Deep Learning for Anomaly Detection: A Survey

DEEP LEARNING FOR ANOMALY DETECTION: A SURVEY

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Raghavendra Chalapathy
University of Sydney,
Capital Markets Co-operative Research Centre (CMCRC)
rcha9612@uni.sydney.edu.au

Sanjay Chawla
Qatar Computing Research Institute (QCRI), HBKU
schawla@qf.org.qa

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ABSTRACT

Anomaly detection is an important problem that has been well-studied within diverse research areas and application domains. The aim of this survey is two fold, firstly we present a structured and comprehensive overview of research methods in deep learning-based anomaly detection. Furthermore, we review the adoption of these methods for anomaly across various application domains and asess their effectiveness. We have grouped state-of-the-art research techniques into different categories based on the underlying assumptions and approach adopted. Within each category we outline the basic anomaly detection technique, alongwith its variants and present key assumptions, to differentiate between normal and anomalous behavior. For each category we present we also present the advantages and limitations and discuss the computational complexity of the techniques in real application domains. Finally, we outline open issues in research and challenges faced while adopting these techniques.

***K*eywords** anomalies, outlier, novelty, deep learning

1 Introduction

A common need when analysing real-world datasets is determining which instances stand out as being dissimilar to all others. Such instances are known as *anomalies*, and the goal of *anomaly detection* (also known as *outlier detection*) is to determine all such instances in a data-driven fashion [1]. Anomalies can be caused by errors in the data but sometimes are indicative of a new, previously unknown, underlying process; in fact Hawkins [2] defines an outlier as an observation that *deviates so significantly from other observations as to arouse suspicion that it was generated by a different mechanism.* In the broader field of machine learning, the recent years have witnessed proliferation of deep neural networks, with unprecedented results across various application domains. Deep learning is subset of machine learning that achieves good performance and flexibility by learning to represent the data as nested hierarchy of concepts within layers of neural network. Deep learning outperforms the traditional machine learning as the scale of data increases as illustrated in Figure 1. In recent years, deep learning-based anomaly detection algorithms has become increasingly popular and has been applied for diverse set of tasks as illustrated in Figure 2; studies have shown that deep learning completely surpasses traditional methods [3, 4].

The aim of this survey is two fold, firstly we present a structured and comprehensive review of research methods in deep anomaly detection (DAD). Furthermore, we also discuss the adoption of DAD methods across various application domains and asess their effectiveness.

2 What are anomalies ?

Anomalies are also referred to as abnormalities, discordants, deviants, or outliers in the data mining and statistics literature [9].

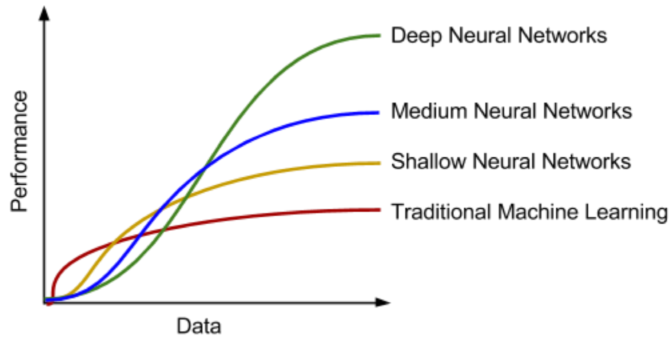
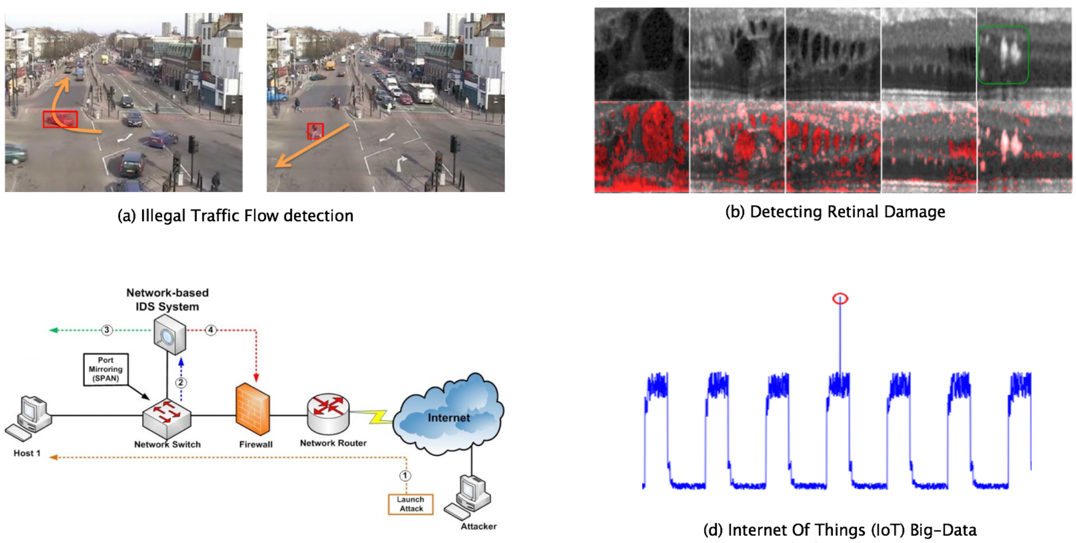


Figure 1: Performance Comparision of Deep learning-based algorithms Vs Traditional Algorithms [5].



(a) Illegal Traffic Flow detection

(b) Detecting Retinal Damage

(c) Cyber-Network Intrusion detection

(d) Internet Of Things (IoT) Big-Data Anomaly detection

Figure 2: Deep learning-based anomaly detection algorithms successfull applications.
(a) Video Survelliance, Image Analysis: Illegal Traffic detection [6] , (b) Healthcare: Detecting Retinal Damage [7] (c) Networks: Cyber-intrusion detection [3] (d) Sensor Networks: Internet of Things (IoT) big-data anomaly detection [8]

As illustrated in Figure 3, N_1 and N_2 are regions consisting of majority of observations and hence considered as normal data instance regions, whereas the region O_3, and data points O_1 and O_2 are few data points which are located further away from the bulk of data points and hence are considered anomalies. Anomalies may arise due to several reasons, such as malicious actions, system failures, intentional fraud, etc. These anomalies reveal interesting insights about the data and are often convey valuable information about data. Therefore, anomaly detection considered an essential step in various decision-making systems.

3 What are novelties ?

Novelty detection is the identification of novel (new) or unobserved patterns in the data. [10]. The novelties detected are not considered as anomalous data points; instead they are incorporated into the normal data model. A novelty score may be assigned for these previously unseen data points, using a decision threshold score. [11]. The points which significanlty deviate from this decision threshold may be deemed as anomalies or outliers. For instance in Figure 4 the images of *(white tigers)* among normal tigers may be considered as novelty, while image of *(horse, panther,lion and cheetah)* are considered as anomalies. The techniques used for anomaly detection are often used for novelty detection and vice versa.

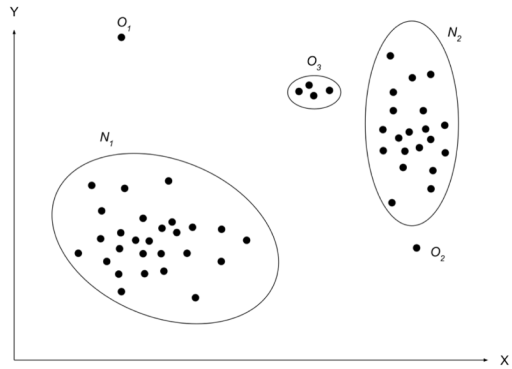


Figure 3: Illustration of anomalies in two-dimensional data set.

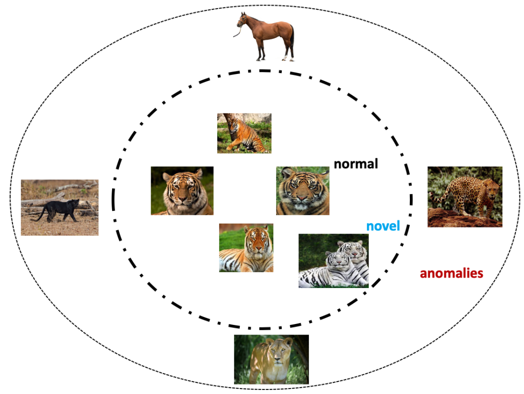


Figure 4: Illustration of novelty in image data set.

4 Motivation and Challenges: Deep anomaly detection (DAD) techniques

- Performance of traditional algorithms in detecting outliers is sub-optimal on complex image (e.g. medical images) and sequence data sets.
- Need for Large-scale anomaly detection : As the volume of data increases let's say to gigabytes then, it becomes nearly impossible for the traditional methods to scale to such large scale data to find outliers.
- Deep anomaly detection (DAD) techniques learn hierarchical discriminative features from data. This automatic feature learning capability eliminates the need of developing manual features by domain experts, therefore advocates to solve the problem end-to-end taking raw input data in domains such as text and speech recognition.
- The boundary between normal and anomalous (erroneous) behavior is often not precisely defined in several data domains and is constantly evolving. This lack of well defined representative normal boundary poses challenges for both conventional and deep learning-based algorithms.

Table 1: Comparison of our Survey to Other Related Survey Articles.
1 —Our Survey, 2 —Kwon and Donghwoon [12], 5 —John and Derek [13]
3 —Kiran and Thomas [14], 6 —Mohammadi and Al-Fuqaha [8]
4 —Adewumi and Andronicus [15] 7 —Geert and Kooi et.al [16].

