
DEEP LEARNING FOR ANOMALY DETECTION: A SURVEY

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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 assess their effectiveness. We have grouped state-of-the-art deep anomaly detection research techniques into different categories based on the underlying assumptions and approach adopted. Within each category, we outline the basic anomaly detection technique, along with its variants and present key assumptions, to differentiate between normal and anomalous behavior. Besides, for each category, 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 deep anomaly detection techniques for real-world problems.

Keywords anomalies, outlier, novelty, deep learning

1 Introduction

A common need when analyzing real-world data-sets 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 (Chandola et al. [2007]). Anomalies can be caused by errors in the data but sometimes are indicative of a new, previously unknown, underlying process; Hawkins [1980] 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 a proliferation of deep neural networks, with unprecedented results across various application domains. Deep learning is a subset of machine learning that achieves good performance and flexibility by learning to represent the data as a nested hierarchy of concepts within layers of the 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 have become increasingly popular and have been applied for a diverse set of tasks as illustrated in Figure 2; studies have shown that deep learning completely surpasses traditional methods (Javaid et al. [2016], Peng and Marculescu [2015]). 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 assess their effectiveness.

2 What are anomalies?

Anomalies are also referred to as abnormalities, deviants, or outliers in the data mining and statistics literature (Aggarwal [2013]). As illustrated in Figure 3, N_1 and N_2 are regions consisting of a 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. arise due to several

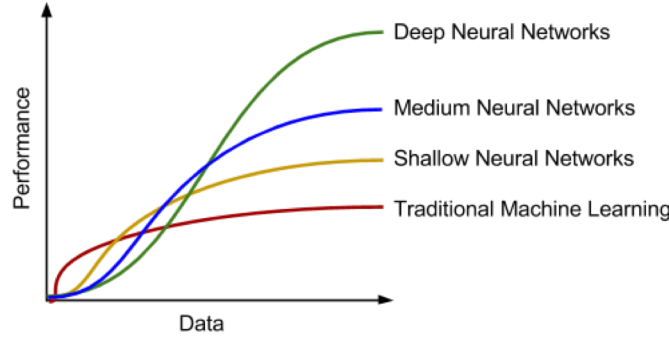


Figure 1: Performance Comparison of Deep learning-based algorithms Vs Traditional Algorithms Alejandro [2016].

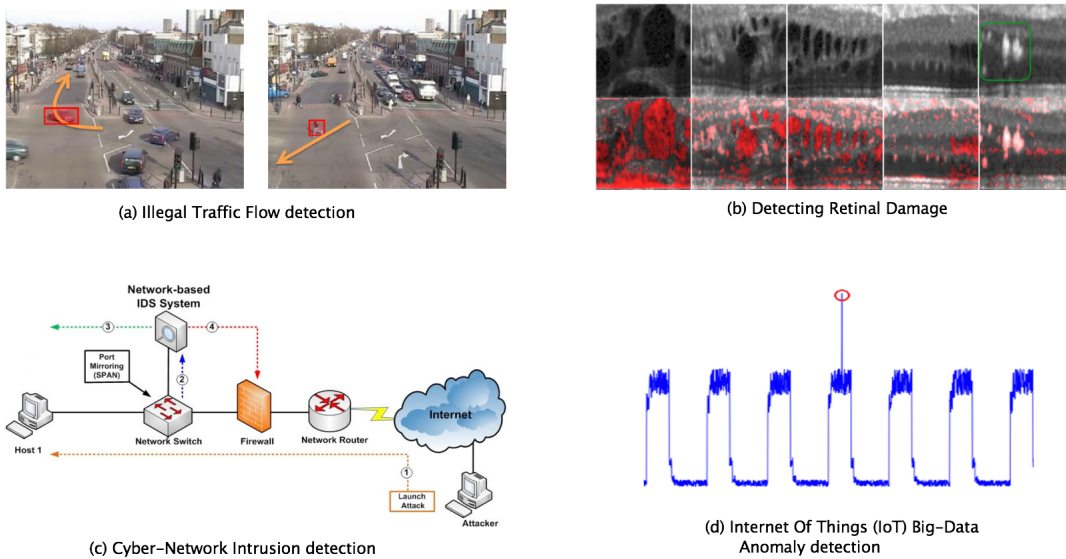


Figure 2: Applications Deep learning-based anomaly detection algorithms.
 (a) Video Surveillance, Image Analysis: Illegal Traffic detection Xie et al. [2017], (b) Health-care: Detecting Retinal Damage Schlegl et al. [2017]
 (c) Networks: Cyber-intrusion detection Javaid et al. [2016] (d) Sensor Networks: Internet of Things (IoT) big-data anomaly detection Mohammadi et al. [2017]

reasons, such as malicious actions, system failures, intentional fraud. These anomalies reveal exciting 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 a novel (new) or unobserved patterns in the data (Miljković [2010]). The novelties detected are not considered as anomalous data points; instead, they are been applied to the regular data model. A novelty score may be assigned for these previously unseen data points, using a decision threshold score (Pimentel et al. [2014]). The points which significantly deviate from this decision threshold may be considered as anomalies or outliers. For instance, in Figure 4 the images of (*white tigers*) among regular tigers may be considered as a novelty, while the 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.

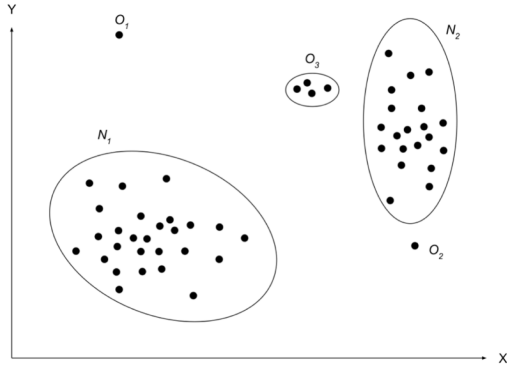


Figure 3: Illustration of anomalies in two-dimensional data set.

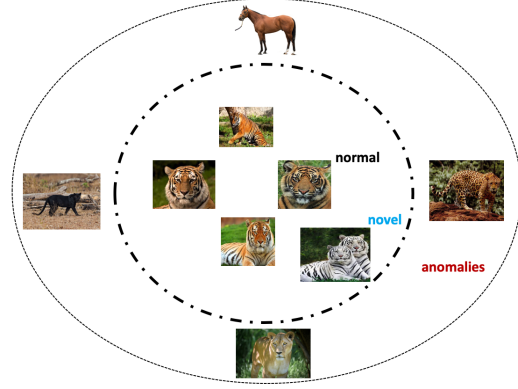


Figure 4: Illustration of novelty in the image data set.

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

- Performance of traditional algorithms in detecting outliers is sub-optimal on the image (e.g. medical images) and sequence datasets since it fails to capture complex structures in the data.
- 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 continually 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 Kwon et al. [2017], 5 —John and Derek Ball et al. [2017]
 3 —Kiran and Thomas Kiran et al. [2018], 6 —Mohammadi and Al-Fuqaha Mohammadi et al. [2017]
 4 —Adewumi and Andronicus Adewumi and Akinyelu [2017] 7 —Geert and Kooi et.al Litjens et al. [2017].

		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 and Akinyelu [2017] 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. [2017]. An extensive review of using DAD techniques in the medical domain is presented by Litjens et al. [2017]. An overview of DAD techniques for the Internet of

Things (IoT) and big-data anomaly detection is introduced by Mohammadi et al. [2017]. Sensor networks anomaly detection has been reviewed by Ball et al. [2017]. The state-of-the-art deep learning based methods for video anomaly detection along with various categories have been presented in Kiran et al. [2018]. Although there are some reviews in applying DAD techniques, there is a 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 a 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.

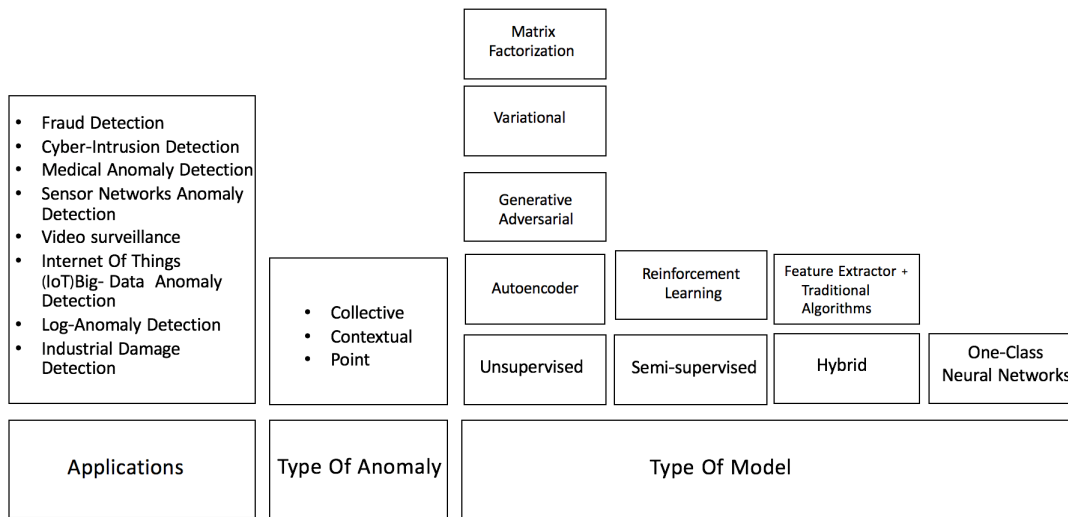


Figure 5: Key components associated with deep learning-based anomaly detection technique.

6 Our Contributions

We follow the survey approach of (Chandola et al. [2007]) 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 (Kiran et al. [2018], Mohammadi et al. [2017], Litjens et al. [2017], Kwon et al. [2017], Adewumi and Akinyelu [2017], Ball et al. [2017]). 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 is presented.
- In recent years several 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 an organized schema for better understanding. We introduce two more sub-categories Hybrid models (Erfani et al. [2016a]) and one-class neural networks techniques (Chalapathy et al. [2018a]) as illustrated in Figure 5 based on the choice of training objective. For each category 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 the 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 the 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 a 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 (LeCun et al. [2015]). The number of layers used in DAD techniques is driven by input data dimension, deeper networks are shown to produce better performance on high dimensional data. Later on, in 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 an outlier. Anomalies are rare entities hence it is challenging to obtain their labels. Furthermore, anomalous behavior 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 liters of untreated sewerage to local waterways (Ramotsoela et al. [2018]).

Deep anomaly detection (DAD) models can be broadly classified into three categories based on the 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. For instance supervised DAD models, formulated as multi-class classifier aids in detecting rare brands, prohibited drug name mention and fraudulent health-care transactions (Chalapathy et al. [2016a,b]). Despite the improved performance of supervised DAD methods, these methods are not as popular as semi-supervised or unsupervised methods, owing to the lack of availability of labeled training samples. Moreover, the performance of deep supervised classifier used an anomaly detector is sub-optimal 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 unusual events (Wulsin et al. [2010], Nadeem et al. [2016], Song et al. [2017]). We consider a detailed review of these methods in Section 10.2.

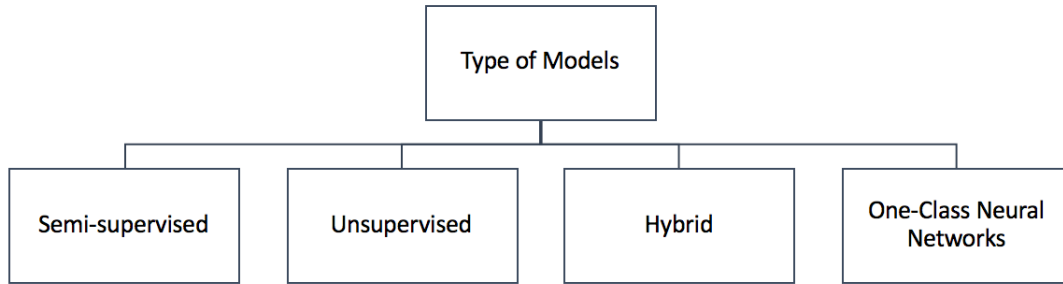


Figure 6: Taxonomy based on the type of deep learning models for anomaly detection.

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 labeling of unlabelled data samples since labeled data is very hard to obtain (Patterson and Gibson [2017]). Variants of Unsupervised DAD models (Tuor et al. [2017]) are shown to outperform traditional methods such as principal component analysis (PCA) (Wold et al. [1987]), support vector machine (SVM) Cortes and Vapnik [1995] and Isolation Forest (Liu et al. [2008]) techniques in applications domains such as health and cyber-security. Autoencoders are the core of all Unsupervised DAD models. These models assume a 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) (Sutskever et al. [2009]), deep Boltzmann machine (DBM), deep belief network (DBN) (Salakhutdinov and Larochelle [2010]), generalized denoising autoencoders (Vincent et al. [2008]), recurrent neural network (RNN) (Rodriguez et al. [1999]) Long short term memory networks (Lample et al. [2016]) which are used to detect outliers are discussed in detail in Section 11.7.

8.3 Based on the training objective

In this survey we introduce two new categories of deep anomaly detection (DAD) techniques based on training objectives 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 learned within the hidden representations of autoencoders are input to traditional anomaly detection algorithms such as one-class SVM (OC-SVM) to detect outliers (Andrews et al. [2016a]). 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 data-sets, hybrid models have also employed these pre-trained transfer learning models as feature extractors with great success (Pan et al. [2010]). A variant of hybrid model was proposed by Ergen et al. [2017] which considers joint training of feature extractor along-with OC-SVM (or SVDD) objective to maximize the detection performance. A notable shortcoming of these hybrid approaches is the lack of trainable objective customized for anomaly detection, hence these models fail to extract rich differential features to detect outliers. In order to overcome this limitation customized objective for anomaly detection such as Deep one-class classification (Ruff et al. [2018a]) and One class neural networks (Chalapathy et al. [2018a]) is introduced.

8.3.2 One-Class Neural Networks (OC-NN)

One class neural network (OC-NN) Chalapathy et al. [2018a] methods are inspired by kernel-based one-class classification which combines the ability of deep networks to extract a 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

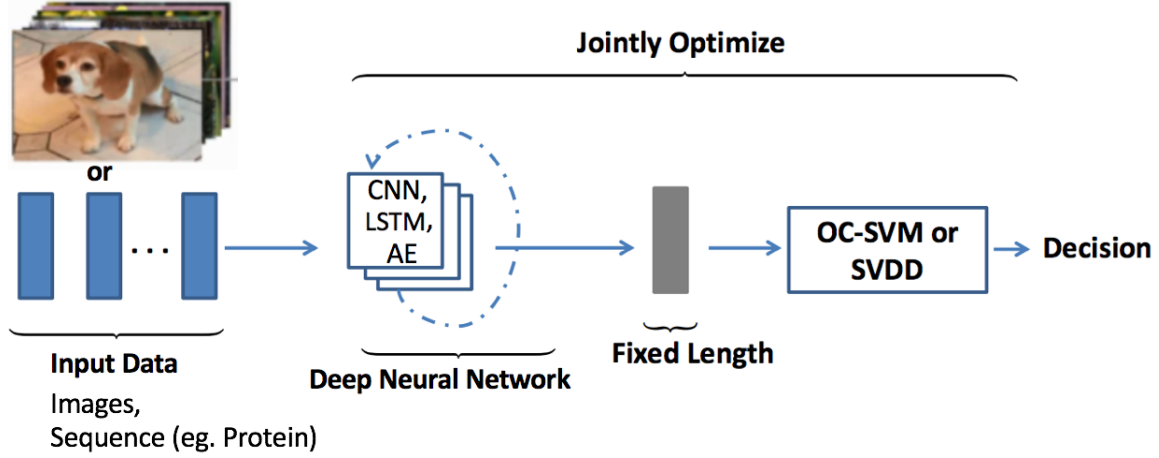


Figure 7: Deep Hybrid Model Architecture.

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 Section 10.4. Another variant of one class neural network architecture Deep Support Vector Data Description (Deep SVDD) (Ruff et al. [2018a]) 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 (LeCun et al. [2010]) and CIFAR-10 (Krizhevsky and Hinton [2009]) 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.

