Diving Deep into Deep Learning: History, Evolution, Types and Applications

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Abstract: Although Machine Learning (ML) has become synonymous for Artificial Intelligence (AI); recently, Deep Learning (DL) is being used in place of machine learning persistently. If statistics is grammar and machine learning is poetry then deep learning is the creation of Socrates. While machine learning is busy in supervised and unsupervised methods, deep learning continues its motivation for replicating the human nervous system by incorporating advanced types of Neural Networks (NN). Due to its practicability, deep learning is finding its applications in various AI solutions such as computer vision, natural language processing, intelligent video analytics, analyzing hyperspectral imagery from satellites and so on. Here we have made an attempt to demonstrate strong learning ability and better usage of the dataset for feature extraction by deep learning. This paper provides an introductory tutorial to the domain of deep learning with its history, evolution, and introduction to some of the sophisticated neural networks such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). This work will serve as an introduction to the amazing field of deep learning and its potential use in dealing with today's large chunk of unstructured data, that it could take decades for humans to comprehend and extract relevant information.

Keywords: Artificial Intelligence, Deep Learning, Machine Learning, Neural networks, Convolutional Neural Network, Deep belief network, Recurrent neural network.

I. INTRODUCTION

The vision of singularity can be achieved if machines can learn in real time and adapt to the situation. Though it seems to be optimistic, there is a long way to achieve. AI as a platform promisingly has a lot of scope to remodel the human civilization and will appulse companies, Industries and how we live our life. Any system is said to be intelligent, if it can learn and adapt to environments without any human intervention. In pursuit of machine intelligence many investigations have been carried out on various living things and some promising approaches emerged such as knowledge representation [1], Genetic algorithms [2], Evolutionary computing and cognitive computing [3].
Though, they were initially promising, but later provided faint results when applied in real time. The lack of intelligence in machines can be traced down to architectural difference between machines and nervous system [4], In

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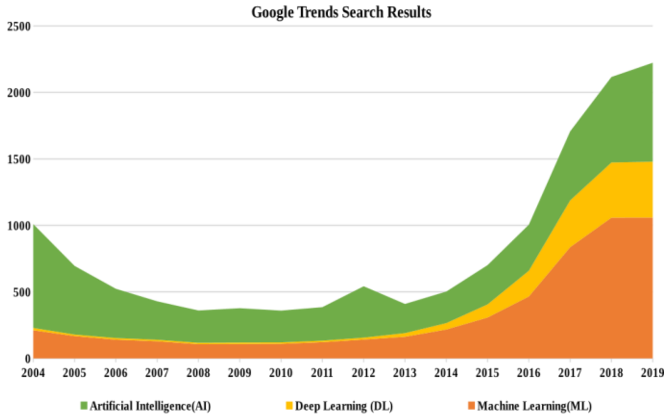

Fig. 1. Google trend search result (past 15 years) for AI, ML, DL as on 14th March 2019.

order to mimic neural behavior many attempts have been made and models have been created.The first among such models was the single layered perceptron [5]. Which later led to neural network with complex architecture, involving many layers. Feed-forward [6] and back-propagation [7] were investigated to enhance the results. Though they performed well, they were just computational equations with huge training data sets.

A major step in our quest to make our machines intelligent, is to give those machines the ability to learn, which is possible through Machine learning. It encompasses supervised, semi-supervised, unsupervised and reinforcement learning.

Algorithmic approaches prevailed over a decade starting from neural networks till early machine learning. Deep learning takes its inspiration from human nervous system which has multi-layer hierarchically connected neural networks [8]. It is an emerging domain of machine learning which got its prominence due to its early achievements in computer vision and image detection. These artificial neural networks have many discrete layer by layer connections between them and direction of data propagation. In artificial neural networks the output of first layer is connected to the input of next layer and so on till the final layer and the result will be produced.

Neural networks are trained using an algorithm called backpropagation, this method does the reverse calculation of the gradient from last layer to first layer.

Deep learning has many architectures such as Deep Neural Networks(DNN), Deep Belief Networks(DBN), Convolutional Neural Networks(CNN), Recurrent Neural Networks(RNN), Recursive Neural Tensor Network(RNTN) etc., which have been applied to fields including speech recognition, video recognition, natural language processing, text recognition, face recognition, drug design and Bio-informatics, sentimental analysis, business applications, digital marketing, object detection.

II. BACKGROUND

Over the past couple of decades there have been waves of new technological development aimed at creating AI systems, that can solve a wide variety of tasks like speech recognition [9] self-driving cars [10] etc. Although most of this advancement is application oriented and business centric, the original motivation for the field of AI was to mimic the way humans think, in real time conditions. This is what led to the first modern neural called as perceptron [11]. The perceptron could learn simple functions to fit linear data. Papert and Minsky [12] demonstrated that it has a few limitations. They stated and proved that it was not having the ability of learning simple functions such as the exclusive-or (XOR) operation, no matter how long the network trained, it couldn't predict right output. The thought of stacking up perceptron into layers and using the "delta rule" [13] to train this model gave rise to complex neural networks, which includes multilayer neural nets and multiple hidden layers would produce deep architecture called deep learning.

"Delta Rule" is gradient descent learning modernizing the weights of the inputs to ANNs and which is more specifically used for backpropagation algorithms.

A neuron j's with activation function $g(x)$, then Delta Rule for j's, i^{th} weight, w_{ij} is given by

$$4w_{ij} = \alpha(t_j - y_j)g\,(h_j)x_i \tag{1}$$

where:

α is a small constant called learning rate. $g(x)$ is the neurons activation function.

t_j is the target output.

h_j is the weighted sum of the neuron's inputs.

y_j is the actual output. x_i is the i^{th} input.