		1	2	3	4	5	6	7
Methods	Supervised	✓						
	Unsupervised	✓						
	Hybrid Models	✓						
	one-Class Neural Networks	✓						
Applications	Fraud Detection	✓			✓			
	Cyber-Intrusion Detection	✓	✓					
	Medical Anomaly Detection	✓						✓
	Sensor Networks Anomaly Detection	✓				✓		
	Internet Of Things (IoT) Big-data Anomaly Detection	✓					✓	
	Log-Anomaly Detection	✓						
	Video Surveillance	✓		✓				
	Industrial Damage Detection	✓						

5 Related Work

Despite the substantial advances made by deep learning methods in many machine learning problems, there is a relative scarcity of deep learning approaches for anomaly detection. Adewumi et.al [15] provide a comprehensive survey of deep learning-based methods for fraud detection. A broad review of deep anomaly detection (DAD) techniques for cyber-intrusion detection is presented by Kwon et.al [12]. An extensive review of using DAD techniques in medical domain has been presented by Litjens et.al [16]. An overview of DAD techniques for Internet of Things (IoT) and big-data anomaly detection is introduced by Mohammadi et.al [8]. Sensor networks anomaly detection has been reviewed by Ball et.al [13]. The state-of-the-art deep learning based methods for video anomaly detection along with various categories has been presented in [14]. Although there are a number of reviews in applying DAD technqiues, there is shortage of comparative analysis of deep learning architecture adopted for outlier detection. For instance a substantial amount of research on anomaly detection is conducted using deep autoencoders, but there is lack of comprehensive survey of various deep architecture's best suited for a given data-set and application domain. We hope that this survey bridges this gap and provides a comprehensive reference for researchers and engineers aspiring to leverage deep learning for anomaly detection. Table 1 shows the set of research methods and application domains covered by our survey.

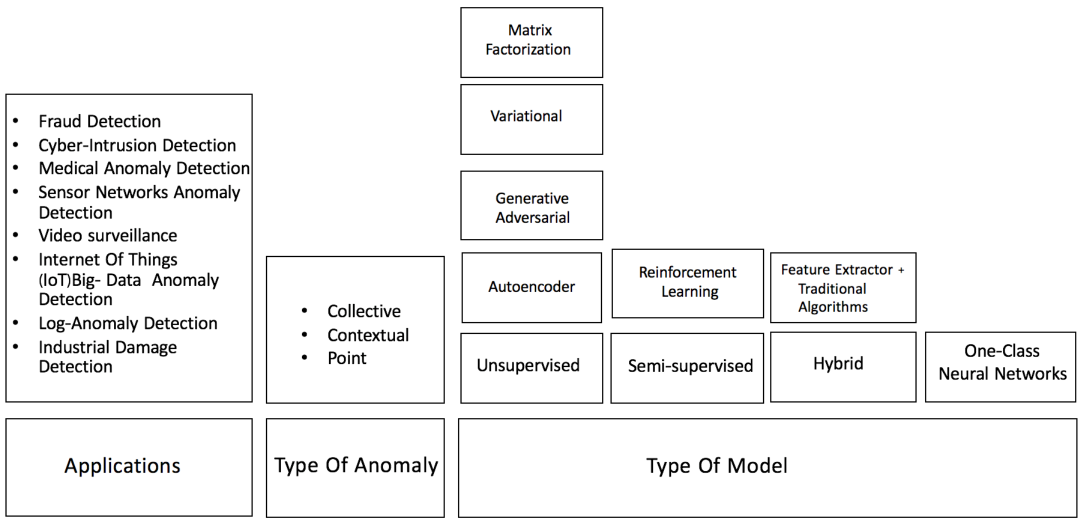


Figure 5: Key components associated with deep learning-based anomaly detection technique.

6 Our Contributions

We follow survey approach of V.Chandola and A.Banerjee et.al [1] for deep anomaly detection (DAD). Our survey presents a detailed and structured overview of research and applications of DAD techniques. We summarize our main contributions as follows:

- Most of the existing surveys on DAD techniques either focus on a particular application domain or specific research area of interest [14, 8, 16, 12, 15, 13]. This review aims to provide a comprehensive outline of state-of-the art research in DAD techniques as well as several real world applications these techniques are discussed.
- In recent years a number of new deep learning based anomaly detection techniques with greatly reduced computational requirements have been developed. The purpose of this paper is to survey these techniques and classify them into organised schema for better understanding. We introduce two more sub-categories Hybrid models [17] and one-class neural networks techniques [18] as illustrated in Figure 5 based on the choice of training objective. For each categories we discuss both the assumptions and techniques adopted for best performance. Furthermore within each category, we also present the challenges, advantages and disadvantages and provide an overview of computational complexity of DAD methods.

7 Organization

This chapter is organized by following structure described in Figure 5. In Section 8, we identify the various aspects that determine the formulation of the problem and highlight the richness and complexity associated with anomaly detection. We introduce and define two types of models: contextual and collective or group anomalies. In Section 9, we briefly describe the different application domains to which deep learning-based anomaly detection has been applied. In subsequent sections we provide a categorization of deep learning-based techniques based on the research area to which they belong. Based on training objectives employed and availability of labels deep learning-based anomaly detection

Type of Data	Examples	DAD model architecture
Sequential	Video,Speech Protein Sequence,Time Series Text (Natural language)	CNN, RNN, LSTM
Non-Sequential	Image,Sensor Other (data)	CNN, AE and its variants

Table 2: Table illustrating nature of input data and corresponding deep anomaly detection model architectures proposed in literature.
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
AE: Autoencoders.

techniques can be categorized into supervised (Section 10.1), unsupervised (Section 10.5), hybrid (Section 10.3), and one-class neural network (Section 10.4). For each category of techniques we also discuss their computational complexity for training and testing phases. In Section 8.4 we discuss point, contextual, and collective (group) deep learning-based anomaly detection techniques. We present some discussion of the limitations and relative performance of various existing techniques in Section 12. Section 13 contains concluding remarks.

8 Different aspects of deep learning-based anomaly detection.

This section identifies and discusses the different aspects of deep learning-based anomaly detection.

8.1 Nature of Input Data

The choice of deep neural network architecture in deep anomaly detection methods primarily depends on the nature of input data. Input data can be broadly classified into sequential (eg, voice, text, music, time series, protein sequences) or non-sequential data (eg, images, other data). Table 2 illustrates the nature of input data and deep model architectures used in anomaly detection. Additionally input data depending on the number of features (or attributes) can be further classified into either low or high-dimensional data. DAD techniques have been to learn complex hierarchical feature relations within high-dimensional raw input data [19]. The number of layers used in DAD techniques is driven by the dimensionality of input data, deeper networks are shown to produce better performance on high dimensional data. Later on in the Section 10 various models considered for outlier detection are reviewed at depth.

8.2 Based on Availability of labels

Labels indicate whether a chosen data instance is normal or outlier. Anomalies are rare entities hence it is very difficult to obtain their labels. Furthermore anomalous behaviour may change over time, for instance the nature of anomaly had changed so significantly and that it remained unnoticed at Maroochy water treatment plant, for a long time which resulted in leakage of 150 million litres of untreated sewerage to local waterways [20].
Deep anomaly detection (DAD) models can be categorized into three categories based on extent of availability of labels. (1) Supervised deep anomaly detection. (2) Semi-supervised deep anomaly detection. (3) Unsupervised deep anomaly detection.

8.2.1 Supervised deep anomaly detection

Supervised deep anomaly detection involves training a deep supervised binary or multi class classifier, using labels of both normal and anomalous data instances. Supervised DAD models, formulated as multiclass classifier in Chapter **??** of thesis, aids in detecting rare brands, prohibited drug name mention and fradulent healthcare transactions [21, 22]. Despite the improved performance of supervised DAD methods, these methods are not as popular as semi-supervised or unsupervised methods, owing to lack of availability of labeled training samples. Moreover the performance of deep supervised classifier used as anomaly detector is suboptimal due to class imbalance (the total number of positive class instances are far more than the total number of (negative) class of data). Therefore we do not consider the review of supervised DAD methods in this survey.

8.2.2 Semi-supervised deep anomaly detection

The labels of normal instances are far more easy to obtain than anomalies, as a result semi-supervised DAD techniques are more widely adopted, these techniques leverage existing labels of single (normally positive class) to separate outliers. One common way of using deep autoencoders in anomaly detection is to train them in a semi-supervised way on data samples with no anomalies. With sufficient training samples, of normal class autoencoders would produce low reconstruction errors for normal instances, over anomalous events. [23, 24, 25]. We consider detailed review of these methods in Section 10.2.

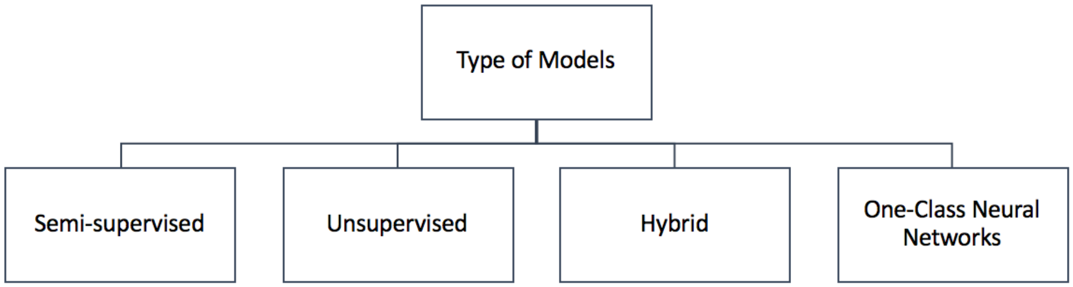


Figure 6: Taxonomy based on type of deep learning models for anomaly detection.

8.2.3 Unsupervised deep anomaly detection

Unsupervised deep anomaly detection techniques detect outliers solely based on intrinsic properties of the data instances. Unsupervised DAD techniques are used in automatic labelling of unlabelled data samples since labeled data is very hard to obtain [26]. Variants of Unsupervised DAD models [27] are shown to outperform traditional methods such as principal component analysis (PCA) [28], support vector machine (SVM) [29] and Isolation Forest [30] techniques in applications domains such as health and cyber security. Autoencoders are the core of all Unsupervised DAD models. These models assume the high prevalence of normal instances than abnormal data instances failing which would result in high false positive rate. Additionally unsupervised learning algorithms such as restricted Boltzmann machine (RBM) [31], deep Boltzmann machine (DBM), deep belief network (DBN) [32], generalized denoising autoencoders [33] , recurrent neural network (RNN) [34] Long short term memory networks [35] which are used to detect outliers are discussed in detail in Section 11.7.

