

A TECHNICAL SURVEY ON IDENTIFICATION AND DIAGNOSIS OF DISEASES USING DEEP LEARNING

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ABSTRACT

This article provides a comprehensive review of recent developments in deep learning, including both its theoretical underpinnings and its innovative practical applications. This article provides a historical overview of the significant uses of deep learning algorithms. Comparing the deep learning approach with more traditional algorithms, this article highlights the method's advantages and benefits. This includes the deep learning approach's layer-based hierarchy and nonlinear operations. The state-of-the-art review also gives a high-level explanation of deep learning's advantages and growth in popularity. With deep learning, meaningful hierarchical linkages within the data can be discovered algorithmically without the need for painstaking hand-crafting of features, which is especially useful in the era of medical big data. We discuss the state-of-the-art in medical picture segmentation, localization, detection, and registration, as well as its most important applications.

KEYWORDS: Artificial intelligence, Convolutional neural network (CNN), Deep learning,

1. INTRODUCTION

1.1 The Evolution of Deep Learning

It may come as a surprise to learn that Deep Learning has actually been there since the 1940s, when it was first introduced, yet most of us associate it with the 21st century. Most of us don't know about the Deep Learning research and development that took place in the 20th century because the methods employed at the time were not widely adopted due to their many flaws and because the field has been renamed several times since then. To do groundbreaking original research in any discipline, one must first be familiar with the background, development, and seminal contributions that have contributed to the field's current prominence.

1.2 Deep Learning

The third wave appeared in 2006, breaking through the previous two slumps. In order to educate Deep Belief Networks, Geoffrey Hinton adopted the strategy of Greedy Layer-wise Training. The simplest version of a DBN is a collection of hidden layers, each of which may contain a different set of latent variables. Layers are connected, but the variables within each layer are not. DBN is often referred to as constrained Boltzmann machines when referring to their simplest implementation. In the fields of learning models represent a novel learning paradigm.

1.2.1 Applications of Deep Learning

Abstract layer analysis and hierarchical approaches are prerequisites for deep learning. It has a wide variety of practical uses, though. To simplify, deep learning can be thought of as a technique for enhancing the quality of outcomes and minimising the time spent on various computations. Pure digital image processing, healthcare, and biometrics are the following fields of use.

1.2.2 Deep Learning Methods

Classic Neural Networks

Multilayer perceptrons, in which neurons are connected to the continuous layer, are a defining feature of the Classical Neural Network, also known as Fully Connected Neural Networks. In 1958, American psychologist Fran Rosenblatt created it. A key part of this process is translating the model into basic binary data. The three components of this model are:

Convolutional Neural Networks

The Convolutional Neural Network (CNN) is a modern and promising variant of the traditional ANN model. It was designed to deal with complicated problems, perform preliminary processing, and aggregate data. In this case, the visual cortex of an animal's brain serves as a model for the arrangement of neurons. It is through the convolution process that feature maps are derived from the input data and then a function is applied to these maps.

Recurrent Neural Networks

For instance, the RNNs like the popular Long Short-Term Memory (LSTM) method were initially developed to aid with sequence prediction. These networks rely solely on input data sequences of varying lengths to function. The RNN uses the information it has gleaned from its prior states as an input value for the prediction being made right now. As a result, it can aid in the development of networked short-term memory.

Deep Reinforcement Learning

Autoencoders

This form of deep learning model is one of the most popular since it can run autonomously based on its inputs, then take an activation function and finally decode its output. The establishment of a bottleneck in this way results in the production of fewer data categories and the use of most of the data structures that are already there.

The Types of Autoencoders are:

- **Contractive** – In the event that the sum of hidden layers exceeds the number of input layers, the loss function is modified by adding a penalty factor to prevent overfitting and data duplication.