There are different neural architectures that are specific for real time applications. This type of learning includes autoencoders [14] useful for extracting required features from the data, the belief nets [15] are used to model statistical variables [16]. The recurrent neural nets and its variant long short-term memory are used for processing sequence of data and the convolutional neural nets [17] are used to process images. Today the power of deep learning helps the computer achieve super human capabilities in image recognition [18]. The main advantage of deep learning is simple configuration, versatility, short development and high performance.

The collective imagination fueled by forward looking technologies like deep neural nets have made tremendous progress in terms of accuracy and they can now recognize complex images and perform voice translation in real time [19].

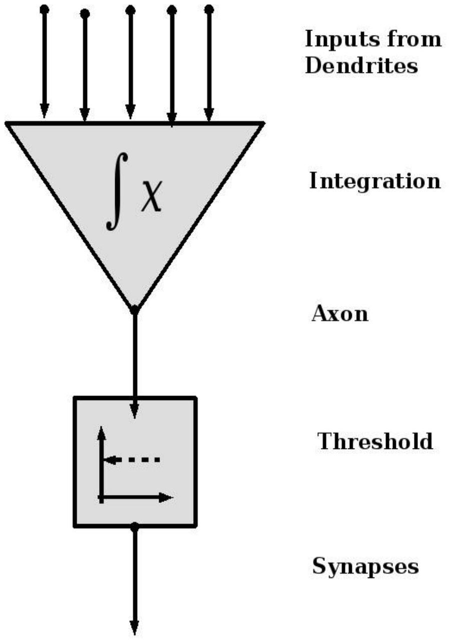

Fig. 2. A schematic representation of a perceptron

The outbreak of deep learning models for supervised learning, using gradient based approaches along with back-propagation algorithm [20] has been working well. Since there is always a necessity for large dataset and pre-training of the model, the hype for unsupervised learning [21] has increased dramatically. This type of approach has each pair of consecutive layers trained separately using an unsupervised model, then the obtained output parameters are propagated through the layers, by training and stacking the layers of networks with previous ones. This type of procedure can be repeated many times which provides us a more sophisticated neural network with deeper architecture. Training the network iteratively with forward and backward passes to refine network weights until the desired accuracy is achieved.

III. EVOLUTION OF DEEP LEARNING

If machine learning is a sub-discipline of artificial intelligence then deep learning could be called sub-discipline of machine learning. There are different algorithms depending on the application they are classified as described in table I. *Supervised learning*, includes training a neural model with labelled datasets and also specifying the desired result, which in turn can be used to predict outputs of a similar kinds of data, however the problem lies in obtaining labelled data sets, which are limited in number as well as expensive. *Semi-supervised learning* uses neural networks that are trained by the mixture of both labelled and un labelled data sets. The computer is given insufficient exposure of data while training the inputs, and some of the output targets are missing in the network. *Unsupervised learning* is a

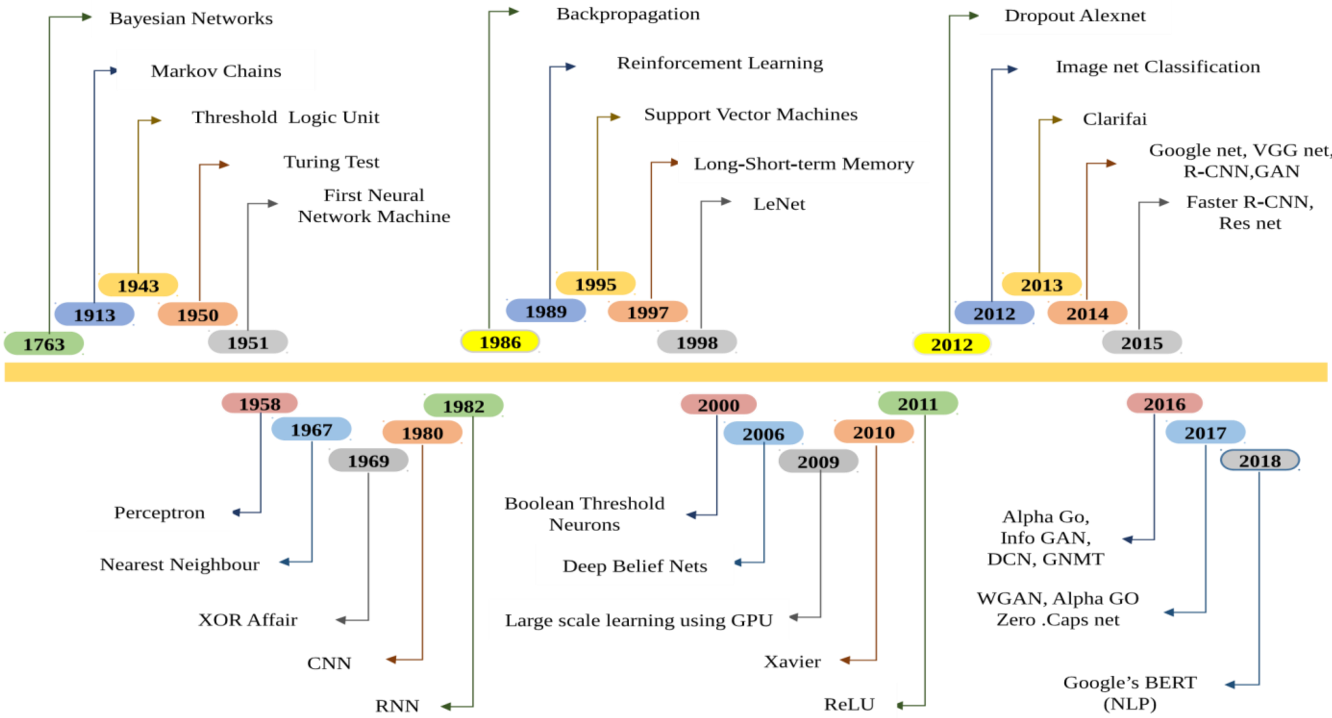

Fig.3. Time line of Deep Learning

process of giving input signals(X) and without defining any corresponding output variables. There is no teacher for these type of networks as that we have seen in supervised learning. These networks explore all types of interesting structures and patterns in the given data. *Reinforcement learning* is a structured algorithm which analyses the problem and solves it as if playing a game with a competitor earn reward points or earning more money. The present state-of-the-art algorithm performs very well on every human task in real world scenario.

