Deep learning in healthcare

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Highlights

- Early deep-learning applications to healthcare data demonstrated efficient ways to model, describe, and learn from complicated and diverse sources.
- To be successfully applied to the healthcare, cutting-edge deep learning algorithms must be enhanced regarding data integration, interpretability, security, and temporal modeling.
- The next generation of predictive healthcare systems, which can expand to encompass billions of patient data and rely on a single, comprehensive patient representation to support doctors in their day-to-day operations successfully, may be made possible by deep learning.
- Based on various data sources, deep learning may be used as a guiding principle to organize healthcare.

ABSTRACT

Understanding and using complex, high-dimensional, and heterogeneous biological data remains a major obstacle in healthcare transformation. Electronic health records, imaging, -omics, sensor data, and text, all of which are complicated, diverse, poorly annotated, and typically unstructured, have all been growing in contemporary biomedical research. Before building prediction or clustering models on top of the features, traditional data mining and statistical learning techniques frequently need feature engineering to extract useful and more robust features from the data. In the case of complex data and insufficient domain expertise, both phases have several problems. The most recent deep learning technology advancements provide new efficient paradigms for creating end-to-end learning models from complex data. This post examines the most recent research on using deep learning techniques to benefit the healthcare industry. We propose that deep learning technologies could be the means of converting large-scale biomedical data into better human health based on the reviewed studies. We also draw attention to several drawbacks and the need for better technique development and implementation, particularly in terms of simplicity of comprehension for subject matter experts and citizen scientists. To connect deep learning models with human interpretability, we examine these problems and recommend creating comprehensive and meaningful interpretable architectures.

Keywords: Deep learning, Healthcare, Health Records

1. INTRODUCTION

A new age in health care is rapidly approaching, one in which the wealth of biological data will play an increasingly significant role. By considering a variety of patient data elements, such as variation in genetic features, environment, electronic health records (EHRs), and lifestyle, precision medicine, for instance, aims to "guarantee that the appropriate therapy is administered to the right patient at the right time" [1-3]. The abundance of biomedical data presents enormous potential and difficulties for healthcare research. To build trustworthy medical solutions based on data-driven techniques and machine learning, a major problem is examining the relationships among all the many bits of information in these data sets. Previous efforts have attempted to integrate various data sources to create collaborative knowledge bases that can be utilized for discovery and predictive analysis [4-6]. Although current models show considerable potential (e.g. [7–11]), machine learning-based prediction tools have not yet been routinely used in medicine [12]. Due to their high dimensionality, variability, temporal dependence, sparsity, and irregularity, biological data still present several obstacles in terms of proper utilization [13–15]. Multiple medical ontologies (e.g., Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT) [16], Unified Medical Language System

(UMLS) [17], and International Classification of Disease-9th edition (ICD-9) [18]) used to generalize the data further exacerbate these difficulties [19]. Sometimes, multiple data sets portray the same clinical characteristic in distinct ways. As an illustration, in the EHRs, a patient with "type 2 diabetes mellitus" can be recognized by test results showing hemoglobin A1C >7.0, the existence of the ICD-9 code 250.00, the mention of "type 2 diabetic Mellitus" in the free-text clinical notes, and other factors. Consequently, it is nontrivial to harmonize all these medical concepts to build a higher-level semantic structure and understand their correlations [6, 20].

Deep learning paradigms provide intriguing new potential for biomedical informatics because of their efficacy in several areas and the quick advancement of methodological advancements. Deep learning initiatives are already planned or underway in the field of healthcare. For instance, Enlitic is utilizing deep learning intelligence to identify health issues on X-rays and Computed Tomography (CT) scans [21], while Google DeepMind has revealed ambitions to apply its knowledge to the field of healthcare [28].

The widespread use of computer-assisted decision-making and outcome evaluation in healthcare delivery underscores the technical significance of modeling expertise and knowledge. However, because they cannot accurately simulate the complexity of human brains and rely heavily on feature representation of problem domains, traditional rule-based models cannot capture the underlying knowledge. As a result, we try to use a deep model to solve this flaw. The deep model combines feature representation and learning into a single model that can mimic human thought processes.

