A Survey on Deep Learning Architectures and Frameworks for Cancer Detection in Medical Images Analysis

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Abstract: ***The various hurdles in machine learning are beaten by deep learning techniques and then the deep learning has gradually become preeminent in artificial intelligence. Deep learning uses neural networks to kindle decisions like humans. Deep learning flourished as an energetic approach and clarity marked its success in various domains. The study includes some dominant deep learning algorithms such as convolution neural network, fully convolutional network, autoencoder, and deep belief network to analyze the medical image and to detect and diagnose of cancer at an early stage. As early as the detection of cancer than to treat the disease is uncomplicated. Early diagnosis was particularly relevant for some cancers such as breast, skin, colon, and rectum, which prohibit the chance to grow and spread. Deep learning contributes to enhanced performance and better prediction in detection of cancer with medical images. The paper presents the study of a few deep learning software frameworks such as tensor flow, theano, caffe, torch, and keras. Tensor Flow provides excellent functionality for deep learning. Keras is a high-level neural network API that operates above on tensor flow or theano. The survey winds up by presenting several future avenues and open challenges that should be addressed by the researcher in the future.***

Keywords: Deep learning, Convolutional neural network, Cancer, Framework.

I. INTRODUCTION

The field of Artificial Intelligence is seeing its brilliant time as deep learning adapting gradually turns it as the pioneer in this area [1]. Also, deep learning has frequently been recognized to overcome all the hindrances in machine learning. The convolutional neural networks, fully convolutional networks, autoencoder, and deep belief network are the key empowering agents in deep learning architecture, it has entirely changed our approach in processing data. An automatic manner can achieve feature extraction with a deep learning algorithm, which permits analysts to select a selective features with reduced domain information and human effort [2]. The deep learning algorithm incorporates architecture in the form of various layers for the representation of data, where the high-level features can be obtained from the last layers, while the low-level features are obtained from the lower layers. These types of structure were first stimulated by the process of artificial intelligence, from the main emotional regions of the human brain. Our brain can consequently get information from the various circumstances in which the input is the visual information that flows from the eye, which produces classified objects as output. This refers to the important benefits of deep learning this is how the human brain responds.

The health care sector is entirely different from other industries. Generally, the analysis of clinical information is scrutinized by the pathologist. It's very difficult for pathology specialists in the analysis of cancer images. Because of the achievement of deep learning in different applications, it is additionally giving energizing and precise solutions in cancer images too [3]. Specifically, convolution neural network in deep learning architecture, have quickly become an approach for better decision making in medical caner images. The enhancement of artificial neural network is deep learning which contains numerous layers in its architecture that improves the prediction of various forms of cancers [4]. Only a few years back, none of the pioneers other than theano were even around. Presently the software frameworks are enormous so based on time and consuming energy can choose accordingly. Every framework is assembled distinctively for various purposes. Today, we look at various deep learning frameworks, to get a better idea on which framework will be perfect in work and completely suitable for solving challenging issues in various domains. The enormous development and accessibility of huge information and the wonderful advancement in hardware equipment innovation have prompted the rise of new studies in deep learning [1]. It is very natural to come across specific obstacles and difficulties. There are as yet various unsolved issues arise, due to those issues in the segment of challenges and future avenues of deep learning, bring up those explicitly. This study gives an outline of deep learning from different perspectives, including, some popular deep learning algorithms, different cancer detection, and diagnosis using deep learning techniques, various software frameworks, and challenges towards future avenues.

II. DEEP LEARNING ARCHITECTURES

Conventional machine learning (ML) algorithms are suitable for datasets with up to hundreds of attributes. Generally in the big-data ecosystem, users develop enormous growth in information. The adoption of a conventional ML approach to such data collection is not intuitive but often highly impossible. If the data size is enormous, deep learning dominates other techniques. Deep learning algorithms run information through various "layers" of the neural network algorithm. Each layer crosses a simplified depiction of the data. Always deep learning algorithms learn more and more about the image while experiencing each neural network layer.

Revised Manuscript Received on September 05, 2020.
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The first layer learns to detect low-level features such as edges, and successive layers blend the features of the previous layer into a more integrated representation. Deep learning architecture is practiced to social network image and speech recognition, audio recognition, computer vision, medical image processing, bioinformatics, and a lot more fields.