The development of Artificial Neural Network [ANNs], shows our interest to understand how the human brain works. Most of the Neural Network architectures (ANNs, DNNs) are designed based on learnings from Computational Neuroscience. Individual nodes of these Neural Network are an over simplification of brain synapses. The neurons [22] at each level make their guesses and most probable predictions and then pass on that info to the next level, all the way to the eventual outcomes. ANNs became more powerful, complex and deeper networks with multiple layers which gives better performance in terms of efficiency.

Deep learning is one of the most significantly noticeable complex field that needs a computational structure. The ground breaking research activity which is going on, will lead to many unprecedented trends in the future. With this, in mind the deep learning tools [23] can be used for simplifying the programming frameworks. Reinforcement learning [24] actively participate to provide more creative solutions in business industries. The solid-state hardware components will accelerate doubling Moore's law [25]. The embedded systems which we interact daily will be revolutionized by the deep learning tools. The computer vision technology with neural networks and deep learning has become empowered like never before.

TABLE I
MACHINE LEARNING ALGORITHMS

Supervised Learning	
Regression	Classification
Simple Linear Regression	Logistic Regression
Multiple Linear Regression	K-Nearest Neighbour (KNN)
Polynomial Regression	Support Vector Machine (SVM)
Support Vector Regression	Kernel SVM
Decision Tree Regression	Naive Bayes
	Decision Tree Classification
	Random Forest Classification

Unsupervised Learning	
Clustering	Dimensionality Reduction
K-Means	Principal Component Analysis (PCA)
K-Median	Partial least Square Regression (PLSR)
Expectation Maximization	Sammon Mapping
Hierarchical Clustering	Linear Discrimination Analysis (LDA)
Apriori	Kernel PCA
Eclat	Flexible Discriminant Analysis

Some of the core areas that Deep learning is considered to give solutions for signal processing [26], medical image recognition [27], data mining [28], robotics [29] etc. This helps deep learning to find applications from industries such as banking [30], customer services [31], retail, defence [32], healthcare [33] etc.

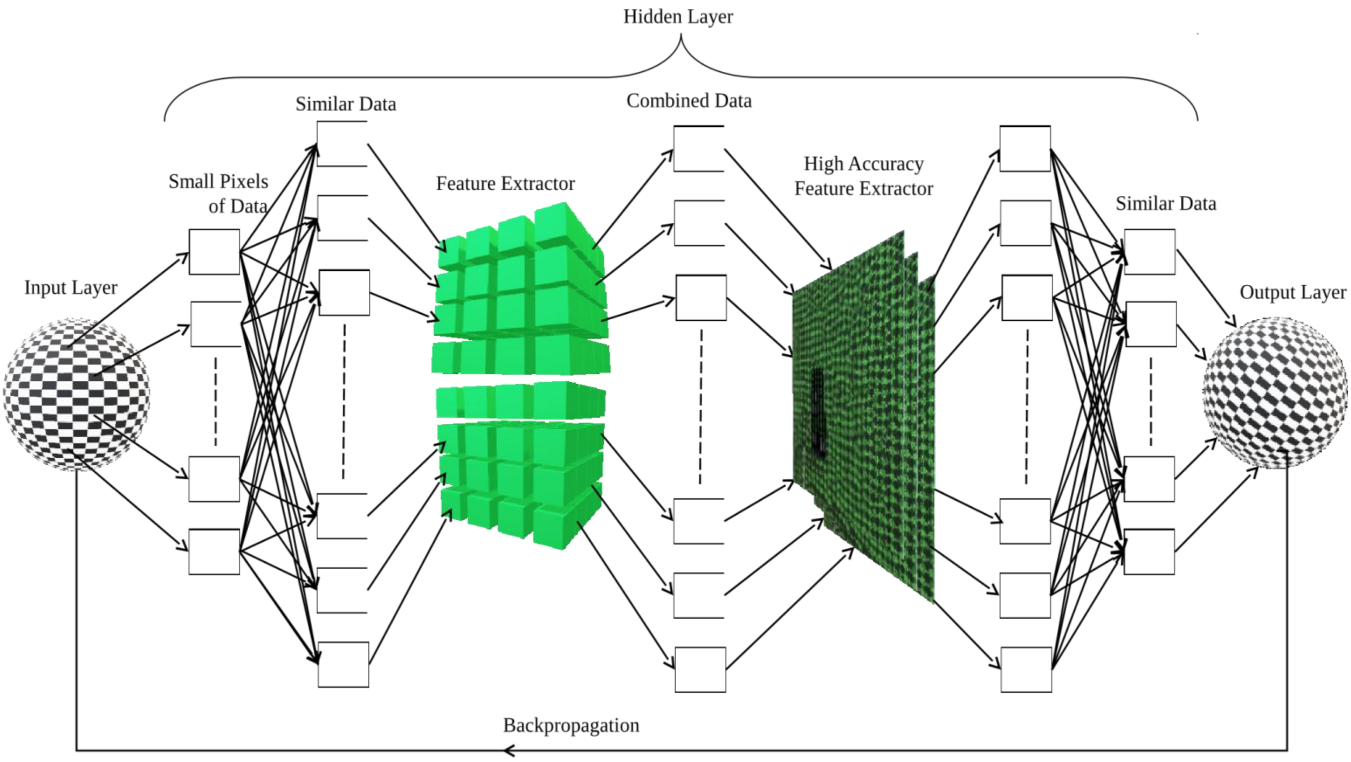

Fig. 4. A typical Deep Learning Neural Network with Feature Extractor and classifiers

Perceptron: The Perceptron was the first electronic equivalent of human brain neuron it would take a number of signals, integrate and if the value crosses a particular threshold, it would give the output as "Correct".