However, deep learning techniques haven't been thoroughly examined for a wide range of medical issues that can benefit from their capabilities. Deep learning has numerous features that might be used in the healthcare industry, including its better performance, end-to-end learning model with integrated feature learning, capacity to handle complex and multi-modality data, and more. The deep learning research community needs to address several issues related to the characteristics of healthcare data (i.e., sparse, noisy, heterogeneous, and time-dependent), as well as the need for improved techniques and tools that allow deep learning to interface with clinical decision support workflows.

In this article, we cover current and upcoming deep learning applications in medicine, emphasizing the crucial elements that substantially influence health care. We do not want to give a thorough background on technological specifics (see, for example, [22–25]) or widespread applications of deep learning (see, e.g., [26]). Instead, we concentrate primarily on biological data derived from wearable technology, EHRs, and clinical imaging. While other data sources, including the metabolome, antibody one, and other omics data, are anticipated to be useful for health monitoring, deep learning has not yet been widely applied in these fields. Thus, in the following, we briefly introduce the general deep learning framework, review some of its applications in the medical domain, and discuss the opportunities, challenges, and applications related to these methods when used in the context of precision medicine and next-generation health care.

2. Deep learning framework

A general-purpose artificial intelligence technique called machine learning may infer associations from data without defining them [27]. The key selling point is the capacity to generate predictive models without making firm assumptions about the underlying processes, which are frequently unidentified or inadequately characterized [28]. Data harmonization, representation learning, model fitting, and assessment are the four phases that make up the traditional machine learning workflow [29]. For many years, building a machine learning system needed meticulous engineering and subject-matter knowledge to convert the raw data into an appropriate internal representation from which the learning subsystem, frequently a classifier, could find patterns in the data set. Conventional techniques are composed of a single, often linear, transformation of the input space and are limited in their ability to process natural data in their raw form [24].

2.1. Fully Connected Neural Networks (FCNNS)

The FCNNs consist of neurons and layers of models, where each layer's input is connected to each neuron in the one below. The most straightforward way to understand neurons is to conceive of them as linear regression models, where each neuron uses input data (x), weights (y), and bias (z) to create an output (y).

2.2. Convolutional Neural Networks (CNN)

CNN is the most well-known and often applied deep learning architecture for image data. CNN's are layers that use convolutional techniques to some inputs to create specific outputs. In the convolution process, filters are used as a sliding window to scan all input areas and create a feature map. To reduce the number of advanced features and the computation, pooling layers with convolution layers are utilized in the downsampling process. The output often has a similar form to the input, which can be a tensor in one, two, or three dimensions. Numerous CNNs designs have been created over the years, including LaNet, ResNet, VGGNET, EfficientNet, and others [30]. CNN's are employed in numerous machine learning applications, including video processing, natural language processing NLP, and time series prediction, in addition to being the most widely used approach for image processing [31]. In the past several years, CNN has also grown in popularity in BDL; it is now employed in a variety of applications, including medical imaging [32], text identification [33], genomic research [34], and others.

2.3. Recurrent Neural Networks (RNNS)

For deep sequential learning, which is utilized for sequence or streaming data, such as video, audio, and time-series prediction, RNNs are one of the most often used architectures [35]. The neurons in the same layer are connected in these networks by recurrent "cycle" linkages. RNNs have memory cells that allow the model to retain past data, which is crucial for predicting future events. To anticipate the network's output, RNNs must maintain a state of the past and current input. To put it another way, technically, computing the outcome requires knowledge of the status of every prior information. The vanishing gradient descent problem arises when the sequence becomes longer, making the starting weight unreachable and lowering the performance of the RNNs. As a result, many architectural designs have been created to address this problem; one such design is the Short-Term Long Memory (LSTM) concept. Throughout the learning process, the LSTM is advised to manage each memory cell for both state and output values. The LSTM model's central element is cell state "C." The LSTM can only regulate a cell's state through various LSTM gates; it cannot alter or delete a cell's value.

3. Deep Learning in Healthcare

DL has been applied to various tasks on various data formats in the healthcare industry. Although it is not frequently used in healthcare, research has been done on multiple healthcare-related topics. The most current BDL work in healthcare applications is reviewed in this section.

3.1. Medical Imaging

In the field of medicine known as medical imaging, sometimes referred to as radiography, clinicians rebuild pictures of various bodily parts for diagnostic or therapeutic purposes. BDL has been applied to medical imaging to address multiple related issues. The application of BDL in medical imaging has grown in popularity more than in other fields. Categorizing medical pictures to enhance prediction performance and quantify various sorts of uncertainty is the most obvious use of DBL in this context. Medical image segmentation, registration, reconstruction, and enhancement are different work areas.