A. Convolution Neural Network (CCN)

CNN receives biological inspiration from the visual cortex. The visual cortex contains small areas of cells that are sensitive to certain areas of the visual field. Convolutional neural networks are feed-forward neural networks and a well-known algorithm in deep learning, is a type of machine learning that teaches you to perform classification tasks directly from images by removing feature extraction manually. CNN takes an image as input, goes through a series of convolutional, rectified linear unit, pooling, and fully connected layers, and gets an output, which is shown in Fig. 1 [5].

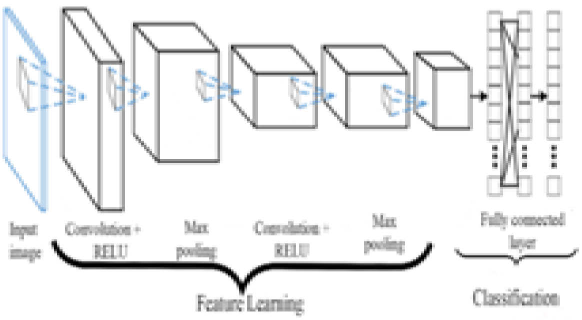

Fig. 1. Architecture of Convolutional Neural Network

i. Convolution Layer

The primary layer on CNN is consistently a Convolutional Layer. The three color channels such as red, green, and blue of a color image make three matrices relating to it. In black and white images need only one matrix, which holds values from 0 to 255. The kernel or filter is a small matrix of values, move it over an image and alter it based on filter values

The feature map values are determined by the accompanying equation (1), where image

$$G[m, n] = (f = h)[m, n] = \Sigma_j \Sigma_k h[j, k] f[m-j, n-k] \qquad (1)$$

inputs are denoted by f and kernel by h [6]. In the result matrix rows and columns, indexes are indicated with m and n respectively.

ii. Pooling layer

The Pooling performs a non-linear down-sampling to simplify the output and reduce the number of parameters that the network needs to learn. Many non-linear functions that perform pooling, while max pooling is the most common one. Fig. 2 presents the max pooling, which divides the input image into a set of non-overlapping rectangles and outputs the maximum value for each sub-region. The pooling layer gradually cut down the spatial size of the representation, for reducing the number of parameters. The pooling layer works freely on each depth slice to resizes it spatially. It is mainly used to cut down the tensor size and accelerate calculations. For instance, for the Max Pooling Layer, we have two hyperparameters which are filter size and stride. The most well-known structure in the pooling layer with filter size 2×2 and a stride of 2 downsamples on each depth slice, which disposes of 75% of the activation.

Other than max pooling, can use other pooling function like average pooling. Average pooling was regularly utilized in classical but become undesirable contrasted with max pooling, which achieves better in practice [7].

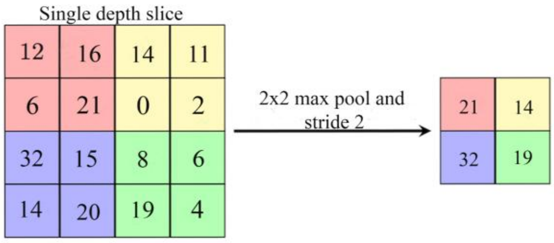

Fig. 2. Max Pooling.

iii. Rectified linear unit (ReLU) Layer

A Rectified linear unit (ReLU), which applies the non-saturating activation function in equation (2) [8].

$$f(x) = \max(0, x) \qquad (2)$$

It enables rapid and more efficient training to remove negative values from an activation map and reset them to zero [9]. This is said to be activation, in fact, that activated features are taken forward into the upcoming layer. It increments the nonlinear properties of the decision function and the entire network without influencing the receptive fields of the convolution layer. Other functions like the saturating hyperbolic tangent $f(x) = \tanh(x)$, $f(x) = |\tanh(x)|$ and the sigmoid function $f(x) = (1 + e^{-x})^{-1}$ are likewise used to build nonlinearity.

iv. Fully connected layer

Neurons in a fully connected layer have associations with all activation in the earlier layer, as found in non-convolutional artificial neural networks. The absolute classification occur in a fully connected layer.