8.3 Based on training objective

In this survey we introduce two new categories of deep anomaly detection (DAD) techniques based on training objective employed 1) Deep hybrid models (DHM). 2) One class neural networks (OC-NN).

8.3.1 Deep Hybrid Models (DHM)

Deep hybrid models for anomaly detection use deep neural networks mainly autoencoders as feature extractors, the features learnt within the hidden representations of autoencoders are input to traditional anomaly detection algorithms such as one-class SVM (OC-SVM) to detect outliers [36]. Figure 7 illustrates the deep hybrid model architecture used for anomaly detection. Following the success of transfer learning to obtain rich representative features from models pre-trained on large datasets, hybrid models have also employed these pre-trained transfer learning models as feature extractors with great success [37]. A variant of hybrid model was proposed by Ergen et.al [38] which considers joint training of feature extractor alongwith OC-SVM (or SVDD) objective to maximize the detection performance. A notable shortcoming of these hybrid approaches is the lack of trainable objective customised for anomaly detection, hence these models fail to extract rich differential features to detect outliers. In order to overcome this limitation customised objective for anomaly detection such Deep one-class classification [39]and One class neural networks [18] are introduced.

8.3.2 One-Class Neural Networks (OC-NN)

One class neural network (OC-NN) [18] methods are inspired by kernel-based one-class classification which combines the ability of deep networks to extract progressively rich representation of data with the one-class objective of creating a tight envelope around normal data. The OC-NN approach breaks new ground for the following crucial reason: data representation in the hidden layer is driven by the OC-NN objective and is thus customized for anomaly detection. This is a departure from other approaches which use a hybrid approach of learning deep features using an autoencoder and then feeding the features into a separate anomaly detection method like one-class SVM (OC-SVM). The details of training and evaluation of one class neural networks is discussed in Chapter **??** . Another variant of one class neural

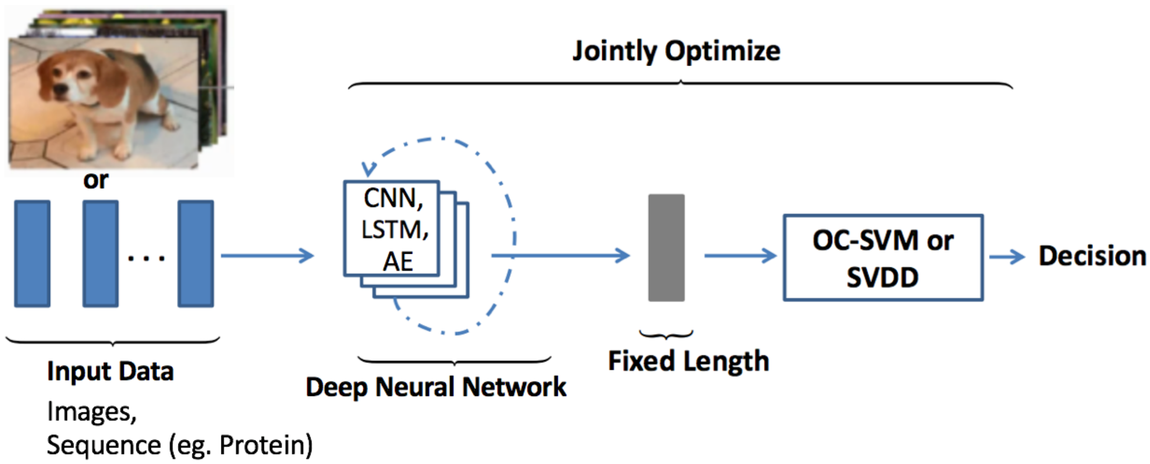


Figure 7: Deep Hybrid Model Architecture.

network architecture Deep Support Vector Data Description (Deep SVDD) [39] trains deep neural network to extract common factors of variation by closely mapping the normal data instances to the center of sphere, is shown to produce performance improvements on MNIST and CIFAR-10 datasets.

8.4 Type of Anomaly

Anomalies can be broadly classified into three types: point anomalies, contextual anomalies and collective anomalies. Deep anomaly detection (DAD) methods have been shown to detect all three types of anomalies with great success.

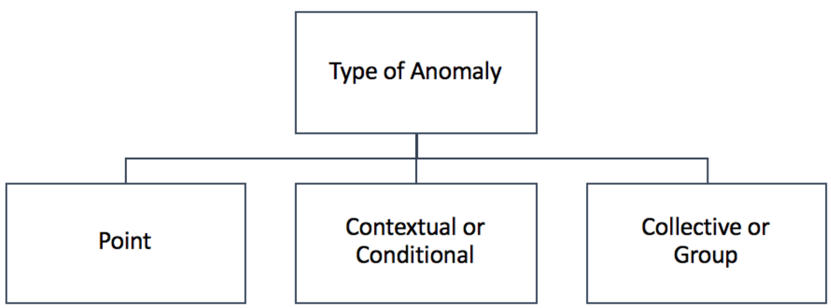


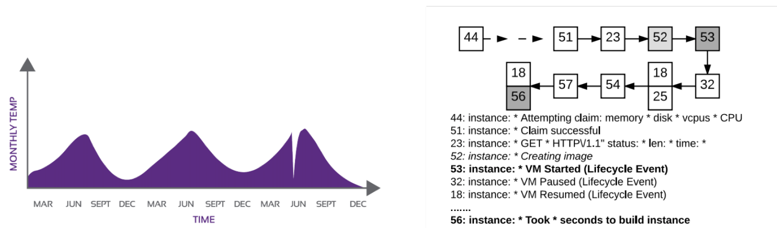
Figure 8: Deep learning techniques classification based on type of anomaly.

8.4.1 Point Anomalies.

The majority of work in literature focuses on point anomalies. Point anomalies often represent an irregularity or deviation that happens randomly and may have no particular interpretation. For instance in Figure 10 a credit card transaction with high expenditure recorded at *Monaco* restaurant seems a point anomaly since it significantly deviates from the rest of the transactions. Several real world applications, considering point anomaly detection are reviewed in Section 9.

8.4.2 Contextual Anomaly Detection

Contextual anomaly also referred as conditional anomaly is a data instance that could be considered as anomalous in some specific context [40]. The contextual anomaly is identified by considering both contextual and behavioural features. The contextual features, normally used are time and space. While the behavioral features may be pattern of spending money, occurence of system log events, or any feature used to describe the normal behaviour. Figure 9a illustrates the example of contextual anomaly considering temperature data indicated by a drastic drop just before June, this value is not indicative of a normal value found during this time. Figure 9b illustrates using deep Long Short-Term Memory (LSTM) [41] based model to identify anomalous system log events [42] in a given context (e.g event 53 is detected as being out of context).



(a) Temperature data [43].   (b) System logs [42].

Figure 9: Illustration of contextual anomaly detection.

8.4.3 Collective or Group Anomaly Detection.

Anomalous collections of individual data points are known as collective or group anomalies, wherein each of the individual points in isolation appear as normal data instances while observed in a group exhibit unusual characteristics. For example, consider an illustration of fraudulent credit card transaction, in the log data shown in Figure 10, if a single transaction of "MISC" would have occured, it might probably not seem as anomalous. The consecutive group of transactions of valued at $75 certainly seems to be a candidate for collective or group anomaly. Group anomaly detection (GAD) with an emphasis on irregular group distributions (e.g. irregular mixtures of image pixels are detected using a variant of autoencoder model [44, 45, 46, 47]

May-22	1:14 pm	FOOD	Monaco Café	$1,127.80
May-22	2:14 pm	WINE	Wine Bistro	$28.00
...				
Jun-14	2:14 pm	MISC	Mobil Mart	$75.00
Jun-14	2:05 pm	MISC	Mobil Mart	$75.00
Jun-15	2:06 pm	MISC	Mobil Mart	$75.00
Jun-15	11:49 pm	MISC	Mobil Mart	$75.00
May-28	6:14 pm	WINE	Acton shop	$31.00
May-29	8:39 pm	FOOD	Crossroads	$128.00
Jun-16	11:14 am	MISC	Mobil Mart	$75.00
Jun-16	11:49 am	MISC	Mobil Mart	$75.00

Point Anomaly

Collective Anomaly

Figure 10: Credit Card Fraud Detection: Illustrating Point and Collective anomaly.

8.5 Output of DAD Techniques

An critical aspect for anomaly detection methods is the way in which the anomalies are identified. Generally, the outputs produced by anomaly detection methods are either anomaly score or binary labels.

8.5.1 Anomaly Score:

Anomaly score describes the level of *outlierness* for each datapoint. The data instances may be ranked according to anomalous score, and a domain specific threshold (commonly known as decision score) will be selected by subject matter expert to identify the anomalies. In general, decision scores reveal more information than binary labels. For instance in Deep SVDD approach the decision score is the measure of distance of data point from center of the sphere, the data points which are farther away from center are considered anomalous [**?**].

8.5.2 Labels:

Instead of assigning scores, some techniques may assign a category label as normal or anomalous to each data instance. Unsupervised anomaly detection techniques using autoencoders measure the magnitude of residual vector (i,e reconstruction error) for obtaining anomaly scores, later on the reconstruction errors are either ranked or thresholded by domain experts to label data instances.

Table 3: Examples of DAD Techniques employed in HIDS
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
GRU: Gated Recurrent Unit, DNN : Deep Neural Networks
SPN: Sum Product Networks

Techniques	Model Architecture	Section	References
Discriminative	LSTM , CNN-LSTM-GRU, DNN	Section 11.7, 11.6, 11.1	[50],[51],[52],[53],[54]
Hybrid	GAN	Section 10.3	[55], [56]
Generative	AE, SPN,	Section 11.8, 11.3	[57],[58],[59]

9 Applications of Deep Anomaly Detection

In this section we discuss several applications of deep anomaly detection. For each application domain we discuss the following four aspects:
—the notion of anomaly;
—nature of the data;
—challenges associated with detecting anomalies;
—existing deep anomaly detection techniques.