Feed-forward Neural Network: It's the highly interconnected web of artificial neurons inspired by human nervous system, working in union to perform given task and at the end gives the decision based on weights and biasing for complex input data [34].

Autoencoder: It is typically a feed forward neural network which aims to learn a compressed, distributed representation(encoding) of a dataset [35].

Restricted Boltzmann Machines: RBM [36] is a generative stochastic artificial neural network which can learn probability distribution over its input datasets. They can be trained either supervised or unsupervised [37] depending on task with a restriction where the pair of nodes from visible and hidden units may have symmetric connection between them and there is no connection between node within a group. This restriction allows more efficient algorithms particularly gradient based contrastive divergence algorithm.

Deep belief networks: It's a generative graphical model composed of multiple layers of RBM and autoencoders. When it is trained without supervision, it can learn to probabilistically restrict its inputs and acts as feature detectors and with supervision to perform classification [38].

Convolution neural networks: CNNs are a specific kind of Neural Network designed for image recognition Just like the ANNs have nodes (neurons), CNNs use kernels [39], which are basically grids of neurons that can learn patterns in images. Kernels in the initial layers of CNN learn basic features like horizontal and vertical lines. As we move deeper into the layers the kernel starts to recognize complex features like ears, nose, mouth etc., and in the final layer, the network can identify the entire image based on this CNN network [40].

Recurrent Neural Networks: These are designed to recognize handwritten text, speech, etc. It is one of the most powerful and useful type, applicable even to images that can be decomposed into series of patches and treated as sequence [41].

Recursive Neural Tensor Networks: These are having tree like structure with a neural net at each node particularly used for natural language processing. which uses external components like Word2vec, where it converts a corpus of words into vectors which can be thrown into a vector space to measure their similarity [42].

Generative adversarial Networks (GANs): GANs are generative models that generate new data similar to the data they have been trained on. GANs are basically dual agent systems in which there are 2 neural networks that are trained against each other. One of these neural networks is the generator, that tries to generate new data, while the other is the discriminator, whose task is to determine whether the generated data is false or not. GANs can be used to generate test datasets when there is a scarcity [43].

A. How Deep learning works

Deep learning models are designed to extract patterns from input data so as to make predictions on new unseen data. These models learn and improve on their own. Deep learning models are designed keeping in mind the functional design of the human brain [44].

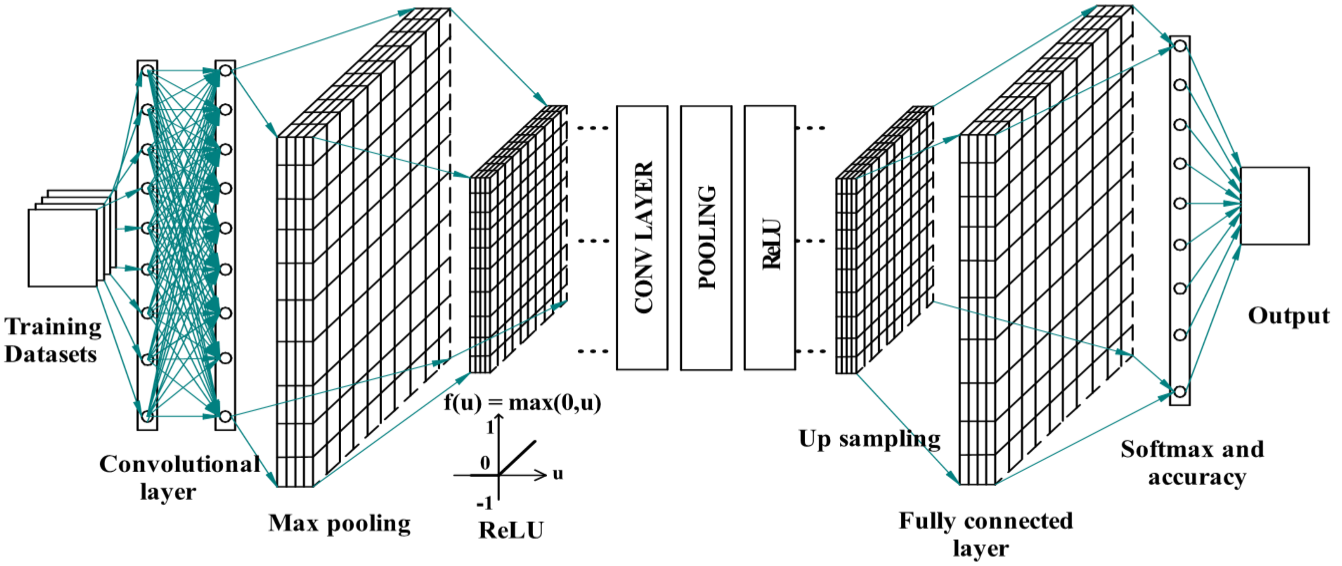

Fig. 5. Convolution Neural Network

In the human brain there are pattern recognition modules (consisting of a group of neurons, roughly 50 to 100 in size) that are responsible for recognizing individual patterns. There is a hierarchy in the arrangement of these modules. The modules in the lower levels of this hierarchy recognize the basic patterns for example in case of reading, these modules recognize individual letters, The module responsible for the letter A, fires when it sees an A, as we move up the hierarchy, modules can start recognizing and making sense of words and sentences, and in even higher levels, modules can make sense of the sarcasm and metaphors in a sentence.