B. Fully Convolutional Networks (FCNs)

To forecast semantic segmentation, Fully Convolutional Networks is a popular algorithm used to practice end to end pixel-wise prediction [10].

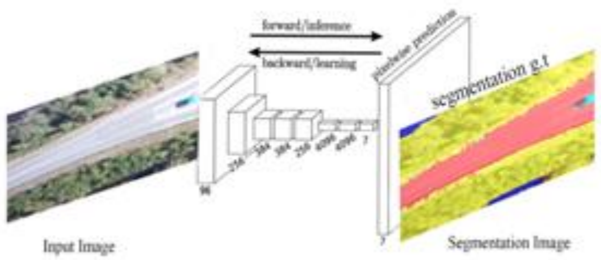

Fig. 3. FCNs Pixelwise Prediction.

FCN is assembled distinctly from locally connected layers, such as convolution, pooling, upsampling, and deconvolution layers. This model uses a different block of convolution and max pool layers to first decompress an image to 1/32 of its original size as shown in Fig. 3. At the level of granularity it does a class prediction. At last it utilizes upsampling and deconvolution layers to resize the picture to its unique dimension.

The fully connected layers are generally not available in fully convolution networks. The purpose of upsampling is to obtain spatial information, while the purpose of the downsampling is used to extract and explain semantic/contextual information.

The final image is a similar size as the original image. To completely recover the fine-grained spatial data lost in downsampling, skip connections are utilized. A skip connection is an association that omits at least one layer. This fully convolution network minimizes the number of parameters and calculation time.

C. Auto-Encoder (AE)

The autoencoder is a neural network, an unsupervised learning algorithm that applies backpropagation, and makes the target value equal to the inputs. A typical autoencoder has a simple structure, as shown in Fig. 4, and generally it has three layers: an input layer, a hidden layer, and an output layer. The encoding stage and decoding stage are the two stages involved during the training of autoencoders.

$$\Phi: Y \rightarrow F \qquad ((3)$$

$$\Psi: F \rightarrow Y \qquad (4)$$

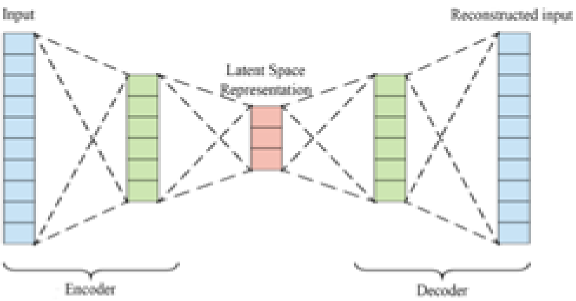

Fig. 4. Architecture of Auto-Encoder.

The encoder function [11], indicated by ϕ, maps the original data Y, to a latent space F, which is available at the bottleneck shown in equation (3). The decoder function, indicated by ψ, maps the latent space F to the output shown in equation (4). In this case, the output matches the input function. So fundamentally making to recreate the original image after some generalized non-linear compression. The encoding network can be described by the standard neural network function that went through an activation function, where z is the latent dimension defined in equation (5).

$$Z = \sigma\,(Wy + b) \qquad (5)$$

Also, the decoding network can be shown similarly, however with various weight, bias, and potential activation functions being utilized in equation.

$$Y' = \sigma'(W'z + b') \qquad (6)$$

Basically, the sparse autoencoder and stacked autoencoder are few varieties of the autoencoder

A stacked autoencoder is a neural network comprise of a lot of a layers of sparse autoencoders where the yield of each hidden layer is associated with the input of the progressive hidden layer. Stacked autoencoder primarily comprises of three steps [12]. The initial step is to prepare the autoencoder by utilizing input information and gain the learned information. They took information from the past layer is utilized as an input for the following layer and this proceeds until the training is completed. In the last step, when all the hidden layers are trained by utilizing the backpropagation algorithm to reduce the cost function and weights are refreshed with the training set to accomplish fine-tuning. Today data denoising, dimensionality reduction for data visualization are the two significant applications of autoencoders. With dimensionality and sparsity limitations, autoencoders can determine data projection, better than principal component analysis [13].