3.1.1 Image Classification

Image classification is classifying pictures into several groups to give each one a label. This traditional image-processing job has become slightly more widespread among BDL researchers. The term "image classification" really refers to a wider range of machine learning applications, even though most people only identify it with supervised learning multiclass classification. For the categorization of histological pictures of colorectal cancer, Raczkowski et al. [43] have developed a BDL model called (ARA-CNN), which stands for Accurate, Reliable, and Active Bayesian Convolutional Neural Network. Their model shows the degree of uncertainty connected to each image, which may be used to spot photographs incorrectly tagged. However, just one balanced dataset was used to assess the suggested technique. It will be intriguing to see how it works with different datasets. Photos of intraoral cancer were classified using BDL by Song et al. [36], and the degree of uncertainty was utilized to suggest more trustworthy interpretations from the images. The proposed model utilized the MC-Dropout technique as a Bayesian approximation and was based on the VGG19. Their work had limitations in that the suggested approach was only tested on a single dataset of 2350 photos of the cheek mucosa, and there were fewer performance details provided than in previous studies that had been published. The robustness of BDL models for classifying diabetic retinopathy was examined by Filos et al. [37] using Mean-Field variational inference (MFVI) and MC-Dropout, among other Bayesian techniques. Most of the studied models were built using the VGG architecture. The results show that MC-Dropout and ensembles approach beat MFVI for the retinopathy dataset and that combining the two methods can increase performance. Even though just one medical dataset and several other non-medical datasets were utilized, the paper's strength derives from comparing several distinct models' performances. Using functional magnetic resonance imaging, Yadav et al. [38] classified Parkinson's illness using convolutional BDL (fMRI). The suggested network was similar to LaNet-5 but for 3D fMRI pictures, and they developed a model of BDL to feed slices of fMRI images to the network.

3.1.2 Image Segmentation

It will be intriguing to see how it works with different datasets. Photos of intraoral cancer were classified using BDL by Song et al. [36], and the degree of uncertainty was utilized to suggest more trustworthy interpretations from the images. The proposed model utilized the MC-Dropout technique as a Bayesian approximation and was based on the VGG19. Their work had limitations in that the suggested approach was only tested on a single dataset of 2350 photos of the cheek mucosa, and there were fewer performance details provided than in previous studies that had been published. The robustness of BDL models for classifying diabetic retinopathy was examined by Filos et al. [37] using Mean-Field variational inference (MFVI) and MC-Dropout, among other Bayesian techniques. The segmentation of medical images using various BDL architectures has been the subject of several publications published in recent years. The most widely used CNN-based deep learning architecture to segment images is U-Net. It mostly comprises sections that are constrictive and expanding. While the expansive component oversamples an input, the constrictive part downsamples it.

BDL was utilized by Orlando et al. [39] to segment photoreceptor layer cells from optical coherence tomography (OCT) pictures. A segmentation model based on the U-NET architecture was suggested. For regions of interest, it estimated epistemic uncertainty and error rate using the Bayes model. The proposed model employed MC-dropout as a Bayesian approximation approach to defining epidemic uncertainty. The article details the suggested method's implementation specifics. Using a single tiny dataset is the only drawback of the proposed approach. Using MRI T1 images of the brain, Roy et al. [40] modified BDL in QuickNAT architecture for full brain segmentation and quality control. The QuickNat uses a full two-dimensional CNN with a U-shaped architecture to divide slices of an image along both coronal and sagittal axes. The suggested technique additionally employed MC-Dropout as a Bayesian approximation for sampling from the posterior distribution. The proposed model's voxel-wise (volume pixel of 3D pictures) uncertainty is defined using the MC dropout. This work stands out from the competition since the suggested model uses the entire brain instead of just one specific region. BDL was utilized by McClure et al. [41] to segment the brain using MRI images.

The suggested model modified spike-and-slab dropout in addition to MC-dropout to get dropout probability and individual uncertainty related to weights. The quality control manual annotation was predicted using the model's uncertainty prediction for the voxel-wise error rate. The use of several Bayesian approaches and the performance evaluation of those methods is the paper's strong points. Muscle segmentation from musculoskeletal for CT scan images was performed by Hiasa et al. [42] using a Bayesian-CNN-based U-Net. As a Bayesian approximation for segmentation and estimating model uncertainty, the proposed model utilized MC-Dropout. The model performed better on the authors' two datasets than in earlier research. The suggested method also looked at ways to use multi-class organ segmentation uncertainty to carry out predicted segmentation without needing ground truth data and minimize manual annotation for samples in the active learning job.