2.LITERATURE SURVEY

2.1 An Robotic Hyperparameter Search-Based DL for Highway Traffic Forecast ^[1]

The purpose of this study is to introduce a method for automating hyperparameter tweaking to speed up the process of learning traffic datasets in an ecosystem. We employ the HyperNet framework to conduct a fully automated search for optimal hyperparameter values. For this reason, a LSTM based deep learning model built on the HyperNet framework has been introduced for studying the temporal datasets in key areas of highway traffic schemes.

2.2 Lung and Pancreatic Tumor Characterization in the DL Era:

Novel Supervised and Unsupervised Learning Methods ^[2]

Two machine learning approaches, one supervised and one unsupervised, are proposed in this study to better characterise tumours. In the first method, we use a graph-regularized sparse presentations into a CAD system by means of a 3D Convolutional Neural Network and Transfer Learning.

2.3 Anomaly Discovery of Industrial Control Schemes Based on Transfer Learning ^[3]

With a little tweaking to the current residual CNN structure with the help of transfer learning, even previously undisclosed assaults will be uncovered. In order to take use of all that CNN has to offer, we first transform the 1-D ICS flow data into the two-dimensional grayscale pictures that CNN prefers.

2.4 Inference of Brain with Meta Learning Based Deep Learning Models ^[4]

In order to categorise brain states when under anaesthetics, this article relies on a deep neural network model (called nes-MetaNet). The Anes-MetaNet combines a Convolutional Neural Network (CNN) for extracting power spectral characteristics, a time importance model based on (LSTM) networks.

2.5 Deep learning for organization and localization of COVID-19 indicators in point-of-care lung ultrasound ^[5]

In this study, we present a new deep network, inspired by Networks, capable of weakly-supervised localisation of pathological artefacts and prediction of the illness severity score associated with an input frame. At long last, a comparison of the best deep models available for predicting segmentations at the pixel level.

2.6 Intelligent and Adaptive Web Data Extraction System Using Convolutional and LSTM Deep Learning Networks^[6]

In order to automate web page recognition with the Tesseract LSTM, this research looks at an intelligent and adaptable web data extraction system with convolutional (LSTM) networks. This cutting-edge solution can effortlessly adjust to each new iteration of a website's design because it doesn't rely on a central data extraction engine.

2.7 Ophthalmic Disease Detection via Deep Learning with A Fresh Mixture Loss Function^[7]

A deep learning network is used with a novel mixed loss function to automatically identify eye diseases by analysing retinal fundus colour pictures. Due to the good generalisation and robustness of these two losses in dealing with complex datasets with data. The effectiveness of this strategy is tested using an actual ophthalmology dataset.

2.8 Deep Multiview Learning for Hyperspectral Image Classification^[8]

To address the limited data available for HSI, we present a deep multi view learning approach. After performing principal component analysis to distinct frequency ranges, two distinct perspectives on an HSI scene are created. Second, in order to map the many perspectives of a sample onto a latent space. In order to quantify efficacy, we conduct extensive tests on four popular hyperspectral data sets.

2.9 ISAR Autofocus Imaging Procedure for Maneuvering Targets based on Transform^[9]

With the use of the keystone transform and a deep learning method, this study details an ISAR imaging technique. Coarsely correcting for the target's motion using the keystone transform paves the way for the deep learning method to produce a super-resolution image. During training, a u-net network is fed a collection of data consisting

2.10 A Model-Driven Deep Dehazing Tactic by Knowledge Deep Priors^[10]

In this work, we develop a haze-related image prior-regularized energy model for single-image dehazing that is constrained by physical constraints in both the colour image space and the haze-related feature space. The priors are then converted into their proximal operators, and an iterative optimization technique is developed to solve the suggested dehazing energy model.

2.11 Weak Human Preference Supervision for Deep Reinforcement learning^[11]

We recognized a human-demonstration estimator via supervised knowledge to generate the predicted preferences in order to reduce we developed a human preference scaling model. The suggested weak human preference supervision system outperforms the single fixed human preference in solving difficult RL tasks and accumulating rewards in MuJoCo games, which are simulations of robot locomotion.