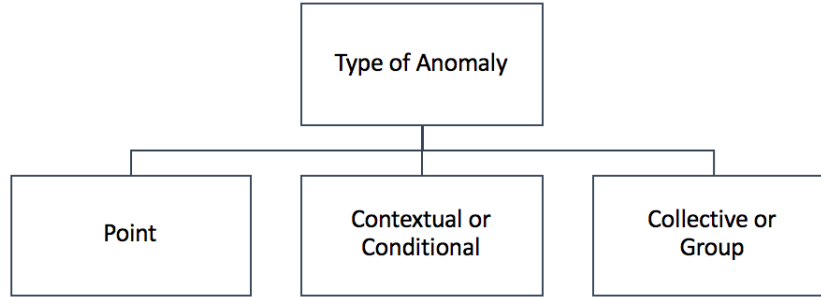


Figure 8: Deep learning techniques classification based on the type of anomaly.

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

A contextual anomaly is also known as the conditional anomaly is a data instance that could be considered as anomalous in some specific context (Song et al. [2007]). Contextual anomaly is identified by considering both contextual and behavioural features. The contextual features, normally used are time and space. While the behavioural features may be

a pattern of spending money, the occurrence of system log events or any feature used to describe the normal behavior. Figure 9a illustrates the example of a 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) (Hochreiter and Schmidhuber [1997]) based model to identify anomalous system log events (Du et al. [2017]) in a given context (e.g event 53 is detected as being out of context).

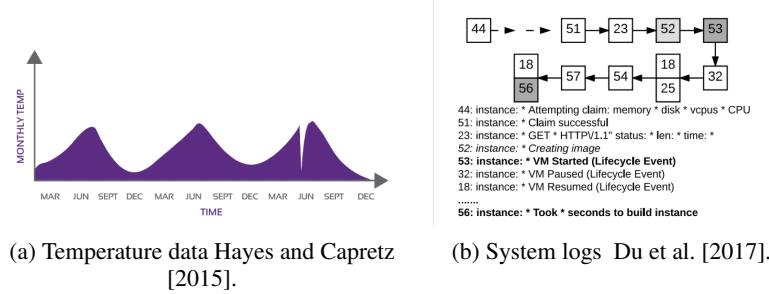


Figure 9: Illustration of contextual anomaly detection.

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 appears as normal data instances while observed in a group exhibit unusual characteristics. For example, consider an illustration of a fraudulent credit card transaction, in the log data shown in Figure 10, if a single transaction of "MISC" would have occurred, it might probably not seem as anomalous. The following 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 (Chalapathy et al. [2018b], Bontemps et al. [2016], Araya et al. [2016], Zhuang et al. [2017])).

May-22	1:14 pm	FOOD	Monaco Café	\$1,127.80	→ Point Anomaly
May-22	2:14 pm	WINE	Wine Bistro	\$28.00	
...					
Jun-14	2:14 pm	MISC	Mobil Mart	\$75.00	Collective Anomaly
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	Collective Anomaly
Jun-16	11:49 am	MISC	Mobil Mart	\$75.00	

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

8.5 Output of DAD Techniques

A critical aspect for anomaly detection methods is the way in which the anomalies are detected. 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 data point. 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 the distance of data point from the center of the sphere, the data points which are farther away from the center are considered anomalous (Ruff et al. [2018b]).

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	Kim et al. [2016],Chawla et al. [2018],Chen et al. [2018],Sohi et al. [2018],Vinayakumar et al. [2017]
Hybrid	GAN	Section 10.3	Aghakhani et al. [2018], Li et al. [2018]
Generative	AE, SPN,	Section 11.8, 11.3	Gao et al. [2014],Peharz et al. [2018],Umer et al. [2018]

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 the 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.

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 an anomaly;
- nature of the data;
- challenges associated with detecting anomalies;
- existing deep anomaly detection techniques.

9.1 Intrusion Detection

The intrusion detection system (IDS) refers to identifying malicious activity in a computer-related system (Phoha [2002]). 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 (Vigna and Kruegel [2005]). 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 the 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 the similarity between sequences. Some of the success-full 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 behavior, the nature of data is synonymous to big data with high volume, velocity, variety. The network data also has a temporal aspect associated with it. Some of the success-full DAD techniques for NIDS is illustrated in Table 4 . This survey also lists the data-sets 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.

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	Yu et al. [2017], Thing [2017], Zolotukhin et al. [2016], Cordero et al. [2016], Alrawashdeh and Purdy [2016], Tang et al. [2016], Lopez-Martin et al. [2017], Al-Qatf et al. [2018], Mirsky et al. [2018], Aygun and Yavuz [2017]
Hybrid	GAN	Section 10.3	Lin et al. [2018], Yin et al. [2018], Ring et al. [2018], Latah [2018], Intrator et al. [2018], Matsuura et al. [2018], Nicolau et al. [2016], Rigaki [2017].
Discriminative	RNN , LSTM ,CNN	Section 11.7, 11.6	Yu et al. [2017], Malaiya et al. [2018] Kwon et al. [2018], Gao et al. [2014], Staudemeyer [2015], Naseer et al. [2018]

Table 5: Datasets Used in Intrusion Detection

DataSet	IDS	Description	Type	References
CTU-UNB	NIDS	CTU-UNB ucs [2017] dataset consists of various botnet traffics from CTU-13 dataset [20] and normal traffics from the UNB ISCX IDS 2012 dataset Shiravi et al. [2012]	Hexadecimal	Yu et al. [2017]
Contagio-CTU-UNB	NIDS	Contagio-CTU-UNB dataset consists of six types of network traffic data. Adam et al. [2008]	Text	Yu et al. [2017].
NSL-KDD ¹	NIDS	The NSL-KDD data set is a refined version of its predecessor KDD-99 data set. ucs [2017]	Text	Yin et al. [2017], Javaid et al. [2016], Tang et al. [2016], Yousefi-Azar et al. [2017], Mohammadi and Namadchian [2017], Lopez-Martin et al. [2017]
DARPA KDD- CUP 99	NIDS	DARPA KDD Stolfo et al. [2000] 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	Alrawashdeh and Purdy [2016], Van et al. [2017], Mohammadi and Namadchian [2017]
MAWI	NIDS	The MAWI Fontugne et al. [2010] dataset consists of network traffic captured from backbone links between Japan and USA. Every days since 2007	Text	Cordero et al. [2016]
Realistic Global Cyber Environment (RGCE)	NIDS	RGCE jam [2009] contains realistic Internet Service Providers (ISPs) and numerous different web services as in the real Internet.	Text	Zolotukhin et al. [2016]
ADFA-LD	HIDS	The ADFA Linux Dataset (ADFA-LD). This dataset provides a contemporary Linux dataset for evaluation by traditional HIDS Creech and Hu [2014]	Text	Kim et al. [2016], Chawla et al. [2018]
UNM-LPR	HIDS	Consists of system calls to evaluate HIDS system University [2012]	Text	Kim et al. [2016]
Infected PDF samples	HIDS	Consists of set of Infected PDF samples, which are used to monitor the malicious traffic	Text	Chen et al. [2018]

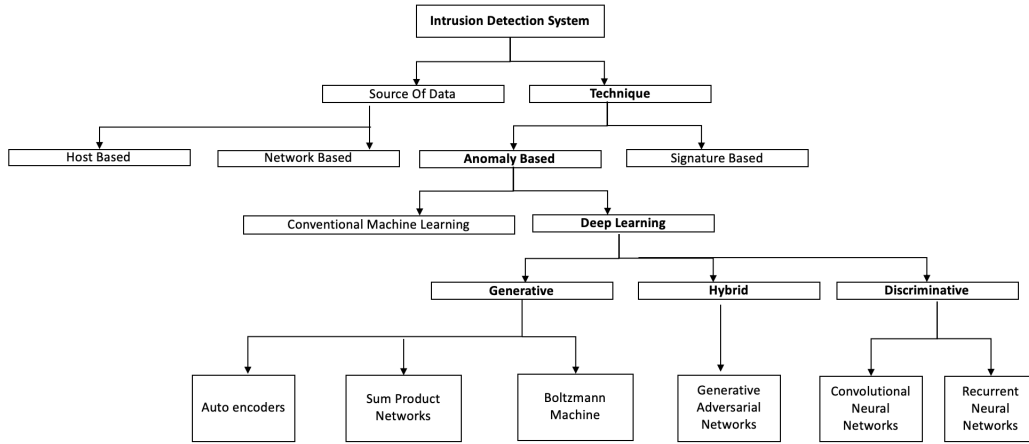


Figure 11: Classification of deep learning methods for intrusion detection.

9.2 Fraud Detection

Fraud is a deliberate act of deception to access valuable resources (Abdallah et al. [2016]). The Pricewaterhouse-Coopers (PwC) global economic crime survey of 2018 (Lavion [2018], Zhao [2013]) found that half of the 7,200 companies they surveyed had experienced fraud of some nature. Fraud detection refers to the detection of unlawful activities across various industries, illustrated in 12.

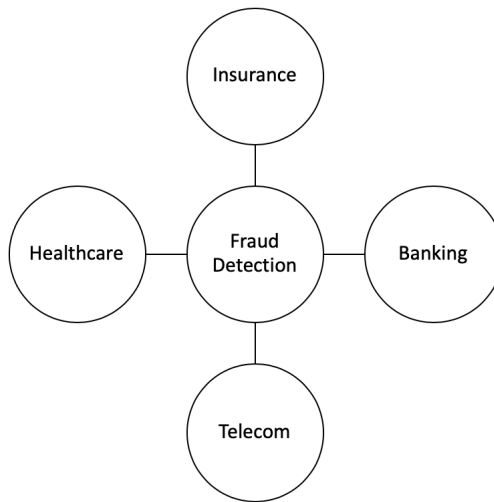


Figure 12: Fraud detection across various application domains.

Fraud in telecommunications, 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 successfully in fraud detection (Sorournejad et al. [2016]). 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.

Table 6: Examples of DAD techniques used in credit card fraud detection.

AE: Autoencoders, LSTM : Long Short Term Memory Networks
RBM: Restricted Boltzmann 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	Schreyer et al. [2017], Wedge et al. [2017] , Paula et al. [2016], Renström and Holmsten [2018], Kazemi and Zarrabi [2017], Zheng et al. [2018a], Pumsirirat and Yan [2018]
RBM	Section 11.1	Pumsirirat and Yan [2018]
DBN	Section 11.1	Seeja and Zareapoor [2014]
VAE	Section 11.5	Sweers et al. [2018]
GAN	Section 11.5	Fiore et al. [2017], Choi and Jang [2018]
DNN	Section 11.1	Dorransoro et al. [1997], Gómez et al. [2018]
LSTM,RNN,GRU	Section 11.7	Wiese and Omlin [2009], Jurgovsky et al. [2018], Heryadi and Warnars [2017], Ando et al. [2016], Wang et al. [2017a], Alowais and Soon [2012], Amarasinghe et al. [2018a], Abroyan [2017a], Lp et al. [2018]
CNN	Section 11.6	Shen et al. [2007], Chouiekh and Haj [2018], Abroyan [2017b], Fu et al. [2016], Lu [2017], Wang et al. [2018a], Abroyan [2017a] , Zhang et al. [2018a]

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	Chouiekh and Haj [2018]
SAE, DBN	Section 11.8, 11.1	Alsheikh et al. [2016], Badhe [2017]
DNN	Section 11.1	Akhter and Ahamad [2012], Jain [2017]
GAN	Section 11.5	Zheng et al. [2018b]

9.2.1 Banking fraud

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 (Zhou et al. [2018], Suganya and Kamalraj [2015]). We will briefly review some of DAD techniques as shown in Table 6. The challenge in credit card fraud detection is that frauds have no consistent 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 scalable. Owing to the inherent scalable nature of DAD techniques techniques are gaining broad spread adoption in credit card fraud detection.

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 vastly diverse array of mobile devices. Due to this broad 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 the 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 (Joudaki et al. [2015], Roy and George [2017]). The traditional approach for fraud detection is based on features

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	Viaene et al. [2005]
VAE	Section 11.5	Fajardo et al. [2018]
GAN	Section 11.5	Fiore et al. [2017], Choi and Jang [2018]
DNN	Section 11.1	Keung et al. [2009]
CNN	Section 11.6	Shen et al. [2007], Zhang et al. [2018a]

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

Technique Used	Section	References
RBM	Section 11.1	Lasaga and Santhana [2018]
GAN	Section 11.5	Ghasedi Dizaji et al. [2018], Finlayson et al. [2018]
CNN	Section 11.6	Esteva et al. [2017]

which are fraud indicators. The challenge with these traditional approaches is that the need for 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 way. In order to overcome these limitations several DAD techniques are proposed which are illustrated in Table 8.

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 significant 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 (Bauder and Khoshgoftaar [2017]). Table 9 presents an overview of DAD methods for health-care 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 (Ye et al. [2017]). In 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 sheer scale of data, for instance considering data as bytes a specific sequence classification problem could be of the order of two million time steps. Furthermore, the malware is very adaptive in nature, wherein the attackers would use advanced techniques to hide the malicious behavior. 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 bio-informatics (Min et al. [2017], Cao et al. [2018a], Zhao et al. [2016], Khan and Yairi [2018]). 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. Even though deep learning models produce outstanding performance, these models lack interpret-ability. In recent times models with good interpret-ability are proposed and shown to produce state-of-the-art performance (Gugulothu et al., Amarasinghe et al. [2018b], Choi [2018]).

Table 10: Examples of DAD techniques used for malware detection.

AE: Autoencoders, LSTM : Long Short Term Memory Networks
RBM: Restricted Boltzmann 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	Yousefi-Azar et al. [2017], Hardy et al. [2016], Yousefi-Azar et al. [2017], De Paola et al. [2018], Sewak et al. [2018], Kebede et al. [2017], De Paola et al. [2018], David and Netanyahu [2015]
word2vec	Section 11.4	Cakir and Dogdu [2018], Silva et al. [2018]
CNN	Section 11.6	Kolosnjaji et al. [2018], Suciu et al. [2018], Srisakaokul et al. [2018], Srisakaokul et al. [2018], King et al. [2018], Huang and Kao [2017], Guo et al. [2017], Abdelsalam et al. [2018], Raff et al. [2017], Karbab et al. [2018], Martinelli et al. [2017], McLaughlin et al. [2017], Gibert et al. [2018], Kolosnjaji et al. [2017]
DNN	Section 11.1	Rosenberg et al. [2018], Wang et al. [2017b]
DBN	Section 11.1	David and Netanyahu [2015], YANG et al. [2016], Ding et al. [2016], Yuxin and Siyi [2017], Selvaganapathy et al. [2018], Yuxin and Siyi [2017], Hou et al. [2017]
LSTM	Section 11.7	Tobiyama et al. [2016], Hu and Tan [2017], Tobiyama et al. [2018], Passalis and Tefas
CNN-BiLSTM	Section 11.6, 11.7	Le et al. [2018], Wang et al. [2017b]
GAN	Section 11.5	Kim et al. [2018]
Hybrid model(AE-CNN),(AE-DBN)	Section 10.3	Wang et al. [2018b], Li et al. [2015]
RNN	Section 11.7	HaddadPajouh et al. [2018]

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	Wang et al. [2016], Cowton et al. [2018], Sato et al. [2018]
DBN	Section 11.1	Turner et al. [2014], Sharma et al. [2016], Wulsin et al. [2010], Ma et al. [2018], Zhang et al. [2016], Wulsin et al. [2011], Wu et al. [2015a]
RBM	Section 11.1	Liao et al. [2016]
VAE	Section 11.5	Xu et al. [2018], Lu and Xu [2018]
GAN	Section 11.5	Ghasedi Dizaji et al. [2018], Chen and Konukoglu [2018]
LSTM ,RNN,GRU	Section 11.7	Yang and Gao [2018], Jagannatha and Yu [2016], Cowton et al. [2018], O'Shea et al. [2016], Latif et al. [2018], Zhang and Zou [2018], Chauhan and Vig [2015], Gugulothu et al., Amarasinghe et al. [2018b]
CNN	Section 11.6	Schmidt-Erfurth et al. [2018], Esteva et al. [2017], Wang et al. [2016], Iakovidis et al. [2018]
Hybrid(AE+ KNN)	Section 11.6	Song et al. [2017]