3.1.3 Image Registration

Image registration is aligning geometrically relative coordinates from two or more photographs to minimize their disparities. This procedure is necessary to assess and prepare pictures produced from various sources, under different circumstances, and multiple times. The examination of medical images makes use of this approach particularly well. This results from the ability to test created real-world photos by a different radiologist utilizing varied perspectives, lightning, and other elements and the many image situations that deep models may be trained on. In this context, Le Folgoc et al. [43] used a sparse Bayesian model and BDL to quantify uncertainty in medical picture registration. The given model uses MCMC as the precise "asymptotically" Bayesian sampling approach and VI as the approximate Bayesian method for sampling from the posterior distribution. The authors claim that the VI mechanism performs similarly to MCMC in the inference phase but does not perform as well when estimating uncertainty. Their employment of both VI and MCMC, infrequently employed by the research community, contributes to the paper's strength.

BDL was used by Deshpande et al. [44] for deformable medical picture registration. Deformable image registration is a crucial step in medical imaging with several uses, such as temporal changes in structure and multi-modality picture fusion. The suggested approach uses BDL for nonlinear geometric distortion-corrupted pictures. The model parameters were adjusted to have a probability distribution according to the properties of the Bayesian model, which improves the effectiveness of the picture registration. A few datasets of distorted picture datasets were used to test the suggested approaches. Khaled et al. [45] employed BDL for unsupervised deformable image registration of brain MRI in a related application. Unsupervised DL models are trained using the currently available data to estimate and quantify the deformation by comparing and contrasting the target and other pictures. The deep learning model was then applied to additional data not utilized in training. Even with a tiny dataset, the posterior distribution of the model prevents overfitting. The uncertainty related to distorted pictures was measured in the suggested model, which employed stochastic gradient Langevin dynamics to sample from the posterior as a Bayesian technique for image registration. One of the rare papers to use MCMC for Bayesian sampling is this one. Bayesian CNN was employed by Cui et al. [46] for brain image registration. The recommended technique produced a geometric uncertainty map for the uncertainty related to the registration process and utilized MC-dropout as a Bayesian method to sample from the posterior for the registration job.

3.1.4 Image Reconstruction and Enhancement

Reconstruction of an image produces two- or three-dimensional pictures from missing or dispersed data. Insufficient or scattered data can be created by various factors, including radiation readings for medical pictures or removing noisy objects from an image. It is very helpful for creating effective graphics in medical applications, which occasionally may necessitate using certain mathematical techniques. This method may convert a variety of two-dimensional pictures into three-dimensional brain images for three-dimensional images used in CT and MRI scans. This method may also be used to sharpen images or the borders of objects in photos to prepare photos for tasks like image segmentation.

On the other hand, image enhancement is changing pictures to produce a visually better image or improve them for further processing and analysis. An accurate visual representation of concepts is made through image enhancement, raising the standard of image characteristics for image processing. Several techniques can be used to do this goal, including picture sharpening, noise reduction, and intensity adjustment.

BDL was used by Schlemper et al. [47] to measure the level of uncertainty related to the model for reconstructing MRI images. In this study, two cardiac MRI datasets were employed. High-uncertainty zones, where the model could not generate the image from the given data, were where the suggested model's uncertainty was most effective. The authors estimated the epistemic uncertainty in the proposed model using a Bayesian approximation and the MC-dropout approach. Additionally, the authors looked at the connection between delay and error related to predicted pictures and discovered a link between the two, showing that most of the model's mistake originates from high-uncertainty regions in images. The paper's strongest point is the implementation of various distinct models and parameters, together with the presentation of their performances. However, these models were not contrasted with other model states already in existence.

4. DL in Diseases Diagnostics/Detection

Medical diagnosis is the process of identifying the illness or condition that is producing a patient's symptoms and indicators. Many machine learning and deep learning studies have been established to identify and diagnose diseases. This section discusses several illnesses that, particularly BDL, have received more attention than others when using deep learning techniques. It is important to keep in mind that only a small number of published studies for each condition or category of disease are mentioned in this section, and certain diseases may have more articles that are not included. The BDL models were employed for the prevalent disorders listed below.

