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Scientific understanding of learning through deep learning algorithms

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Abstract:
Deeplearning(DL),abranchofmachinelearning(ML)andartificial intelligence (AI), is recognized as a core technology of today's Fourth Industrial Revolution (4IR or Industry4.0).Originating fromartificial neural networks (ANNs), DL technology has become a hot topic incomputing due to its abilityto learn from data, and is widely applied in various application areas such as healthcare, visual recognition,text analysis, and cyber security. It has been. much more. However, creating good DL models is a difficult task due to thedynamic nature and fluctuations of real-world problems and data. Moreover, the lack of understanding of the core makes DLmethods a black-box machine that preventsstandard-leveldevelopment. Thisarticle provides astructuredandcomprehensive overview of DL techniques. This includes classifications that consider different kinds of real-world tasks, suchas supervisedorunsupervised. Ourtaxonomyconsiders supervisedordiscriminativelearning,unsupervisedorgenerative learning, hybridlearningand otherrelateddeepnetworks.It also summarizespracticalusecases where deeplearning techniques can be used. Finally, we point out ten potential aspects of next-generation DL modelling, along with research directions. Overall, this article aims to paintapicture ofDLmodellingthatcanbeusedasareferenceguideforacademicandindustryprofessionals.

Keywords: *Deeplearning·Artificialneuralnetwork·Artificialintelligence·Discriminativelearning Generative learning· Hybrid learning· Intelligent systems*

Introduction:
In the late 1980s, neural networks became a prevalent topicin the area of Machine Learning (ML) as well as ArtificialIntelligence (AI), due to the invention of various efficientlearning methods and network structures [52]. Multilayerperceptronnetworkstrainedby“Backpropagation”typealgorithms,self-organizingmaps,andradialbasisfunctionnetworksweresuchinnovativemethods[26,36,37].Whileneuralnetworksaresuccessfullyusedin manyapplications,theinterestinresearching this topic decreased later on. After that, in 2006, “Deep Learning” (DL) was introduced by Hinton et al. [41],which was based on the concept of artificial neural network (ANN). Deep learning became a prominent topic after that,resulting in a rebirth in neural network research, hence, sometimes referred to as “new- generation neural networks”. This isbecause deep networks,whenproperly trained, have produced significant success ina variety of classification and regressionchallenges[42].

Nowadays, DL technology is considered as one of the intelligences as well as data science and analytics, due to its learningcapabilitiesfromthegivendata.ManycorporationsincludingGoogle,Microsoft, Nokia,etc.,studyitactivelyasitcanprovidesignificant results in different classification and regression problems and datasets [42]. In terms of working domain, DL isconsideredasa subset ofMLand AI,andthusDLcanbeseenasanAIfunctionthatmimicsthehumanbrain’sprocessingofdata.Theworldwidepopulaityof“Deeplearning”isincreasingdaybyday, whichisshowninourearlierpaper[26]basedonthe historical data collected from Google trends [33]. Deep learning differs from standard machine learning in terms ofefficiency as the volume of data increases, discussed briefly inSection “Why Deep Learning in Today's Research andApplications?”.DLtechnologyusesmultiplelayerstorepresenttheabstractionsofdata tobuildcomputational models.Whiledeep learningtakes a long time to train a model due to a large number of parameters, it takes a short amount of time to runduringtestingascomparedtoothermachinelearningalgorithms[12].
While today’s Fourth Industrial Revolution (4IR or Indus-try 4.0) is typically focusing on technology-driven “automa-tion,smart and intelligent systems”, DL technology, whichis originated from ANN, has become one of the core tech- nologies toachievethegoal[10,11].Atypicalneuralnetworkismainlycomposedofmanysimple,connectedpro-cessingelements or

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processors called neurons, each of whichgenerates a series of real-valued activations for the target outcome. Figure 1 shows aschematic representation of the mathematical model of an artificial neuron, i.e., processing element, highlighting input (X_i),weight(w),bias(b),sum-
mationfunction(),activation function(f)andcorrespond-
ing output signal (y). Neural network-based DL technologyis now widely applied in many fields and research areas suchashealthcare,sentimentanalysis,naturallanguageprocess-
ing,visualrecognition,businessintelligence,cybersecurity,andmanymorethathavebeensummarizedinthelatterpartofthispaper.
Although DL models are successfully applied in variousapplication areas, mentioned above, building an appropri- atemodelof deeplearning is a challenging task, due tothe dynamic nature and variations of real-world problems and data.Moreover,DLmodelsaretypicallyconsideredas

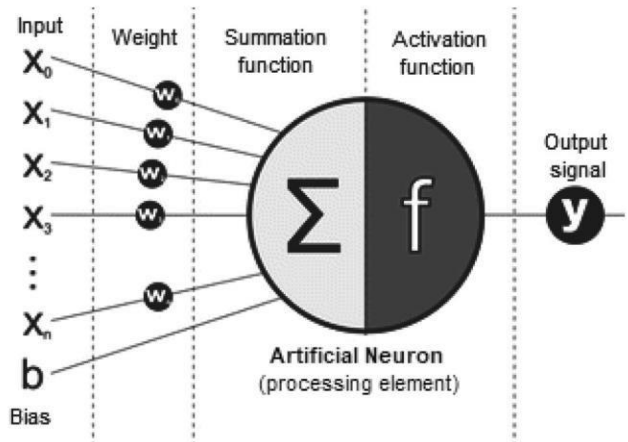

Fig. 1 Schematic representation of the mathematical model of an artificial neuron (processing element), highlighting input (Xi), weight(w), bias (b),summationfunction(x), activationfunction(f)andout-put signal(y)

"black-box" machines that hamper the standard development of deep learning research and applications. Thus for clearunderstanding, in this paper, we present a structured and comprehensive view on DL techniques considering thevariations inreal-worldproblemsand tasks.To achieve our goal, we briefly discuss various DL techniques and present a *taxonomy* bytaking into account three major categories: (i) deep networks for supervised or *discriminative learning* that is utilized toprovideadiscriminative function in supervised deeplearningorclassificationapplications;(ii)deepnetworksforunsupervised or*generative learning* that are used to characterize the high-order correlation properties or features for patternanalysisorsynthesis,thuscanbeusedaspreprocessing for the supervised algorithm; and (ii) deep networks for *hybridlearning* that is an integration of bothsupervised and unsupervised model and relevant others. We take into account suchcategories based on the nature and learning capabilities of different DL techniques and how they are used to solve problemsinreal-worldapplications[47].Moreover,identifyingkeyresearchissuesandprospectsincludingeffectivedatarepresentation, new algorithm design, data-driven hyper-parameter learning, and model optimization, integrating domainknowledge, adapting resource-constrained devices, etc. is one of the key targets of this study, which can lead to "FutureGeneration DL- Modeling". Thus the goal of this paper is set to assist those in *academia and industry* as a reference guide,whowantto*researchanddevelop*data-drivensmartandintelligentsystemsbasedonDLtechniques.
Theoverallcontributionofthispaperissummarizedas
follows:

– This article focuses on different aspects of deep learningmodeling, i.e., the learning capabilities of DL techniquesindifferent dimensions such as supervised or unsuper- vised tasks, to function in an automated and intelligent manner,whichcanplayas acoretechnologyoftoday'sFourthIndustrialRevolution(Industry4.0).
– We explore a variety of prominent DL techniques and present a taxonomy by taking into account the variationsin deeplearning tasks andhowtheyareusedfordiffer- entpurposes.Inourtaxonomy,wedividethetechniquesintothreemajorcategories such as deep networks for supervised or discriminative learning, unsupervised or generative learning, as wellas deepnetworksforhybridlearning,andrelevantothers.
– Wehavesummarizedseveralpotentialreal-worldappli-cationareasofdeeplearning,toassistdevelopersaswellas

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researchers in broadening their perspectives on DL techniques. Different categories of DL techniques high-lighted in ourtaxonomy can be used to solve various issues accordingly. Finally, we point out and discuss ten potential aspects withresearchdirectionsforfuturegeneration DLmod- elingin termsofconducting futureresearch andsystemdevelopment.