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	Zhang et al. [2017], Castellini et al. [2017]
CNN-LSTM	Section 11.6, 11.7	Sun et al. [2018], Shu et al. [2017], Yang et al. [2018]
DNN	Section 11.1	Li et al. [2017a]
Hybrid Models (CNN-LSTM-SVM)	Section 10.3	Wei [2017]

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	Hochreiter and Schmidhuber [1997], Brown et al. [2018], Tuor et al. [2017], Das et al. [2018], Malhotra et al. [2015]
AE	Section 11.8	Du et al. [2017], Andrews et al. [2016a], Sakurada and Yairi [2014], Nolle et al. [2018a], Nolle et al. [2016]
LSTM-AE	Section 11.7, 11.8	Grover [2018], Wolpher [2018]
RNN	Section 11.7	Brown et al. [2018], Zhang et al. [2018b], Nanduri and Sherry [2016], Fengming et al. [2017]
DAE	Section 11.8	Marchi et al. [2015], Nolle et al. [2016]
CNN	Section 11.6	Lu et al. [2018], Yuan et al. [2018a], Racki et al. [2018], Zhou et al. [2016], Gorokhov et al. [2017], Liao et al. [2017], Cheng et al. [2017], Zhang et al. [2018c]

9.5 Deep learning for Anomaly detection in Social Networks

In recent times, online social networks have become part and parcel of daily life. Anomalies in a social network are irregular often unlawful behavior pattern of individuals within a social network; such individuals may be identified as spammers, sexual predators, online fraudsters, fake users or rumor-mongers. Detecting these irregular patterns is of prime importance since if not detected, the act of such individuals can have a 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 (Liu and Chawla [2017], Savage et al. [2014], Anand et al. [2017], Yu et al. [2016], Cao et al. [2018b], Yu et al. [2016]). The heterogeneous 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 the 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 (Memon [2008]). 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 the concurrent set 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 model the log data as a 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 are interconnected with soft-wares, servers, sensors and etc. In the field of the Internet of things (IoT), data generated by weather stations, Radio-frequency identification (RFID) tags, IT infrastructure components, and some other sensors are mostly time-series sequential data. Anomaly detection in these

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	Luo and Nagarajany [2018], Mohammadi and Kwasinski [2018]
DBN	Section 11.1	Kakanakova and Stoyanov [2017]
LSTM	Section 11.7	Zhang et al. [2018d], Mudassar et al. [2018]

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	Inoue et al. [2017], Thi et al. [2017], Kravchik and Shabtai [2018], Huang et al. [2018], Park et al. [2018a], Chang et al. [2018]
AE	Section 11.8	Yuan and Jia [2015], Araya et al. [2017], Qu et al. [2017], Sakurada and Yairi [2014], Bhattad et al. [2018]
DNN	Section 11.1	Lodhi et al. [2017]
CNN	Section 11.6	Faghih-Roohi et al. [2016], Christiansen et al. [2016], Lee et al. [2016], Faghih-Roohi et al. [2016], Dong et al. [2016], Nanduri and Sherry [2016], Fuentes et al. [2017], Huang et al. [2018], Chang et al. [2018]
SDAE,DAE	Section 11.8	Yan and Yu [2015], Luo and Zhong [2017], Dai et al. [2017]
RNN	Section 11.7	Banjanovic-Mehmedovic et al. [2017], Thi et al. [2017]
Hybrid Models (DNN-SVM)	Section 10.3	Inoue et al. [2017]

IoT networks identifies fraudulent, faulty behavior of these massive scales of interconnected devices. The challenges associated with outlier detection is that heterogeneous devices are interconnected which renders the system more complex. A thorough overview of using deep learning (DL), to facilitate analytics and learning in the IoT domain is presented by (Mohammadi et al. [2018]). Table 14 illustrates the DAD techniques employed IoT devices.

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 (Ramotsoela et al. [2018], Martí et al. [2015]). Several papers published utilizing deep learning models for detecting early industrial damage show great promise (Atha and Jahanshahi [2018], de Deijn [2018], Wang et al. [2018c]). Damages caused to equipment are rare events, thus detecting such events can be formulated as an outlier detection problem. The challenges associated with outlier detection in this domain is both volumes as well as the dynamic nature of data since failure is caused due to a 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 duration is known as time series. Time series data can be broadly classified into univariate and multivariate time series. In case of univariate time series, only single variable (or feature) varies over time. For instance, the data collected from a temperature sensor within the room for each second is an uni-variate time series data. A multivariate time series consists several variables (or features) which change over time. An accelerometer which produces three-dimensional data for every second one for each axis (x, y, z) is a perfect example of multivariate time series data. In the literature, types of anomalies in univariate and multivariate time series are categorized into following groups: (1) Point Anomalies. 8.4.1 (2) Contextual Anomalies 8.4.2 (3) Collective Anomalies

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

Techniques	Section	References
LSTM	Section 11.7	Shipmon et al. [2017a], Hundman et al. [2018], Zhu and Laptev [2017], Malhotra et al. [2015], Chauhan and Vig [2015], As-sendorp [2017] Ahmad et al. [2017], Malhotra et al. [2016a], Bontemps et al. [2016], Taylor et al. [2016], Cheng et al. [2016], Loganathan et al. [2018], Chauhan and Vig [2015], Malhotra et al. [2015], Gorokhov et al. [2017], Munir et al. [2018]
AE, LSTM-AE, CNN-AE, GRU-AE	Section 11.8	Shipmon et al. [2017b], Malhotra et al. [2016b], Filonov et al. [2016], Sugimoto et al. [2018], Oh and Yun [2018], Ebrahimzadeh and Kleinberg, Veeramachaneni et al. [2016], Dau et al. [2014]
RNN	Section 11.7	Wielgosz et al. [2017], Saurav et al. [2018], Wielgosz et al. [2018], Guo et al. [2016], Filonov et al. [2017]
CNN, CNN-LSTM	Section 11.6, 11.7	Kanarachos et al. [2017], Du et al., Gorokhov et al. [2017], Napoletano et al. [2018], Shanmugam et al. [2018], Medel and Savakis [2016]
LSTM-VAE	Section 11.7, 11.5	Park et al. [2018b], Sölch et al. [2016]
DNN	Section 11.1	Amarasinghe et al. [2018b]
GAN	Section 11.5	Li et al. [2018], Zenati et al. [2018], Lim et al. [2018], Laptev, Wei et al. [2018]

8.4.3. In recent times, many deep learning models have been proposed for detecting anomalies within univariate and multivariate time series data as illustrated in Table 16 and Table 17 respectively. Some of the challenges to detect anomalies in time series using deep learning models data are:

- Lack of defined pattern in which an anomaly is occurring may be defined.
- Noise within the input data seriously affects 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.

9.9.1 Uni-variate time series deep anomaly detection

The advancements in deep learning domain offer opportunities to extract rich hierarchical features which can greatly improve outlier detection within uni-variate time series data. The list of industry standard tools and datasets (both deep learning based and non-deep learning based) for benchmarking anomaly detection algorithms on both univariate and multivariate time-series data is presented and maintained at Github repository ². Table 16 illustrates various deep architectures adopted for anomaly detection within uni-variate time series data.

9.9.2 Multi-variate time series deep anomaly detection

Anomaly detection in multivariate time series data is a challenging task. Effective multivariate anomaly detection enables fault isolation diagnostics. RNN and LSTM based methods ³ are shown to perform well in detecting interpretable anomalies within multivariate time series dataset. DeepAD, a generic framework based on deep learning for multivariate time series anomaly detection is proposed by (Buda et al. [2018]). Interpretable, anomaly detection systems designed using deep attention based models are effective in explaining the anomalies detected (Yuan et al. [2018b], Guo and Lin [2018]). Table 17 illustrates various deep architectures adopted for anomaly detection within multivariate time series data.

²<https://github.com/rob-med/awesome-TS-anomaly-detection>

³<https://github.com/pnnl/safekit>

Table 17: Examples of DAD techniques used in multivariate time series data.
CNN: Convolution Neural Networks, GAN: Generative Adversarial networks,
DNN: Deep Neural Networks, AE: Autoencoders, DAE: Denoising Autoencoders,
VAE: Variational Autoencoder, SDAE: Stacked Denoising Autoencoders,
LSTM: Long Short Term Memory Networks, GRU: Gated Recurrent Unit

Techniques	Section	References
LSTM	Section 11.7	Nucci et al. [2018], Hundman et al. [2018], Assendorp et al. [2017], Nolle et al. [2018b]
AE,LSTM-AE,CNN-AE,GRU-AE	Section 11.8	Zhang et al. [2018e] Guo et al. [2018], Fu et al. [2019], Kieu et al. [2018]
CNN, CNN-LSTM	Section 11.6, 11.7	Basumallik et al. [2019], Shanmugam et al. [2018]
LSTM-VAE	Section 11.7, 11.5	Ikeda et al. [2018], Park et al. [2018b]
GAN	Section 11.5	Assendorp [2017], Li et al. [2018], Li et al. [2019] Cowton et al. [2018]
DNN-RNN	Section 11.7	Tuor et al. [2017], Tuor et al. [2018]

Table 18: Datasets used in multivariate anomaly detection.

Dataset	Description	References
NASA Shuttle Valve Data ¹	Includes spacecraft anomaly data and experiments from the Mars Science Laboratory and SMAP missions	Hundman et al. [2018] ²
Vessels ³	Multivariate temporal data analysis for Vessels behavior anomaly detection	Maia [2017]
SWaT and WADI	Secure Water Treatment (SWaT) and the Water Distribution (WADI)	Li et al. [2019]
Credit Card Fraud Detection	Anonymized credit card transactions labeled as fraudulent or genuine	Dal Pozzolo et al. [2015]
NYC taxi passenger count ⁵	The New York City taxi passenger data stream	Cui et al. [2016]

¹ <https://cs.fit.edu/~pkc/nasa/data/>

² <https://github.com/khundman/telemanom>

³ <http://conferences.inf.ed.ac.uk/EuroDW2018/papers/eurodw18-Maia.pdf>

⁴ <https://www.kaggle.com/peterkim95/multivariate-gaussian-anomaly-detection/data>

⁵ <https://github.com/chickenbestlover/RNN-Time-series-Anomaly-Detection>

9.10 Video Surveillance

Video Surveillance also popularly known as Closed-circuit television (CCTV) involves monitoring 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 modeled as anomaly detection problems owing to lack of availability of labeled 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 (Kiran et al. [2018], Chong and Tay [2015]). The challenges of robust 24/7 video surveillance systems are discussed in detail by (Boghossian and Black [2005]). The lack of an explicit definition of an 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 19.

Table 19: 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	Dong et al. [2016],Andrewsa et al.,Sabokrou et al. [2016a],Sabokrou et al. [2017],Munawar et al. [2017],Li et al. [2017b],Qiao et al. [2017],Tripathi et al. [2018],Nogas et al. [2018],Christiansen et al. [2016],Li et al. [2017b],
SAE (AE-CNN-LSTM)	Section 11.8, 11.6, 11.7	Chong and Tay [2017], Qiao et al. [2017], Khaleghi and Moin [2018]
AE	Section 11.8	Qiao et al. [2017],Yang et al. [2015],Chen et al. [2015],Gutoski et al.,D’Avino et al. [2017],Dotti et al. [2017],Yang et al. [2015],Chen et al. [2015],Sabokrou et al. [2016b],Tran and Hogg [2017],Chen et al. [2015],D’Avino et al. [2017],Hasan et al. [2016],Yang et al. [2015],Cinelli [2017],Sultani et al. [2018]
Hybrid Model (CAE-OCSVM)	Section 10.3	Gutoski et al., Dotti et al. [2017]
LSTM-AE	Section 11.7, 11.8	D’Avino et al. [2017]
STN	Section 11.2	Chianucci and Savakis [2016]
RBM	Section 11.1	Munawar et al. [2017]
LSTM	Section 11.7	Medel and Savakis [2016], Luo et al. [2017a], Ben-Ari and Shwartz-Ziv [2018], Singh [2017]
RNN	Section 11.7	Luo et al. [2017b],Zhou and Zhang [2015],Hu et al. [2016], Chong and Tay [2015]
AAE	Section 11.5	Ravanbakhsh et al. [2017a]

10 Deep Anomaly Detection (DAD) Models

In this section, we discuss various DAD models classified based on the 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 (Görnitz et al. [2013]). Supervised anomaly detection 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 learned 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 assumes that the training data contains labeled instances of multiple normal classes (Shilton et al. [2013], Jumutc and Suykens [2014], Kim et al. [2015], Erfani et al. [2017]). 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 sub-networks, a feature extraction network followed by a classifier network. Deep models require a substantial number of training samples (in the order of thousands or millions) to learn feature representations to discriminate various class instances effectively. 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 **input data dimension** and the **number of hidden layers** trained **using back-propagation** algorithm. High dimensional data tend to have more hidden layers to ensure meaning-full hierarchical learning of input features. The computational complexity also increases linearly 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.**

Table 20: 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	Edmunds and Feinstein [2017] , Estiri and Murphy [2018]
RBM	Section 11.1	Jia et al. [2014]
DBN	Section 11.1	Wulsin et al. [2010], Wulsin et al. [2011]
CorGAN,GAN	Section 11.5	Gu et al. [2018] Akcay et al. [2018], Sabokrou et al. [2018]
AAE	Section 11.5	Dimokranitou [2017]
Hybrid Models (DAE-KNN Altman [1992]), (DBN-Random Forest Ho [1995]),CNN-Relief Kira and Rendell [1992],CNN-SVM Cortes and Vapnik [1995]	Section 8.3.1	Song et al. [2017], Shi et al. [2017], Zhu et al. [2018]
CNN	Section 11.6	Racah et al. [2017], Perera and Patel [2018]
RNN	Section 11.7	Wu and Prasad [2018]
GAN	Section 11.5	Kliger and Fleishman [2018], Gu et al. [2018]

- The **testing phase** of classification based techniques is **fast** since each test instance needs to be compared against the precomputed 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 for anomaly detection is presented by Kiran et al. [2018] and Min et al. [2018]. 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 (Perera and Patel [2018], Blanchard et al. [2010]). Various semi-supervised DAD model architectures are illustrated in Table 20.

Assumptions: Semi-supervised DAD methods proposed to rely on one of 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 learned feature space are more likely to share the same label.
- Robust features are learned 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

Table 21: 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 Cortes and Vapnik [1995]

SVDD: Support Vector Data Description, RNN : Recurrent Neural Networks

Relief: Feature selection Algorithm Kira and Rendell [1992], KNN: K- Nearest Neighbours Altman [1992]

CSI: Capture, Score, and Integrate Ruchansky et al. [2017].

Techniques	Section	References
AE-OCSVM, AE-SVM	Section 11.8,	Andrews et al. [2016a]
DBN-SVDD, AE-SVDD	Section 11.1,	Erfani et al. [2016a], Kim et al. [2015]
DNN-SVM	21D	Inoue et al. [2017]
DAE-KNN, DBN-Random Forest Ho [1995], CNN-Relief, CNN-SVM	Section 11.1, 11.8	Song et al. [2017], Shi et al. [2017], Zhu et al. [2018], Urbanowicz et al. [2018]
AE-CNN, AE-DBN	Section 11.1, 11.6, 11.8	Wang et al. [2018b], Li et al. [2015]
AE+ KNN	Section 11.8	Song et al. [2017]
CNN-LSTM-SVM	Section 11.6, 11.7	Wei [2017]
RNN-CSI	Section 11.7	Ruchansky et al. [2017]
CAE-OCSVM	Section 11.8	Gutoski et al., Dotti et al. [2017]

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 [2009]) are applicable even in a deep learning context. Furthermore, the hierarchical features extracted within hidden layers may not be representative of fewer anomalous instances hence are prone to the over-fitting problem.

10.3 Hybrid deep anomaly detection

Deep learning models are widely used as feature extractors to learn robust features (Andrews et al. [2016a]). In deep hybrid models, the representative features learned 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 (Erfani et al. [2016a,b], Wu et al. [2015b]). Deep hybrid architectures used in anomaly detection is presented in Table 21.