2.12 A New Malware Classification Outline Based on DL Algorithms^[12]

We present a novel deep-learning-based architecture for malware classification that uses a hybrid model. The primary result of this research is a proposed hybrid architecture for optimally combining two different types of pre-trained network models. This framework has training the network, and then assessing its performance. We put the suggested technique through its paces on the Maling, Microsoft BIG 2015, and Malevis datasets.

2.13 Clustering-Based Dual Deep Learning Red Blood Cells in Malaria Analytic Smears^[13]

To this end, we propose RBCNet, a novel pipeline that employs a dual deep learning. U-Net is used in the first stage of RBCNet for cell-cluster or superpixel segmentation, and then Faster R-CNN is used in the second stage to detect tiny cell objects inside the linked component clusters. Instead of employing region suggestions, RBCNet trains on non-overlapping tiles and adapts to the size of cell-clusters.

2.14 Collaborative Robots Human-Centered with Deep Reinforcement Knowledge^[14]

Proactively lowering the overall time needed to complete the activity, the framework strikes a balance between the advantages of timely activities and the risk of performing inappropriate ones.

An unsupervised learning approach is used to learn the entire process from start to finish, including consideration of perceptual doubts and the making of choices. When using supervised learning.

2.15 Weakly Supervised Deep Learning for Entire Slide Lung Cancer Image Analysis^[15]

This paper introduces a semi-supervised method for efficiently classifying lung cancer images from whole slides. We first employ a fully convolutional network (FCN) based on patches to quickly recover discriminative blocks and supply representative deep features.

2.16 A Deep Learning Outline for Assessing Physical Reintegration Exercises^[16]

Because of this, we offer a deep learning-based paradigm for the impartial assessment of PT therapies. The key components of the system include measures for assessing the performance of movements, scoring functions for translating

2.17 Step-wise DL Replicas for Solving Routing Problems^[17]

A novel step-by-step plan in which the nodes that have already been visited are omitted from the selection process. We implement this strategy into two widely-used deep models for routing problems—the Pointer Network (PtrNet) and the Transformer Attention Model (TAM)—and see substantial gains in performance compared to the baseline

2.18 CleftNet: Augmented DL for Synaptic Cleft Discovery from Brain Electron Microscopy^[18]

To begin with, we propose labels to enhance cleft representations. The feature augmentor may learn common morphological patterns in clefts and combine global information from inputs to provide enhanced cleft characteristics.

2.19 Deep Air Quality Forecasting Using Hybrid Deep Learning Framework^[19]

This paper presents a novel deep learning model for air quality (mainly PM_{2.5}) forecasting, which learns the spatial-temporal correlation features and interdependence of multivariate air quality related time series data by hybrid deep learning architecture. Due to the nonlinear and dynamic characteristics of multivariate air quality time series data, the base modules of our model include one-dimensional Convolutional Neural Networks (1D-CNNs) and Bi-directional Long Short-term Memory networks (Bi-LSTM). The former is to extract the local trend features and spatial correlation features, and the latter is to learn spatial-temporal dependencies.

2.20 Crop Yield Forecast Using DL Model for Sustainable Agrarian Requests^[20]

To make accurate predictions about harvest production, the authors of the present study build a Deep Recurrent Q-Network model, which is a algorithm.

3.COMPARATIVE ANALYSIS

The deep convolution network, used for feature isolation, and the support vector machines, used for classification, are trained independently. Feature extraction and classification have been merged into a single framework in the rapid R- CNN technique [13]. Fast R-CNN is nine times quicker throughout the training process compared to R-CNN.