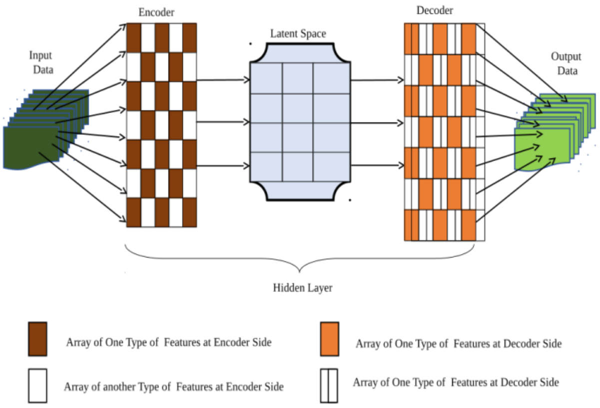

Fig.6 Auto Encoder

Deep learning models have a similar structure, with individual neurons, resembling the pattern recognition modules of the brain. In the training stage these neurons learn to recognize features by tuning their weights. After the neurons are set and the model performs well on the training set, it is tested on unseen data, Now the neurons are responsible for finding their respective patterns on the test-set. If the pattern is found by a neuron the information is sent to the next layer of neurons that recognize more complex features.

This ultimately leads to the output layer which based on probability of all features spotted decides if the input data was of a particular kind or not.

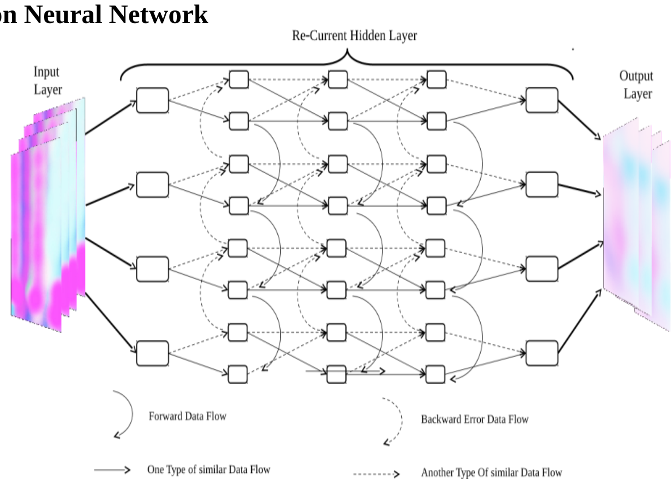

Fig.7 Recurrent Neural Network

B. Algorithms for Deep learning

The field of deep learning deals with many algorithms, each one designed to solve a specific task. Some of these algorithms are listed below

1) Feed Forward Neural Networks (Artificial Neuron).
2) Radial Basis Function Neural Network.
3) Multilayer Perceptron.
4) Unsupervised pretrained network
   - Autoencoders
   - Deep Belief Networks
   - Generative Adversarial Networks (GANs)
5) Convolutional Neural Networks
6) Recurrent Neural Network/LSTMs
7) Recursive Neural Networks.

C. Mathematics used for deep learning analysis

While computing the task such as speech recognition, image recognition, text recognition, computer vision etc. we need basics of mathematics such as linear algebra, optimization theory, probability and statistics and multi-variable calculus etc.

(a) Linear algebra: It is a form continuous rather than discrete mathematics. It includes topics such as scalar, vectors, matrices, tensor, norms, eigen decomposition, singular value decomposition etc. [46].

(b) Optimization theory: In order to train the weights of a model and minimize the training error, it is required to know about the derivatives of the loss functions with respect some parameters which helps to carry-out gradient descent optimization. Along with this we need to know about gradient mean, hessians, converges etc. [47].

(c) Probability and Statistics: Machine intelligence, most of the times deals with data that is not certain. Probability helps in solving problems related to uncertainty and approximations. Statistics helps with normalizations, distributions, finding means and standard deviations to obtain faster convergence [48].

(d) Multivariable calculus: Calculus is used all over the place in Deep Learning, the reason for it is that many problems in the field have to do with extrapolating based on data and we want to minimize error in some way. Where regularly calculus deals with functions of one variable ($y = f(x)$), multivariable calculus deals with functions of multiple variables ($z = f(x,y)$). Generally, what this looks like is applying the things we learned how to do in single-variable calculus to analogous scenarios in three and higher dimensional spaces [49].

IV. LITERATURE REVIEW

In a subject like deep learning, that has proved to be so important for a wide variety of applications across a range of fields, and with more and more papers being published every day, it is ever more important to have a survey that lists out research publications in each field. The above table tries to do the same. The table shows the number of deep learning conference papers, journals and articles that have been published pertaining to different fields and applications, in IEEE Xplore. The list is well segmented into 4 sub tables. i.e., all the papers that can be grouped under general applications are listed in the first part, and the papers in the fields of medical applications, computer vision and robotics are placed in respective groups.

A keyword search in IEEE Xplore gives us 12,276 results for deep learning. The survey tells us that though the first papers related to deep learning were published in the 1980's, almost 98% of these papers were published in just the past decade. This shows the rise in interest among researchers and institutions in this field. Most of these papers have been concentrated on specific topics

Methodology: It is highly unlikely to have an exhaustive survey on a topic like Deep learning based on applications (adoption and deployment) with page bound. The research methodology employed here is a literature review followed by a practical scenario. The former is carried out in 3 phases: Literature identification, categorization, and analysis. The later gives a theoretical SWOT analysis and the results of the literature review of all peer-reviewed articles dealing with Deep learning systems and applications in Table III. Articles (conference papers, journal articles, books, standards, early access, and courses) were gathered from IEEE Xplore with keywords: Deep learning + speech recognition, Deep learning + medical applications, Deep learning + computer vision, Deep learning + robotics. After filtering the irrelevant results from the search, we found around 12,295 articles cumulatively. It is noteworthy that years created an immense growth in the last decade. This proliferation of Deep learning can be owed to the sudden increase in demand for Personal AI system applications, which is our main focus too.