Assumptions:

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

- Robust features are extracted within hidden layers of the deep neural network, aid in separating 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 21

Computational Complexity :

The computational complexity of a hybrid model includes the 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 significantly reduces the ‘curse of dimensionality’, especially in the 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 the customized objective for anomaly detection.
- The deeper hybrid models tend to perform better if the individual layers are (Saxe et al. [2011]) 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 a progressively rich representation of data alongwith the one-class objective, such as a hyperplane (Chalapathy et al. [2018a]) or hypersphere (Ruff et al. [2018a]) 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 optimizing the objective function customized for anomaly detection as illustrated in The experimental results in (Chalapathy et al. [2018a], Ruff et al. [2018a]) 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:

- OC-NN models extract the common factors of variation within the data distribution within the hidden layers of the deep neural network.
- Performs combined representation learning and produces an outlier score for a test data instance.
- Anomalous samples do not contain common factors of variation and hence hidden layers fail 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 the deep network of choice (Saxe et al. [2011]). 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 train 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.

Table 22: 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	Singh [2017], Chandola et al. [2008], Dasigi and Hovy [2014], Malhotra et al. [2015]
AE	Section 11.8	Abati et al. [2018], Zong et al. [2018], Tagawa et al. [2015], Dau et al. [2014], Sakurada and Yairi [2014], Wu et al. [2015a], Xu et al. [2015], Hawkins et al. [2002], Zhao et al. [2015], Qi et al. [2014], Chalapathy et al. [2017], Yang et al. [2015], Zhai et al. [2016], Lyudchik [2016], Lu et al. [2017], Mehrotra et al. [2017], Meng et al. [2018], Parchami et al. [2017]
STN	Section 11.2	Chianucci and Savakis [2016]
GAN	Section 11.5	Lawson et al. [2017]
RNN	Section 11.7	Dasigi and Hovy [2014], Filonov et al. [2017]
AAE	Section 11.5	Dimokranitou [2017], Leveau and Joly [2017]
VAE	Section 11.5	An and Cho [2015], Suh et al. [2016], Sölch et al. [2016], Xu et al. [2018], Mishra et al. [2017]

10.5 Unsupervised Deep Anomaly Detection

Unsupervised DAD is an essential area of research in both fundamental machine learning research and industrial applications. Several deep learning frameworks that address challenges in unsupervised anomaly detection are proposed and shown to produce a state-of-the-art performance as illustrated in Table 22. Autoencoders are the fundamental unsupervised deep architectures used in anomaly detection (Baldi [2012]).

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

- The “normal” regions in the original or latent feature space can be distinguished from “anomalous” regions in the original or 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 data-set such as distances or densities. The hidden layers of deep neural network aim to capture these intrinsic properties within the dataset (Goldstein and Uchida [2016]).

Computational Complexity: The autoencoders are the most common architecture employed in outlier detection with quadratic cost, the optimization problem is non-convex, similar to any other neural network architecture. The computational complexity of model 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 (Meng et al. [2018], Parchami et al. [2017]).

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

- Learns the inherent data characteristics to separate normal from an anomalous data point. This technique identifies commonalities within the data and 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 challenging 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 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 criticized for the need to have enough data to produce good results. Both Litjens et al. [2017] and Pan et al. [2010] present the review of deep transfer learning approaches and illustrate their significance to learn good feature representations. Transfer learning is an essential tool in machine learning to solve the fundamental 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 by (Andrews et al. [2016b], Vercruyssen et al. [2017], Li et al. [2012], Almajai et al. [2012], Kumar and Vaidehi [2017], Liang et al. [2018]) are shown to produce very promising results. The open research questions using transfer learning for anomaly detection is, the degree of transfer-ability, 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 to recognize objects never seen before within training set (Romera-Paredes and Torr [2015]). 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 the real world since one may not be able to obtain images of all the possible classes at training. The primary 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 (Mishra et al. [2017], Socher et al. [2013], Xian et al. [2017], Liu et al. [2017], Rivero et al. [2017]).

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 extensive training data to perform robustly (Kim et al. [2016]). In order to achieve robustness even in noisy data an idea to randomly vary on the connectivity architecture of the autoencoder is shown to obtain significantly better performance. Autoencoder ensembles consisting of various randomly connected autoencoders are experimented by Chen et al. [2017] to achieve promising results on several benchmark 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 (Ester et al. [1996]). 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 (Sreekanth et al. [2010]), 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 (Mikolov et al. [2013]) models to get the semantical presentations of normal data and anomalies to form clusters and detect outliers (Yuan et al. [2017]). Several works rely on variants of hybrid models along with auto-encoders for obtaining representative features for clustering to find anomalies.

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 de La Bourdonnaye et al. [2017], Chengqiang Huang [2016]. 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 the research gap and its applications.

10.6.6 Statistical techniques deep anomaly detection

Hilbert transform is a statistical signal processing technique which derives the analytic representation of a real-valued signal. This property is leveraged by (Kanarachos et al. [2015]) 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 understand their potential and applicability for anomaly detections fully.

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 (Schmidhuber [2015], Bengio et al. [2009]). Deep architectures overcome the limitations of traditional machine learning approaches of scalability, and generalization to new variations within data (LeCun et al. [2015]) and the need for manual feature engineering. Deep Belief Networks (DBNs) are class of deep neural network which comprises multiple layers of graphical models known as Restricted Boltzmann Machine (RBMs). The hypothesis in using DBNs for anomaly detection is that RBMs are used as a directed encoder-decoder network with backpropagation algorithm (Werbos [1990]). DBNs fail to capture the characteristic variations of anomalous samples, resulting in high reconstruction error. DBNs are shown to scale efficiently to big-data and improve interpretability (Wulsin et al. [2010]).

11.2 Spatio Temporal Networks (STN)

Researchers for long have explored techniques to learn both spatial and temporal relation features (Zhang et al. [2018f]). Deep learning architectures is leveraged to perform well at learning spatial aspects (using CNN's) and temporal features (using LSTMs) individually. Spatio Temporal Networks (STNs) comprises of deep neural architectures combining both CNN's and LSTMs to extract spatiotemporal features. The temporal features (modeling correlations between near time points via LSTM), spatial features (modeling local spatial correlation via local CNN's) are shown to be effective in detecting outliers (Lee et al. [2018], SZEKÉR [2014], Nie et al. [2018], Dereszynski and Dietterich [2011]).

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 (Poon and Domingos [2011], Peharz et al. [2018]). 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 (Peharz et al. [2018]). 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 (Mikolov et al. [2013]). These models are capable of capturing sequential relationships within data instance such as sentences, time sequence data. Obtaining word embedding features as inputs are shown to improve the performance in several deep learning architectures (Rezaeinia et al. [2017], Naili et al. [2017], Altszyler et al. [2016]). Anomaly detection models leveraging the word2vec embeddings are shown to significantly improve performance (Schnabel et al. [2015], Bertero et al. [2017], Bakarov et al. [2018], Bamler and Mandt [2017]).

11.5 Generative Models

Generative models aim to learn exact data distribution in order to generate new data points with some variations. The two most common and efficient generative approaches are Variational Autoencoders (VAE) (Kingma and Welling

[2013]) and Generative Adversarial Networks (GAN) (Goodfellow et al. [2014a,b]). A variant of GAN architecture known as Adversarial autoencoders (AAE) (Makhzani et al. [2015]) that use adversarial training to impose an arbitrary prior on the latent code learned within hidden layers of autoencoder are also shown to learn the input distribution effectively. Leveraging this ability of learning input distributions, several Generative Adversarial Networks-based Anomaly Detection (GAN-AD) frameworks (Li et al. [2018], Deecke et al. [2018], Schlegl et al. [2017], Ravanbakhsh et al. [2017b], Eide [2018]) proposed are shown to be effective in identifying anomalies on high dimensional and complex datasets. However traditional methods such as K-nearest neighbors (KNN) are shown to perform better in scenarios which have a lesser number of anomalies when compared to deep generative models (Škvára et al. [2018]).

11.6 Convolutional Neural Networks

Convolutional Neural Networks (CNN), are the popular choice of neural networks for analyzing visual imagery (Krizhevsky et al. [2012]). CNN's ability to extract complex 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 (Gorokhov et al. [2017], Kim [2014]). Evaluation of CNN's based frameworks for anomaly detection is currently still an active area of research (Kwon et al. [2018]).

11.7 Sequence Models

Recurrent Neural Networks (RNNs) (Williams [1989]) 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 (Hochreiter and Schmidhuber [1997]) networks were introduced, they are a particular type of RNNs comprising of a memory cell that can store information about previous time steps. Gated Recurrent Unit (Cho et al. [2014]) (GRU) 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 the literature due to 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 (Ergen et al. [2017]).

11.8 Autoencoders

Autoencoders with single layer along with a linear activation function are nearly equivalent to Principal Component Analysis (PCA) (Pearson [1901]). While PCA is restricted to a linear dimensionality reduction, auto encoders enable both linear or nonlinear transformations (Liou et al. [2008, 2014]). One of the popular applications of Autoencoders is anomaly detection. Autoencoders are also referenced by the name Replicator Neural Networks (RNN) (Hawkins et al. [2002], Williams et al. [2002]). 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 the 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) eliminates the need for preparing hand-crafted features and facilitates the use of raw data with minimal preprocessing in anomaly detection tasks. Although autoencoders are simple and effective architectures for outlier detection, the performance gets degraded due to noisy training data (Zhou and Paffenroth [2017]).

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 weaknesses of different categories of techniques for a few simple problem settings. Classification based supervised DAD techniques illustrated in Section 10.1 are better choices in scenario consisting of the equal amount of labels for both normal

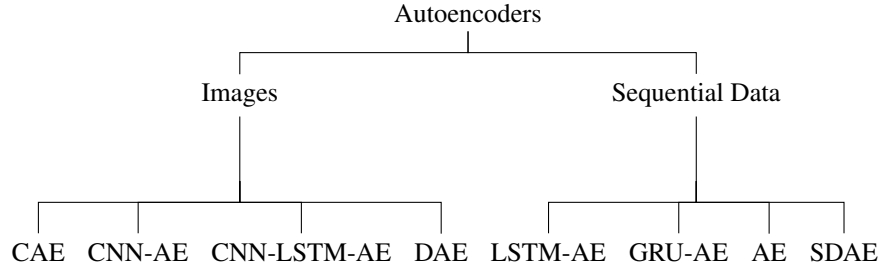


Figure 13: Autoencoder architectures for anomaly detection.

AE: Autoencoders Liou et al. [2014], LSTM : Long Short Term Memory Networks Hochreiter and Schmidhuber [1997]

SDAE: Stacked Denoising Autoencoder Vincent et al. [2010], DAE : Denoising Autoencoders Vincent et al. [2010]

GRU: Gated Recurrent Unit Cho et al. [2014], CNN: Convolutional Neural Networks Krizhevsky et al. [2012]

CNN-LSTM-AE: Convolution Long Short Term Memory Autoencoders Haque et al. [2018]

CAE: Convolutional Autoencoders Masci et al. [2011]

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 a pre-trained model. Unsupervised DAD techniques presented in Section 10.5 are being widely used since label acquisition is a costly 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 the 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 a progressively rich representation of data along with the one-class objective, such as a hyperplane (Chalapathy et al. [2018a]) or hypersphere (Ruff et al. [2018a]) to separate all the normal data points from anomalous data points. Further research and exploration is necessary to comprehend better the benefits of this new architecture proposed.

13 Conclusion

In this survey paper, we have discussed various research methods in deep learning-based anomaly detection along with 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 active research, and a possible future work would be to extend and update this survey as more sophisticated techniques are proposed.

References

- Varun Chandola, Arindam Banerjee, and Vipin Kumar. Outlier detection: A survey. *ACM Computing Surveys*, 2007.
- D. Hawkins. *Identification of Outliers*. Chapman and Hall, London, 1980.
- Ahmad Javaid, Quamar Niyaz, Weiqing Sun, and Mansoor Alam. A deep learning approach for network intrusion detection system. In *Proceedings of the 9th EAI International Conference on Bio-inspired Information and Communications Technologies (formerly BIONETICS)*, pages 21–26. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2016.
- Huan-Kai Peng and Radu Marculescu. Multi-scale compositionality: identifying the compositional structures of social dynamics using deep learning. *PloS one*, 10(4):e0118309, 2015.

- Bahnsen Alejandro, Correa. Building ai applications using deep learning. 2016. URL <https://blog.easysol.net/wp-content/uploads/2017/06/image1.png>.
- Xuemei Xie, Chenye Wang, Shu Chen, Guangming Shi, and Zhifu Zhao. Real-time illegal parking detection system based on deep learning. In *Proceedings of the 2017 International Conference on Deep Learning Technologies*, pages 23–27. ACM, 2017.
- Thomas Schlegl, Philipp Seeböck, Sebastian M Waldstein, Ursula Schmidt-Erfurth, and Georg Langs. Unsupervised anomaly detection with generative adversarial networks to guide marker discovery. In *International Conference on Information Processing in Medical Imaging*, pages 146–157. Springer, 2017.
- Mehdi Mohammadi, Ala Al-Fuqaha, Sameh Sorour, and Mohsen Guizani. Deep learning for iot big data and streaming analytics: A survey. *arXiv preprint arXiv:1712.04301*, 2017.
- Charu C Aggarwal. An introduction to outlier analysis. In *Outlier analysis*, pages 1–40. Springer, 2013.
- Dubravko Miljković. Review of novelty detection methods. In *MIPRO, 2010 proceedings of the 33rd international convention*, pages 593–598. IEEE, 2010.
- Marco AF Pimentel, David A Clifton, Lei Clifton, and Lionel Tarassenko. A review of novelty detection. *Signal Processing*, 99:215–249, 2014.
- Donghwoon Kwon, Hyunjo Kim, Jinoh Kim, Sang C Suh, Ikkyun Kim, and Kuinam J Kim. A survey of deep learning-based network anomaly detection. *Cluster Computing*, pages 1–13, 2017.
- John E Ball, Derek T Anderson, and Chee Seng Chan. Comprehensive survey of deep learning in remote sensing: theories, tools, and challenges for the community. *Journal of Applied Remote Sensing*, 11(4):042609, 2017.
- B Ravi Kiran, Dilip Mathew Thomas, and Ranjith Parakkal. An overview of deep learning based methods for unsupervised and semi-supervised anomaly detection in videos. *arXiv preprint arXiv:1801.03149*, 2018.
- Aderemi O Adewumi and Andronicus A Akinyelu. A survey of machine-learning and nature-inspired based credit card fraud detection techniques. *International Journal of System Assurance Engineering and Management*, 8(2): 937–953, 2017.
- Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Mohsen Ghafoorian, Jeroen Awm Van Der Laak, Bram Van Ginneken, and Clara I Sánchez. A survey on deep learning in medical image analysis. *Medical image analysis*, 42:60–88, 2017.
- Sarah M Erfani, Sutharshan Rajasegarar, Shanika Karunasekera, and Christopher Leckie. High-dimensional and large-scale anomaly detection using a linear one-class svm with deep learning. *Pattern Recognition*, 58:121–134, 2016a.
- Raghavendra Chalapathy, Aditya Krishna Menon, and Sanjay Chawla. Anomaly detection using one-class neural networks. *arXiv preprint arXiv:1802.06360*, 2018a.
- Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521(7553):436, 2015.
- Daniel Ramotsoela, Adnan Abu-Mahfouz, and Gerhard Hancke. A survey of anomaly detection in industrial wireless sensor networks with critical water system infrastructure as a case study. *Sensors*, 18(8):2491, 2018.
- Raghavendra Chalapathy, Ehsan Zare Borzeshi, and Massimo Piccardi. An investigation of recurrent neural architectures for drug name recognition. *arXiv preprint arXiv:1609.07585*, 2016a.
- Raghavendra Chalapathy, Ehsan Zare Borzeshi, and Massimo Piccardi. Bidirectional lstm-crf for clinical concept extraction. *arXiv preprint arXiv:1611.08373*, 2016b.
- Drausin Wulsin, Justin Blanco, Ram Mani, and Brian Litt. Semi-supervised anomaly detection for eeg waveforms using deep belief nets. In *Machine Learning and Applications (ICMLA), 2010 Ninth International Conference on*, pages 436–441. IEEE, 2010.
- Mutahir Nadeem, Ochaun Marshall, Sarbjit Singh, Xing Fang, and Xiaohong Yuan. Semi-supervised deep neural network for network intrusion detection. 2016.
- Hongchao Song, Zhuqing Jiang, Aidong Men, and Bo Yang. A hybrid semi-supervised anomaly detection model for high-dimensional data. *Computational intelligence and neuroscience*, 2017, 2017.