D. Deep Belief Network (DBN)

The RBMs (Restricted Boltzmann Machines) can be stacked and trained in greedy manner to make Deep Belief Networks (DBN). RBM has two layers, a visible layer, and a hidden layer, as shown in Fig. 5.

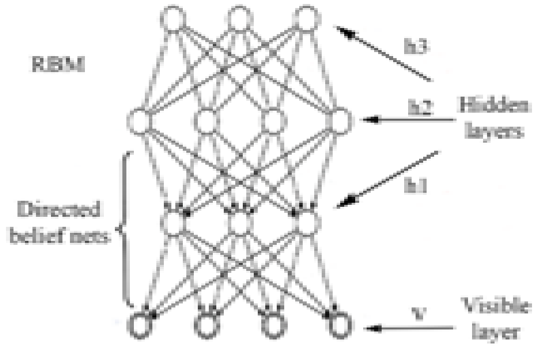

Fig. 5. Architecture of Deep Belief Network.

The energy function E(v, h) of an RBM is defined in equation (7) [14] :

$$E(v, h) = -c'v - d'h - h'Wv \qquad (7)$$

It represents the weights W that connects the hidden and visible units, in which c, d is the offset of the visible and hidden layers, respectively in equation . DBN is a generative hybrid graphical model, which contains both undirected layers, usually at the top layer, and the bottom layer is directed layer. Greedy learning algorithms are utilized to pre-train deep belief networks, which start from the base layer and climb with calibrating the generative weights. Greedy learning algorithms are fast and proficient. Fine-tuning changes the features marginally to get the classification limits right. Adding fine-tuning assists with segregating between various classes better. Fine-tuning can be accomplished by Wake Sleep algorithm and Backpropagation. Image recognition and video recognition are the few applications of DBN.

III. DETECTION OF CANCERS

Early recognition in cancer determination can enhance endurance rates. Clinical imaging is a significant procedure for the identification of cancer at an early stage. The paper includes a study for the identification and analysis of some particular kinds of cancer, by utilizing deep learning strategies. Breast cancer, lung cancer, skin cancer, prostate cancer, brain cancer, and colorectal cancer are some kinds of cancer.

A. Breast Cancer

Breast cancer is a disease, where breast cells develop wildly. Cancer typically forms in the duct or lobules of the breast. There are various sorts of breast cancer and the most widely recognized ductal carcinoma in situ (DCIS) and invasive carcinoma. The proposed [15] the model for detection and classification of breast cancer, where it depends on machine learning, in which 91% right analysis is obtained utilizing these strategies. In proposed work [16], a fully connected layer uses average pooling classification to performs categorizing of malignant and benign cells which are attained with features extracted from pre-trained convolution neural network. Decreasing false positives is one of the most challenging avenues to improve the outcome of diagnosis frameworks [17]. In this way proposed a residual neural network depends on convolution neural network to reduce false positives. Precision, recall, and F-score are used to measure the performance of the proposed algorithm.

B. Lung Cancer

Lung cancer is the most well-known cancer due to lung cancer people are affected all over the world. Lung cancer arises to a mature level only then Signs and symptoms of lung cancer can be noticed. Non-small cell lung cancer and small cell lung cancer are the two main types of lung cancer and they are treated uniquely. The Optimal Deep Neural Network is trained by a modified Gravitational Search algorithm. The automated analysis of lung cancer [18] in computed tomography images with a proposed new methodology. Enhanced image detection and classification using convolutional neural network (CNN) models applied on 3D lung CT scan images with few phases on the proposed work [19]. To classify [20] automatically and more precisely on Lung adenocarcinoma, lung squamous cell carcinoma, or normal lung tissue with whole slide images using the trained deep convolutional neural network.

C. Skin Cancer

The uncontrolled development of abnormal cells in the epidermis, the outermost skin layer leads to skin cancer, the unimproved DNA damage that makes alterations. These changes cause skin cells to increase quickly and create deadly tumors. Basel cell carcinoma(BCC), Squamous cell carcinoma(SCC), Melanoma, and Merkel cell carcinoma(MCC) are major forms of skin cancer. To make models that help in anticipating skin cancer more precisely by using deep learning algorithms in their implementations, this is a cloud-based classical architecture [21].