Thispaperisorganizedasfollows. Section"WhyDeepLearninginToday'sResearchandApplications?"motivateswhydeeplearningisimportanttobuilddata-drivenintel-ligentsystems.InSection"DeepLearningTechniquesandApplications",wepresent our DL taxonomy by taking into account the variations of deep learning tasks and how they are used in solving real-worldissuesandbriefly discussthe techniques with summarizing the potential application areas. InSection"ResearchDirections and Future Aspects", we discuss various research issues of deep learning-based mod- eling and highlight thepromising topics for future researchwithin the scope of our study. Finally, Section "ConcludingRemarks" concludes thispaper.

WhyDeepLearninginToday'sResearchandApplications?

The main focus of today's Fourth Industrial Revolution (Industry 4.0) is typically technology-driven automation, smart andintelligentsystems,invariousapplicationareasincludingsmarthealthcare,businessintelligence,smartcit-ies,cybersecurityintelligence, and many more [45]. Deep learning approaches have grown dramatically in terms of performance in a widerange of applications considering security technologies, particularly, as anexcellent solutionforuncovering complexarchitecture in high-dimensional data. Thus, DL techniques can play a key role in building intelligent data-driven systemsaccording to today's needs, because of their excellent learning capabilities from histori-caldata.Consequently,DLcanchangetheworldaswellashumans'everydaylifethroughitsautomationpowerandlearningfromexperience. DLtechnologyis therefore rel- evant to artificial intelligence [13], machine learning [57] and data science with advanced analytics [45] thatare well- known areas in computer science, particularly, today's intel-ligent computing. In the following, we first discussregardingthepositionofdeeplearninginAI,orhowDLtechnologyisrelatedtotheseareasofcomputing.

ThePositionofDeepLearninginAI

Nowadays, artificial intelligence (AI), machine learning(ML), and deep learning (DL) are three popular terms that aresometimes used interchangeably to describe systems or software that behaves intelligently. In Fig. 2, we illustrate thepositionofdeepLearning,comparingwithmachinelearningandartificial intelligence.AccordingtoFig.2,DLisapart

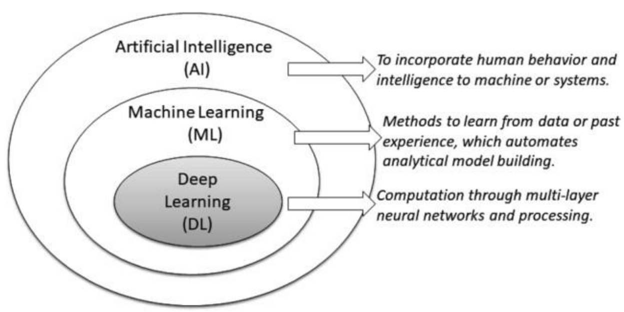

Fig.2 Anillustrationofthepositionofdeeplearning(DL),compar-ingwithmachinelearning(ML)andartificialintelligence(AI)

ML as well as a part of the broad area AI. In general, AI incorporates human behavior and intelligence to machines orsystems[13],whileMListhemethodtolearn fromdataorexperience[37],whichautomatesanalyticalmodelbuild-ing.DLalsorepresentslearningmethodsfromdatawherethecomputationisdonethroughmulti-layerneuralnetworksandprocessing.The term "Deep" in the deep learning meth-odology refers to the concept of multiple levels or stages through which data isprocessedforbuildingadata-drivenmodel.
Thus, DL can be considered as one of the core technol- ogy of AI, a frontier for artificial intelligence, which can beusedforbuildingintelligentsystemsandautomation.Moreimportantly,itpushesAItoanewlevel,termed"SmarterAI".AsDLarecapableoflearningfrom data, thereisastrongrelationofdeeplearningwith"DataScience"[45]aswell.Typically,datasciencerepresentstheentireprocessoffindingmeaningorinsightsindatainaparticularproblemdomain,whereDLmethods can play a key role for advancedanalytics and intelligent decision-making [10, 16]. Over-all, we can conclude that DLtechnology is capable to changethe current world, particularly, in terms of a powerful com-putational engine and contributetotechnology-drivenauto-mation,smartandintelligentsystemsaccordingly,

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andmeetsthegoalofIndustry4.0.

UnderstandingVariousFormsofData

As DL models learn from data, an in-depth understanding and representation of data are important to build a data- drivenintelligent system in a particular application area. Inthe real world, data can be in various forms, which typicallycan berepresentedasbelowfordeeplearningmodeling:

– *Sequential Data* Sequential data is any kind of datawhere the order matters, i,e., a set of sequences. It needsto explicitlyaccount for the sequential nature of input data while building the model. Text streams, audio fragments, video clips,time-seriesdata,aresomeexamplesofsequentialdata.
– *Image or 2D Data* A digital image is made up of a matrix, which is a rectangular array of numbers, sym- bolls,orexpressions arranged in rows and columns ina 2D array of numbers. Matrix, pixels, voxels, and bit depth are the fouressentialcharacteristicsorfundamentalparametersofadigitalimage.
– *Tabular Data* A tabular dataset consists primarily of rows and columns. Thus tabular datasets contain data ina columnarformatasinadatabasetable.Eachcolumn(field)musthaveanameandeachcolumnmayonlycon-taindata ofthedefinedtype. Overall, it is a logical and systematic arrangement of data in the form of rows and columns that are based on datapropertiesorfeatures.Deeplearningmodelscanlearnefficientlyontabulardataandallowustobuilddata-drivenintelligentsystems.

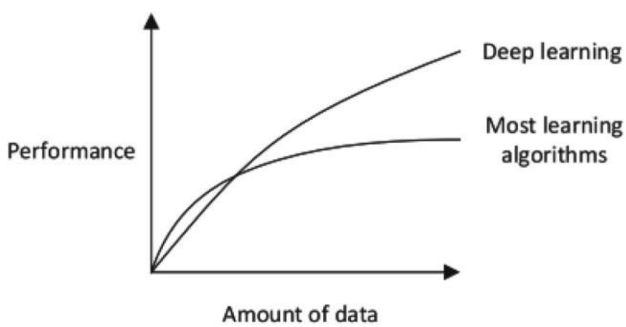

Fig. 3 An illustration of the performance comparison between deeplearning (DL)and other machine learning (ML)algori thms,whereDL modelingfromlargeamounts ofdata canincreasetheperfor- mance

The above-discussed data forms are common in the real- world application areas of deep learning. Different cat- egories ofDL techniques perform differently dependingon the nature and characteristics of data, discussed briefly in Section “DeepLearning Techniques and Applications” with a taxonomy presentation. However, in many real-worldapplication areas, thestandard machine learning techniques, particularly,logic-ruleortree-basedtechniques[93,11]performsignificantlydepending on the application nature. Figure 3 also shows the performance comparison of DL andML modeling consideringtheamountofdata.Inthefol- lowing,wehighlightseveralcases,wheredeeplearningisusefultosolvereal-worldproblems,accordingtoourmainfocusinthispaper.