9.1 Intrusion Detection

Intrusion detection system (IDS) refers to identifying malicious activity in a computer related system [48]. IDS may be deployed at single computers known as Host Intrusion Detection (HIDS) to large networks Network Intrusion Detection (NIDS). The classification of deep anomaly detection techniques for intrusion detection is in Figure 11. IDS depending on detection method are classified into signature based or anomaly based. Using signature based IDS is not efficient to detect new attacks, for which no specific signature pattern is available, hence anomaly based detection methods are more popular. In this survey we focus on deep anomaly detection (DAD) methods and architectures employed in intrusion detection.

9.1.1 Host-Based Intrusion Detection Systems (HIDS):

Such systems are installed software programs which monitors a single host or computer for malicious activity or policy violations by listening to system calls or events occurring within that host [49]. The system call logs could be generated by programs or by user interaction resulting in logs as shown in Figure 9b. Malicious interactions lead to execution of these system calls in different sequences. HIDS may also monitor the state of a system, its stored information, in Random Access Memory (RAM), in the file system, log files or elsewhere for a valid sequence. Deep anomaly detection (DAD) techniques applied for HIDS are required to handle the variable length and sequential nature of data. The DAD techniques have to either model the sequence data or compute similarity between sequences. Some of the successfull DAD techniques for HIDS is illustrated in Table 3.

9.1.2 Network Intrusion Detection Systems (NIDS):

NIDS systems deal with monitoring the entire network for suspicious traffic by examining each and every network packet. Owing to real-time streaming behaviour, the nature of data is synomynous to big data with high volume, velocity, variety. The network data also has a temporal aspect associated with it. Some of the successfull DAD techniques for NIDS is illustrated in Table 4. This survey also lists the datasets used for evaluating the DAD intrusion detection methods in Table 5. A challenge faced by DAD techniques in intrusion detection is that the nature of anomalies keeps changing over time as the intruders adapt their network attacks to evade the existing intrusion detection solutions.

9.2 Fraud Detection

Fraud is a deliberate act of deception to access valuable resources [94]. The PwC global economic crime survey of 2018 [95, 96] found that half of the 7,200 companies they surveyed had experienced fraud of some nature. Fraud detection refers to detection of unlawfull activities across various industries, illustrated in Figure 12.

Fraud in Telecom, insurance *(health, automobile, etc)* claims, banking *(tax return claims, credit card transactions etc)* represent significant problems in both governments and private businesses. Detecting and preventing fraud is not a simple task since fraud is an adaptive crime. Many traditional machine learning algorithms have been applied

Table 4: Examples of DAD Techniques employed in NIDS.
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
RNN: Recurrent Neural Networks, RBM : Restricted Boltzmann Machines
DCA: Dilated Convolution Autoencoders, DBN : Deep Belief Network
AE: Autoencoders, SAE: Stacked Autoencoders
GAN: Generative Adversarial Networks, CVAE : Convolutional Variational Autoencoder.

Techniques	Model Architecture	Section	References
Generative	DCA, SAE, RBM, DBN, CVAE	Section 11.6, 11.8, 11.1, 11.5	[60],[61], [62], [63],[64],[65],[66],[67],[68],[69]
Hybrid	GAN	Section 10.3	[70],[71], [72], [73],[74],[75], [76] ,[77].
Discriminative	RNN , LSTM ,CNN	Section 11.7, 11.6	[60], [78] [79],[57],[80],[81]

Table 5: Datasets Used in Intrusion Detection

DataSet	IDS	Description	Type	References
CTU-UNB	NIDS	CTU-UNB [82] dataset consists of various botnet traffics from CTU-13 dataset [20] and normal traffics from the UNB ISCX IDS 2012 dataset [83]	Hexadecimal	[60]
Contagio-CTU-UNB	NIDS	Contagio-CTU-UNB dataset consists of six types of network traffic data. [84]	Text	[60].
NSL-KDD [1]	NIDS	The NSL-KDD data set is a refined version of its predecessor KDD-99 data set. [82]	Text	[85], [3], [65], [86], [87], [66]
DARPA KDD- CUP 99	NIDS	DARPA KDD [88] The competition task was to build a network intrusion detector, a predictive model capable of distinguishing between “bad” connections, called intrusions or attacks, and “good” normal connections.	Text	[64] , [89], [87]
MAWI	NIDS	The MAWI [90] dataset consists of network traffic capturedfrom backbone links between Japan and USA. Every daysince 2007	Text	[63]
Realistic Global Cyber Environment (RGCE)	NIDS	RGCE [91] contains realistic Internet Service Providers (ISPs) and numerous different web services as in the real Internet.	Text	[62]
ADFA-LD	HIDS	The ADFA Linux Dataset (ADFA-LD). This dataset provides a contemporary Linux dataset for evaluation by traditional HIDS [92]	Text	[50], [51]
UNM-LPR	HIDS	Consists of system calls to evalute HIDS system [93]	Text	[50]
Infected PDF samples	HIDS	Consists of set of Infected PDF samples, which are used to monitor the malicious traffic	Text	[52]

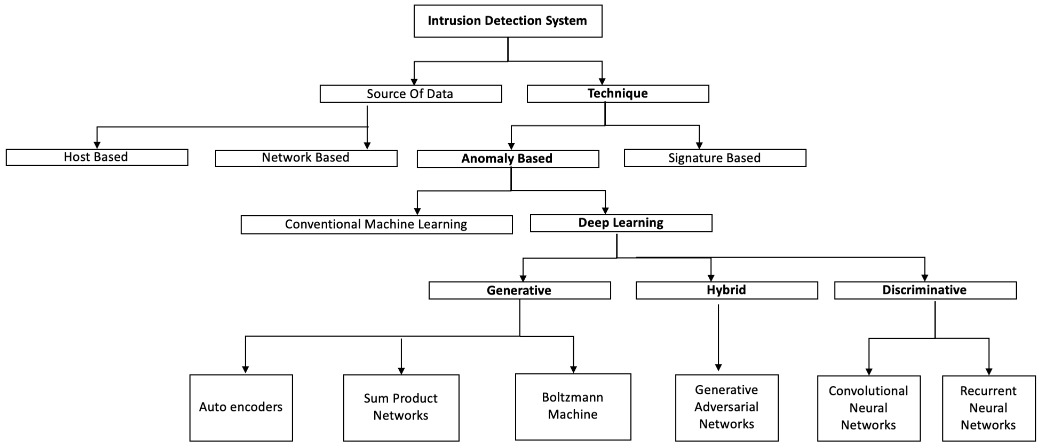


Figure 11: Classification of deep learning methods for Intrusion Detection.

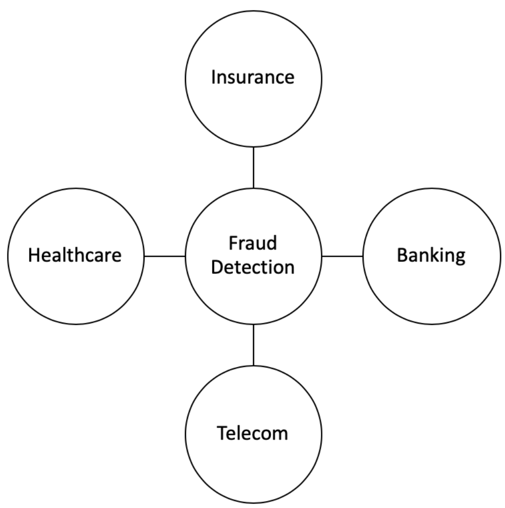


Figure 12: Fraud detection across various application domains.

successfully in fraud detection [97]. The challenge associated with detecting fraud is that it requires real time detection and prevention. This section focuses on deep anomaly detection (DAD) techniques for fraud detection.

9.2.1 Banking fraud

In the past decade, credit card was introduced in the banking sector. Now, credit card has become a popular payment method in online shopping for goods and services. Credit card fraud involves theft of a payment card details, and use it as a fraudulent source of funds in a transaction. Many techniques for credit card fraud detection have been presented in the last few years [98], [99]. We will briefly review some of DAD techniques as shown Table 6. The challenge in credit card fraud detection is that frauds have no constant patterns. The typical approach in credit card fraud detection is to maintain a usage profile for each user and monitor the user profiles to detect any deviations. Since there are billions of credit card users this technique of user profile approach is not very scalabale. Owing to the inherent scalabe nature of DAD techniques, these techniques are gaining wide spread adoption in credit card fraud detection.

Table 6: Examples of DAD techniques used in credit card fraud detection.
AE: Autoencoders, LSTM : Long Short Term Memory Networks
RBM: Restricted Botlzmann Machines, DNN : Deep Neural Networks
GRU: Gated Recurrent Unit, RNN: Recurrent Neural Networks
CNN: Convolutional Neural Networks,VAE: Variational Autoencoders
GAN: Generative Adversarial Networks

Technique Used	Section	References
AE	Section 11.8	[100], [101] , [102], [103], [104], [105], [106]
RBM	Section 11.1	[106]
DBN	Section 11.1	[107]
VAE	Section 11.5	[108]
GAN	Section 11.5	[109], [110]
DNN	Section 11.1	[111], [112]
LSTM,RNN,GRU	Section 11.7	[113], [114], [115], [116], [117], [118], [119], [120], [121]
CNN	Section 11.6	[122], [123], [124], [125], [126], [127], [120] , [128]

Table 7: Examples of DAD techniques used in mobile cellular network fraud detection.
CNN: convolution neural networks,DBN: Deep Belief Networks
SAE: Stacked Autoencoders, DNN : Deep neural networks
GAN: Generative Adversarial Networks

Technique Used	Section	References
CNN	Section 11.6	[123]
SAE, DBN	Section 11.8, 11.1	[129], [130]
DNN	Section 11.1	[131], [132]
GAN	Section 11.5	[133]

9.2.2 Mobile cellular network fraud

In recent times, mobile cellular networks have witnessed rapid deployment and evolution supporting billions of users and a vast diverse array of mobile devices. Due to this wide adoption and low mobile cellular service rates mobile cellular networks is now faced with frauds such as voice scams targeted to steal customer private information, and messaging related scams to extort money from customers. Detecting such fraud is of paramount interest and not an easy task due to volume and velocity of mobile cellular network. Traditional machine learning methods with static feature engineering techniques fail to adapt to the nature of evolving fraud. Table 7 lists DAD techniques for mobile cellular network fraud detection.