The proposed implementation [22] work on the identification of melanoma and generation index calculations through deep learning systems and contrasted with conventional feature-based strategies is introduced. The Systems are commonly remembered for classical image analysis modules like preprocessing, segmentation, feature extraction, and classifications. The proposed model [23] is utilized to achieve better hyperparameters of deep convolution neural network. The dermoscopic feature determination is done with particle swarm optimization (PSO)

D. Prostate Cancer

Prostate cancer is a type of cancer that creates in the prostate gland. The prostate is a little walnut shape organ found in the male pelvis situated after the bladder. It is the second-largest cancer leading cancer that leads demise of men. The most significant prognostic prostate cancer grading system is the Gleason grading system. This score depends on the measure of tumors that viewed like fresh tissue when seen under a microscope. Less forceful tumors are commonly similar to fresh tissues. The most forceful tumors will in general develop and spread to different parts of the body. They are less similar to fresh tissues.

It is proposed to utilize the deep convolution neural network model [24] to perform segmentation automatically on the microscopic images. The algorithm performs segmentation on Haemotoxylin and Eosin(H&E) stained tissue into four classifications such as benign, Gleason grade 3, Gleason grade 4, and Gleason grade 5. The proposed model intended to have both training and evaluation process depends on detailed comment on Gleason grading on image sub-regions within each Tissue Microarrays image [25]. Our methodology [26] is a two-phase deep learning framework: the initial phase does classifies on regional Gleason pattern using deep convolutional neural network and in the next phase does classifies on whole-slide Gleason Grade Group using k-nearest-neighbor.

E. Brain Cancer

A brain tumor is a mass or growth of abnormal cells, it can be in the brain anywhere. But a wide variety of brain tumors are remained in which, few such brain tumors are Meningiomas, Gliomas, and glioblastomas. It has a few stages from grade 1 to grade 4, where at grade 1, at this stage, the tumor develops gradually, doesn't influence different tissues, and in grade 4, is exceptionally forceful. To enhance the segmentation[27] in the brain tumor the proposed work in deep learning with the combination of FCNNs and CRF-RNN from axial, coronal, and sagittal views. With these the proposed system includes four steps are pre-processing, segmentation on images, fusing the segmented, and post-processing.

The proposed system [28] for classification of MRI images dataset into 4 classes such as normal, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors which are achieved with a deep learning architecture as deep Neural Network classifier. This deep Neural Network classifier is an integration of Discrete Wavelet Transform (DWT) and principal components analysis (PCA). The proposed system for the segmentation of brain tumors with fully automated technique achieves fast and exact one and it is competing for the state of the art in forms of exactness and speed [29]. These proposed new convolutional neural networks generally used in computer vision, which differs from the classical one. The present novel architecture accomplishes both local and global context features.

F. Colorectal Cancer

Colorectal cancer (CRC) is the third most leading cancer in both men and women. Colon cancer is a kind of cancer that starts in the large intestine. The rectum is the last part of the large intestine that ends with the anus. Most colorectal cancers create from polyps. It’s very difficult to diagnosis colorectal cancer by pathologists.

In this way, to support pathologists, a few automated computerized image investigation strategies have been proposed for the exact detection of cancer. To enable clinical foundations to analyze colorectal cancer, analysts are attempting to utilize deep learning techniques to identify polyps in the colon. By screening the colonoscopies images [30] to detect polyps using the novel designed and trained deep CNN. The Convolutional neural network recognized polyps with a cross-validation precision of 96.4%. The proposed architecture of CNN [31] is constructed with the stochastic gradient descent algorithm which is applied to multispectral biopsy images. To segment image regions of pathological tissue, an active contour model was used, thus the proposed approach on pre-segmenting can improve the precision in classification.

