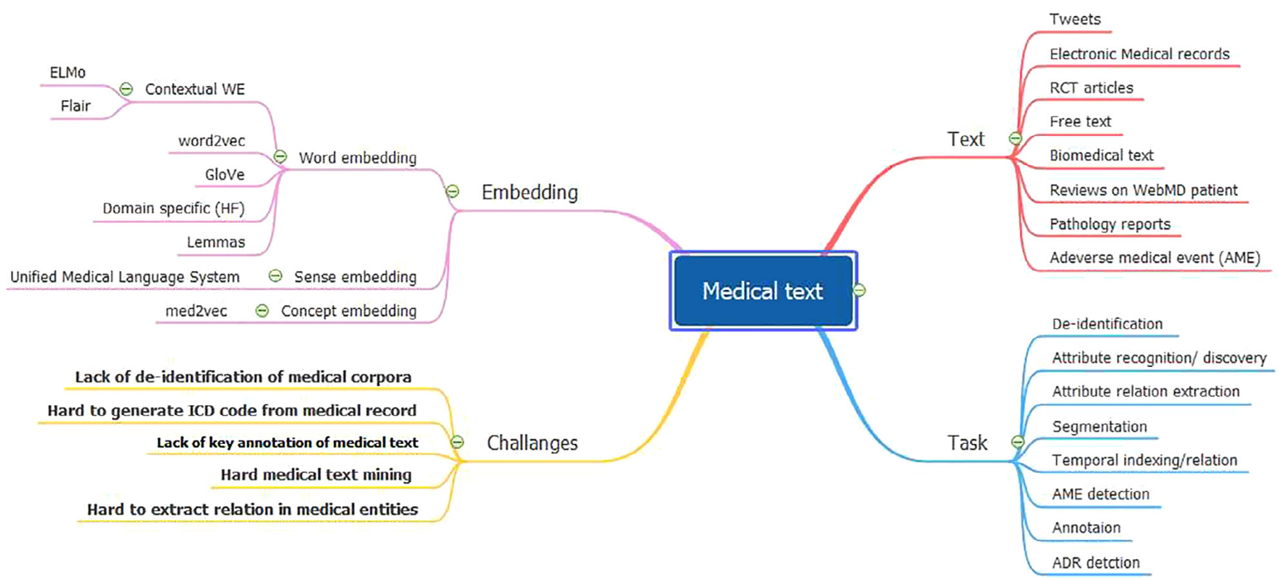

Fig 6. summarizes the embedding type, text type, task and challenges encountered in our study, from the medical NLP.

task because it contains ambiguous words and narrative sentences, ambiguous concepts, ambiguous sentence boundary ambiguous abbreviations. This lack of key annotation is one of the crucial factors that prevent medical text from being used in other related research areas (Newton et al., 2013; Wang et al., 2009; Lependu et al., 2012; Yadav et al., 2013).

Hard medical text mining: Mining medical text available on social media and EHR for various purpose such as identify death due to drug overdose (Sarker et al., 2019), mining adverse event (Xie et al., 2018), serendipitous drug usage (Ru et al., 2019, 2018), detecting medication (Weissenbacher et al., 2019), drug abuse detection (Hu et al., 2019)suffers many problems such as imbalanced data (Sarker et al., 2019); missing context tweet, hard interpretation of consumer vocabulary, misspellings or ambiguity with common words (Weissenbacher et al., 2019) and high lexical variability (Santiso et al., 2019). These barriers remain a major issue in building effective classifiers for medical text.

Hard to extract relation in medical entities: The medical text contains a lot of unstructured information which is useful for decision making. The manual process of converting the unstructured information into structured information is very tedious and costly. It needs trained persons. Although automatic relation extraction methods, such as rule-based and machine learning-based methods are available. But they are based on extracting modifiers of clinical entities. In 2010 i2b2/VA challenge focused on extracting the relation of clinical entities. Machine learning-based methods work well for this purpose but they require tedious feature engineering tasks. Deep learning resolves this issue but it is limited due to there is a lack of methods that can effectively represent and capture all the semantic and syntactic features from long and complex sentences (Li et al., 2019). This is why the relation extraction task challenging for researchers.

Fig. 6 Embedding type, text type, task and challenges encountered in our study, from the medical NLP

5.4. Limitation

1. In our study, while reviewing the literature, we found many papers that do not explicitly mention the deployed DL type and embedding type. In that case, we have put them in the category of DL and embedded type mentioned (as given in Tables 1 and 2).
2. Some papers do not explicitly mention the pipeline; in that case we have considered the complete processing from giving input to producing output as the pipeline.
3. We only found those kinds of literature, which implemented the position embedding technique integrated with other embedding techniques. In that case, we have included that paper in position embedding and hybrid embedding both.

6. Conclusion

Deep learning has gained popularity in the last 5 years in medical imaging and medical NLP. The literature included in the present work is collected from the Scopus database from 2017 to 2020. A total of 211 published manuscripts are surveyed. The number of literature from MI is approximately doubled as compared to medical NLP. This shows that, the popularity of DL is more in MI as compared to medical text. In this paper, we have performed a comparative study of various DL architecture deployed in MI and medical NLP. Some of the DL architecture such as variants of CNN, DBN, DTN, DIM, and GAN are deployed only in MI whereas some DL architectures such as LSTM, GRU, joint, and ensemble models are only deployed in medical NLP. CNN with word processing is most suitable architecture for NLP based image processing. Other suitable combinations can be encoder with word embedding and autoencoder with word embedding.

In this paper, we have outlined how deep learning deals with laborious manual feature engineering task, segmentation challenges, ambiguity in medical terms, the small volume of data, blurred boundaries of segments, the expensive computational overhead of processing pipeline and task, low-resolution images, reconstruction overhead of images and annotation issues of medical text.

We have highlighted some major challenges in deploying DL in MI and medical NLP. Some common challenges in both sub-area are ambiguity in medical terms, ambiguity in segment boundaries in images, labelling issues in both medical images and medical text, and requirement of an expert in both sub domains. This survey is very helpful for novices working in the area of health informatics.

In future we will deploy CNN with word processing, encoder with word embedding and autoencoder with word embedding for NLP based medical imaging.

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