DLPropertiesandDependencies

A DL model typically follows the same processing stages as machine learning modeling. In Fig. 4, we have shown a deeplearning workflow to solve real-world problems, whichconsists of three processing steps, such as data understand- ing andpreprocessing, DL model building, and training, and validation and interpretation. However, unlike the ML modeling [58,18], feature extraction in the DL model is automated rather than manual. K-nearest neighbor, support vector machines,decision tree, random forest, naive Bayes,linear regression, association rules, k-means clustering, are some examples ofmachine learning techniques that are com- monly used in various application areas [47]. On the other hand, the DL modelincludesconvolutionneuralnetwork,recurrentneuralnetwork,autoencoder,deepbeliefnetwork,andmanymore,discussedbrieflywi ththeirpotentialappli-cation areasin Section3.In thefollowing,wediscussthe keyproperties and dependencies of DL techniques, that are Generative Adversarial Network (GAN), designed by IanGoodfellow [32], is a type of neuralnetworkarchitectureforgenerative modelingtocreate new plausiblesampleson demand.It involvesautomaticallydiscovering and learningregularities or patterns in input data so that the model may be used to generate or output newexamplesfromtheoriginaldataset.AsshowninFig.9,GANsarecomposedoftwoneuralnetworks,ageneratorGthatcreatesnew data havingproperties similar to the original data, and a discriminator *D* that predicts the likelihood of a subsequentsamplebeingdrawn

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fromactualdataratherthandataprovided bythegenerator.Thus,in GANmodeling,boththegeneratorand discriminator are trained to compete with each other. Whilethe generator tries to fool and confuse the discriminator bycreating more realistic data, the discriminator tries to distingush the genuine data from the fake data generated by *G*.Generally,GANnetworkdeploymentisdesignedforunsupervisedlearningtasks,butithasalsoproventobeabettersolutionfor semi-supervised and reinforcement learning as well depending on the task [3]. GANs are also used in state-of-the-arttransferlearning

Auto-Encoder(AE)andItsVariants

An auto-encoder (AE) [31] is a popular unsupervised learn-ing technique in which neural networks are used to learnrepresentations.Typically,auto-encodersareusedtoworkwithhigh-dimensionaldata,anddimensionalityreductionexplainshowasetofdataisrepresented.Encoder,code,anddecoderare thethreepartsofanautoencoder. Theencodercompressestheinputandgeneratesthecode,whichthedecodersubsequentlyusestoreconstructtheinput.TheAEshaverecentlybeenusedto learn generative data mod-els [69].The auto-encoder is widely used in many unsuper- vised learning tasks, e.g.,dimensionality reduction, feature extraction, efficient coding, generative modeling, denoising,anomaly or outlier detection,etc.[31,132].Principal com-ponentanalysis(PCA)[99],whichisalsousedtoreducethedimensionalityofhugedatasets, isessentiallysimilartoasingle-layeredAEwithalinearactivationfunction.Regular-izedautoencoderssuchassparse,denoising,andcontractiveareusefulforlearningrepresentationsforlaterclassificationtasks[119], whilevariational autoencoderscanbeusedasgenerativemodels[56], discussedbelow.

– *Sparse Autoencoder (SAE)* A sparse autoencoder [73] has a sparsity penalty on the coding layer as a part of itstrainingrequirement.SAEsmayhavemorehiddenunitsthaninputs,butonlyasmallnumberofhiddenunitsarepermittedtobeactiveat the same time, resulting in a sparse model. Figure 10 shows a schematic structure of a sparse autoencoder with severalactive units in the hid-den layer. This model is thus obliged to respond to the unique statistical features of the training datafollowingitsconstraints.

– D*enoising Autoencoder (DAE)* A denoising autoencoderis a variant on the basic autoencoder that attempts to improverepresentation (to extract useful features) by altering the reconstruction criterion, and thus reduces therisk of learning theidentity function [31, 119]. In other words, it receives a corrupted data point as input and is trained to recover the originalundistortedinputasitsout-putthroughminimizingtheaveragereconstructionerror

RestrictedBoltzmannMachine(RBM)

ARestrictedBoltzmannMachine(RBM)[75]isalsoagen-erativestochasticneuralnetworkcapableoflearningaprob-abilitydistribution across its inputs. Boltzmann machines typically consist of visible and hidden nodes and each nodeis connectedto every other node, which helps us understandirregularities by learning how the system works in normal circumstances.RBMs are a subset of Boltzmann machines that have a limit on the number of connections between thevisible and hiddenlayers [77]. This restriction permits train-ing algorithms like the gradient-based contrastive divergencealgorithm to be moreefficient than those for Boltzmann machines in general [41]. RBMs have found applicationsin dimensionality reduction,classification, regression, col- laborative filtering, feature learning, topic modeling, and many others. In the area of deeplearning modeling, they can be trained either supervised or unsupervised, depend- ing on the task. Overall, the RBMs canrecognizepatternsindataautomaticallyanddevelopprobabilisticorstochasticmodels,whichareutilizedforfeatureselectionorextraction,aswellasformingadeepbeliefnetwork.

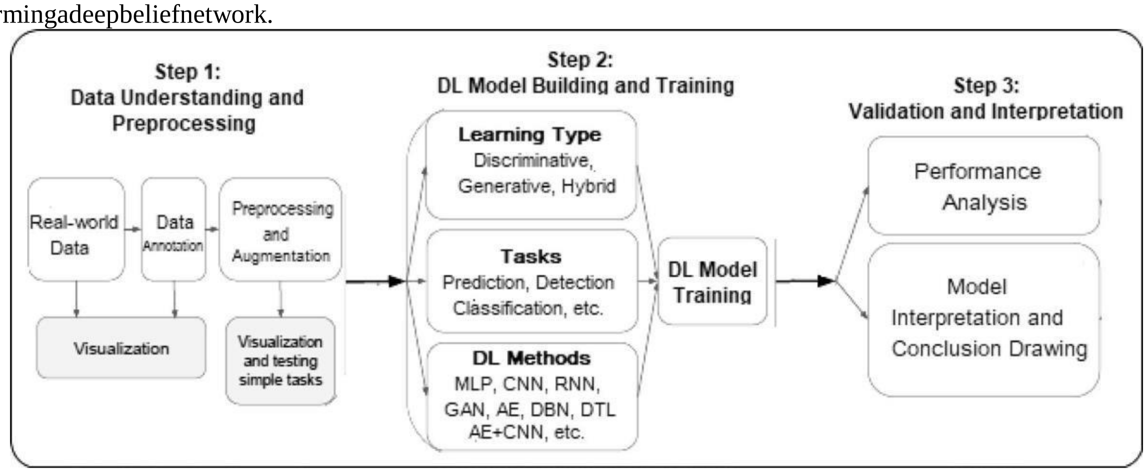

Fig.4 AtypicalDLworkflowtosolvereal-worldproblems,whichconsistsofthreesequentialstages(i)dataunderstandingandpreprocessing

(ii)DLmodelbuildingandtraining(iii) validationandinterpretation

neededtotakeintoaccountbeforestartedworkingonDLmodelingforreal-world applications.

– *Data Dependencies* Deep learning is typically dependenton a large amount of data to build a data-driven model for aparticularproblemdomain.Thereasonisthatwhenthedatavolumeissmall,deeplearningalgorithmsoftenperformpoorly[44]. In such circumstances, however, the performance of the standard machine-learning algo-rithms will be improved ifthespecifiedrulesareused[64, 17].
– *Hardware Dependencies* The DL algorithms require large computational operations while training a model with largedatasets.Asthelargerthecomputations,themoretheadvantageofaGPUoveraCPU,theGPUismostlyusedtooptimizethe operations efficiently. Thus,to work properly with the deep learning training, GPU hardware is necessary. Therefore,DLrelies moreonhigh-performancemachines withGPUsthanstandardmachinelearningmethods [19,17].
– *Feature Engineering Process* Feature engineering is theprocess of extracting features (characteristics, properties, andattributes) from raw data using domain knowledge. Afundamental distinction between DL and other machine-learningtechniques istheattempttoextracthigh-levelcharacteristicsdirectlyfromdata[22,57].Thus, DLdecreasesthetimeandeffortrequiredtoconstructafea-tureextractorforeachproblem.
– *ModelTraining and Executiontime*Ingeneral,train- ing a deep learning algorithm takes a long time due to a largenumberof parametersin theDLalgorithm;thus,themodeltrainingprocesstakeslonger.Forinstance,theDLmodelscantake more than one week to complete a training session, whereas training with ML algorithms takes relatively little time,only seconds to hours [17, 17]. During testing, deep learning algorithms take extremely little time to run [12], whencomparedtocertainmachinelearningmethods.
– *Black-box Perception and Interpretability* Interpret- ability is an important factor when comparing DL with ML. It'sdifficult to explain how a deep learning result was obtained, i.e., "black-box". On the other hand, the machine-learningalgorithms, particularly, rule-based machine learning techniques [17] provide explicit logic rules (IF-THEN) for makingdecisions that are easily interpretable for humans. For instance, in our earlier works, we have presented several machineslearning rule-based techniques [10, 12, 15], where the extracted rules are human-understandable and easier to interpret,updateordeleteaccordingtothetarget applications.