4.1 COVID-19

The SARS-CoV-2 virus is the cause of the infectious illness coronavirus disease (COVID-19). The COVID-19 epidemic has had a significant influence on a large number of people worldwide and altered most people's way of life. In the past two years, COVID-19 has grown to be one of, if not the, largest problems in the whole globe. It thus received the media attention that had never before been given to an illness in human history. On COVID-19, several research works in medicine, and other academic disciplines have been published. Several articles have studied the detection and classification of COVID-19 using machine learning and deep learning methods. Only a few studies, however, have employed BDL. To calculate the degree of uncertainty in chest X-ray images for COVID-19 detection, Ghoshal et al. [48] employed a Bayesian-based CNN model. For their suggested model, the authors used pre-trained ResNet50V2 as a baseline and adjusted its parameters using the data at hand. They sampled from the posterior distribution via the MC-Drop weight method. Like dropout, drop weight eliminates only a portion of a neuron's weight with a predetermined probability instead of completely removing the neuron from the network. To estimate COVID-19 dissemination in Spain for 14 consecutive days, Cabras et al. [49] also employed BDL. The suggested approach counted the "likelihood" of the provided data using the Poisson distribution and was created using the LSTM architecture. The proposed technique employs Gamma priors to measure model uncertainty as opposed to Gaussian priors, which is what most BDL articles rely on.

4.1 Cardiovascular Disease

A disturbance of the heart's functioning is referred to as a cardiac disease. A form of the illness called cardiovascular disease affects the heart and blood vessels. Cardiovascular disease risk factors include smoking, high blood pressure, high cholesterol, a poor diet, and obesity. Researchers have applied machine learning and deep learning approaches to help medical personnel recognize and diagnose heart problems. Nevertheless, only a small number of published research have used BDL for cardiac disorders. BDL was used by Sander et al. [50] to segment the left ventricle cavity, right ventricle, endocardium, and myocardium at the end of diastole and systole. The developed approach, which employed MC-dropout sampling, was evaluated using the MICCAI 2017 dataset, which included 100 cases—75 for training and 25 for testing. Based on ECG signals, Aseeri et al. [51] .'s classification of cardiac arrhythmias also employed BDL. The model performance was tested on three datasets (MIT-BIH for 48 patients, St. Petersburg IN CART with 75 records for 34 patients, and BIDMC dataset for 15 patients), which produced an F1-score of 98.8%, 99.2%, and 97.2%, respectively. The recommended approach employed MC-dropout for sampling. To extract the foetal cardiac signals from the ECG, Jagannath et al. [52] used BDL. The authors used the Physionet and DaISy datasets to test the suggested methodology. To test the performance, four alternative approaches were employed. However, they did not compare their outcomes to other cutting-edge techniques.

4.2 Cancer

Cancer is a condition that develops when cells in a particular area of the body grow uncontrolled and abruptly, with the potential to spread to other areas of the body. Cancer may affect every sort of person. Therefore, it can harm any living component of the human body. Cancer can develop in human cells for various reasons, including genetic predisposition, continuous exposure to damaging radiation, and environmental factors. Most cancer types are deadly when it is found in their advanced stages. As a result, early cancer identification is essential since it can save many lives each year. Several studies have used machine learning and active learning approaches to identify and diagnose this condition, with some of them depending on BDL. For instance, Liu et al. [53] .'s application of BDL for prostate cancer segmentation and uncertainty assessment on MRI slices. The suggested technique uses a Bayesian U-Net structure based on attention for segmentation and uncertainty estimates. To reach a total of 351 MRI scans, the data for model training and testing were gathered from two public sources. In a different research, Song et al. [54] used BDL to categorize photos of intraoral cancer while using uncertainty quantification to ensure relatability. The pre-trained VGG19 served as the authors' backbone and was tweaked using intraoral data with a probability of 0.5 as a dropout rate. The writers employed the MC-dropout sampling approach. The suggested technique was evaluated on a dataset including pictures of 2350 cheek mucosa, and the model achieved a 90% accuracy rate. Additionally, Billah et al. [55] used BDL to categorize cancer pictures and measure uncertainty for cancer of the blood cells (lymphocytes) (lymphoblast). The 50 samples per picture were taken using the MC-dropout sampling technique in the suggested model. The model had a 94% accuracy rate when the scientists employed the (ALL-IDB2) dataset, which contains 260 pictures of cancer cells (lymphocytes).