9.2.3 Insurance fraud

Several traditional machine learning methods have been applied successfully to detect fraud in insurance claims [134, 135]. The traditional approach for fraud detection is based on features which are fraud indicators. The challenge with these traditional approaches is that the need of manual expertise to extract robust features. Another challenge is insurance fraud detection is the that the incidence of frauds is far less than the total number of claims, and also each fraud is unique in its own way. In order to overcome these limitations several DAD techniques are proposed which are illustrated in Table 8

Table 8: Examples of DAD techniques used in insurance fraud detection.
DBN: Deep Belief Networks, DNN : Deep Neural Networks
CNN: Convolutional Neural Networks,VAE: Variational Autoencoders
GAN: Generative Adversarial Networks

DBN	Section 11.1	[136]
VAE	Section 11.5	[137]
GAN	Section 11.5	[109], [110]
DNN	Section 11.1	[138]
CNN	Section 11.6	[122], [128]

Table 9: Examples of DAD techniques used in healthcare fraud detection.
RBM: Restricted Botlzmann Machines, GAN: Generative Adversarial Networks

Technique Used	Section	References
RBM	Section 11.1	[140]
GAN	Section 11.5	[141], [142]
CNN	Section 11.6	[143]

Table 10: Examples of DAD techniques used for malware detection.
AE: Autoencoders, LSTM : Long Short Term Memory Networks
RBM: Restricted Botlzmann Machines, DNN : Deep Neural Networks
GRU: Gated Recurrent Unit, RNN: Recurrent Neural Networks
CNN: Convolutional Neural Networks,VAE: Variational Autoencoders
GAN: Generative Adversarial Networks,CNN-BiLSTM: CNN- Bidirectional LSTM

Technique Used	**Section**	**References**
AE	Section 11.8	[86], [145], [86], [146], [147], [148], [146], [149]
word2vec	Section 11.4	[150], [151]
CNN	Section 11.6	[152], [153], [154], [154], [155], [156], [157], [158], [159], [160], [161], [162], [163], [164]
DNN	Section 11.1	[165], [166]
DBN	Section 11.1	[149], [167], [168], [169], [170], [169], [171]
LSTM	Section 11.7	[172], [173], [174] , [175]
CNN-BiLSTM	Section 11.6, 11.7	[176], [166]
GAN	Section 11.5	[177]
Hybrid model(AE-CNN),(AE-DBN)	Section 10.3	[178], [179]
RNN	Section 11.7	[180]

9.2.4 Healthcare fraud

Healthcare is an integral component in people's lives, waste, abuse and fraud drive up costs in healthcare by tens of billions of dollars each year. Healthcare insurance claims fraud is a major contributor to increased healthcare costs, but its impact can be mitigated through fraud detection. Several machine learning models have been used effectively in health care insurance fraud [139]. Table 9 presents the overview of DAD methods for healthcare fraud identification.

9.3 Malware Detection

Malware, short for Malicious Software. In order to protect legitimate users from malware, machine learning based efficient malware detection methods are proposed [144]. In the classical machine learning methods, the process of malware detection is usually divided into two stages: feature extraction and classification/clustering. The performance of traditional malware detection approaches critically depend on the extracted features and the methods for classification/clustering. The challenge associated in malware detection problems is the seer scale of data, for instance considering data as bytes a certain sequence classification problem could be of the order of two million time steps. Furthermore the malware is very adpative in nature, wherein the attackers would use advanced techniques to hide the malicious behaviour. Some DAD techniques which address these challenges effectively and detect malware are shown in Table 10.

9.4 Medical Anomaly Detection:

Several studies have been conducted to understand the theoretical and practical applications of deep learning in medical and bioinformatics [181, 182, 183, 184]. Finding rare events (anomalies) in areas such as medical image analysis, clinical electroencephalography (EEG) records, enable to diagnose and provide preventive treatments for a variety of medical conditions. Deep learning based architectures are employed with great success to detect medical anomalies as illustrated in Table 11. The vast amount of imbalanced data in medical domain presents significant challenges to detect outliers. Additionally deep learning techniques for long have been considered as black-box techniques, i,e even though deep learning models produce outstanding performance, these models lack interpretability. In recent times models with good interpretability are proposed and shown to produce state-of-the-art performance [185, 186, 187].

Table 11: Examples of DAD techniques Used for medical anomaly detection.
AE: Autoencoders, LSTM : Long Short Term Memory Networks
GRU: Gated Recurrent Unit, RNN: Recurrent Neural Networks
CNN: Convolutional Neural Networks,VAE: Variational Autoencoders
GAN: Generative Adversarial Networks, KNN: K-nearest neighbours
RBM: Restricted Boltzmann Machines.

Technique Used	Section	References
AE	Section 11.8	[188, 189], [190]
DBN	Section 11.1	[191], [192], [23], [193], [194], [195] , [196]
RBM	Section 11.1	[197]
VAE	Section 11.5	[198], [199]
GAN	Section 11.5	[141], [200]
LSTM ,RNN,GRU	Section 11.7	[201], [202], [189], [203], [204], [205], [206], [185, 186]
CNN	Section 11.6	[207], [143], [188], [208]
Hybrid(AE+ KNN)	Section 11.6	[25]

Table 12: Examples of DAD techniques used to detect anomalies in social network.
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
AE: Autoencoders, DAE: Denoising Autoencoders
SVM : Support Vector Machines., DNN : Deep Neural Network

Technique Used	**Section**	**References**
AE,DAE	Section 11.8	[214], [215]
CNN-LSTM	Section 11.6, 11.7	[216], [217], [218]
DNN	Section 11.1	[219]
Hybrid Models (CNN-LSTM-SVM)	Section 10.3	[220]

9.5 Deep learning for Anomaly detection in Social Networks

In recent times, online social networks has become part and parcel of daily life. Anomalies in social network are irregular often unlawfull behaviour pattern of individuals within a social network, such individuals may be identified as spammers, sexual predators, online fraudsters, fake users or rumour-mongers. Detecting these irregular patterns is of prime importance since if not detected, the act of such indivuals can have serious social impact. A survey of traditional anomaly detection techniques and its challenges to detect anomalies in social networks is a well studied topic in literature [209, 210, 211, 212, 213, 212]. The heterogenous and dynamic nature of data presents significant challenges to DAD techniques. Despite these challenges several DAD techniques illustrated in Table 12 are shown outperform state-of-the-art methods.

9.6 Log Anomaly Detection:

Anomaly detection in log file aims to find text, which can indicate the reasons and the nature of failure of a system. Most commonly, a domain specific regular-expression is constructed from past experience which finds new faults by pattern matching. The limitation of such approaches is that newer messages of failures are easily are not detected [221].

The unstructured and diversity in both format and semantics of log data pose significant challenges to log anomaly detection. Anomaly detection techniques should adapt to concurrent setting of log data generated and detect outliers in real time. Following the success of deep neural networks in real time text analysis, several DAD techniques illustrated in Table 13 which model the log data as natural language sequence are shown very effective in detecting outliers.

9.7 Internet of things (IoT) Big Data Anomaly Detection

IoT is identified as a network of devices that is interconnected with softwares, servers, sensors and etc. In the field of Internet of things (IoT), data generated by weather stations, RFID tags, IT infrastructure components, and some other sensors are mostly time series sequential data. Anomaly detection in these IoT networks identifies fraudulent, faulty behaviour of these massive scale of interconnected devices. The challenges associated in outlier detection is that heterogeneous devices are interconnected which renders the system more complex. A thorough overview on using deep learning (DL), to facilitate the analytics and learning in the IoT domain is presented by [242]. In this section we present some of the DAD techniques used in this domain in Table 14.

Table 13: Examples of Deep learning anomaly detection techniques used in system logs.
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
GRU: Gated Recurrent Unit, DNN : Deep Neural Networks
AE: Autoencoders, DAE: Denoising Autoencoders

Techniques	Section	References
LSTM	Section 11.7	[41], [222], [27], [223], [224]
AE	Section 11.8	[42], [36] , [225], [226], [227]
LSTM-AE	Section 11.7, 11.8	[228], [229]
RNN	Section 11.7	[222], [230], [231], [232]
DAE	Section 11.8	[233], [227]
CNN	Section 11.6	[234], [235], [236], [237], [238], [239], [240], [241]

Table 14: Examples of DAD techniques used in Internet of things (IoT) Big Data Anomaly Detection.
AE: Autoencoders, LSTM : Long Short Term Memory Networks
DBN : Deep Belief Networks.

Techniques	Section	References
AE	Section 11.8	[243], [244]
DBN	Section 11.1	[245]
LSTM	Section 11.7	[246], [247]

9.8 Industrial Anomalies Detection

Industrial systems consisting of wind turbines, power plants, high-temperature energy systems, storage devices and with rotating mechanical parts are exposed to enormous stress on a day-to-day basis. Damage to these type of systems not only causes economic loss but also a loss of reputation, therefore detecting and repairing them early is of utmost importance. Several machine learning techniques have been used to detect such damage in industrial systems [20, 248]. Several papers published utilizing deep learning models for detecting early industrial damage show great promise [249, 250, 251]. Damages caused to equipments are rare events, thus detecting such events can be formulated as outlier detection problem. The challenges associated with outlier detection in this domain is both volume as well as dynamic nature of data, since failure can be caused due to variety of factors. Some of the DAD techniques employed across various industries are illustrated in Table 15.