The most significant distinction between deep learning andregular machine learning is how well it performs when datagrows exponentially. An illustration of the performance comparison between DL and standard ML algorithms has beenshowninFig.3, where DL modelingcanincreasetheperformancewiththeamountofdata.Thus,DLmodelingisextremelyuseful when dealing with a large amount of data because of its capacity to process vast amounts of features to build aneffective data-driven model. In terms of develop-ing and training DL models, it relies on parallelized matrix and tensoroperations as well as computing gradients and optimization. Several, DL libraries and resources [30] suchasPyTorch [52](with a high-level API called Lightning) andTensorFlow [1] (which also offers Keras as a high-level API) offers these coreutilities including many pre-trained models,as well as many other necessary functions for implementa- tion and DL modelbuilding.

DeepLearningTechniquesandApplications

Inthissection,wegothroughthevarioustypesofdeepneuralnetworktechniques,whichtypicallyconsidersev-erallayersof information-processing stages in hierarchical structures to learn. A typical deep neural network contains multiple hiddenlayersincludinginputand outputlayers.Figure5shows ageneralstructureofadeepneuralnetwork(*hiddenlayer*=*N*and $N \geq 2$) comparing with a shallow network (*hidden layer* = 1). We also present our taxonomyon DL techniques based onhowtheyareusedtosolvevari-ousproblems,inthissection.However,beforeexploringthedetailsofthe DLtechniques,it's usefultoreviewvarioustypesoflearningtaskssuchas(i)Supervised:atask-drivenapproachthatuseslabeledtrainingdata,
(ii) Unsupervised: a data-driven process that analyzes unlabeled datasets, (iii) Semi-supervised: a hybridization of both thesupervised andunsupervised methods, and (iv) Reinforcement: an environ-ment driven approach, discussed briefly in ourearlier paper[17]. Thus, to present our taxonomy, we divide DL tech- niques broadly into three major categories: (i) deepnetworksfor supervised or discriminative learning; (ii) deep networksfor unsupervised or generative learning; and (ii) deepnet-worksforhybridlearningcombingbothandrelevantothers,asshowninFig.6.Inthefollowing,webrieflydiscusseachof these techniques that can be used to solve real-world prob-lems in various application areas according to their learningcapabilities.

DeepNetworksforSupervisedorDiscriminativeLearning

This category of DL techniques is utilized to provide a discriminative function in supervised or classification applications.Discriminative deeparchitecturesaretypicallydesignedtogivediscriminativepowerforpattern

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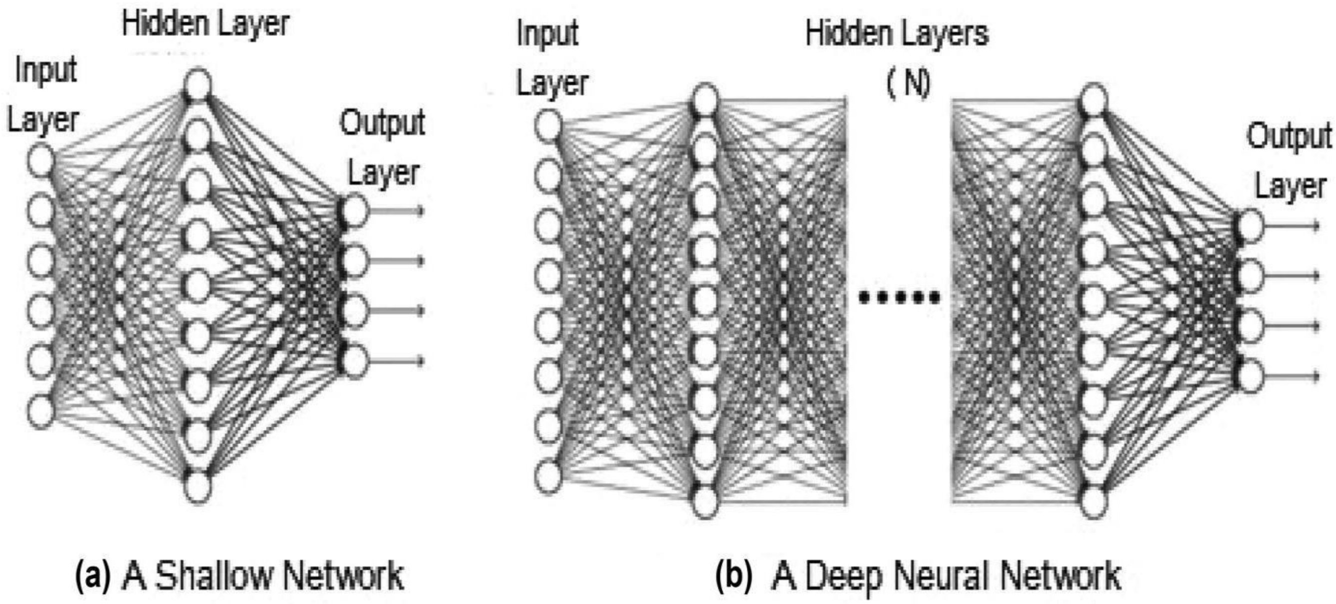

Fig.5 Ageneralarchitectureof**a**ashallownetworkwithonehiddenlayerand**b**adeepneuralnetworkwithmultiplehiddenlayers

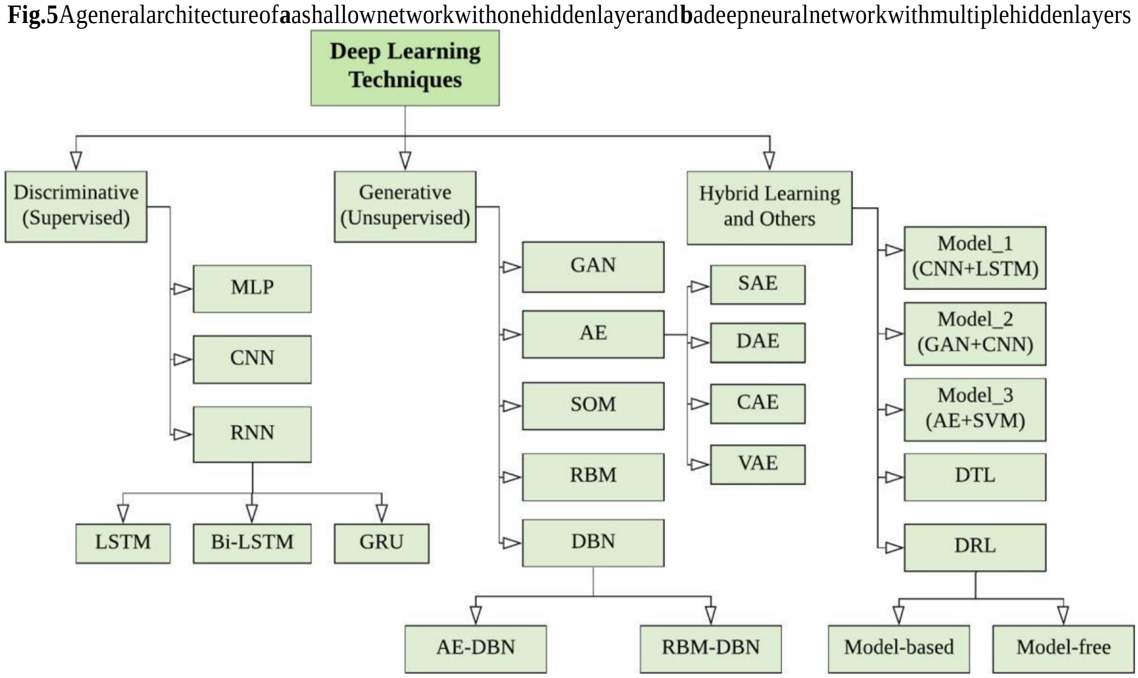

Fig.6 AtaxonomyofDLtechniques,broadlydividedintothreemajorcategories(i)deepnetworksforsupervisedordiscriminativelearning, (ii)deepnetworksforunsupervisedorgenerativelearning,and(ii)deepnetworksforhybridlearningandrelevantothers