- Josh Patterson and Adam Gibson. *Deep Learning: A Practitioner's Approach*. "O'Reilly Media, Inc.", 2017.
- Aaron Tuor, Samuel Kaplan, Brian Hutchinson, Nicole Nichols, and Sean Robinson. Deep learning for unsupervised insider threat detection in structured cybersecurity data streams. *arXiv preprint arXiv:1710.00811*, 2017.
- Svante Wold, Kim Esbensen, and Paul Geladi. Principal component analysis. *Chemometrics and intelligent laboratory systems*, 2(1-3):37–52, 1987.
- Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995.
- Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. Isolation forest. In *Data Mining, 2008. ICDM'08. Eighth IEEE International Conference on*, pages 413–422. IEEE, 2008.
- Ilya Sutskever, Geoffrey E Hinton, and Graham W Taylor. The recurrent temporal restricted boltzmann machine. In *Advances in Neural Information Processing Systems*, pages 1601–1608, 2009.
- Ruslan Salakhutdinov and Hugo Larochelle. Efficient learning of deep boltzmann machines. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*, pages 693–700, 2010.
- Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the 25th international conference on Machine learning*, pages 1096–1103. ACM, 2008.
- Paul Rodriguez, Janet Wiles, and Jeffrey L Elman. A recurrent neural network that learns to count. *Connection Science*, 11(1):5–40, 1999.
- Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. Neural architectures for named entity recognition. *arXiv preprint arXiv:1603.01360*, 2016.
- Jerone TA Andrews, Edward J Morton, and Lewis D Griffin. Detecting anomalous data using auto-encoders. *International Journal of Machine Learning and Computing*, 6(1):21, 2016a.
- Sinno Jialin Pan, Qiang Yang, et al. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2010.
- Tolga Ergen, Ali Hassan Mirza, and Suleyman Serdar Kozat. Unsupervised and semi-supervised anomaly detection with lstm neural networks. *arXiv preprint arXiv:1710.09207*, 2017.
- Lukas Ruff, Nico Görnitz, Lucas Deecke, Shoaib Ahmed Siddiqui, Robert Vandermeulen, Alexander Binder, Emmanuel Müller, and Marius Kloft. Deep one-class classification. In *International Conference on Machine Learning*, pages 4390–4399, 2018a.
- Yann LeCun, Corinna Cortes, and Christopher JC Burges. Mnist handwritten digit database. *AT&T Labs [Online]*. Available: <http://yann.lecun.com/exdb/mnist>, 2, 2010.
- Alex Krizhevsky and Geoffrey Hinton. Learning multiple layers of features from tiny images. Technical report, 2009.
- Xiuyao Song, Mingxi Wu, Christopher Jermaine, and Sanjay Ranka. Conditional anomaly detection. *IEEE Transactions on Knowledge and Data Engineering*, 19(5):631–645, 2007.
- Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.
- Min Du, Feifei Li, Guineng Zheng, and Vivek Srikumar. Deeplog: Anomaly detection and diagnosis from system logs through deep learning. In *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, pages 1285–1298. ACM, 2017.
- Michael A Hayes and Miriam AM Capretz. Contextual anomaly detection framework for big sensor data. *Journal of Big Data*, 2(1):2, 2015.
- Raghavendra Chalapathy, Edward Toth, and Sanjay Chawla. Group anomaly detection using deep generative models. *arXiv preprint arXiv:1804.04876*, 2018b.
- Loïc Bontemps, James McDermott, Nhien-An Le-Khac, et al. Collective anomaly detection based on long short-term memory recurrent neural networks. In *International Conference on Future Data and Security Engineering*, pages 141–152. Springer, 2016.

- Daniel B Araya, Katarina Grolinger, Hany F ElYamany, Miriam AM Capretz, and G Bitsuamlak. Collective contextual anomaly detection framework for smart buildings. In *Neural Networks (IJCNN), 2016 International Joint Conference on*, pages 511–518. IEEE, 2016.
- Naifan Zhuang, Tuoerhongjiang Yusufu, Jun Ye, and Kien A Hua. Group activity recognition with differential recurrent convolutional neural networks. In *Automatic Face & Gesture Recognition (FG 2017), 2017 12th IEEE International Conference on*, pages 526–531. IEEE, 2017.
- Lukas Ruff, Robert Vandermeulen, Nico Goernitz, Lucas Deecke, Shoaib Ahmed Siddiqui, Alexander Binder, Emmanuel Müller, and Marius Kloft. Deep one-class classification. In Jennifer Dy and Andreas Krause, editors, *Proceedings of the 35th International Conference on Machine Learning*, volume 80 of *Proceedings of Machine Learning Research*, pages 4393–4402, Stockholmsmässan, Stockholm Sweden, 10–15 Jul 2018b. PMLR. URL <http://proceedings.mlr.press/v80/ruff18a.html>.
- Vir V Phoha. *Internet security dictionary*, volume 1. Taylor & Francis, 2002.
- Giovanna Vigna and Christopher Kruegel. Host-based intrusion detection. 2005.
- Gyuwan Kim, Hayoon Yi, Jangho Lee, Yunheung Paek, and Sungroh Yoon. Lstm-based system-call language modeling and robust ensemble method for designing host-based intrusion detection systems. *arXiv preprint arXiv:1611.01726*, 2016.
- Ashima Chawla, Brian Lee, Sheila Fallon, and Paul Jacob. Host based intrusion detection system with combined cnn/rnn model. In *Proceedings of Second International Workshop on AI in Security*, 2018.
- Li Chen, Salmin Sultana, and Ravi Sahita. Henet: A deep learning approach on intel® processor trace for effective exploit detection. In *2018 IEEE Security and Privacy Workshops (SPW)*, pages 109–115. IEEE, 2018.
- Soroush M Sohi, Fatemeh Ganji, and Jean-Pierre Seifert. Recurrent neural networks for enhancement of signature-based network intrusion detection systems. *arXiv preprint arXiv:1807.03212*, 2018.
- R Vinayakumar, KP Soman, and Prabakaran Poornachandran. Applying convolutional neural network for network intrusion detection. In *Advances in Computing, Communications and Informatics (ICACCI), 2017 International Conference on*, pages 1222–1228. IEEE, 2017.
- Hojjat Aghakhani, Aravind Machiry, Shirin Nilizadeh, Christopher Kruegel, and Giovanni Vigna. Detecting deceptive reviews using generative adversarial networks. *arXiv preprint arXiv:1805.10364*, 2018.
- Dan Li, Dacheng Chen, Jonathan Goh, and See-kiong Ng. Anomaly detection with generative adversarial networks for multivariate time series. *arXiv preprint arXiv:1809.04758*, 2018.
- Ni Gao, Ling Gao, Quanli Gao, and Hai Wang. An intrusion detection model based on deep belief networks. In *Advanced Cloud and Big Data (CBD), 2014 Second International Conference on*, pages 247–252. IEEE, 2014.
- Robert Peharz, Antonio Vergari, Karl Stelzner, Alejandro Molina, Martin Trapp, Kristian Kersting, and Zoubin Ghahramani. Probabilistic deep learning using random sum-product networks. *arXiv preprint arXiv:1806.01910*, 2018.
- Muhammad Fahad Umer, Muhammad Sher, and Yaxin Bi. A two-stage flow-based intrusion detection model for next-generation networks. *PloS one*, 13(1):e0180945, 2018.
- Yang Yu, Jun Long, and Zhiping Cai. Network intrusion detection through stacking dilated convolutional autoencoders. *Security and Communication Networks*, 2017, 2017.
- Vrizlynn LL Thing. Ieee 802.11 network anomaly detection and attack classification: A deep learning approach. In *Wireless Communications and Networking Conference (WCNC), 2017 IEEE*, pages 1–6. IEEE, 2017.
- Mikhail Zolotukhin, Timo Hämmäläinen, Tero Kokkonen, and Jarmo Siltanen. Increasing web service availability by detecting application-layer ddos attacks in encrypted traffic. In *Telecommunications (ICT), 2016 23rd International Conference on*, pages 1–6. IEEE, 2016.
- Carlos García Cordero, Sascha Hauke, Max Mühlhäuser, and Mathias Fischer. Analyzing flow-based anomaly intrusion detection using replicator neural networks. In *Privacy, Security and Trust (PST), 2016 14th Annual Conference on*, pages 317–324. IEEE, 2016.

- Khaled Alrawashdeh and Carla Purdy. Toward an online anomaly intrusion detection system based on deep learning. In *Machine Learning and Applications (ICMLA), 2016 15th IEEE International Conference on*, pages 195–200. IEEE, 2016.
- Tuan A Tang, Lotfi Mhamdi, Des McLernon, Syed Ali Raza Zaidi, and Mounir Ghogho. Deep learning approach for network intrusion detection in software defined networking. In *Wireless Networks and Mobile Communications (WINCOM), 2016 International Conference on*, pages 258–263. IEEE, 2016.
- Manuel Lopez-Martin, Belen Carro, Antonio Sanchez-Esguevillas, and Jaime Lloret. Conditional variational autoencoder for prediction and feature recovery applied to intrusion detection in iot. *Sensors*, 17(9):1967, 2017.
- Majjed Al-Qatf, Mohammed Alhabib, Kamal Al-Sabahi, et al. Deep learning approach combining sparse autoencoder with svm for network intrusion detection. *IEEE Access*, 2018.
- Yisroel Mirsky, Tomer Doitshman, Yuval Elovici, and Asaf Shabtai. Kitsune: an ensemble of autoencoders for online network intrusion detection. *arXiv preprint arXiv:1802.09089*, 2018.
- R Can Aygun and A Gokhan Yavuz. Network anomaly detection with stochastically improved autoencoder based models. In *Cyber Security and Cloud Computing (CSCloud), 2017 IEEE 4th International Conference on*, pages 193–198. IEEE, 2017.
- Zilong Lin, Yong Shi, and Zhi Xue. Idsgan: Generative adversarial networks for attack generation against intrusion detection. *arXiv preprint arXiv:1809.02077*, 2018.
- Chuanlong Yin, Yuefei Zhu, Shengli Liu, Jinlong Fei, and Hetong Zhang. An enhancing framework for botnet detection using generative adversarial networks. In *2018 International Conference on Artificial Intelligence and Big Data (ICAIBD)*, pages 228–234. IEEE, 2018.
- Markus Ring, Daniel Schlör, Dieter Landes, and Andreas Hotho. Flow-based network traffic generation using generative adversarial networks. *arXiv preprint arXiv:1810.07795*, 2018.
- Majd Latah. When deep learning meets security. *arXiv preprint arXiv:1807.04739*, 2018.
- Yotam Intrator, Gilad Katz, and Asaf Shabtai. Mdgan: Boosting anomaly detection using multi-discriminator generative adversarial networks. *arXiv preprint arXiv:1810.05221*, 2018.
- Takashi Matsubara, Ryosuke Tachibana, and Kuniaki Uehara. Anomaly machine component detection by deep generative model with unregularized score. In *2018 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, 2018.
- Miguel Nicolau, James McDermott, et al. A hybrid autoencoder and density estimation model for anomaly detection. In *International Conference on Parallel Problem Solving from Nature*, pages 717–726. Springer, 2016.
- Maria Rigaki. Adversarial deep learning against intrusion detection classifiers, 2017.
- Ritesh K Malaiya, Donghwoon Kwon, Jinoh Kim, Sang C Suh, Hyunjo Kim, and Ikkyun Kim. An empirical evaluation of deep learning for network anomaly detection. In *2018 International Conference on Computing, Networking and Communications (ICNC)*, pages 893–898. IEEE, 2018.
- Donghwoon Kwon, Kathiravan Natarajan, Sang C Suh, Hyunjo Kim, and Jinoh Kim. An empirical study on network anomaly detection using convolutional neural networks. In *2018 IEEE 38th International Conference on Distributed Computing Systems (ICDCS)*, pages 1595–1598. IEEE, 2018.
- Ralf C Staudemeyer. Applying long short-term memory recurrent neural networks to intrusion detection. *South African Computer Journal*, 56(1):136–154, 2015.
- Sheraz Naseer, Yasir Saleem, Shehzad Khalid, Muhammad Khawar Bashir, Jihun Han, Muhammad Munwar Iqbal, and Kijun Han. Enhanced network anomaly detection based on deep neural networks. *IEEE Access*, 6:48231–48246, 2018.
- Ucsd anomaly detection dataset. 2017.
- Ali Shiravi, Hadi Shiravi, Mahbod Tavallaei, and Ali A Ghorbani. Toward developing a systematic approach to generate benchmark datasets for intrusion detection. *computers & security*, 31(3):357–374, 2012.

- Amit Adam, Ehud Rivlin, Ilan Shimshoni, and Daviv Reinitz. Robust real-time unusual event detection using multiple fixed-location monitors. *IEEE transactions on pattern analysis and machine intelligence*, 30(3):555–560, 2008.
- Chuanlong Yin, Yuefei Zhu, Jinlong Fei, and Xinzheng He. A deep learning approach for intrusion detection using recurrent neural networks. *IEEE Access*, 5:21954–21961, 2017.
- Mahmood Yousefi-Azar, Vijay Varadharajan, Len Hamey, and Uday Tupakula. Autoencoder-based feature learning for cyber security applications. In *Neural Networks (IJCNN), 2017 International Joint Conference on*, pages 3854–3861. IEEE, 2017.
- Shahriar Mohammadi and Amin Namadchian. A new deep learning approach for anomaly base ids using memetic classifier. *International Journal of Computers, Communications & Control*, 12(5), 2017.
- J Stolfo, Wei Fan, Wenke Lee, Andreas Prodromidis, and Philip K Chan. Cost-based modeling and evaluation for data mining with application to fraud and intrusion detection. *Results from the JAM Project by Salvatore*, pages 1–15, 2000.
- Nguyen Thanh Van, Tran Ngoc Thinh, and Le Thanh Sach. An anomaly-based network intrusion detection system using deep learning. In *System Science and Engineering (ICSSE), 2017 International Conference on*, pages 210–214. IEEE, 2017.
- Romain Fontugne, Pierre Borgnat, Patrice Abry, and Kensuke Fukuda. Mawilab: combining diverse anomaly detectors for automated anomaly labeling and performance benchmarking. In *Proceedings of the 6th International Conference*, page 8. ACM, 2010.
- Jamk university of applied sciences, realistic global cyber environment (rgce). 2009.
- Gideon Creech and Jiankun Hu. A semantic approach to host-based intrusion detection systems using contiguous and discontiguous system call patterns. *IEEE Transactions on Computers*, 63(4):807–819, 2014.
- New Mexico University. Computer immune systems data sets. 2012.
- Aisha Abdallah, Mohd Aizaini Maarof, and Anazida Zainal. Fraud detection system: A survey. *Journal of Network and Computer Applications*, 68:90–113, 2016.
- Didier; et al Lavion. Pwc’s global economic crime and fraud survey 2018. PwC.com, 2018. URL <https://www.pwc.com/gx/en/forensics/global-economic-crime-and-fraud-survey-2018.pdf>.
- Lucy Ma Zhao. Fraud detection system, December 12 2013. US Patent App. 13/494,741.
- Samaneh Sorournejad, Zahra Zojaji, Reza Ebrahimi Atani, and Amir Hassan Monadjemi. A survey of credit card fraud detection techniques: data and technique oriented perspective. *CoRR abs/1611.06439*, 2016.
- Xun Zhou, Sicong Cheng, Meng Zhu, Chengkun Guo, Sida Zhou, Peng Xu, Zhenghua Xue, and Weishi Zhang. A state of the art survey of data mining-based fraud detection and credit scoring. In *MATEC Web of Conferences*, volume 189, page 03002. EDP Sciences, 2018.
- S Suganya and N Kamalraj. A survey on credit card fraud detection. *International Journal of Computer Science and Mobile Computing*, 4:241–244, 2015.
- Marco Schreyer, Timur Sattarov, Damian Borth, Andreas Dengel, and Bernd Reimer. Detection of anomalies in large scale accounting data using deep autoencoder networks. *arXiv preprint arXiv:1709.05254*, 2017.
- Roy Wedge, James Max Kanter, Santiago Moral Rubio, Sergio Iglesias Perez, and Kalyan Veeramachaneni. Solving the” false positives” problem in fraud prediction. *arXiv preprint arXiv:1710.07709*, 2017.
- Ebberth L Paula, Marcelo Ladeira, Rommel N Carvalho, and Thiago Marzagão. Deep learning anomaly detection as support fraud investigation in brazilian exports and anti-money laundering. In *Machine Learning and Applications (ICMLA), 2016 15th IEEE International Conference on*, pages 954–960. IEEE, 2016.
- Martin Renström and Timothy Holmsten. Fraud detection on unlabeled data with unsupervised machine learning, 2018.
- Zahra Kazemi and Housman Zarrabi. Using deep networks for fraud detection in the credit card transactions. In *Knowledge-Based Engineering and Innovation (KBEI), 2017 IEEE 4th International Conference on*, pages 0630–0633. IEEE, 2017.