V. APPLICATIONS

Deep learning (DL) is applied in many areas of artificial intelligence (AI) such as speech recognition, image recognition and natural language processing (NLP) and many more such as robot navigation systems, self-driving cars for example.

1) Speech recognition: Speech recognition [50] is the easiest and most efficient way to communicate, so much that is synonymous with communication. It is this reason, that is driving researchers to develop machine interface designed on speech recognition. This way we can communicate with our machines much better than by using traditional mouse and keyboard, joystick etc. But production and recognition of voice/speech by machines takes up a huge complex phenomenon. Nowadays automatic speech recognition (ASR) [51]is powered by the deep learning neural networks for the application like voice search/speech transcription. ASR is a complex and cumbersome job as it uses sophisticated tools for processing. The main methods used for the following process are speech recording, pre-processing, feature extraction, speech classification and recognition.

(a) **Speech Recording:** The voice vocalized by human interaction is in the analog waveform and it should be recorded.

(b) **Pre-Processing:** It helps to eliminate the irrelevant sources of variation in the given signal and hence improves the accuracy, further it involves noise filtering, smoothing, end-point detection, framing, windowing, reverberation cancelling and echo removing.

(c) **Feature extraction:** It uses different methods such as Mel frequency spectral coefficients (MFSC) [52] on frequency domain which is again based on human ear scale] linear predicting coding (LPC) [53] used for medium or low bit rate coder] where digital signal is compressed for efficient transmission and storage.

(d) **Speech classification:** It involves complex mathematical functions and take out hidden information from the input processed signal. It uses various techniques like Hidden markov modelling (HMM)[54], Dynamic time wrapping(DTW) [55],Vector Quantization(VQ)[56].

TABLE II QUICK GUIDE TO DEEP LEARNING NETWORKS

Model	type	Architecture	Learning	inputs and outputs
CNN	Feed forward ANN	Fully connected multi layers of perceptron's	Supervised	Fixed size inputs and outputs
RNN	Uses their internal memory to process arbitrary sequence of inputs	Made up of one node, result back into itself	Supervised	Arbitrary input and outputs
DBN	Generative energy-based model	Input layers, multiple hidden layers with bipartite, output layers	Supervised	Arbitrary input and outputs with Backpropagation
RBM	Generative stochastic ANN	Input layers, multiple hidden layers with bipartite, output layers	Supervised and Unsupervised	Random no of inputs and outputs
RNTN	Generative	Recursive cascade correlation	Unsupervised	Variable input and output size

(e) Recognition: It is the mapping of uploaded speech with the pre-trained one and gives the probabilistic results with minimum errors.

Speech recognition is widely used in many industrial applications like Voice recognition [57] (Automotive, Security, IoT), Voice Search [58] (Hand set maker, Telecom), Sentiment Analysis (CRM) [59], Engine noise (Automotive, Aviation), Fraud detection [60] (Finance, Credit Cards).

2) Image recognition: Identifying beautiful flowers in the garden, different animals in the wild, recognizing human face and many different kinds of things that we see in our daily lives can be done with the help of deep learning algorithms. The technique of recognizing patterns and images can be easily done by a human brain within fraction of seconds with different views and environmental conditions [61].

In recent days the artificial intelligence with deep learning algorithm has outperformed human beings in various tasks like face recognition, sentiment analysis [62], image recognition, etc. This opens a new path to many disruptive ideas and leverage deep learning to solve real world problems. While humans can intuitively make sense of image data, Computers lack this ability. They can only operate on numbers. So, to enable computer to process pictorial data, pictures should be rendered as numbers.

There are many common ways to convert an image into numbers in image processing. some important ways are:

(a) Greyscale values: In Greyscale format the image is represented in pixel values that vary in intensity. This intensity has numeric value ranging from 0 to 255. 0 being the least intense is used for black and 255 being the most intense resembling white color [63].

(b) RGB values: In this format the image contains pixels, with each pixel having 3 different components namely Red, Green, Blue. The intensity of these components is given by a numeric value again ranging from (0 to 255). 0 being the least bright value and 255 being the brightest value. Different combinations of these intensities give different colors. So RGB format can hold the colored part of an image.

The steps used for image recognition techniques are Preprocessing, splitting the dataset, Building the CNN

(a) Preprocessing: The two main pre-processing techniques: normalization and augmentation [64]. the augmentation is a way of reducing over-fitting [65] and expanding of our dataset. Often a very simple and accessible solution excludes feature extraction. We usually want convolutional network to learn from the image data. Doing as little as possible aligns with the tendency to make the least amount of assumptions or tampering with your data and leave to the model to figure it out as far as the design choices are compatible with the wide input value ranges.

(b) Splitting the dataset: The splitting acts as a partition for a dataset it separates the datasets into two or more number of new datasets. The number of test samples should be high enough for process to occur. split by class, so that it can make sure that the distribution of classes is same for the training and for the test set.