classification by describing the posterior distributions of classes conditioned on visible data [21]. DiscriminativearchitecturesmainlyincludeMulti-LayerPerceptron(MLP),ConvolutionalNeuralNetworks(CNNorConvNet),Recur-rentNeuralNetworks(RNN),alongwiththeirvariants.Inthefollowing,webrieflydiscussthesetechniques.

Multi-layerPerceptron(MLP)

Multi-layer Perceptron (MLP), a supervised learning approach[43],isatypeoffeedforwardartificialneural network(ANN). It is also known as the foundation architecture of deep neural networks (DNN) or deep learning. Atypical MLP is afully connected network that consists ofan input layer that receives input data, an output layer that makes a decision orprediction about the input signal, and one or more hidden layers between these two that are considered as the network'scomputational engine [36, 13]. The output of an

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MLP network is determined using a variety of activation functions, alsoknown as transfer functions, suchasReLU (Rectified Linear Unit), Tanh, Sigmoid, and Soft-max [33, 46]. To train MLPemploysthemostextensively used algorithm "Backpropagation" [36], a supervised learn-ing technique, which is also known as the most basic build-ingblockofaneuralnetwork.Duringthetrainingprocess,variousoptimizationapproachessuchasStochasticGradi-entDescent(SGD), Limited Memory BFGS (L-BFGS), andAdaptive Moment Estimation (Adam) are applied. MLP requires tuning ofseveral hyperparameters such as the num- berof hiddenlayers,neurons,and iterations,whichcouldmakesolving acomplicatedmodelcomputationallyexpen-sive.However,throughpartialfit,MLPoffersadvantageoflearning non-linearmodelsinreal-time oronline [43].

ConvolutionalNeuralNetwork(CNNorConvNet)

The Convolutional Neural Network (CNN or ConvNet) [25]is a popular discriminative deep learning architecture that learnsdirectlyfromtheinputwithouttheneedforhumanfeatureextraction.Figure7showsanexampleofaCNNincludingmultipleconvolutionsandpoolinglayers.
Asaresult,theCNNenhancesthedesignoftraditionalANNlikeregularizedMLPnetworks.EachlayerinCNNtakesintoaccountoptimumparametersforameaningfuloutputaswellasreducesmodelcomplexity.CNNalsousesa'dropout'[30]thatcandealwiththeproblemofover-fitting,which mayoccurinatraditionalnetwork.
CNNs are specifically intended to deal with a variety of 2D shapes and are thus widely employed in visual recogni-tion,medical image analysis, image segmentation, natural language processing, and many more [45, 26]. The capa- bility ofautomatically discovering essential features from the input without the need for human intervention makes it more powerfulthan a traditional network. Several variants of CNN are exist in the area that includes visual geometry group (VGG) [38],AlexNet [42], Xception[17], Inception [16], ResNet [39], etc. that can be used in various applica-tion domains according totheirlearningcapabilities.

RecurrentNeuralNetwork(RNN)anditsVariants

A Recurrent Neural Network (RNN) is another popular neu-ral network, which employs sequential or time-series data andfeeds the output from the previous step as input to the current stage [27, 24]. Like feedforward and CNN, recurrentnetworkslearn from training input, however, distinguish by their "memory", which allows them to impact current inputand outputthrough using information from previous inputs.Unlike typical DNN, which assumes that inputs and outputsare independentofoneanother,theoutputofRNNisreliantonpriorelementswithinthesequence.However,standardrecurrentnetworkshavetheissueofvanishinggradients,whichmakeslearninglongdatasequenceschallenging.Inthefollowing,wediscussseveralpopularvariantsoftherecurrentnetworkthatminimizestheissuesandperformwellinmanyreal-worldapplicationdomains.

– *Long short-term memory (LSTM)* This is a popular formof RNN architecture that uses special units to deal with thevanishinggradientproblem,whichwasintroducedbyHochreiteretal.[42].Amemorycell inanLSTMunitcanstoredataforlongperiodsandtheflowofinforma- tionintoandout ofthecellismanagedbythreegates.Forinstance,the'ForgetGate'determineswhatinforma-tionfromthepreviousstatecellwillbememorizedand whatinformationwillberemovedthat is no longer use- ful, while the 'Input Gate' determines which informationshould enter the cell state and the 'OutputGate' deter- mines and controls the outputs.As itsolvestheissuesof training a recurrent network, the LSTM networkis consideredoneofthemostsuccessfulRNN.
– *BidirectionalRNN/LSTM*BidirectionalRNNsconnecttwohiddenlayersthatruninoppositedirectionstoasingleoutput,allowing them to accept data from both the past and future. Bidirectional RNNs, unlike tradi- tional recurrent networks,are trained to predict both positive and negative time directions at the same time.A BidirectionalLSTM,often knownas a BiLSTM, isan extension of the standard LSTM that can increase model performance on sequence classificationissues[13]. It is a sequence processing model comprising of two LSTMs: one takes the input forward and the other takesitbackward. BidirectionalLSTMinparticularisapopularchoiceinnaturallanguage processingtasks.
Gated recurrent units (GRUs) A Gated Recurrent Unit (GRU) is another popular variant of the recurrent net- work thatuses gating methods to control and manage information flow between cells in the neural network, introduced by Cho etal.[16].TheGRUislikeanLSTM,however,hasfewerparameters,asithasareset gateand an update gate but lacks the output gate, as shown in Fig. 8. Thus, the key difference between a GRU and an LSTM is that aGRU has two gates (reset and update gates) whereas an LSTM has three gates (namely input, output and forget gates). TheGRU's structure enablesit to capture dependencies from large sequences of data in an adaptive manner, without discardinginformation from earlier parts of the sequence. Thus GRU is a slightlymore streamlined variant that often offers comparableperformance and is significantly faster to compute [18]. Although GRUs have been shown to exhibit better per- formance oncertainsmallerandlessfrequentdatasets [18,34],bothvariantsofRNNhaveproventheireffec-tivenesswhileproducingtheoutcome.
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Fig. 7 An example ofa convo-lutional neural network (CNNor ConvNet)includingmultipleconvolutionandpoolinglayers