9.9 Anomaly Detection in Time Series

Data recorded continuously over a duration is known the time series. Time series data are the best examples of collective outliers. In recent times, deep learning models for detecting time series anomalies has been well studied [272, 273, 274, 275]. The advancements in deep learning domain offer opportunities to extract rich hierarchical features which can greatly improve outlier detection as illustrated by various techniques illustrated in Table 16. Furthermore DeepAD, an anomaly detection framework to detect anomalies precisely, even in complex data patterns is proposed by [276]. Some of the challenges to detect anomalies in time series using deep learning models data are:

Table 15: Examples of DAD techniques used in industrial operations.
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
GRU: Gated Recurrent Unit, DNN : Deep Neural Networks
AE: Autoencoders, DAE: Denoising Autoencoders, SVM: Support Vector Machines
SDAE: Stacked Denoising Autoencoders, RNN : Recurrent Neural Networks.

Techniques	Section	References
LSTM	Section 11.7	[252], [253], [254], [255], [256], [257]
AE	Section 11.8	[258], [259], [260], [225], [261]
DNN	Section 11.1	[262]
CNN	Section 11.6	[263], [264], [265], [263], [266], [231], [267], [255], [257]
SDAE,DAE	Section 11.8	[268], [269], [270]
RNN	Section 11.7	[271], [253]
Hybrid Models (DNN-SVM)	Section 10.3	[252]

Table 16: Examples of DAD techniques used in time series data.
CNN: Convolution Neural Networks, GAN: Generative Adversarial networks,LSTM : Long Short Term Memory Networks
GRU: Gated Recurrent Unit, DNN : Deep Neural Networks,
AE: Autoencoders, DAE: Denoising Autoencoders, VAE: Variational Autoencoder
SDAE: Stacked Denoising Autoencoders

Techniques	**Section**	**References**
LSTM	Section 11.7	[277],[278],[279],[278],[224],[206],[280],[276],[281],[282],[45],[283],[284],[285],[206],[224],[238]
AE,LSTM-AE,CNN-AE,GRU-AE	Section 11.8	[286], [287], [189], [288], [282], [289], [290], [291], [292]
RNN	Section 11.7	[293], [294], [295], [296]
CNN, CNN-LSTM	Section 11.6, 11.7	[297], [298], [238], [299], [300],[301]
LSTM-VAE	Section 11.7, 11.5	[302], [303]
DNN	Section 11.1	[186]
GAN	Section 11.5	[56], [304], [305], [306]

Table 17: Examples of DAD techniques used in video surveillance.
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
RBM: Restricted Boltzmann Machine, DNN : Deep Neural Networks
AE: Autoencoders, DAE: Denoising Autoencoders
OCSVM: One class Support vector machines, CAE: Convolutional Autoencoders
SDAE: Stacked Denoising Autoencoders, STN : Spatial Transformer Networks

Technique Used	**Section**	**References**
CNN	Section 11.6	[266],[307],[308],[309],[310],[311],[312],[313],[314],[264],[311]
SAE (AE-CNN-LSTM)	Section 11.8, 11.6, 11.7	[315], [312], [316]
AE	Section 11.8	[312],[317],[318],[319],[320],[321],[317],[318],[322],[323],[318],[320],[324],[317],[325]
Hybrid Model (CAE-OCSVM)	Section 10.3	[319], [321]
LSTM-AE	Section 11.7, 11.8	[320]
STN	Section 11.2	[326]
RBM	Section 11.1	[310]
LSTM	Section 11.7	[301], [327], [328], [329]
RNN	Section 11.7	[330],[331] ,[332], [333]
AAE	Section 11.5	[334]

- Lack of defined pattern in which an anomaly occuring may be defined.
- Noise within the input data seriously effects the performance of algorithms.
- As the length of the time series data increases the computational complexity also increases.
- Time series data is usually non-stationary, non-linear and dynamically evolving, hence DAD models should be able to detect anomalies in real time.

9.10 Video Surveillance

Video Surveillance also popularly known as Closed-circuit television (CCTV) involves monitoring a designated areas of interest in order to ensure security. In videos surveillance applications unlabelled data is available in large amounts, this is a significant challenge for supervised machine learning and deep learning methods. Hence video surveillance applications have been modelled as anomaly detection problems owing to lack of availability of labelled data. Several works have studied the state-of-the-art deep models for video anomaly detection and have classified them based on the type of model and criteria of detection [14, 333]. The challenges of robust 24/7 video surveillance systems is discussed in detail by Boghossian et.al [335]. The lack of explicit definition of anomaly in real-life video surveillance is a significant issue that hampers the performance of DAD methods as well. DAD techniques used in video surveillance are illustrated in Table 17.

10 Deep Anomaly Detection (DAD) Models

In this section we discuss various DAD models classified based on availability of labels and training objective. For each model types domain we discuss the following four aspects:
—assumptions;
—type of model architectures;
—computational complexity;
—advantages and disadvantages;

10.1 Supervised deep anomaly detection

Supervised anomaly detection techniques are superior in performance compared to unsupervised anomaly detection techniques since these techniques use labeled samples. [336]. Supervised anomaly detection illustrated in Chapter **??** learns the separating boundary from a set of annotated data instances (training) and then, classify a test instance into either normal or anomalous classes with the learnt model (testing).
Assumptions :
Deep supervised learning methods depend on separating data classes whereas unsupervised techniques focus on explaining and understanding the characteristics of data. Multi-class classification based anomaly detection techniques assume that the training data contains labeled instances of multiple normal classes [337, 338, 339, 340]. Multi-class anomaly detection techniques learn a classifier to distinguish between anomalous class from the rest of the classes. In general, supervised deep learning-based classification schemes for anomaly detection have two subnetworks, a feature extraction network followed by a classifier network. Deep models require extremely large number of training samples (in the order of thousands or millions) to effectively learn feature representations to discriminate various class instances. Due to, lack of availability of clean data labels supervised deep anomaly detection techniques are not so popular as semi-supervised and unsupervised methods.

Computational Complexity :
The computational complexity of deep supervised anomaly detection methods based techniques depends on the dimensionality of the input data and the number of hidden layers trained using back-propogation algorithm. High dimensional data tend to have more hidden layers to ensure meaningfull hierarchical learning of input features.The computational complexity also increases linearily with the number of hidden layers and require greater model training and update time.

Advantages and Disadvantages :
The advantages of supervised DAD techniques are as follows:

- Supervised DAD methods are more accurate than semi-supervised and unsupervised models.
- The testing phase of classification based techniques is fast since each test instance needs to be compared against the pre-computed model.

The disadvantages of Supervised DAD techniques are as follows:

- Multi-class supervised techniques require accurate labels for various normal classes and anomalous instances, which is often not available.
- Deep supervised techniques fail to separate normal from anomalous data , if the feature space is highly complex and non-linear.

10.2 Semi-supervised deep anomaly detection

Semi-supervised or (one-class classification) DAD techniques assume that all training instances have only one class label. A review of deep learning based semi-supervised techniques is presented by Kiran et.al and Min et.al [14, 341]. DAD techniques learn a discriminative boundary around the normal instances. The test instance that does not belong to the majority class is flagged as being anomalous [342, 343]. Various semi-supervised DAD model architectures are illustrated in Table 18.

Assumptions :
Semi-supervised DAD methods proposed rely on one the following assumptions to score a data instance as an anomaly.

- Proximity and Continuity: Points which are close to each other both in input space and learnt feature space are more likely to share a same label.

Table 18: Semi-supervised DAD models overview
AE: Autoencoders, DAE: Denoising Autoencoders, KNN : K- Nearest Neighbours
CorGAN: Corrupted Generative Adversarial Networks, DBN: Deep Belief Networks
AAE: Adversarial Autoencoders, CNN: Convolution neural networks
SVM: Support vector machines.

Techniques	**Section**	**References**
AE	Section 11.8	[344] , [345]
RBM	Section 11.1	[346]
DBN	Section 11.1	[23], [195]
CorGAN,GAN	Section 11.5	[347] [348], [349]
AAE	Section 11.5	[350]
Hybrid Models (DAE-KNN [351]), (DBN-Random Forest [352]),CNN-Relief [353],CNN-SVM [29]	Section 8.3.1	[25], [354], [355]
CNN	Section 11.6	[356], [342]
RNN	Section 11.7	[357]
GAN	Section 11.5	[358], [347]

- Robust features are learnt within hidden layers of deep neural network layers and retain the discriminative attributes for separating normal from outlier data points.

Computational Complexity :
The computational complexity of semi-supervised DAD methods based techniques is similar to supervised DAD techniques, which primarily depends on the dimensionality of the input data and the number of hidden layers used for representative feature learning.

Advantages and Disadvantages:
The advantages of semi-supervised deep anomaly detection techniques are as follows:

- Generative Adversarial Networks (GANs) trained in semi-supervised learning mode have shown great promise, even with very few labeled data.
- Use of labeled data (usually of one class), can produce considerable performance improvement over unsupervised techniques.

The fundamental disadvantages of semi-supervised techniques presented by Lu et.al [359] is applicable even in deep learning context. Furthermore the hierarchical features extracted within hidden layers may not be representative of fewer anomalous instances hence are prone to over-fitting problem.

10.3 Hybrid deep anomaly detection

Deep learning models are widely used as feature extractors to learn robust features [36]. In hybrid deep models, the representative features learnt within deep models are input to traditional algorithms like one-class Radial Basis Function (RBF) , Support Vector Machine (SVM) classifiers. The hybrid models employ two step learning and are shown to produce state-of-the-art results [17, 362, 363]. Deep hybrid architectures used in anomaly detection are illustrated in Table 19.

Assumptions :
The deep hybrid models proposed for anomaly detection rely on one the following assumptions to detect outliers:

- Robust features are extracted within hidden layers of deep neural network, aid in separating out the irrelevant features which can conceal the presence of anomalies.
- Building a robust anomaly detection model on complex, high-dimensional spaces require feature extractor and an anomaly detector. Various anomaly detectors used alongwith are illustrated in Table 19

Table 19: Examples of Hybrid DAD techniques.
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
DBN: Deep Belief Networks, DNN : Deep Neural Networks.
AE: Autoencoders, DAE: Denoising Autoencoders, SVM: Support Vector Machines [29]
SVDD: Support Vector Data Description, RNN : Recurrent Neural Networks
Relief: Feature selection Algorithm [353], KNN: K- Nearest Neighbours [351]
CSI: Capture, Score, and Integrate [360].