Table 3.1 Comparative Analysis

S. No.	Paper title	Year	Algorithm and Technique	Tools	Parameter Analysis	Future scope
1	A Deep Learning Perfect for Highway Traffic Forecasting Based on Automated Hyperparameter Search [1]	2020	<ul style="list-style-type: none"> Sequential Model-Based Optimization M-SMBO Bayesian optimization and meta-learning 	Stacked Autoencoder	<ul style="list-style-type: none"> Learning rate, Batch size, Dropout 	Traffic forecasting by using another DL model (e.g., ConvLSTM or Graph Neural Networks)
2	Using Deep Learning to Better Classify Lung and Pancreatic Tumors: Emerging Supervised and Unsupervised Learning Techniques [2]	2019	<ul style="list-style-type: none"> K-means algorithm 3D CNN based graph Regularized sparse MTL 	CAD	<ul style="list-style-type: none"> Calcification Sphericity Margin Lobulation 	Clinicians can benefit greatly from activation map visualisation when trying to locate novel imaging biomarkers for diagnostic application.
3	Transfer Learning for Anomaly Detection in Industrial Control Systems [3]	2021	<ul style="list-style-type: none"> One Class Support Vector Machine (OCSVM) Transfer learning 	ImageNet and MS COCO	<ul style="list-style-type: none"> Mahalanobis Distance Precision 	Multiclassification of abnormal traffic data
4	Deep Learning Models Based on Meta-Learning for Inferring Anesthesia-Induced Brain States [4]	2022	<ul style="list-style-type: none"> Artifacts removal algorithms optimization algorithm 	Chronux Toolbox	<ul style="list-style-type: none"> EEG RASS 	Model correctness and interpretability require a comprehensive analysis of OBA EEG and HBA EEG data obtained under a variety of anaesthetics.
5	Application of deep learning to the categorization and localisation of lung ultrasonography [5]	2020	<ul style="list-style-type: none"> Spatial Transformer Networks Adam optimization 	Labelme	LUS Score	Full end-to-end training combining frame-based and video-based supervision will be investigated in future work.
6	Built on a foundation of Convolutional and LSTM Deep Learning Networks, an Intelligent and Adaptive Web Data Extraction Scheme [6]	2021	<ul style="list-style-type: none"> Clustering algorithms Semantic segmentation algorithms 	Crawlers	<ul style="list-style-type: none"> Object extraction accuracy, Character extraction accuracy 	Advancements in deep learning networks to reimagine the end-to-end automated web data extraction process
7	Ophthalmic Disease Detection via DL with A Original Mixture Loss Function [7]	2021	<ul style="list-style-type: none"> FCL-EfficientNet-B3 CNN-based transfer learning with SVM 	Adaptive Histogram Equalization	<ul style="list-style-type: none"> Accuracy, Sensitivity, Specificity, Kappa, AUC, 	Further feature extraction technologies to assist the detection of glaucoma and AMD