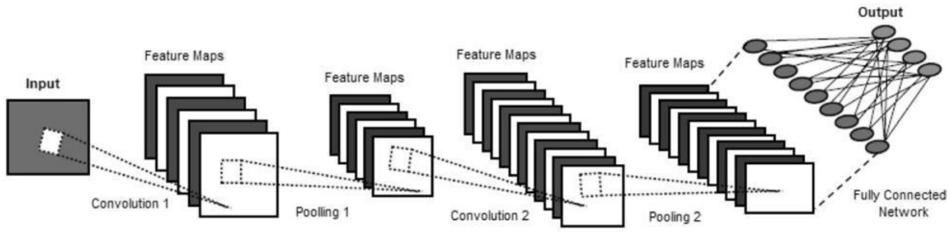
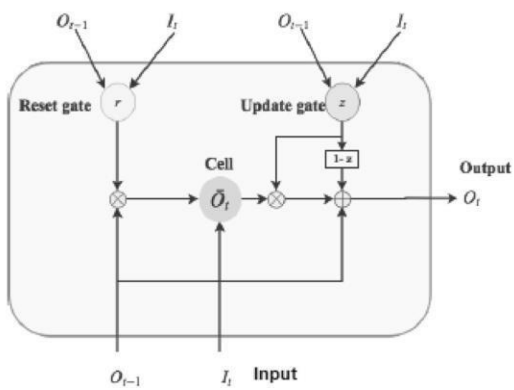


Fig. 8 Basic structure of agated recurrentunit(GRU) cell consistingof reset and updategate



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Overall,thebasicpropertyofarecurrentnetworkisthatithasatleast onefeedbackconnection,whichenablesacti-vationsto loop.This allows the networks to do temporal processing and sequence learning, such as sequence recogni- tion orreproduction,temporalassociationorprediction,etc.Followingaresomepopularapplicationareasofrecurrentnetworkssuchas prediction problems, machine translation,natural language processing, text summarization, speech recognition, and manymore.

DeepNetworksforGenerativeorUnsupervisedLearning

This category of DL techniques is typically used to charac-terize the high-order correlation properties or features for patternanalysis or synthesis, as well as the joint statistical distributions of the visible data and their associated classes [21]. The keyidea of generative deep architectures is that during the learning process, precise supervisory information such as target classlabels is not of concern. As a result,the methods under this category are essentially applied for unsupervised learning as themethods are typically used forfeature learning or data generating and representation [20, 21]. Thus generative modeling canbeusedaspreprocessingforthesupervisedlearningtasksaswell,whichensuresthediscriminativemodelaccuracy.Commonlyused deep neuralnetwork techniques for unsupervised or generative learningare Generative Adversarial Network (GAN),Autoencoder(AE),RestrictedBoltzmannMachine(RBM),Self-Organ-izingMap(SOM),andDeepBeliefNetwork(DBN)alongwiththeirvariants.

HybridDeepNeuralNetworks

Generative models are adaptable, with the capacity to learnfrom both labeled and unlabeled data. Discriminative mod-els, onthe other hand, are unable to learn from unlabeleddata yet outperform their generative counterparts in super-vised tasks. Aframework for training both deep generativeand discriminative models simultaneously can enjoy thebenefits of both models,which motivates hybrid networks. Hybrid deep learning models are typically composed of multiple (two or more) deep basiclearning models, wherethe basic model is a discriminative or generative deep learn-ing model discussed earlier. Based on theintegration of dif-ferent basic generative or discriminative models, the belowthree categories of hybrid deep learning modelsmightbeusefulforsolvingreal-worldproblems.Theseareasfollows:

– *HybridModel*_1:Anintegrationofdifferentgenerativeordiscriminativemodelstoextractmoremeaningfulandrobustfeatures. ExamplescouldbeCNN+LSTM,AE+GAN,andsoon.
– *HybridModel*_2:Anintegrationofgenerativemodelfollowedbyadiscriminativemodel.ExamplescouldbeDBN+MLP,GAN+CNN,AE+CNN,andsoon.
– *HybridModel*_3:Anintegrationofgenerativeordiscrim-inativemodelfollowedbyanon-deeplearningclassifier.ExamplescouldbeAE+SVM,CNN+SVM,andsoon.

Thus, in a broad sense, we can conclude that hybrid mod- els can be either classification-focused or non-classificationdepending onthe targetuse.However, mostof the hybridlearning-relatedstudiesinthe area of deeplearning areclassification-focused or supervised learning tasks, sum- marized in Table 1. The unsupervised generative models withmeaningfulrepresentationsareemployed toenhancethediscriminativemodels.The generativemodelswithuse-fulrepresentationcanprovidemoreinformativeandlow-dimensionalfeaturesfordiscrimination,andtheycanalso enabletoenhancethetrainingdataqualityandquantity,providingadditionalinformation forclassification.

DeepTransferLearning(DTL)

Transfer Learning is a technique for effectively using previ- ously learned model knowledge to solve a new task withminimum training or fine-tuning. In comparison to typical machine learning techniques [27], DL takes a large amountoftrainingdata.Asaresult,theneed for asubstantialvol- umeoflabeled dataisasignificantbarrier toaddress someessentialdomain-specifictasks,particularly,inthemedicalsector,wherecreatinglarge-scale,high-qualityannotatedmedicalorhealthdatasetsisbothdifficult andcostly.Fur-thermore,thestandardDLmodeldemandsalotofcomputa-tionalresources,suchasaGPU-enabledserver,eventhoughresearchersareworkinghardtoimproveit.Asaresult,DeepTransferLearning(DTL),aDL-basedtransferlearningmethod,might behelpfultoaddressthisissue. Figure11showsageneralstructureofthetransferlearning process, where knowledge from the pre-trained model is transferredinto a new DL model. It’s especially popular indeeplearningrightnowsinceitallowstotraindeepneuralnetworkswithverylittledata[26].
Transferlearningisatwo-stageapproachfortraininga
DL model that consists of a pre-training step and a fine- tuning step in which the model is trained on the target task.Sincedeep neural networks have gained popularity in a vari-ety of fields, a large number of DTL methods have been pre-sented,makingitcrucialtocategorizeandsummarizethem.Basedonthetechniquesusedintheliterature,DTLcanbeclassifiedintofour categories [117]. These are (i) instances- based deep transfer learning that utilizes instances in sourcedomainbyappropriate weight, (ii) mapping-based deeptransfer learning that maps instances from two domains intoa new data spacewith better similarity, (iii)

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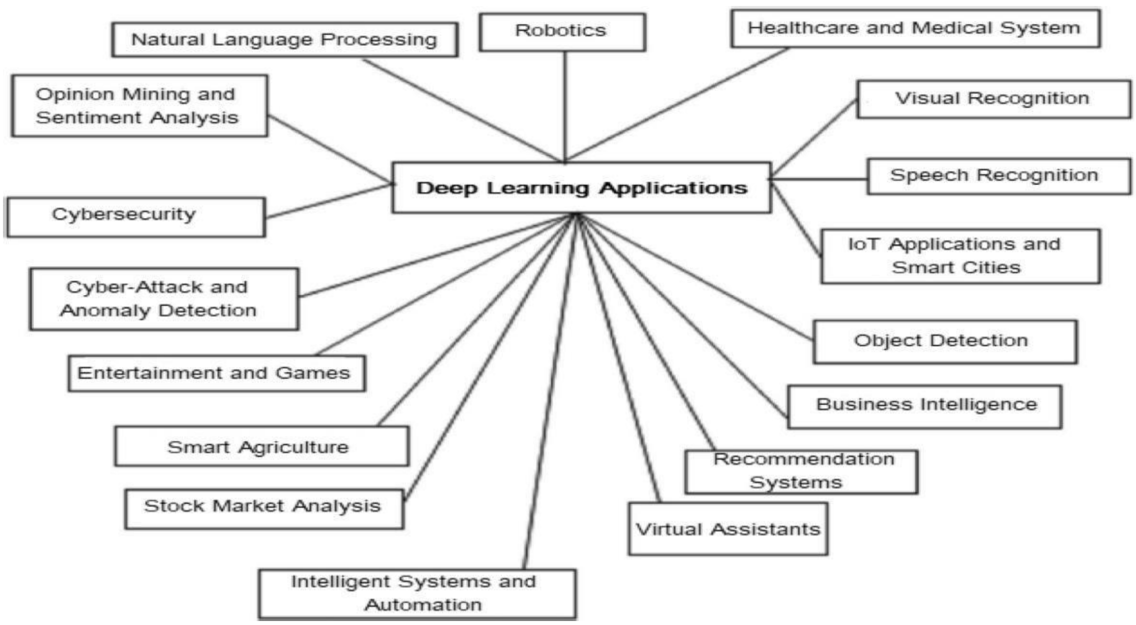
network-based deep transfer learning that reuses the partial of network pre-trained in the sourcedomain, and (iv) adversarial based deeptransfer learning that uses adversarial technology to find transferable features thatboth suitable for two domains. Dueto its high effectiveness and practicality, adversarial-based deep transfer learning hasexploded in popularity in recent years. Transfer learning can also be classified into inductive,transductive, and unsupervisedtransfer learning depending on the circumstances between the source and target domainsand activities [21]. While mostcurrent research focuses on supervised learning, how deep neural networks can transferknowledge in unsupervised or semi-supervised learning maygain further interest in the future. DTL techniques are usefulin a variety of fields including naturallanguageprocessing,sentimentclassification,visualrecognition,speechrecogni-tion,spamfiltering,andrelevantothers.