- Panpan Zheng, Shuhan Yuan, Xintao Wu, Jun Li, and Aidong Lu. One-class adversarial nets for fraud detection. *arXiv preprint arXiv:1803.01798*, 2018a.
- Apapan Pumsirirat and Liu Yan. Credit card fraud detection using deep learning based on auto-encoder and restricted boltzmann machine. *INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS*, 9(1):18–25, 2018.
- KR Seeja and Masoumeh Zareapoor. Fraudminer: A novel credit card fraud detection model based on frequent itemset mining. *The Scientific World Journal*, 2014, 2014.
- Tom Sweers, Tom Heskes, and Jesse Krijthe. Autoencoding credit card fraud. 2018.
- Ugo Fiore, Alfredo De Santis, Francesca Perla, Paolo Zanetti, and Francesco Palmieri. Using generative adversarial networks for improving classification effectiveness in credit card fraud detection. *Information Sciences*, 2017.
- Hyunsun Choi and Eric Jang. Generative ensembles for robust anomaly detection. *arXiv preprint arXiv:1810.01392*, 2018.
- Jose R Dorronsoro, Francisco Ginel, Carmen R Sánchez, and Carlos Santa Cruz. Neural fraud detection in credit card operations. *IEEE transactions on neural networks*, 1997.
- Jon Ander Gómez, Juan Arévalo, Roberto Paredes, and Jordi Nin. End-to-end neural network architecture for fraud scoring in card payments. *Pattern Recognition Letters*, 105:175–181, 2018.
- Bénard Wiese and Christian Omlin. Credit card transactions, fraud detection, and machine learning: Modelling time with lstm recurrent neural networks. In *Innovations in neural information paradigms and applications*, pages 231–268. Springer, 2009.
- Johannes Jurgovsky, Michael Granitzer, Konstantin Ziegler, Sylvie Calabretto, Pierre-Edouard Portier, Liyun He-Guelton, and Olivier Caelen. Sequence classification for credit-card fraud detection. *Expert Systems with Applications*, 100:234–245, 2018.
- Yaya Heryadi and Harco Leslie Hendric Spits Warnars. Learning temporal representation of transaction amount for fraudulent transaction recognition using cnn, stacked lstm, and cnn-lstm. In *Cybernetics and Computational Intelligence (CyberneticsCom), 2017 IEEE International Conference on*, pages 84–89. IEEE, 2017.
- Yoshihiro Ando, Hidehito Gomi, and Hidehiko Tanaka. Detecting fraudulent behavior using recurrent neural networks. 2016.
- Shuhao Wang, Cancheng Liu, Xiang Gao, Hongtao Qu, and Wei Xu. Session-based fraud detection in online e-commerce transactions using recurrent neural networks. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 241–252. Springer, 2017a.
- Mohammed Ibrahim Alowais and Lay-Ki Soon. Credit card fraud detection: Personalized or aggregated model. In *Mobile, Ubiquitous, and Intelligent Computing (MUSIC), 2012 Third FTRA International Conference on*, pages 114–119. IEEE, 2012.
- Thushara Amarasinghe, Achala Aponso, and Naomi Krishnarajah. Critical analysis of machine learning based approaches for fraud detection in financial transactions. In *Proceedings of the 2018 International Conference on Machine Learning Technologies*, pages 12–17. ACM, 2018a.
- Narek Abroyan. Neural networks for financial market risk classification. 2017a.
- Xurui Lp, Wei Yu, Tianyu Luwang, Jianbin Zheng, Xuetao Qiu, Jintao Zhao, Lei Xia, and Yujiao Li. Transaction fraud detection using gru-centered sandwich-structured model. In *2018 IEEE 22nd International Conference on Computer Supported Cooperative Work in Design ((CSCWD))*, pages 467–472. IEEE, 2018.
- Aihua Shen, Rencheng Tong, and Yaochen Deng. Application of classification models on credit card fraud detection. In *Service Systems and Service Management, 2007 International Conference on*, pages 1–4. IEEE, 2007.
- Alae Chouiekh and EL Hassane Ibn EL Haj. Convnets for fraud detection analysis. *Procedia Computer Science*, 127: 133–138, 2018.
- Narek Abroyan. Convolutional and recurrent neural networks for real-time data classification. In *Innovative Computing Technology (INTECH), 2017 Seventh International Conference on*, pages 42–45. IEEE, 2017b.

- Kang Fu, Dawei Cheng, Yi Tu, and Liqing Zhang. Credit card fraud detection using convolutional neural networks. In *International Conference on Neural Information Processing*, pages 483–490. Springer, 2016.
- Yifei Lu. Deep neural networks and fraud detection, 2017.
- Chunzhi Wang, Yichao Wang, Zhiwei Ye, Lingyu Yan, Wencheng Cai, and Shang Pan. Credit card fraud detection based on whale algorithm optimized bp neural network. In *2018 13th International Conference on Computer Science & Education (ICCSE)*, pages 1–4. IEEE, 2018a.
- Zhaohui Zhang, Xinxin Zhou, Xiaobo Zhang, Lizhi Wang, and Pengwei Wang. A model based on convolutional neural network for online transaction fraud detection. *Security and Communication Networks*, 2018, 2018a.
- Mohammad Abu Alsheikh, Dusit Niyato, Shaowei Lin, Hwee-Pink Tan, and Zhu Han. Mobile big data analytics using deep learning and apache spark. *IEEE network*, 30(3):22–29, 2016.
- Anup Badhe. Click fraud detection in mobile ads served in programmatic inventory. *Neural Networks & Machine Learning*, 1(1):1–1, 2017.
- Mohammad Iquebal Akhter and Mohammad Gulam Ahamad. Detecting telecommunication fraud using neural networks through data mining. *International Journal of Scientific and Engineering Research*, 3(3):601–6, 2012.
- Vanita Jain. Perspective analysis of telecommunication fraud detection using data stream analytics and neural network classification based data mining. *International Journal of Information Technology*, 9(3):303–310, 2017.
- Yu-Jun Zheng, Xiao-Han Zhou, Wei-Guo Sheng, Yu Xue, and Sheng-Yong Chen. Generative adversarial network based telecom fraud detection at the receiving bank. *Neural Networks*, 102:78–86, 2018b.
- Hossein Joudaki, Arash Rashidian, Behrouz Minaei-Bidgoli, Mahmood Mahmoodi, Bijan Geraili, Mahdi Nasiri, and Mohammad Arab. Using data mining to detect health care fraud and abuse: a review of literature. *Global journal of health science*, 7(1):194, 2015.
- Riya Roy and K Thomas George. Detecting insurance claims fraud using machine learning techniques. In *Circuit, Power and Computing Technologies (ICCPCT), 2017 International Conference on*, pages 1–6. IEEE, 2017.
- Stijn Viaene, Guido Dedene, and Richard A Derrig. Auto claim fraud detection using bayesian learning neural networks. *Expert Systems with Applications*, 29(3):653–666, 2005.
- Val Andrei Fajardo, David Findlay, Roshanak Houmanfar, Charu Jaiswal, Jiaxi Liang, and Honglei Xie. Vos: a method for variational oversampling of imbalanced data. *arXiv preprint arXiv:1809.02596*, 2018.
- Phillip Keung, Joycelin Karel, and Curtis Bright. Neural networks for insurance fraud detection, 2009.
- Richard A Bauder and Taghi M Khoshgoftaar. Medicare fraud detection using machine learning methods. In *Machine Learning and Applications (ICMLA), 2017 16th IEEE International Conference on*, pages 858–865. IEEE, 2017.
- Daniel Lasaga and Prakash Santhana. Deep learning to detect medical treatment fraud. In *KDD 2017 Workshop on Anomaly Detection in Finance*, pages 114–120, 2018.
- Kamran Ghasedi Dizaji, Xiaoqian Wang, and Heng Huang. Semi-supervised generative adversarial network for gene expression inference. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1435–1444. ACM, 2018.
- Samuel G Finlayson, Isaac S Kohane, and Andrew L Beam. Adversarial attacks against medical deep learning systems. *arXiv preprint arXiv:1804.05296*, 2018.
- Andre Esteva, Brett Kuprel, Roberto A Novoa, Justin Ko, Susan M Swetter, Helen M Blau, and Sebastian Thrun. Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639):115, 2017.
- Yanfang Ye, Tao Li, Donald Adjero, and S Sitharama Iyengar. A survey on malware detection using data mining techniques. *ACM Computing Surveys (CSUR)*, 50(3):41, 2017.
- William Hardy, Lingwei Chen, Shifu Hou, Yanfang Ye, and Xin Li. D14md: A deep learning framework for intelligent malware detection. In *Proceedings of the International Conference on Data Mining (DMIN)*, page 61. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2016.

- Alessandra De Paola, Salvatore Favaloro, Salvatore Gaglio, G Lo Re, and Marco Morana. Malware detection through low-level features and stacked denoising autoencoders. In *2nd Italian Conference on Cyber Security, ITASEC 2018*, volume 2058. CEUR-WS, 2018.
- Mohit Sewak, Sanjay K Sahay, and Hemant Rathore. An investigation of a deep learning based malware detection system. In *Proceedings of the 13th International Conference on Availability, Reliability and Security*, page 26. ACM, 2018.
- Temesguen Messay Kebede, Ouboti Djaneye-Boundjou, Barath Narayanan Narayanan, Anca Ralescu, and David Kapp. Classification of malware programs using autoencoders based deep learning architecture and its application to the microsoft malware classification challenge (big 2015) dataset. In *Aerospace and Electronics Conference (NAECON), 2017 IEEE National*, pages 70–75. IEEE, 2017.
- Omid E David and Nathan S Netanyahu. Deepsign: Deep learning for automatic malware signature generation and classification. In *Neural Networks (IJCNN), 2015 International Joint Conference on*, pages 1–8. IEEE, 2015.
- Bugra Cakir and Erdogan Dogdu. Malware classification using deep learning methods. In *Proceedings of the ACMSE 2018 Conference*, page 10. ACM, 2018.
- Pedro Silva, Sepehr Akhavan-Masouleh, and Li Li. Improving malware detection accuracy by extracting icon information. In *2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR)*, pages 408–411. IEEE, 2018.
- Bojan Kolosnjaji, Ambra Demontis, Battista Biggio, Davide Maiorca, Giorgio Giacinto, Claudia Eckert, and Fabio Roli. Adversarial malware binaries: Evading deep learning for malware detection in executables. *arXiv preprint arXiv:1803.04173*, 2018.
- Octavian Suci, Scott E Coull, and Jeffrey Johns. Exploring adversarial examples in malware detection. *arXiv preprint arXiv:1810.08280*, 2018.
- Siwakorn Srisakaokul, Zexuan Zhong, Yuhao Zhang, Wei Yang, and Tao Xie. Muldef: Multi-model-based defense against adversarial examples for neural networks. *arXiv preprint arXiv:1809.00065*, 2018.
- Thomas King, Nikita Aggarwal, Mariarosaria Taddeo, and Luciano Floridi. Artificial intelligence crime: An interdisciplinary analysis of foreseeable threats and solutions. 2018.
- TonTon Hsien-De Huang and Hung-Yu Kao. R2-d2: color-inspired convolutional neural network (cnn)-based android malware detections. *arXiv preprint arXiv:1705.04448*, 2017.
- Wei Guo, Tenghai Wang, and Jizeng Wei. Malware detection with convolutional neural network using hardware events. In *CCF National Conference on Computer Engineering and Technology*, pages 104–115. Springer, 2017.
- Mahmoud Abdelsalam, Ram Krishnan, Yufei Huang, and Ravi Sandhu. Malware detection in cloud infrastructures using convolutional neural networks. In *2018 IEEE 11th International Conference on Cloud Computing (CLOUD)*, pages 162–169. IEEE, 2018.
- Edward Raff, Jon Barker, Jared Sylvester, Robert Brandon, Bryan Catanzaro, and Charles Nicholas. Malware detection by eating a whole exe. *arXiv preprint arXiv:1710.09435*, 2017.
- ElMouatez Billah Karbab, Mourad Debbabi, Abdelouahid Derhab, and Djedjiga Mouheb. Maldozer: Automatic framework for android malware detection using deep learning. *Digital Investigation*, 24:S48–S59, 2018.
- Fabio Martinelli, Fiammetta Marulli, and Francesco Mercaldo. Evaluating convolutional neural network for effective mobile malware detection. *Procedia Computer Science*, 112:2372–2381, 2017.
- Niall McLaughlin, Jesus Martinez del Rincon, BooJoong Kang, Suleiman Yerima, Paul Miller, Sakir Sezer, Yeganeh Safaei, Erik Trickle, Ziming Zhao, Adam Doupe, et al. Deep android malware detection. In *Proceedings of the Seventh ACM on Conference on Data and Application Security and Privacy*, pages 301–308. ACM, 2017.
- Daniel Gibert, Carles Mateu, Jordi Planes, and Ramon Vicens. Using convolutional neural networks for classification of malware represented as images. *Journal of Computer Virology and Hacking Techniques*, pages 1–14, 2018.
- Bojan Kolosnjaji, Ghadir Eraisha, George Webster, Apostolis Zarras, and Claudia Eckert. Empowering convolutional networks for malware classification and analysis. In *Neural Networks (IJCNN), 2017 International Joint Conference on*, pages 3838–3845. IEEE, 2017.