Techniques	Section	References
AE-OCSVM, AE-SVM	Section 11.8,	[36]
DBN-SVDD, AE-SVDD	Section 11.1,	[17], [339]
DNN-SVM	21D	[252]
DAE-KNN, DBN-Random Forest [352],CNN-Relief,CNN-SVM	Section 11.1,11.8	[25], [354], [355, 361]
AE-CNN, AE-DBN	Section 11.1, 11.6,11.8	[178], [179]
AE+ KNN	Section 11.8	[25]
CNN-LSTM-SVM RNN-CSI CAE-OCSVM	Section 11.6,11.7 Section 11.7 Section 11.8	[220] [360] [319], [321]

Computational Complexity :
Computational complexity of an hybrid model includes complexity of both deep architectures as well as traditional algorithms used within. Additionally an inherent issue of non-trivial choice of deep network architecture and parameters which involves searching optimized parameters in a considerably larger space introduces the computational complexity of using deep layers within hybrid models. Furthermore considering the classical algorithms such as linear SVM which has prediction complexity of $O(d)$ with d the number of input dimensions. For most kernels, including polynomial and RBF, the complexity is $O(nd)$ where n is the number of support vectors although an approximation $O(d^2)$ is considered for SVMs with an RBF kernel.

Advantages and Disadvantages
The advantages of hybrid DAD techniques are as follows:

- The feature extractor greatly reduce the 'curse of dimensionality' especially in high dimensional domain.
- Hybrid models are more scalable and computationally efficient since the linear or nonlinear kernel models operate on reduced input dimension.

The significant disadvantages of hybrid DAD techniques are:

- The hybrid approach is suboptimal because it is unable to influence representational learning within the hidden layers of feature extractor, since generic loss functions are employed instead of customised objective for anomaly detection.
- The deeper hybrid models tend to perform better, if the individual layers are pre-trained [364] which introduces computational expenditure.

10.4 One-class neural networks (OC-NN) for anomaly detection

One-class neural networks (OC-NN) combines the ability of deep networks to extract progressively rich representation of data alongwith the one-class objective, such as an hyperplane [18] or hypersphere [39] to separate all the normal data points from the outliers. The OC-NN approach is novel for the following crucial reason: data representation in the hidden layer are learned by optimising the objective function customised for anomaly detection as illustrated in The experimental results in [18, 39] demonstrate that OC-NN can achieve comparable or better performance than existing state-of-the art methods for complex datasets, while having reasonable training and testing time compared to the existing methods.

Assumptions :
The OC-NN models proposed for anomaly detection rely on the following assumptions to detect outliers:

Table 20: Examples of Un-supervised DAD techniques .
CNN: Convolution Neural Networks, LSTM : Long Short Term Memory Networks
DNN : Deep Neural Networks., GAN: Generative Adversarial Network
AE: Autoencoders, DAE: Denoising Autoencoders, SVM: Support Vector Machines
STN: Spatial Transformer Networks, RNN : Recurrent Neural Networks
AAE: Adversarial Autoencoders, VAE : Variational Autoencoders.

Techniques	**Section**	**References**
LSTM	Section 11.7	[329], [366], [367],[224]
AE	Section 11.8	[368], [369], [370], [371], [225], [196], [372], [373], [374], [375], [376], [317], [377], [378], [275], [379], [380],[381]
STN	Section 11.2	[326]
GAN	Section 11.5	[382]
RNN	Section 11.7	[367],[383]
AAE	Section 11.5	[350], [384]
VAE	Section 11.5	[385], [386], [303], [198], [387]

- OC-NN models extracts the common factors of variation within the data distribution within the hidden layers of deep neural network.
- Performs combined representation learning and produces a outlier score for test data instance.
- Anomalous samples do not contain common factors of variation and hence hidden layers fails to capture the representations of outliers.

Computational Complexity :
The Computational complexity of an OC-NN model as against the hybrid model includes only the complexity of deep network of choice [364]. OC-NN models do not require data to be stored for prediction, thus have very low memory complexity. However it is evident that the OC-NN training time is proportional to the input dimension.

Advantages and Disadvantages:
The advantages of OC-NN are as follows:

- OC-NN models jointly trains a deep neural network while optimizing a data-enclosing hypersphere or hyperplane in output space.
- OC-NN propose an alternating minimization algorithm for learning the parameters of the OC-NN model. We observe that the subproblem of the OC-NN objective is equivalent to a solving a quantile selection problem which is well defined.

The significant disadvantages of OC-NN for anomaly detection are:

- Training times and model update time may be longer for high dimensional input data.
- Model updates would also take longer time, given the change in input space.

10.5 Un-supervised Deep Anomaly Detection

Unsupervised DAD is an important area of research in both fundamental machine learning research and industrial applications. Several deep learning frameworks that addresses challenges in unsupervised anomaly detection are proposed and shown to produce state-of-the-art performance as illustrated in Table 20. Autoencoders are the fundamental unsupervised deep architectures used in anomaly detection [365].

Assumptions :
The deep unsupervised models proposed for anomaly detection rely on one the following assumptions to detect outliers:

- The “normal” regions in the original or some latent feature space can be distinguished from ”anomalous” regions in the original or some latent feature space.
- The majority of the data instances are normal compared to the remainder of the data set.
- Unsupervised anomaly detection algorithm produces an outlier score of the data instances based on intrinsic properties of the dataset such as distances or densities. The hidden layers of deep neural network aim to capture these intrinsic properties within the dataset [388].

Computational Complexity :
The autoencoders is the most common architecture employed in outlier detection with quadratic cost, the optimization problem is non-convex in nature, similar to any other neural network architecture. The model computational complexity depends on the number of operations, network parameters and hidden layers. However, the computational complexity of training an autoencoder is much higher than traditional methods such as Principal Component Analysis (PCA) since PCA is based on matrix decomposition [380, 381].

Advantages and Disadvantages: The advantages of unsupervised deep anomaly detection techniques are as follows:

- Learns the inherent data characteristics to separate normal from anomalous data point. These technique identifies commonalities within the data therefore facilitates outlier detection.
- Cost effective technique to find the anomalies since it does not require annotated data for training the algorithms.

The significant disadvantages of unsupervised deep anomaly detection techniques are:

- Often it is difficult to learn commonalities within data in a complex and high dimensional space.
- While using autoencoders the choice of right degree of compression, i.e. dimensionality reduction is often an hyper-parameter that requires tuning for optimal results.
- Unsupervised techniques techniques are very sensitive to noise, and data corruptions and are often less accurate than supervised or semi-supervised techniques.

10.6 Miscellaneous Techniques

This section explores, various DAD techniques which are shown to be effective and promising, we discuss the key idea behind those techniques, and their area of applicability.

10.6.1 Transfer Learning based anomaly detection :

Deep learning for long has been critized for the need to have enough data to produce good results. Transfer learning relaxes this data dependence and helps to achieve good performance even with limited training data instances. Litjens et.al and Pan et.al [16, 37] present the review on deep transfer learning approaches. Transfer learning is an important tool in machine learning to solve the basic problem of insufficient training data. It aims to transfer the knowledge from the source domain to the target domain by relaxing the assumption that training and future data must be in the same feature space and have the same distribution. Deep transfer representation-learning has been explored [389, 390, 391, 392, 393, 394] and shown to produce very promising results. The open research questions using transfer learning for anomaly detection is , the degree of transferability, that is to define how well features transfer the knowledge and improve the classification performance from one task to another.

10.6.2 Zero Shot learning based anomaly detection:

Zero shot learning (ZSL) aims recognize objects never seen before within training set [395]. ZSL achieves this in two phases: Firstly the knowledge about the objects in natural language descriptions or attributes (commonly known as meta-data) is captured Secondly this knowledge is then used to classify instances among a new set of classes. This setting is important in real world since one may not be able to obtain images of all the possible classes at training. The main challenge associated with this approach is the obtaining the meta-data about the data instances. However several approaches of using ZSL in anomaly and novelty detection are shown to produce state-of-the-art results [387, 396, 397, 398, 399].

10.6.3 Ensemble based anomaly detection:

A notable issue with deep neural networks is that they are sensitive to noise within input data and often require large training data to perform robustly [50]. In order to achieve robustness even in noisy data an idea to randomly vary on the connectivity architecture of the autoencoder are shown to obtain signicantly better performance. An autoencoder ensembles consisting of various randomly connected autoencoders are experimented by Chen et.al [400] to achieve promising results on several bench-mark datasets. The ensemble approaches are still an active area of research which has been shown to produce improved diversity, thus avoid overfitting problem while reducing training time.

10.6.4 Clustering based anomaly detection:

Several anomaly detection algorithms based on clustering have been proposed in literature [401]. Clustering involves grouping together similar patterns based on features extracted detect new anomalies. The time and space complexity grows linearly with number of classes to be clustered [402], which renders the clustering based anomaly detection prohibitive for real-time practical applications. The dimensionality of the input data is reduced extracting features within the hidden layers of deep neural network which ensures scalability for complex and high dimensional datasets. Deep learning enabled clustering approach anomaly detection utilizes e.g word2vec [403] models to get the semantical presentations of normal data and anomalies to form clusters and detect outliers [404]. Several works rely on variants of hybrid models along with auto-encoders for obtaining representative features for clustering to find anomalies [405, 406, 407, 406, 408, 409, 410].

10.6.5 Deep Reinforcement Learning (DRL) based anomaly detection:

, Deep reinforcement learning (DRL) methods have attracted significant interest due to its ability to learn complex behaviors in high-dimensional data space. Efforts to detect anomalies using deep reinforcement learning have been proposed by [411, 412]. The DRL based anomaly detector does not consider any assumption about the concept of the anomaly, the detector identifies new anomalies by consistently enhancing its knowledge through reward signals accumulated. DRL based anomaly detection is a very novel concept which requires further investigation and identification of research gap and its applications.