Severalpotentialreal-worldapplicationareasofdeeplearning

Table1 Asummaryofdeeplearningtasksandmethodsinseveralpopularreal-worldapplicationsareas

Applicationareas	Tasks	Methods	References
HealthcareandMedicalapplications	Regularhealthfactorsanalysis	CNN-based	Ismailetal.[48]
	Identifying maliciousbehaviorsheart disease riskpredictionCancerclassification	RNN-basedAutoencoder basedTransferlearningbased	Xue et al.[29] CoronaryAmarbayasgalanetal.[6]Sevakula et al.[10]
	DiagnosisofCOVID-19	CNNandBiLSTMbased	Aslanetal.[10]
	DetectionofCOVID-19	CNN-LSTMbased	Islametal.[47]
NaturalLanguageProcessing	Textsummarization	Auto-encoderbased	Yousefiet al.[30]
	Sentimentanalysis	CNN-LSTMbased	Wangetal.[10]
	Sentimentanalysis	CNNandBi-LSTMbased	Minaeeetal.
[78]Aspect-levelsentimentclassification		Attention-basedLSTM	Wangetal.[14]
Speechrecognition	Distantspeechrecognition	Attention-basedLSTM	Zhangetal.[15]
	Speech emotion classificationEmotionrecognitionfrom speech	TransferlearningbasedCNN andLSTMbased	Latif et al.[63]Sattetal.[19]

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Cybersecurity	Zero-day malware detectionSecurityincidentsandfraudanalysisAndroidmalwaredetection	AutoencodersandGANbasedSOM-based AutoencoderandCNNbased	Kim et al. [54]Lopezetal.[70]Wangetal.[12]
	intrusiondetectionclassification	DBN-based	Weietal.[15]
	DoSattackdetection	RBM-based	Imamverdiyevetal.[46]
	Suspiciousflowdetection	Hybriddeep-learning-based	Gargetal.[29]
andSmartcities	NetworkintrusiondetectionSmartenergymanagement	AEandSVMbased CNNandAttentionmechanism	Al et al. [4] IoTAbdeletal.[2]
	ParticulatematterforecastingSmartparkingsystem	CNN-LSTM basedCNN-LSTMbased	Huang et al. [43]Picciallietal.[85]
	Disastermanagement	DNN-based	Aqibetal.[8]
	Airqualityprediction	LSTM-RNNbased	Koketal.[61]
Cybersecurityinsmartcities agricultureIoTsystem	RBM, DBN, RNN, CNN, GAN RL-based	Chen et al. [15]SmartAgriculture Buetal.[11]	Asmart
Plantdiseasedetection		CNN-based	Aleetal.[5]
Automatedsoilqualityevaluation	DNN-based Predictingcustomers'purchasebehavior	Sumathietal.[15]BusinessandFinancial DNNbased	Services Chaudhuri[14]
Stocktrendprediction al.[7]Financialloandefaultprediction		CNNandLSTMbased CNN-based	anuradha et Dengetal.[23]
Powerconsumptionforecasting	LSTM-based Anintelligentchatbot	Shao et al. [12]VirtualAssistantandChatbotServices Bi-RNNandAttentionmodel	Dhyanietal.[24]
Virtuallisteneragent		GRUandLSTMbased	Huangetal.[44]
Smartblindassistant	CNN-based ObjectdetectioninX-rayimages	Rahmanetal.[88]ObjectDetectionandRecognition CNN-based	Guetal. [35]
Objectdetectionfordisasterresponse Medicinerecognitionsystem		CNN-based CNN-based Changetal.[12]FacerecognitioninIoT-	Pietal.[84]
cloudenviron-ment			

ResearchDirectionsandFutureAspects

While existing methods have established a solid foundationfordeeplearningsystemsandresearch,thissection outlinesthe below ten potential future research directions based onourstudy.

– *AutomationinDataAnnotation*Accordingtotheexistingliterature,discussedinSection3,mostofthedeeplearn-ingmodelsaretrainedthroughpubliclyavailabledatasetsthatareannotated.However,tobuildasystemforanewproblem domain or recent data-driven system, raw datafromrelevantsourcesareneededtocollect.Thus,data annotation, e.g., categorization, tagging, or labeling of alarge amount of raw data, is important for building dis-criminative deep learning models or supervised tasks,which is challenging. A technique with the capability ofautomaticanddynamicdataannotation,ratherthanman-ualannotationorhiringannotators,particularly,forlargedatasets, could be more effective for supervised learningas well as minimizing human effort. Therefore, a morein-depth investigation of data collection and annotationmethods, or designing an unsupervised learning-basedsolution could be one of the primary research directionsintheareaofdeeplearningmodeling.
*DataPreparationforEnsuringDataQuality*Asdis-cussed earlier throughout the paper, the deep learningalgorithmshighlyimpactdataquality, andavailabilityfortraining, and consequently on the resultant model for aparticular problem domain. Thus, deep learning modelsmay become worthless or yield decreased accuracy if thedataisbad,suchasdatasparsity,non-representative,poor-quality,ambiguousvalues,noise,dataimbalance,irrelevant features, data inconsistency, insufficient quan-tity,and so onfortraining. Consequently,such issuesin data can lead to poor processing and

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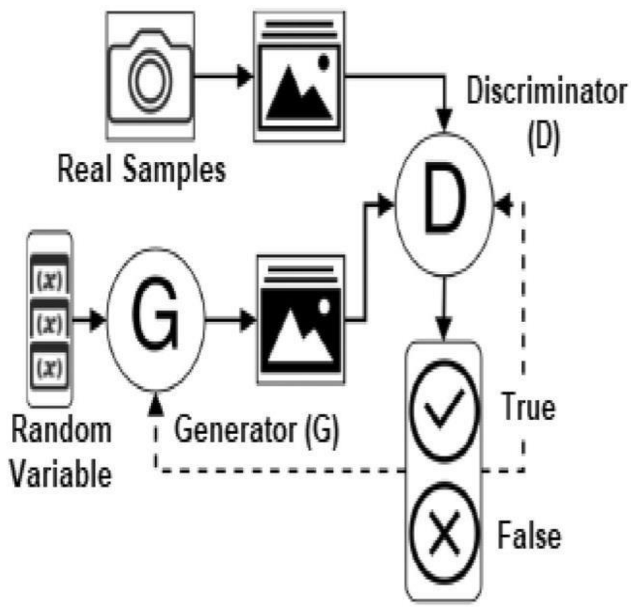
inaccurate findings,whichisamajorproblemwhilediscoveringinsightsfrom data. Thus deep learning models also need to adaptto such rising issues in data, to capture approximatedinformation from observations. Therefore, effective datapre-processing techniques are needed to design accord-ing to the nature of the data problem and characteristics,to handling such emerging challenges, which could beanotherresearchdirectioninthearea.