4.3 Parkinson and Alzheimer

The brain is the body's primary control center, and several illnesses that affect it may impair its performance. Parkinson's and Alzheimer's are two diseases that impair brain function. While both conditions may have some of the same symptoms, the key distinction between them is that while Parkinson's disease affects thinking and certain physical issues, Alzheimer's impacts memory and language skills. Few researchers have employed BDL, but many have used machine learning and deep learning techniques to apply to various tasks, including classification and segmentation. One of them is the study of Yadav et al. [56], which employed Bayesian CNN to categorize Parkinson's disease-related fMRI images. The suggested approach employed MC-dropout for sampling, and the performance of the proposed method was evaluated using the data of 30 participants. This yielded an average accuracy of 97.92%. BDL was used by Roy et al. [57] in another study to automatically segment the entire brain for Alzheimer's disease using the QuickNAT architecture.

Additionally, they employed MC-Dropout to sample BDL. Four datasets (MALC-15, ADNI-29, CANDI-13, and IBSR-18) were used to evaluate the proposed technique; only the first dataset was used for training, and the number of occurrences for each dataset was listed next to the dataset name. According to their findings, the datasets' average dice scores ranged between 81% and 88%. Using EEG readings for Parkinson's patients, Handojoseno et al. [58] employed BDL to predict frozen gait for 5 seconds before its occurrence. The use of BDL in the suggested strategy was done to prevent the model from being overfitting. With an average age of 70, 16 patient data sets totaling 11 for training and 5 for testing were employed. The suggested model scored 80.25% for specificity and 85.86% for sensitivity.

4.4 Diabetes

Diabetes is a long-term condition that affects blood sugar (glucose) levels. Food is broken down into glucose in the stomach during the digestive process, and glucose is subsequently transported throughout the body via the bloodstream. The pancreas is in charge of regulating blood sugar; when it increases, it produces insulin to bring it back to normal. Diabetes is brought on by the pancreas' inability to release enough insulin to keep the blood sugar level balanced. Several researchers have applied machine learning and deep learning approaches for various diabetes-related tasks. For instance, Filos et al. [59] examined the effectiveness of several BDL approaches for classifying diabetic retinopathy. The Kaggle diabetic retinopathy dataset, which contains five classifications based on the severity of the condition, was used to assess the performance of the suggested model. The best model was the Ensemble MC-dropout model, which had accuracy and AUC of 92.4% and 88.1%, respectively. To segment pictures of diabetic retinopathy, Garifullin et al. [60] suggested a BDL model. They used MC dropout to calculate the uncertainty of the anticipated output. The authors scored the ROC-AUC measure between 97.7% and 99.7% using the IDRiD dataset for diabetic retinopathy.

5. Discussion

The analysis of medical images and healthcare data, such as whole-slide pathology [63], X-ray [64], diabetes [65, 66], breast cancer [67], heart [68], time series [69], medicinal plants [70], stock market [71], stroke [72], etc., have been successfully carried out using machine learning and deep learning [61]. In this study, the bulk of the published papers on BDL in healthcare applications have been evaluated, and their Bayesian approaches have been illustrated. Most research on BDL in healthcare has focused on medical image processing, whereas other jobs have received less attention. Overall, as seen in section 6.1, picture classification and segmentation have the most published articles employing BDL compared to other tasks. Interestingly, while the VI approach gained popularity for non-image activities in healthcare, the MC-Dropout method was still the most often utilized for processing medical images. It is hardly shocking that MCMC has not attracted a lot of attention. Despite being employed for less than a tenth of the labour, it merits considerably greater consideration and research since it has the potential to replace several methods now in use. The difficulties and restrictions of BDL techniques in healthcare will be covered in this part from both the Bayesian and healthcare viewpoints. Future projects and various research needs are also highlighted.

6. Conclusion

We discussed deep learning for computer vision, natural language processing, reinforcement learning, and generalized methodologies as we presented deep learning strategies for healthcare. We explored how to create end-to-end systems and discussed how these computational approaches could affect a few important medical fields. Most of our discussion on deep learning pertains to healthcare. Similarly, generalized deep learning techniques for healthcare are examined.

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