- Ishai Rosenberg, Guillaume Sicard, and Eli Omid David. End-to-end deep neural networks and transfer learning for automatic analysis of nation-state malware. *Entropy*, 20(5):390, 2018.
- Qinglong Wang, Wenbo Guo, Kaixuan Zhang, Alexander G Ororbia II, Xinyu Xing, Xue Liu, and C Lee Giles. Adversary resistant deep neural networks with an application to malware detection. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1145–1153. ACM, 2017b.
- JIA YANG, HUIXIANG ZHANG, BAOLEI MAO, and CHUNLEI CHEN. Application of deep belief networks for android malware detection. *ICIC express letters. Part B, Applications: an international journal of research and surveys*, 7(7):1505–1510, 2016.
- Yuxin Ding, Sheng Chen, and Jun Xu. Application of deep belief networks for opcode based malware detection. In *Neural Networks (IJCNN), 2016 International Joint Conference on*, pages 3901–3908. IEEE, 2016.
- Ding Yuxin and Zhu Siyi. Malware detection based on deep learning algorithm. *Neural Computing and Applications*, pages 1–12, 2017.
- ShymalaGowri Selvaganapathy, Mathappan Nivaashini, and HemaPriya Natarajan. Deep belief network based detection and categorization of malicious urls. *Information Security Journal: A Global Perspective*, 27(3):145–161, 2018.
- Shifu Hou, Aaron Saas, Lingwei Chen, Yanfang Ye, and Thirimachos Bourlai. Deep neural networks for automatic android malware detection. In *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017*, pages 803–810. ACM, 2017.
- Shun Tobiyama, Yukiko Yamaguchi, Hajime Shimada, Tomonori Ikuse, and Takeshi Yagi. Malware detection with deep neural network using process behavior. In *Computer Software and Applications Conference (COMPSAC), 2016 IEEE 40th Annual*, volume 2, pages 577–582. IEEE, 2016.
- Weiwei Hu and Ying Tan. Black-box attacks against rnn based malware detection algorithms. *arXiv preprint arXiv:1705.08131*, 2017.
- Shun Tobiyama, Yukiko Yamaguchi, Hirokazu Hasegawa, Hajime Shimada, Mitsuaki Akiyama, and Takeshi Yagi. A method for estimating process maliciousness with seq2seq model. In *2018 International Conference on Information Networking (ICOIN)*, pages 255–260. IEEE, 2018.
- Nikolaos Passalis and Anastasios Tefas. Long-term temporal averaging for stochastic optimization of deep neural networks. *Neural Computing and Applications*, pages 1–13.
- Quan Le, Oisín Boydell, Brian Mac Namee, and Mark Scanlon. Deep learning at the shallow end: Malware classification for non-domain experts. *Digital Investigation*, 26:S118–S126, 2018.
- Jin-Young Kim, Seok-Jun Bu, and Sung-Bae Cho. Zero-day malware detection using transferred generative adversarial networks based on deep autoencoders. *Information Sciences*, 460:83–102, 2018.
- Wei Wang, Mengxue Zhao, and Jigang Wang. Effective android malware detection with a hybrid model based on deep autoencoder and convolutional neural network. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–9, 2018b.
- Yuancheng Li, Rong Ma, and Runhai Jiao. A hybrid malicious code detection method based on deep learning. *methods*, 9(5), 2015.
- Hamed HaddadPajouh, Ali Dehghantanha, Raouf Khayami, and Kim-Kwang Raymond Choo. A deep recurrent neural network based approach for internet of things malware threat hunting. *Future Generation Computer Systems*, 85: 88–96, 2018.
- Seonwoo Min, Byunghan Lee, and Sungroh Yoon. Deep learning in bioinformatics. *Briefings in bioinformatics*, 18(5):851–869, 2017.
- Chensi Cao, Feng Liu, Hai Tan, Deshou Song, Wenjie Shu, Weizhong Li, Yiming Zhou, Xiaochen Bo, and Zhi Xie. Deep learning and its applications in biomedicine. *Genomics, proteomics & bioinformatics*, 2018a.
- Rui Zhao, Ruqiang Yan, Zhenghua Chen, Kezhi Mao, Peng Wang, and Robert X Gao. Deep learning and its applications to machine health monitoring: A survey. *arXiv preprint arXiv:1612.07640*, 2016.

- Samir Khan and Takehisa Yairi. A review on the application of deep learning in system health management. *Mechanical Systems and Signal Processing*, 107:241–265, 2018.
- Narendhar Gugulothu, Pankaj Malhotra, Lovekesh Vig, and Gautam Shroff. Sparse neural networks for anomaly detection in high-dimensional time series.
- Kasun Amarasinghe, Kevin Kenney, and Milos Manic. Toward explainable deep neural network based anomaly detection. In *2018 11th International Conference on Human System Interaction (HSI)*, pages 311–317. IEEE, 2018b.
- Edward Choi. *Doctor AI: Interpretable Deep Learning for Modeling Electronic Health Records*. PhD thesis, Georgia Institute of Technology, 2018.
- Kai Wang, Youjin Zhao, Qingyu Xiong, Min Fan, Guotan Sun, Longkun Ma, and Tong Liu. Research on healthy anomaly detection model based on deep learning from multiple time-series physiological signals. *Scientific Programming*, 2016, 2016.
- Jake Cowton, Ilias Kyriazakis, Thomas Plötz, and Jaume Bacardit. A combined deep learning gru-autoencoder for the early detection of respiratory disease in pigs using multiple environmental sensors. *Sensors*, 18(8):2521, 2018.
- Daisuke Sato, Shouhei Hanaoka, Yukihiro Nomura, Tomomi Takenaga, Soichiro Miki, Takeharu Yoshikawa, Naoto Hayashi, and Osamu Abe. A primitive study on unsupervised anomaly detection with an autoencoder in emergency head ct volumes. In *Medical Imaging 2018: Computer-Aided Diagnosis*, volume 10575, page 105751P. International Society for Optics and Photonics, 2018.
- JT Turner, Adam Page, Tinoosh Mohsenin, and Tim Oates. Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection. In *2014 AAAI Spring Symposium Series*, 2014.
- Manoj Kumar Sharma, Debdoot Sheet, and Prabir Kumar Biswas. Abnormality detecting deep belief network. In *Proceedings of the International Conference on Advances in Information Communication Technology & Computing*, page 11. ACM, 2016.
- Ning Ma, Yu Peng, Shaojun Wang, and Philip HW Leong. An unsupervised deep hyperspectral anomaly detector. *Sensors*, 18(3):693, 2018.
- Junming Zhang, Yan Wu, Jing Bai, and Fuqiang Chen. Automatic sleep stage classification based on sparse deep belief net and combination of multiple classifiers. *Transactions of the Institute of Measurement and Control*, 38(4): 435–451, 2016.
- DF Wulsin, JR Gupta, R Mani, JA Blanco, and B Litt. Modeling electroencephalography waveforms with semi-supervised deep belief nets: fast classification and anomaly measurement. *Journal of neural engineering*, 8(3): 036015, 2011.
- C Wu, Y Guo, and Y Ma. Adaptive anomalies detection with deep network. In *Proceeding of the Seventh International Conference on Adaptive and Self-Adaptive Systems and Applications*, 2015a.
- Linxia Liao, Wenjing Jin, and Radu Pavel. Enhanced restricted boltzmann machine with prognosability regularization for prognostics and health assessment. *IEEE Transactions on Industrial Electronics*, 63(11):7076–7083, 2016.
- Haowen Xu, Wenxiao Chen, Nengwen Zhao, Zeyan Li, Jiahao Bu, Zhihan Li, Ying Liu, Youjian Zhao, Dan Pei, Yang Feng, et al. Unsupervised anomaly detection via variational auto-encoder for seasonal kpis in web applications. In *Proceedings of the 2018 World Wide Web Conference on World Wide Web*, pages 187–196. International World Wide Web Conferences Steering Committee, 2018.
- Yuchen Lu and Peng Xu. Anomaly detection for skin disease images using variational autoencoder. *arXiv preprint arXiv:1807.01349*, 2018.
- Xiaoran Chen and Ender Konukoglu. Unsupervised detection of lesions in brain mri using constrained adversarial auto-encoders. *arXiv preprint arXiv:1806.04972*, 2018.
- Hangzhou Yang and Huiying Gao. Toward sustainable virtualized healthcare: Extracting medical entities from chinese online health consultations using deep neural networks. *Sustainability*, 10(9):3292, 2018.

- Abhyuday N Jagannatha and Hong Yu. Bidirectional rnn for medical event detection in electronic health records. In *Proceedings of the conference. Association for Computational Linguistics. North American Chapter. Meeting*, volume 2016, page 473. NIH Public Access, 2016.
- Timothy J O'Shea, T Charles Clancy, and Robert W McGwier. Recurrent neural radio anomaly detection. *arXiv preprint arXiv:1611.00301*, 2016.
- Siddique Latif, Muhammad Usman, Rajib Rana, and Junaid Qadir. Phonocardiographic sensing using deep learning for abnormal heartbeat detection. *IEEE Sensors Journal*, 18(22):9393–9400, 2018.
- Runtian Zhang and Qian Zou. Time series prediction and anomaly detection of light curve using lstm neural network. In *Journal of Physics: Conference Series*, volume 1061, page 012012. IOP Publishing, 2018.
- Sucheta Chauhan and Lovekesh Vig. Anomaly detection in ecg time signals via deep long short-term memory networks. In *Data Science and Advanced Analytics (DSAA), 2015. 36678 2015. IEEE International Conference on*, pages 1–7. IEEE, 2015.
- Ursula Schmidt-Erfurth, Amir Sadeghipour, Bianca S Gerendas, Sebastian M Waldstein, and Hrvoje Bogunović. Artificial intelligence in retina. *Progress in retinal and eye research*, 2018.
- Dimitris K Iakovidis, Spiros V Georgakopoulos, Michael Vasilakakis, Anastasios Koulaouzidis, and Vassilis P Plagianakos. Detecting and locating gastrointestinal anomalies using deep learning and iterative cluster unification. *IEEE Transactions on Medical Imaging*, 2018.
- Yan Liu and Sanjay Chawla. Social media anomaly detection: Challenges and solutions. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, pages 817–818. ACM, 2017.
- David Savage, Xiuzhen Zhang, Xinghuo Yu, Pauline Chou, and Qingmai Wang. Anomaly detection in online social networks. *Social Networks*, 39:62–70, 2014.
- Ketan Anand, Jay Kumar, and Kunal Anand. Anomaly detection in online social network: A survey. In *Inventive Communication and Computational Technologies (ICICCT), 2017 International Conference on*, pages 456–459. IEEE, 2017.
- Rose Yu, Huida Qiu, Zhen Wen, ChingYung Lin, and Yan Liu. A survey on social media anomaly detection. *ACM SIGKDD Explorations Newsletter*, 18(1):1–14, 2016.
- Juan Cao, Junbo Guo, Xirong Li, Zhiwei Jin, Han Guo, and Jintao Li. Automatic rumor detection on microblogs: A survey. *arXiv preprint arXiv:1807.03505*, 2018b.
- Yan Zhang, Weiling Chen, Chai Kiat Yeo, Chiew Tong Lau, and Bu Sung Lee. Detecting rumors on online social networks using multi-layer autoencoder. In *Technology & Engineering Management Conference (TEMSCON), 2017 IEEE*, pages 437–441. IEEE, 2017.
- Jacopo Castellini, Valentina Poggioni, and Giulia Sorbi. Fake twitter followers detection by denoising autoencoder. In *Proceedings of the International Conference on Web Intelligence*, pages 195–202. ACM, 2017.
- Xiao Sun, Chen Zhang, Shuai Ding, and Changqin Quan. Detecting anomalous emotion through big data from social networks based on a deep learning method. *Multimedia Tools and Applications*, pages 1–22, 2018.
- Lei Shu, Hu Xu, and Bing Liu. Doc: Deep open classification of text documents. *arXiv preprint arXiv:1709.08716*, 2017.
- Biao Yang, Jinmeng Cao, Rongrong Ni, and Ling Zou. Anomaly detection in moving crowds through spatiotemporal autoencoding and additional attention. *Advances in Multimedia*, 2018, 2018.
- Ze Li, Duoyong Sun, Renqi Zhu, and Zihan Lin. Detecting event-related changes in organizational networks using optimized neural network models. *PloS one*, 12(11):e0188733, 2017a.
- Wei. Hybrid models for anomaly detection in social networks. *arXiv preprint arXiv:1709.08716*, 2017.
- Ahmed Umar Memon. *Log file categorization and anomaly analysis using grammar inference*. PhD thesis, 2008.
- Andy Brown, Aaron Tuor, Brian Hutchinson, and Nicole Nichols. Recurrent neural network attention mechanisms for interpretable system log anomaly detection. *arXiv preprint arXiv:1803.04967*, 2018.

- Anwesha Das, Frank Mueller, Charles Siegel, and Abhinav Vishnu. Desh: deep learning for system health prediction of lead times to failure in hpc. In *Proceedings of the 27th International Symposium on High-Performance Parallel and Distributed Computing*, pages 40–51. ACM, 2018.
- Pankaj Malhotra, Lovekesh Vig, Gautam Shroff, and Puneet Agarwal. Long short term memory networks for anomaly detection in time series. In *Proceedings*, page 89. Presses universitaires de Louvain, 2015.
- Mayu Sakurada and Takehisa Yairi. Anomaly detection using autoencoders with nonlinear dimensionality reduction. In *Proceedings of the MLSDA 2014 2nd Workshop on Machine Learning for Sensory Data Analysis*, page 4. ACM, 2014.
- Timo Nolle, Stefan Luetzgen, Alexander Seeliger, and Max Mühlhäuser. Analyzing business process anomalies using autoencoders. *Machine Learning*, pages 1–19, 2018a.
- Timo Nolle, Alexander Seeliger, and Max Mühlhäuser. Unsupervised anomaly detection in noisy business process event logs using denoising autoencoders. In *International conference on discovery science*, pages 442–456. Springer, 2016.
- Aarish Grover. Anomaly detection for application log data. 2018.
- Maxim Wolpher. Anomaly detection in unstructured time series data using an lstm autoencoder, 2018.
- Dongxue Zhang, Yang Zheng, Yu Wen, Yujue Xu, Jingchuo Wang, Yang Yu, and Dan Meng. Role-based log analysis applying deep learning for insider threat detection. In *Proceedings of the 1st Workshop on Security-Oriented Designs of Computer Architectures and Processors*, pages 18–20. ACM, 2018b.
- Anvardh Nanduri and Lance Sherry. Anomaly detection in aircraft data using recurrent neural networks (rnn). In *Integrated Communications Navigation and Surveillance (ICNS), 2016*, pages 5C2–1. IEEE, 2016.
- Zheng Fengming, Li Shufang, Guo Zhimin, Wu Bo, Tian Shiming, and Pan Mingming. Anomaly detection in smart grid based on encoder-decoder framework with recurrent neural network. *The Journal of China Universities of Posts and Telecommunications*, 24(6):67–73, 2017.
- Erik Marchi, Fabio Vesperini, Felix Weninger, Florian Eyben, Stefano Squartini, and Björn Schuller. Non-linear prediction with lstm recurrent neural networks for acoustic novelty detection. In *Neural Networks (IJCNN), 2015 International Joint Conference on*, pages 1–7. IEEE, 2015.
- Siyang Lu, Xiang Wei, Yandong Li, and Liqiang Wang. Detecting anomaly in big data system logs using convolutional neural network. In *2018 IEEE 16th Intl Conf on Dependable, Autonomic and Secure Computing, 16th Intl Conf on Pervasive Intelligence and Computing, 4th Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech)*, pages 151–158. IEEE, 2018.
- Fangfang Yuan, Yanan Cao, Yanmin Shang, Yanbing Liu, Jianlong Tan, and Binxing Fang. Insider threat detection with deep neural network. In *International Conference on Computational Science*, pages 43–54. Springer, 2018a.
- Domen Racki, Dejan Tomazevic, and Danijel Skocaj. A compact convolutional neural network for textured surface anomaly detection. In *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1331–1339. IEEE, 2018.
- Shifu Zhou, Wei Shen, Dan Zeng, Mei Fang, Yuanwang Wei, and Zhijiang Zhang. Spatial-temporal convolutional neural networks for anomaly detection and localization in crowded scenes. *Signal Processing: Image Communication*, 47:358–368, 2016.
- Oleg Gorokhov, Mikhail Petrovskiy, and Igor Mashechkin. Convolutional neural networks for unsupervised anomaly detection in text data. In *International Conference on Intelligent Data Engineering and Automated Learning*, pages 500–507. Springer, 2017.
- Nicholas Liao, Matthew Guzdial, and Mark Riedl. Deep convolutional player modeling on log and level data. In *Proceedings of the 12th International Conference on the Foundations of Digital Games*, page 41. ACM, 2017.
- Jiechao Cheng, Rui Ren, Lei Wang, and Jianfeng Zhan. Deep convolutional neural networks for anomaly event classification on distributed systems. *arXiv preprint arXiv:1710.09052*, 2017.
- Boxue Zhang, Qi Zhao, Wenquan Feng, and Shuchang Lyu. Alphamex: A smarter global pooling method for convolutional neural networks. *Neurocomputing*, 321:36–48, 2018c.