– *Black-boxPerceptionandProperDL/MLAlgorithmSelection* In general, it's difficult to explain how a deeplearning result is obtained or how they get the ultimatedecisions for a particular model. Although DL modelsachievesignificantperformancewhilelearningfromlargedatasets,asdiscussedinSection2,this"black-box"perceptionofDLmodelingtypically representsweakstatisticalinterpretabilitythatcouldbeamajorissuein thearea.Ontheotherhand,MLalgorithms,particularly,rule-based machine learning techniques provide explicitlogicrules (IF-THEN) for making decisions that are eas-ier tointerpret,updateordeleteaccordingtothetargetapplications [97, 100, 105]. If the wrong learning algo-rithmischosen,unanticipatedresultsmayoccur,result-ingina lossofeffortaswellasthemodel'sefficacyandaccuracy. Thus by taking into account the performance,complexity, model accuracy, and applicability, selectingan appropriate model for the target application is chal-lenging,andin-depthanalysisisneededforbetterunder-standinganddecisionmaking



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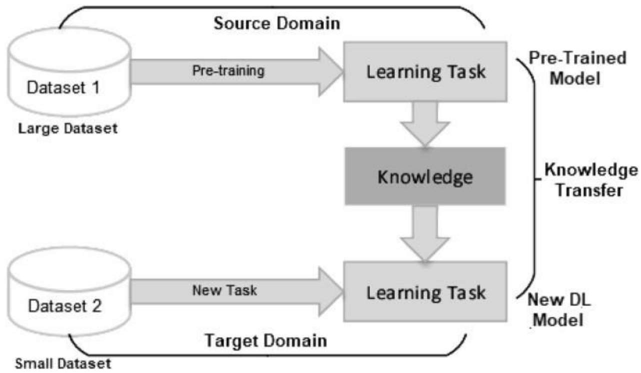

– *DeepNetworksforSupervisedorDiscriminativeLearn-ing:* According to our designed taxonomy of deep learn-ing techniques, as shown in Fig. 6, discriminative archi-tectures mainly include MLP, CNN, and RNN, alongwith their variants that are applied widely in variousapplication domains. However, designing new techniquesortheirvariantsofsuchdiscriminativetechniquesbytak-ingintoaccountmodeloptimization,accuracy,andappli-cability, according to the target real-world applicationandthenatureofthedata, couldbe anovelcontribution,which can also be considered as a major future aspect intheareaofsupervisedordiscriminative learning.

– *Deep Networks for Unsupervised or Generative Learn-ing*As discussed in Section 3, unsupervised learning orgenerative deep learning modeling is one of the majortasksinthearea,asitallowsustocharacterizethehigh-ordercorrelationpropertiesorfeaturesindata,orgeneratinganewrepresentationofdatathroughexplor-atory analysis.Moreover, unlike supervisedlearning[97], it does not require labeled data due to its capa-bility to deriveinsights directly fromthe data aswellas data-driven decision making. Consequently, it thuscanbe usedas preprocessing forsupervisedlearningor discriminative modeling as well as semi-supervisedlearningtasks,whichensurelearningaccuracyandmodel efficiency. According to our designed taxonomyofdeeplearningtechniques,asshown in Fig.6,genera-tive techniques mainly include GAN, AE, SOM, RBM,DBN,and their variants. Thus,designing new tech-niquesortheirvariantsforaneffectivedatamodelingorrepresentationaccordingtothetargetreal-worldapplication could be a novel contribution, which canalso be considered as a major future aspect in the areaofunsupervisedorgenerativelearning.

– *Hybrid/Ensemble Modeling and Uncertainty Handling*AccordingtoourdesignedtaxonomyofDLtechniques,as shown in Fig 6, this is considered as another majorcategory in deep learning tasks. As hybrid modelingenjoysthebenefitsofbothgenerativeanddiscrimina-movestorecentdeeplearningtechniquesandbreakthroughsin different applications. Then, the key algorithms in thisarea, as well as deep neural network modeling in variousdimensions are explored. For this, we have also presented ataxonomy considering the variations of deep learning tasksandhowtheyareusedfordifferentpurposes. Inourcompre-hensivestudy,wehavetakenintoaccountnotonlythedeepnetworksforsupervisedordiscriminativelearningbutalso tive learning, an effective hybridization can outperformothers in terms of performance as well as uncertaintyhandling in high-risk applications. In Section 3, we havesummarizedvarioustypesofhybridization,e.g.,AE+CNN/SVM. Since a group of neural networks istrained with distinct parameters or with separate sub-sampling training datasets, hybridization or ensem- blesof such techniques, i.e., DLwithDL/ML,can play akey role in the area. Thus designing effective blendeddiscriminativeandgenerativemodelsaccord-inglyratherthannaivemethod,couldbeanimportantresearchopportunity to solve various real-world issues includingsemi-supervisedlearningtasksandmodeluncertainty.

– *DynamisminSelectingThreshold/Hyper-parameters Values,andNetworkStructureswithComputationalEffi-ciency*In general, the relationship among performance,model complexity, and computational requirements is akey issue in deep learning modeling and applications. Acombination of algorithmic advancements with improvedaccuracyaswellasmaintainingcomputationalefficiency,i.e., achieving the maximum throughput while consum-ing the least amount of resources, without significantinformationloss,canleadtoabreakthroughin theeffec-tiveness of deep learning modeling in future real-worldapplications. The concept of incremental approaches orrecency-based learning [100] might be effective in sev-eralcasesdependingonthenatureoftargetapplications.Moreover, assuming the network structures with a staticnumber of nodes and layers, hyper-parameters values orthreshold settings, or selecting them by the trial-and-error process may not be effective in many cases, as itcan be changed due to the changes in data. Thus, a data-driven approach to select them dynamically

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could bemore effective while building a deep learning model interms of both performance and real-world applicability.Such type of data-driven automation can lead to futuregeneration deep learning modeling with additional intel- ligence,whichcouldbeasignificantfutureaspect

ConcludingRemarks

In this article, we have presented a structured and compre-hensive view of deep learning technology, which is consid-ered a core part of artificial intelligence as well as data sci-ence.Itstartswithahistoryofartificialneuralnetworksand the deep networks for unsupervised or generative learning,andhybridlearningthatcanbeusedtosolveavarietyofreal-worldissuesaccordingtothenature ofproblems.

Deep learning, unlike traditional machine learning anddata mining algorithms, can produce extremely high-leveldatarepresentationsfromenormousamountsofrawdata.Asaresult, it has provided an excellent solution to a variety ofreal-world problems. A successful deep learning techniquemustpossesstherelevantdata-drivenmodelingdependingon the characteristics of raw data. The sophisticated learn- ingalgorithmsthenneedtobetrainedthroughthecollecteddataand knowledge related to the target application before thesystem can assist with intelligent decision-making. Deeplearning has shown to be useful in a wide range of applica-tionsandresearch areassuchashealthcare,sentimentanaly-sis, visual recognition, business intelligence, cybersecurity,andmanymorethataresummarizedinthepaper.

Finally, we have summarized and discussed the chal- lengesfacedandthepotentialresearchdirections,andfutureaspectsinthearea.Althoughdeeplearningisconsidered a black-box solution for many applications due to its poorreasoning and interpretability, addressing the challenges orfuture aspects that are identified could lead to future genera-tion deep learning modeling and smarter systems. This canalso help the researchers for in-depth analysis to producemorereliableandrealisticoutcomes.Overall,webelievethatourstudyonneuralnetworksanddeeplearning-basedadvancedanalyticspointsinapromisingpathandcanbeuti-lized as a reference guide for future research and implemen- tationsinrelevantapplicationdomainsbybothacademicandindustryprofessionals.

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