Building the CNN: The net uses a technical operation of the convolution to search for a particular pattern. Although one important note is that the weights and biases of this layer affect how this operation is performed, tweaking these numbers impacts the effectiveness of the filtering process. Apart from the convolutional layer, the CNN usually includes a pooling and an activation layer. The pooling layer [66] is used to reduce the size of input data so as to decrease the number of computations. Pooling involves using a feature grid/block of a particular size that can overlap on the input and based on the type of pooling, only the relevant information from the overlapped region is extracted. The most commonly used type of pooling is Max Pooling, where only the maximum pixel value is retained from each region. Activation layers are used to add non-linearity to the network. Without these the network cannot learn complex nonlinear patterns. It also makes backpropagating errors to adjust it weights much easier. The most widely preferred activation function is ReLU (Rectified linear unit, because it is simple and since it has a range [0,00), it prevents the vanishing gradient problems. Convolution, pooling and activation combined together can learn complex features, but to make sense of these features, for classifying and labelling an image a final layer called as fully connected layer is also attached. Image recognition is widely used in many industrial applications like Facial recognition, Image search [67] (social media), Machine vision [68] (Automotive, aviation), Photo clustering [69] (Telecom, Handset makers).

3) Time series signal analysis: Time series is data that changes with respect to time. Most often it involves periodically changing data like weather, stock markets, etc.

TABLE III CLASSIFICATION OF LITERATURE

Sl.No.	Search keyword	Conferences	Journals	Articles	Total	Contribution(%)
		General Applications				
01	DL + Speech recognition	700	130	7	837	7.23
02	DL + Image recognition	2343	382	59	2,784	24.05
03	DL + Natural language processing	458	81	8	547	4.72
04	DL + Machine translation	69	12	2	84	0.72
05	DL + Earth observation	49	20	12	81	0.69
06	DL + Remote sensing	239	192	37	468	4.04
07	DL + vehicular systems	14	13	4	31	0.26
08	DL + VLSI systems	37	14	6	57	0.49
09	DL + hand-writing recognition	6	3	1	10	0.08
10	DL + Robotics	357	126	14	497	4.29
11	DL + computer intelligence	3528	835	79	4,442	38.37
12	DL + water imaging	21	6	1	28	0.24
13	DL + education	431	163	31	625	5.4
14	DL + Military	54	5	3	62	0.53
15	DL + IOT	120	32	19	171	1.47
16	DL + Data mining	549	117	26	692	5.97
17	DL + Smartphone	54	7	5	66	0.57
18	DL + Intelligent traffic systems	67	22	3	92	0.79
		Deep learning + Medical applications				
01	DL + Oncology	13	7	2	22	5.16
02	DL + Dermatology	8	1	1	10	2.34
03	DL + Endoscopy	11	4	3	18	4.22
04	DL + MRI	167	36	11	214	50.23
05	DL + Cardiology	48	12	0	60	14.08
06	DL + Neurology	21	7	1	29	6.8
07	DL + Genetics	64	8	1	73	17.13
		Deep learning + computer vision				
01	DL + Feature extraction	3665	872	218	4,755	78.22
02	DL + Color vision	144	18	0	162	2.66
03	DL + Transformations	87	41	6	134	2.20
04	DL + Pose estimation	205	30	9	244	3.68
05	DL + Registration	45	13	2	60	0.98
06	DL + Visual recognition	540	129	35	704	11.58
		Deep learning + Robotics				
01	DL + Adaptive control	54	21	8	83	5.57
02	DL + Aerial robotics	20	6	1	27	1.81
03	DL + Android science	17	2	3	22	1.47
04	DL + Autonomous car	24	6	2	32	2.14
05	DL + Cognitive robotics	29	10	2	41	2.75
06	DL + Computational neuroscience	16	5	4	25	1.67
07	DL + Robot control	154	27	3	184	12.34
08	DL+ Digital control	33	11	1	45	3.02
09	DL + Digital Image processing	129	47	5	181	12.14
10	DL + Human computer interaction	135	32	4	171	11.47
11	DL + Human robot interaction	47	11	1	59	3.95
12	DL + Kinematics	65	11	2	78	5.23
13	DL + Robot learning	421	78	10	509	34.16
14	DL + Motor control	24	6	3	33	2.21

Time series is widely used in statistics, signal processing, pattern recognition [70], econometrics [71], earthquake prediction and communication engineering. Time series analysis involves finding patterns in temporal (time based) data and understanding the underlying forces to predict future trends in such data. Deep learning models perform really well with such organized and uniform data, with the help of this model we can make very accurate prediction in better stock market predictions, Time and frequency-based signal analysis, weather forecasting, etc.

TABLE IV MAJOR SOFTARE LIBRARIES FOR DEEP LEARNING

Library	Written in	Year	Remarks
Gensim	Python	2009	Vector space modelling
Eblearn	C++	2009	Energy based learning models
Open NN	C++	2014	Data mining and predictive analysis
ND4j	Java,C++	2014	Linear algebra and matrix manipulation
Neural designer	C++	2014	Data mining and big data analytic
MXNet	C++,Python,R,Pearl	2015	Ultra-scalable deep learning
Apache SINGA	C++,Python,Java	2015	Multilayer perceptron’s
Tensor flow	Python,C++,CUDA	2015	Automated image captioning software
Keras	Python	2015	Activation functions and optimizers
PyTorch	Python,C,CUDA	2016	Natural language processing
Microsoft Cognitive Tool kit	C++	2016	NN via directed graphs
Theano	Python	2017	Runs efficiently on CPU and GPU
Caffe	C++	2017	Image classification and Image segmentation
Deep learning 4j	Java,C,C++,Python	2017	Visualization tool

There are many types of data analysis available for time series, which are appropriate for different purposes.

(a) **Exploratory analysis:** This technique involves applying basic statistical methods like mean, standard deviation, gaussian distribution. So as to understand and make sense of the data, it also involves methods like autocorrelation and spectral analysis which helps us to explore serial and cyclic behaviors of a system [72]. Exploratory analysis gives a clear-cut picture of our data and helps in data cleaning and also designing better modules.

(b) **Curve fitting:** curve fitting is the process of constructing a curve or mathematical function, that has the best suit for a series of data points with subjected constraints [73].