10.6.6 Statistical techniques deep anomaly detection:

Hilbert transform is statistical signal processing technique which derives the analytic representation of a real-valued signal. This property is leveraged by Kanarachos et.al [413] for real time detection of anomalies in health related time series dataset and is shown to be a very promising technique. The algorithm combines the ability of wavelet analysis, neural networks and Hilbert transform in a sequential manner to detect real-time anomalies. The topic of statistical techniques DAD techniques requires further investigation to fully understand thier potential and applicability for anomaly detections.

11 Deep neural network architectures for locating anomalies

11.1 Deep Neural Networks (DNN)

The ”deep” in ”deep neural networks” refers to the number of layers through which the features of data are extracted [414, 415]. Deep architectures overcome the limitations of traditional machine learning approaches of scalability, and generalization to new variations within data [19] and the need for manual feature engineering. Deep Belief Networks (DBNs) are class of deep neural network which comprises of multiple layer of graphical models known as Restricted Boltzmann Machine (RBMs). The hypothesis in using DBNs for anomaly detection is that RBMs are used as directed encoder-decoder network that can be trained with backpropogation algorithm [416]. DBNs fail to capture the common variations of anomalous samples, resulting in high reconstruction error. DBNs are shown to scale efficiently to big-data and improve interpretability [23].

11.2 Spatio Temporal Networks (STN)

Researchers for long have explored techniques to learn both both spatial and temporal relation features [417]. Deep learning architectures have been shown perform well at learning spatial aspects (using CNNs) and temporal features (using LSTMs) individually. Spatio Temporal Networks (STNs) comprise of deep neural architectures combining both CNNs and LSTMs to extract spatio-temporal features. The temporal features (modeling correlations between near time points via LSTM), spatial features (modeling local spatial correlation via local CNNs) are shown to be effective in detecting outliers [418, 419, 420, 421].

11.3 Sum-Product Networks (SPN)

Sum-Product Networks (SPNs) are directed acyclic graphs with variables as leaves, and the internal nodes, and weighted edges constitute the sums and products. SPNs are considered as a combination of mixture models which have fast exact probabilistic inference over many layers [422, 58]. The main advantage of SPNs is that, unlike graphical models, SPNs are more traceable over high treewidth models without requiring approximate inference. Furthermore, SPNs are shown to capture uncertainty over their inputs in a convincing manner, yielding robust anomaly detection [58]. SPNs are shown to be impressive results on numerous datasets, while much remains to be further explored in relation to outlier detection.

11.4 Word2vec Models

Word2vec is a group of deep neural network models used to produce word embeddings [403]. These models are capable of capturing sequential relationships within data instance such as sentences, time sequence data. Obtaining word embedding features as inputs is shown to improve the performance in several deep learning architectures [423, 424, 425]. Anomaly detection models leveraging the word2vec embeddings are shown to significantly improve performance. [426, 427, 428, 429].

11.5 Generative Models

Generative models aim to learn true data distribution in order to generate new data points with some variations. The two most common and efficient generative approaches are Variational Autoencoders (VAE) [430] and Generative Adversarial Networks (GAN) [431, 432]. A variant of GAN architecture known as Adversarial autoencoders (AAE) [433] that use adversarial training to impose an arbitrary prior on the latent code learnt within hidden layers of autoencoder are also shown to effectively learn the input distribution. Leveraging this ability of learning input distributions, several Generative Adversarial Networks-based Anomaly Detection (GAN-AD) frameworks [56, 434, 7, 435, 436] proposed are shown to be effective in identifying anomalies on high dimensional and complex datasets. However traditional methods such as K-nearest neighbours (KNN) are shown to perform better in scenarios which have lesser number of anomalies when compared to deep generative models [437].

11.6 Convolutional Neural Networks

Convolutional Neural Networks (CNNs), are the popular choice of neural networks for analyzing visual imagery [438]. CNN's ability to extract complicated hidden features from high dimensional data with complex structure has enabled its use as feature extractors in outlier detection for both sequential and image dataset [238, 439]. Evaluation of CNNs based frameworks for anomaly detection is still an active area of research being explored currently [79].

11.7 Sequence Models

Recurrent Neural Networks (RNNs) [440] are shown to capture features of time sequence data. The limitations with RNNs is that they fail to capture the context as time steps increases, in order to resolve this problem, Long Short-Term Memory [41] networks was introduced, they are a special type of RNNs comprising of memory cell that can store information about previous time steps. Gated Recurrent Unit [441] (GRUs) are similar to LSTMs, but use a set of gates to control the flow of information, instead of separate memory cells. Anomaly detection in sequential data has attracted significant interest in literature due its applications in a wide range of engineering problems illustrated in Section 9.9. Long Short Term Memory (LSTM) neural network based algorithms for anomaly detection have been investigated and reported to produce significant performance gains over conventional methods [38].

11.8 Autoencoders

Autoencoders with single layer alongwith a linear activation function is nearly equivalent to Principal Component Analysis (PCA) [442]. While PCA is restricted to a linear dimensionality reduction, auto encoders enable both linear or nonlinear tranformations [443, 444]. One of the popular applications of Autoencoders is anomaly detection. Autoencoders represent data within multiple hidden layers by reconstructing the input data, effectively learning an identity function. The autoencoders when trained solely on normal data instances (which are the majority in anomaly detection tasks) fail to reconstruct the anomalous data samples therefore producing a large reconstruction error. The data samples which produce high residual errors are considered outliers. Several variants of autoencoder architectures are proposed as illustrated in Figure 13 produce promising results in anomaly detection. The choice of autoencoder architecture depends on the nature of data, convolution networks are preferred for image datasets while Long short-term memory (LSTM) based models tend to produce good results for sequential data. Efforts to combine both convolution and LSTM layers where encoder is a convolutional neural network (CNN) and decoder is a multilayer LSTM network to reconstruct input images are shown to be effective in detecting anomalies within data. The use of combined models such as Gated recurrent unit autoencoders (GRU-AE), Convolutional neural networks autoencoders (CNN-AE), Long short-term memory (LSTM) autoencoder (LSTM-AE) eliminate the need for preparing hand-crafted features, and facilitates the use of raw data with minimal preprocessing in anomaly detection tasks.

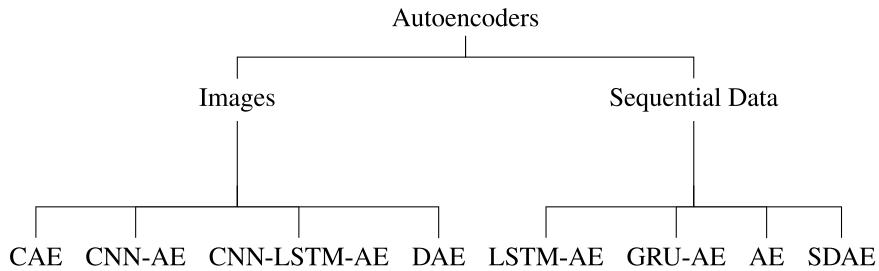


Figure 13: Autoencoder architectures for anomaly detection.
AE: Autoencoders [444], LSTM : Long Short Term Memory Networks [41]
SDAE: Stacked Denoising Autoencoder [445], DAE : Denoising Autoencoders [445]
GRU: Gated Recurrent Unit [441], CNN: Convolutional Neural Networks [438]
CNN-LSTM-AE: Convolution Long Short Term Memory Autoencoders [446]
CAE: Convolutional Autoencoders [447]

Although autoencoders are simple and effective architectures for outlier detection. However, the performance gets degraded due to noisy training data with a large fraction of corruptions [448].

12 Relative Strengths and Weakness : Deep Anomaly Detection Methods

Each of the deep anomaly detection (DAD) techniques discussed in previous sections have their unique strengths and weaknesses. It is critical to understand which anomaly detection technique is best suited for a given anomaly detection problem context. Given the fact that DAD is an active research area, it is not feasible to provide such an understanding for every anomaly detection problem. Hence in this section we analyze the relative strengths and weakenesses of different categories of techniques for a few simple problem settings.
Classification based supervised DAD techniques illustrated in Chapter **??** are better choices in scenario consisting of equal amount of labels for both normal and anomalous instances. The computational complexity of supervised DAD technique is a key aspect, especially when the technique is applied to a real domain. While classification based, supervised or semi-supervised techniques have expensive training times, testing is usually fast since it uses pre-trained model. Unsupervised DAD techniques presented in Chapter **??** are being widely used since label acquisition is very expensive and time consuming process. Most of the unsupervised deep anomaly detection requires priors to be assumed on the anomaly distribution hence the models are less robust in handling noisy data. Hybrid models illustrated in Section 10.3 extract robust features within hidden layers of deep neural network, and feed to best performing classical anomaly detection algorithms. The hybrid model approach is suboptimal because it is unable to influence representational learning in the hidden layers. The One-class Neural Networks (OC-NN) described in Section 10.4 combines the ability of deep networks to extract progressively rich representation of data alongwith the one-class objective, such as an hyperplane [18] or hypersphere [39] to separate all the normal data points from the origin. Further research and exploration is necessary to better comprehend the benefits of this new architecture proposed.

13 Conclusion

In this chapter we have discussed various research methods in deep learning-based anomaly detection alongwith its application across various domains. This article discusses the challenges in deep anomaly detection and presents several existing solutions to these challenges. For each category of deep anomaly detection techniques, we present the assumption regarding the notion of normal and anomalous data along with its strength and weakness. The goal of this survey was to investigate and identify the various deep learning models for anomaly detection and evaluate its suitability for a given dataset. When choosing a deep learning model to a particular domain or data, these assumptions can be used as guidelines to assess the effectiveness of the technique in that domain. Deep learning based anomaly detection is still an active research, a possible future work would be to extend and update as more mature techniques are proposed.

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