IV. DEEP LEARNING FRAMEWORKS

Several new software environments are formed to aid the implementations of deep learning. Due to the reason, that Deep learning has lead to a notable increase in performance under different application areas. Caffe, DeepLearning4J, Deepmat, Eblearn, Neon, PyLearn, TensorFlow, Theano, Torch, are few in available frameworks (for a more complete list of Deep Learning Softwares see http://deeplearning.net/software links/). Constant improvement of these frameworks is done by adding new features and speed enhancements by the developers and it entices more users [34, 35]. TensorFlow, Theano, Caffe, Torch, and Keras, the five deep learning frameworks are analyzed to provide a study in it. This research will afford users and companies with an overview of their strengths and limitations of the deep learning frameworks studied to enable them to evaluate their suitability in the circumstances of their requirements.

A. Tensor Flow

Tensor Flow mainly uses C++ as its fundamental in its deep learning framework. It is also based on the python APIs developed and open-sourced under the Apache 2.0 Google license [32]. Tensor Flow also has an extensible architecture that supports server or mobile platforms, multiple backends, and CPUs or GPUs of a system. To create deep learning models and wrapper libraries, it uses Python, C++, and R, which are supported languages. TensorFlow works great on images and sequence-based data. It has an extensive and ever-changing ecosystem of tools, libraries, and resources that enable researchers to drive the latest in machine learning and innovators can designing and deploying machine learning-based applications. It is a simple and adjustable architecture design for bringing in new ideas from concept to code, and to make modern forms. Tensorboard visualization is the most impressive and useful features of Tensorflow. Generally, in training, one must fine-tune their hyperparameter or to report data-related problems. Using Tensorboard makes it much easier to identify and view problems. Tensor-Flow uses data flow graphs to perform mathematical calculations in which the nodes represent a numeric operation and the edges represent the multidimensional data array passed between them. The most common use case of TensorFlow may be Google Translator includes capabilities like natural language processing, data or image recognition, prediction, editing, and tagging.

B. Theano

Theano is a free Python symbolic manipulation library, under the BSD license, which aims to optimize the development and execution time of machine learning algorithms. [34, 33]. Theano, which uses GPU and the efficiency in performing symbolic differentiation. Theano is not a formal programming language if you write a Python program that builds expression for Theano. However, it is like a programming language, then variables (a, b) are declared with their types, create expressions for how to put those variables collectively, and then compile expression graphs to use it for evaluating. Theano is a Python library and compiler optimizer for handling and evaluating expressions, especially those of matrix value. Theano Features are made a combination with NumPy, transparent GPU usage far quicker than CPUs, effective symbolic differentiation, improved speed and stability, extensive unit testing, and self-verification.

C. Caffe

The Caffe deep learning tool developed by Berkeley Vision and Learning Center and its society members, licensed under the BSD license, Clause-2 [35]. It was developed in C ++ including expression, fast, and modularity in nature, which uses CUDA for GPU computing. Caffe has interfaces like command-line, Python, and Matlab for training and deployment. Convolution, fully connected and pooling layers, etc. are supported by Caffe. Caffe support expressive architecture, flexible code, and speed. Caffe can process over 60M images per day with one NVIDIA K40 GPU *. That the interface of 1 ms/image and learning in 4 ms/image with recent versions of the library and hardware is even faster.

D. Torch

It is originally formed by Facebook's AI Research lab (FAIR). It's free, open-source software, and released with Modified BSD licensed. It is a scientific computational framework developed using Lua that operates on Lua (JIT) compiler [36]. It has powerful CUDA and CPU backends and has advanced machine learning optimization packages. The goal of Torch is to have maximum extensibility and fast in building your scientific algorithms, while at the same time making the process simplistic.

The main purpose of the torch is the popular neural network and user-friendly optimization libraries are easy to use while providing maximum adjustable in achieving a difficult neural network topology. After partial coding itself can run and view whether it works well and good, do no need to wait the entire code gets completed. The latest version of the torch has Multi-GPU support that is easy to use and very powerful parallel packages to training deep learning architecture. Many companies have internal teams to configure the torch for deep learning platforms that have recently gained popularity. The Torch can take advantage of extensive libraries and enhanced capabilities and improved debugging tools. The Torch is a big ecosystem of community-driven packages in machine learning, computer vision, image processing, and it is built over Lua community.