8	Deep Multiview Learning for Hyperspectral Image Classification ^[8]	2021	<ul style="list-style-type: none"> Minibatch Training Procedure algorithm CNN-based transfer learning with SVM 	PCA and RF Classifier	Clache, Contrastive loss	Construct more views to further improve classification performance
9	ISAR for maneuvering targets based on DL and keystone transform ^[9]	2020	<ul style="list-style-type: none"> Motion compensation algorithms FFT algorithm 	Titan Black GPU	<ul style="list-style-type: none"> ISAR signal, echo, , Transmit signal bandwidth, 	Keystone transform
10	A Model-Driven DL Approach by Learning Deep Priors ^[10]	2021	<ul style="list-style-type: none"> Iterative optimization algorithm Half-quadratic splitting algorithm Optimization algorithm 	<ul style="list-style-type: none"> SOTS NTIRE 2018 	Haze Image	Domain adaptation to better handle it.
11	Weak Human Preference Supervision for Deep Learning ^[11]	2021	<ul style="list-style-type: none"> RL algorithms Support vector regression (SVR) 	MuJoCo scenarios	<ul style="list-style-type: none"> Policy gradient strategy 	Explore the human preference scaling in concerning
12	A New Malware Classification Framework Based on DL Algorithms ^[12]	2021	<ul style="list-style-type: none"> State-of-the-art algorithms Data mining & rule-based learning techniques with hybrid approach 	<ul style="list-style-type: none"> Monitor, API Monitor, Regshot, Apat eDNS, Wirshark, Sandboxes 	Signature extraction	On order to decrease the complexity of the model, consider constructing it in the cloud.
13	Clustering-Based Dual Deep Learning Architecture for Detecting Red Blood Cells in Malaria Diagnostic Smears ^[13]	2020	<ul style="list-style-type: none"> Active contour and Watershed, Otsu's method, k-means adaptive histogram thresholding 	<ul style="list-style-type: none"> Firefly annotation tool MATLAB 	Active contours	combine cell detection pipeline with a cell classifier to differentiate between infected and uninfected cells
14	Deep Reinforcement Learning Robots That Work In Collaboration With Humans ^[14]	2021	<ul style="list-style-type: none"> Cost-based planning algorithm, Q learning algorithm CNNs and Graph convolutional networks 	<ul style="list-style-type: none"> GM, ProMPs 	Human action	Quicker transition from one execution plan to another, maybe more complicated one, and faster adaptability to new human partners,

15	For the analysis of lung cancer images on a whole slide, we use unsupervised deep learning. ^[15]	2019	<ul style="list-style-type: none"> ● K-means algorithm, ● OTSU algorithm ● CNNs and RF Classifier 	Image Net	Image-level labels	replace the RF classifier with MLP classifier to make it end-to-end
16	A DL Outline for Assessing Physical Rehabilitation Exercises ^[16]	2020	<ul style="list-style-type: none"> ● Expectation Maximization (EM) algorithm ● Dynamic Time Warping 	<ul style="list-style-type: none"> ● Ada boost classifier ● k-nearest neighbors ● Bayesian classifier 	Log-likelihood	Implement the framework for assessment of patient
17	Step-wise DL Models for Solving Routing Problems ^[17]	2020	<ul style="list-style-type: none"> ● Policy Gradient algorithm ● Reinforcement learning 	<ul style="list-style-type: none"> ● Encoder ● Decoder ● TSP 20 	Distance	Designing network architectures considering the recursive nature of sequential decision-making problems.
18	CleftNet: Augmented DL for Synaptic Cleft Discovery from Brain Electron Microscopy ^[18]	2021	<ul style="list-style-type: none"> ● Machine learning algorithm ● Deep neural networks 	NVIDIA GeForce RTX 2080 Ti GPUs	Electron Microscopy	Increase efficiency some noncleft cracks in tissues appear to be similar as clefts,
19	Deep Air Quality Forecasting Using Hybrid DL Framework ^[19]	2019	<ul style="list-style-type: none"> ● Classic shallow machine learning algorithms ● Hidden semi-Markov models 	<ul style="list-style-type: none"> ● PM2.5 ● PM10 	<ul style="list-style-type: none"> ● Humidity ● Wind speed ● SO2 	We can predict the sudden change of air pollution in advance.
20	Predicting Crop Yield with a Deep Reinforcement Learning Model for Sustainable Agricultural Applications ^[20]	2020	<ul style="list-style-type: none"> ● Machine learning algorithms ● Deep Q-Learning based DRL algorithm ● Deep reinforcement learning 	MET data tool	<ul style="list-style-type: none"> ● climatic, ● soil ● groundwater 	Pest, infestations and crop damage can be included in the current framework to construct a working model in the future

4.CONCLUSION

In this article, we will discuss the many facets of deep learning modelling, that is, the ability of DL approaches to learn and perform in a fully autonomous and intelligent fashion across a variety of domains and settings. Some of the characteristics are portrayed in the published works, I discovered. Abstraction is used to minimise the spatial complexity of feature maps. The feature maps are generated by iteratively applying filters to a dataset.

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