These time series are also used for many use cases like signal estimation, segmentation, prediction and forecasting. Time series data can have several models and it is represented in different stochastic processes. when the level of a process is varied, models can be classified into many types based on practical importance. Time series signal analysis can be widely used in many industrial applications like Recommendation engine [74] (E-commerce, Media, Social media), Predictive analysis [75] using sensor data (IoT, Smart home, Hardware manufacturers), Log analysis/Risk detection (Data centers, Security, Finance) etc.

4) Machine translation and Natural language processing: In pursuit of creating Artificially Intelligent machines, one of the most important problems to solve is to enable the machines to understand all types of regional languages. Natural language processing deals with creating models that analyze to understand patterns in different languages. Machine translation deals with translating text or voice from one language to another. NLP algorithms are based on Machine learning algorithms but they deal with specific tasks like lemmatization [76], part of speech tagging [77], named entity recognition [78], syntactic parsing, fact extraction [79], sentiment analysis [80], machine translation and many others. Languages can be very complex, because they are not entirely structured, they can be ambiguous, involving metaphors, sarcasm, homophones etc. It’s important to understand the context in which a certain statement is used. So, NLP requires a lot of manual curation to develop a language model. This comes at a cost of variable quality and consistency.

Deep learning enables us to overcome these deficiencies by using techniques like Bidirectional Recurrent Neural Network [81], LSTM [82], GRU [83], One hot vector [84], skip gram model [85], word embeddings, etc.

(a) **Bi directional recurrent net:** When the data we are dealing with is temporal, the most suitable algorithm to use is the Recurrent Neural Network. But one drawback is that RNNs can only use information it has seen in the past. Consider an example” An apple a day keeps a ……..”. When this incomplete sentence is fed to an RNN, it can only understand the given words, but fails to complete it. However, a bidirectional RNN can be based on the probability of the most occurred words in similar sentences. A Bidirectional RNN is much like two RNNs receiving parallelly but opposite in nature. One contains the information from past whereas the other has future information. This helps the network to predict better and contextually accurate sentences.

(b) **LSTM, GRU:** Gating is a means that helps the net decide when to forget the present input and when to remember it, for further time steps. The most popular gating techniques used in today’s modern world are LSTM, GRU. An LSTM, or Long Short-Term Memory Network, is a kind of recurrent neural network that is good at learning dependencies between two points in a sequence that are separated very far in time. These powerful algorithms can classify, cluster and make predictions about data,

(c) particularly time series and text. A gated recurrent unit (GRU) is essentially an LSTM without any output gate, which therefore thoroughly writes the contents from its memory cell to the larger net at each time steps.

(d) Word Embeddings: Word embedding is a method of representing a language’s vocabulary, this uses vectors to represent a particular word. All these vectors form a vector space where all the synonyms of a particular word are placed closely, therefore represented by similar vectors.

(e) This kind of representation helps the model generalize letters.

(f) Skip grams: The bag-of-words model is used to represent an unordered collection of words as a vector. The goal of word embedding models is to train a high-dimensional dense representation for each vocabulary term in which the similarity between embedding vectors shows the semantic or syntactic similarity between the corresponding words. Skip-gram is a model for training word embedding algorithms.

(g) Recursive neural tensor network (RNTN): Syntactic parsing was an old problem in NLP which received a big boost from the use of recursive neural tensor network (RNTN). The RNTN involves parent and child nodes, the passed bits of the data are fed to the child nodes that is connected to these child nodes and is hierarchically above the children, finds a relation among them (Here nodes represent neural networks). RNTNs can learn the contextual meaning embedded in a sentence, It can also learn the underlying semantics of different languages, This can be very useful in machine translation modules.

Machine translation and natural language processing can be widely used in many industrial applications like Sentiment analysis (chatbots, CRM, Social media), Augmented search [87], Theme detection [88] (Finance), Threat detection (Social media, Government), Fraud detection (Insurance, Finance).

VI. RESULTS

The investigations have led to an understanding of the possible potential applications of Deep learning in various domains. The results are summarized as below:

TABLE V. MAPPING OF VARIOUS APPLICATIONS WITH THE POSSIBLE USE OF DEEP LEARNING VARIANT.

Sl.no.	Application	Type of DL
01	Classification	Neural Networks
02	Face Recognition	Convolutional Neural Networks(CNNs)
03	Self-Driving Cars	CNNs
04	Voice Search	Recurrent Neural Networks(RNNs)
05	Machine Translation	RNNs
06	Deep Fakes	Generative Adversarial Networks (GANs)
07	Weather Forecasting	Neural Networks
08	3D Reconstruction	Deep Reinforcement Learning(DRL)
09	Multi-Agent Systems (Games)	DRL
10	Robotics	DRL

VII. CONCLUSION

The aim of this paper was to give a brief introduction to the field of deep learning starting from its historical perspective and evolution. We have attempted to provide a list of algorithms, beginning with the most basic unit of composition (the perceptron) and progressing through various effective and popular architectures like feed forward network, CNN's, RNN's, GAN's. In order to satisfy the demands of various unconstrained environments, our study summarizes that: deep NN should be equipped with huge datasets, additional modalities, additional temporal scales, feedback mechanism to handle noisy or missing channels. We have explained the advantages and performance of deep learning models, and also the major software libraries used for programming. Finally, we highlighted lessons learned in making the deep learning more intelligent; and conclude with research challenges yet to be addressed in order to fully exploit the potential offered by learning systems.

As for future work, we aim at applying the knowledge of deep learning to a greater number of specific applications especially related to convolutional nets and recurrent nets. Ultimately, major progress in AI will be achieved through systems that combine representation learning with complex reasoning. With deep learning and reinforcement learning the future of intelligent system is not only bright but intelligent too.

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