E. Keras

Keras was developed by Google researcher Francois Chollet. It is a high-level neural network API, composed in Python and capable of operating above TensorFlow or Theano. It designed to allow for fast implementation. The same Python code is used to work on a CPU or GPU is the advantage of keras. Keras is a Python framework that supports both convolutional networks and recurrent networks, as well as combinations of the two in deep learning. It's used for making model, research, and production with three key advantages: User-friendly, adaptable and easy to extend

V. RESULTS

The Convolution Neural Network, Fully Convolutional Networks, Auto-Encoder, and Deep belief Network architectures are the most successful deep learning method are discussed. The CNN is originally used much for image recognition and computer vision to determine various cancers such as Breast cancer, lung cancer, skin cancer, prostate cancer, brain cancer, and colorectal cancer in early stage to increase the survival rate of human. The prominent framework in this deep learning includes TensorFlow, Theano, Caffe, Torch, and Keras are presented. The Tensor Flow provides excellent functionality in deep learning. Theano is high level API designed for fast implementation and capable of operating above TensorFlow or Theano.

VI. CHALLENGES AND FUTURE DIRECTIONS

There are more challenges for deep learning in various fields. Thus in this section, we will pinpoint those problems explicitly as challenges and future avenues. In hyperparameter whose parameter values are prescribed in early to the beginning of the learning phase. Altering slightly the value of such parameters can make a huge change in the model’s performance. Depending on the default parameters and not performing hyperparameter Optimization can significantly affect the model’s performance. Likewise, having very few hyperparameters and hand-tuning them instead of optimizing through demonstrated techniques is a performance driving viewpoint. In preparing a data set for the solution in deep Learning requires a great deal of information. To solve real-world issues with deep learning, the machine should be furnished with enhanced power in processing. To guarantee better performance and less utilization time, data scientists change to multi-core high performing GPUs and comparative processing units. These processing units are excessive and huge power consumption. Deep Learning models, when trained, can provide an extremely efficient and accurate solutions for particular issues. In the present scenario, the neural network architecture is specialized in specific domains of application but lack in flexibility and multitasking. Deep learning works best when it has huge bunches of data set accessible to it, and its efficiency develops as the data accessible develops. However, when enough quality data essentially is not taken care which is applied to a deep learning framework, it can be defective [37]. With little input data quality varies having such significant changes in result outcomes and expectations, thus deep learning models are data eager, which means they need enough quality data. By including "random noise" into datasets, have indicated that their performance drops. Existing super-resolution work mostly associated with supervised learning, i.e., learning with coordinated LR-HR image sets [38]. Since it is hard to gather an image of a similar scene however differs in its resolutions, the LR image in SR datasets are achieved by making predefined deterioration on HR images. So future direction give increasingly more consideration to unsupervised SR, in which case just unpaired LR-HR images are accommodated for training so the subsequent models are bound to adapt to the SR issues. Artificial neural networks require a vast amount of data for training and learning [39]. A vast dataset is useful to acquire exact and correct outcomes. A deep learning classifier depends massively on quality dataset. If the dataset limited is accessible, it could straightforwardly hamper the achievement of deep learning, explicitly in the clinical domain. CNN based breast cancer diagnosis and detection model recognizes mass abnormality and categories them into benign and malignant from mammogram images [40]. In this way, the exploration can be stretched out to incorporate macro calcification abnormalities which are not considered here. The network's prediction extremely changes by rescaling the image as demonstrated by many authors [41]. Thus the shown issue emerges because of image rescaling in neural systems thus protecting high accuracy, stays unsolved.

VII. CONCULSION

The numerous complications in machine learning are ruined by deep learning techniques. Deep learning uses neural networks with several layers to stimulate decisions like humans. Deep learning approach marked its success in various applications. The review article first briefly introduces about the deep learning gradually turn pioneer in the area of artificial intelligence. The state-of-the-art architecture in deep learning used while having huge data set. Deep learning algorithms run across several layers of in neural network. Finally, in challenges and future direction pinpoint still there are many unsolved issues to be addressed as a future work. Most significantly the deep learning transfers machine learning to a new phase, namely, the “Trendy Artificial Intelligence”.

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