- Mehdi Mohammadi, Ala Al-Fuqaha, Sameh Sorour, and Mohsen Guizani. Deep learning for iot big data and streaming analytics: A survey. *IEEE Communications Surveys & Tutorials*, 2018.
- Tie Luo and Sai G Nagarajany. Distributed anomaly detection using autoencoder neural networks in wsn for iot. In *2018 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE, 2018.
- Fatemeh Shah Mohammadi and Andres Kwasinski. Neural network cognitive engine for autonomous and distributed underlay dynamic spectrum access. *arXiv preprint arXiv:1806.11038*, 2018.
- Irina Kakanakova and Stefan Stoyanov. Outlier detection via deep learning architecture. In *Proceedings of the 18th International Conference on Computer Systems and Technologies*, pages 73–79. ACM, 2017.
- Weishan Zhang, Wuwu Guo, Xin Liu, Yan Liu, Jiehan Zhou, Bo Li, Qinghua Lu, and Su Yang. Lstm-based analysis of industrial iot equipment. *IEEE Access*, 6:23551–23560, 2018d.
- Burhan A Mudassar, Jong Hwan Ko, and Saibal Mukhopadhyay. An unsupervised anomalous event detection framework with class aware source separation. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 2671–2675. IEEE, 2018.
- Luis Martí, Nayat Sanchez-Pi, José Manuel Molina, and Ana Cristina Bicharra Garcia. Anomaly detection based on sensor data in petroleum industry applications. *Sensors*, 15(2):2774–2797, 2015.
- Deegan J Atha and Mohammad R Jahanshahi. Evaluation of deep learning approaches based on convolutional neural networks for corrosion detection. *Structural Health Monitoring*, 17(5):1110–1128, 2018.
- Jeffrey de Deijn. Automatic car damage recognition using convolutional neural networks. 2018.
- Fan Wang, John P Kerekes, Zhuoyi Xu, and Yandong Wang. Residential roof condition assessment system using deep learning. *Journal of Applied Remote Sensing*, 12(1):016040, 2018c.
- Jun Inoue, Yoriyuki Yamagata, Yuqi Chen, Christopher M Poskitt, and Jun Sun. Anomaly detection for a water treatment system using unsupervised machine learning. In *Data Mining Workshops (ICDMW), 2017 IEEE International Conference on*, pages 1058–1065. IEEE, 2017.
- Nga Nguyen Thi, Nhien-An Le-Khac, et al. One-class collective anomaly detection based on lstm-rnns. In *Transactions on Large-Scale Data-and Knowledge-Centered Systems XXXVI*, pages 73–85. Springer, 2017.
- Moshe Kravchik and Asaf Shabtai. Detecting cyber attacks in industrial control systems using convolutional neural networks. In *Proceedings of the 2018 Workshop on Cyber-Physical Systems Security and Privacy*, pages 72–83. ACM, 2018.
- Guanjie Huang, Chao-Hsien Chu, and Xiaodan Wu. A deep learning-based method for sleep stage classification using physiological signal. In *International Conference on Smart Health*, pages 249–260. Springer, 2018.
- Donghyun Park, Seulgi Kim, Yelin An, and Jae-Yoon Jung. Lired: A light-weight real-time fault detection system for edge computing using lstm recurrent neural networks. *Sensors*, 18(7):2110, 2018a.
- Chih-Wen Chang, Hau-Wei Lee, and Chein-Hung Liu. A review of artificial intelligence algorithms used for smart machine tools. *Inventions*, 3(3):41, 2018.
- Ye Yuan and Kebin Jia. A distributed anomaly detection method of operation energy consumption using smart meter data. In *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2015 International Conference on*, pages 310–313. IEEE, 2015.
- Daniel B Araya, Katarina Grolinger, Hany F ElYamany, Miriam AM Capretz, and Girma Bitsuamlak. An ensemble learning framework for anomaly detection in building energy consumption. *Energy and Buildings*, 144:191–206, 2017.
- Yongzhi Qu, Miao He, Jason Deutsch, and David He. Detection of pitting in gears using a deep sparse autoencoder. *Applied Sciences*, 7(5):515, 2017.
- Anand Bhattad, Jason Rock, and David Forsyth. Detecting anomalous faces with ‘no peeking’ autoencoders. *arXiv preprint arXiv:1802.05798*, 2018.

- Faiq Khalid Lodhi, Syed Rafay Hasan, Osman Hasan, and Falah Awwadl. Power profiling of microcontroller's instruction set for runtime hardware trojans detection without golden circuit models. In *Proceedings of the Conference on Design, Automation & Test in Europe*, pages 294–297. European Design and Automation Association, 2017.
- Shahrzad Faghieh-Roohi, Siamak Hajizadeh, Alfredo Núñez, Robert Babuska, and Bart De Schutter. Deep convolutional neural networks for detection of rail surface defects. In *Neural Networks (IJCNN), 2016 International Joint Conference on*, pages 2584–2589. IEEE, 2016.
- Peter Christiansen, Lars N Nielsen, Kim A Steen, Rasmus N Jørgensen, and Henrik Karstoft. Deepanomaly: Combining background subtraction and deep learning for detecting obstacles and anomalies in an agricultural field. *Sensors*, 16(11):1904, 2016.
- Dean Lee, Vincent Siu, Rick Cruz, and Charles Yetman. Convolutional neural net and bearing fault analysis. In *Proceedings of the International Conference on Data Mining series (ICDM) Barcelona*, pages 194–200, 2016.
- Lingping Dong, Yongliang Zhang, Conglin Wen, and Hongtao Wu. Camera anomaly detection based on morphological analysis and deep learning. In *Digital Signal Processing (DSP), 2016 IEEE International Conference on*, pages 266–270. IEEE, 2016.
- Alvaro Fuentes, Sook Yoon, Sang Cheol Kim, and Dong Sun Park. A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors*, 17(9):2022, 2017.
- Weizhong Yan and Lijie Yu. On accurate and reliable anomaly detection for gas turbine combustors: A deep learning approach. In *Proceedings of the annual conference of the prognostics and health management society*, 2015.
- Hui Luo and Shisheng Zhong. Gas turbine engine gas path anomaly detection using deep learning with gaussian distribution. In *Prognostics and System Health Management Conference (PHM-Harbin), 2017*, pages 1–6. IEEE, 2017.
- Jiejie Dai, Hui Song, Gehao Sheng, and Xiuchen Jiang. Cleaning method for status monitoring data of power equipment based on stacked denoising autoencoders. *IEEE Access*, 5:22863–22870, 2017.
- Lejla Banjanovic-Mehmedovic, Amel Hajdarevic, Mehmed Kantardzic, Fahrudin Mehmedovic, and Izet Džananovic. Neural network-based data-driven modelling of anomaly detection in thermal power plant. *Automatika*, 58(1): 69–79, 2017.
- Dominique T Shipmon, Jason M Gurevitch, Paolo M Piselli, and Stephen T Edwards. Time series anomaly detection; detection of anomalous drops with limited features and sparse examples in noisy highly periodic data. *arXiv preprint arXiv:1708.03665*, 2017a.
- Kyle Hundman, Valentino Constantinou, Christopher Laporte, Ian Colwell, and Tom Soderstrom. Detecting spacecraft anomalies using lstms and nonparametric dynamic thresholding. *arXiv preprint arXiv:1802.04431*, 2018.
- Lingxue Zhu and Nikolay Laptev. Deep and confident prediction for time series at uber. In *Data Mining Workshops (ICDMW), 2017 IEEE International Conference on*, pages 103–110. IEEE, 2017.
- Jan Paul Assendorp. *Deep learning for anomaly detection in multivariate time series data*. PhD thesis, Hochschule für Angewandte Wissenschaften Hamburg, 2017.
- Subutai Ahmad, Alexander Lavin, Scott Purdy, and Zuha Agha. Unsupervised real-time anomaly detection for streaming data. *Neurocomputing*, 262:134–147, 2017.
- Pankaj Malhotra, Anusha Ramakrishnan, Gaurangi Anand, Lovekesh Vig, Puneet Agarwal, and Gautam Shroff. Lstm-based encoder-decoder for multi-sensor anomaly detection. *arXiv preprint arXiv:1607.00148*, 2016a.
- Adrian Taylor, Sylvain Leblanc, and Nathalie Japkowicz. Anomaly detection in automobile control network data with long short-term memory networks. In *Data Science and Advanced Analytics (DSAA), 2016 IEEE International Conference on*, pages 130–139. IEEE, 2016.
- Min Cheng, Qian Xu, Jianming Lv, Wenyin Liu, Qing Li, Jianping Wang, et al. Ms-lstm: A multi-scale lstm model for bgp anomaly detection. In *2016 IEEE 24th International Conference on Network Protocols (ICNP)*, pages 1–6. IEEE, 2016.

- Gobinath Loganathan, Jagath Samarabandu, and Xianbin Wang. Sequence to sequence pattern learning algorithm for real-time anomaly detection in network traffic. In *2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE)*, pages 1–4. IEEE, 2018.
- Mohsin Munir, Shoaib Ahmed Siddiqui, Andreas Dengel, and Sheraz Ahmed. Deepant: A deep learning approach for unsupervised anomaly detection in time series. *IEEE Access*, 2018.
- Dominique Shipmon, Jason Gurevitch, Paolo M Piselli, and Steve Edwards. Time series anomaly detection: Detection of anomalous drops with limited features and sparse examples in noisy periodic data. Technical report, Google Inc., 2017b. URL <https://arxiv.org/abs/1708.03665>.
- Pankaj Malhotra, Vishnu TV, Anusha Ramakrishnan, Gaurangi Anand, Lovekesh Vig, Puneet Agarwal, and Gautam Shroff. Multi-sensor prognostics using an unsupervised health index based on lstm encoder-decoder. *arXiv preprint arXiv:1608.06154*, 2016b.
- Pavel Filonov, Andrey Lavrentyev, and Artem Vorontsov. Multivariate industrial time series with cyber-attack simulation: Fault detection using an lstm-based predictive data model. *arXiv preprint arXiv:1612.06676*, 2016.
- Kaiji Sugimoto, Saerom Lee, and Yoshifumi Okada. Deep learning-based detection of periodic abnormal waves in ecg data. In *Proceedings of the International MultiConference of Engineers and Computer Scientists*, volume 1, 2018.
- Dong Yul Oh and Il Dong Yun. Residual error based anomaly detection using auto-encoder in smd machine sound. *Sensors (Basel, Switzerland)*, 18(5), 2018.
- Zahra Ebrahimzadeh and Samantha Kleinberg. Multi-scale change point detection in multivariate time series.
- Kalyan Veeramachaneni, Ignacio Araldo, Vamsi Korrapati, Constantinos Bassias, and Ke Li. Ai²: training a big data machine to defend. In *Big Data Security on Cloud (BigDataSecurity)*, *IEEE International Conference on High Performance and Smart Computing (HPSC)*, and *IEEE International Conference on Intelligent Data and Security (IDS)*, 2016 *IEEE 2nd International Conference on*, pages 49–54. IEEE, 2016.
- Hoang Anh Dau, Vic Ciesielski, and Andy Song. Anomaly detection using replicator neural networks trained on examples of one class. In *Asia-Pacific Conference on Simulated Evolution and Learning*, pages 311–322. Springer, 2014.
- Maciej Wielgosz, Andrzej Skoczeń, and Matej Mertik. Recurrent neural networks for anomaly detection in the post-mortem time series of lhc superconducting magnets. *arXiv preprint arXiv:1702.00833*, 2017.
- Sakti Saurav, Pankaj Malhotra, Vishnu TV, Narendhar Gugulothu, Lovekesh Vig, Puneet Agarwal, and Gautam Shroff. Online anomaly detection with concept drift adaptation using recurrent neural networks. In *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data*, pages 78–87. ACM, 2018.
- Maciej Wielgosz, Matej Mertik, Andrzej Skoczeń, and Ernesto De Matteis. The model of an anomaly detector for lhc magnets based on recurrent neural networks and adaptive quantization. *Engineering Applications of Artificial Intelligence*, 74:166–185, 2018.
- Tian Guo, Zhao Xu, Xin Yao, Haifeng Chen, Karl Aberer, and Koichi Funaya. Robust online time series prediction with recurrent neural networks. In *Data Science and Advanced Analytics (DSAA)*, 2016 *IEEE International Conference on*, pages 816–825. Ieee, 2016.
- Pavel Filonov, Fedor Kitashov, and Andrey Lavrentyev. Rnn-based early cyber-attack detection for the tennessee eastman process. *arXiv preprint arXiv:1709.02232*, 2017.
- Stratis Kanarachos, Stavros-Richard G Christopoulos, Alexander Chroneos, and Michael E Fitzpatrick. Detecting anomalies in time series data via a deep learning algorithm combining wavelets, neural networks and hilbert transform. *Expert Systems with Applications*, 85:292–304, 2017.
- Shuyang Du, Madhulima Pandey, and Cuiqun Xing. Modeling approaches for time series forecasting and anomaly detection.
- Paolo Napoletano, Flavio Piccoli, and Raimondo Schettini. Anomaly detection in nanofibrous materials by cnn-based self-similarity. *Sensors*, 18(1):209, 2018.
- Divya Shanmugam, Davis Blalock, and John Guttag. Jiffy: A convolutional approach to learning time series similarity. 2018.

- Jefferson Ryan Medel and Andreas Savakis. Anomaly detection in video using predictive convolutional long short-term memory networks. *arXiv preprint arXiv:1612.00390*, 2016.
- Daehyung Park, Yuuna Hoshi, and Charles C Kemp. A multimodal anomaly detector for robot-assisted feeding using an lstm-based variational autoencoder. *IEEE Robotics and Automation Letters*, 3(3):1544–1551, 2018b.
- Maximilian Sölch, Justin Bayer, Marvin Ludersdorfer, and Patrick van der Smagt. Variational inference for on-line anomaly detection in high-dimensional time series. *arXiv preprint arXiv:1602.07109*, 2016.
- Houssam Zenati, Chuan Sheng Foo, Bruno Lecouat, Gaurav Manek, and Vijay Ramaseshan Chandrasekhar. Efficient gan-based anomaly detection. *arXiv preprint arXiv:1802.06222*, 2018.
- Swee Kiat Lim, Yi Loo, Ngoc-Trung Tran, Ngai-Man Cheung, Gemma Roig, and Yuval Elovici. Doping: Generative data augmentation for unsupervised anomaly detection with gan. *arXiv preprint arXiv:1808.07632*, 2018.
- Nikolay Laptev. Anogen: Deep anomaly generator.
- JiaYi Wei, JianFei Zhao, YanYun Zhao, and ZhiCheng Zhao. Unsupervised anomaly detection for traffic surveillance based on background modeling. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 129–136, 2018.
- Teodora Sandra Buda, Bora Caglayan, and Haytham Assem. Deepad: A generic framework based on deep learning for time series anomaly detection. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 577–588. Springer, 2018.
- Ye Yuan, Guangxu Xun, Fenglong Ma, Yaqing Wang, Nan Du, Kebin Jia, Lu Su, and Aidong Zhang. Muvan: A multi-view attention network for multivariate temporal data. In *2018 IEEE International Conference on Data Mining (ICDM)*, pages 717–726. IEEE, 2018b.
- Tian Guo and Tao Lin. Exploring the interpretability of lstm neural networks over multi-variable data. 2018.
- Antonio Nucci, Song Cui, John Garrett, Gurvinder Singh, and Kenneth Croley. Real-time multi-variate multi-time-scale anomaly detection system for next generation networks. 2018.
- Jan Paul Assendorp, Andreas Meisel, H. Glenn Bohlen, and C Sommer. Deep learning for anomaly detection in multivariate time series data. 2017.
- Timo Nolle, Alexander Seeliger, and Max Mühlhäuser. Binet: Multivariate business process anomaly detection using deep learning. In *International Conference on Business Process Management*, pages 271–287. Springer, 2018b.
- Chuxu Zhang, Dongjin Song, Yuncong Chen, Xinyang Feng, Cristian Lumezanu, Wei Cheng, Jingchao Ni, Bo Zong, Haifeng Chen, and Nitesh V Chawla. A deep neural network for unsupervised anomaly detection and diagnosis in multivariate time series data. *arXiv preprint arXiv:1811.08055*, 2018e.
- Yifan Guo, Weixian Liao, Qianlong Wang, Lixing Yu, Tianxi Ji, and Pan Li. Multidimensional time series anomaly detection: A gru-based gaussian mixture variational autoencoder approach. In *Asian Conference on Machine Learning*, pages 97–112, 2018.
- Xuyun Fu, Hui Luo, Shisheng Zhong, and Lin Lin. Aircraft engine fault detection based on grouped convolutional denoising autoencoders. *Chinese Journal of Aeronautics*, 2019.
- Tung Kieu, Bin Yang, and Christian S Jensen. Outlier detection for multidimensional time series using deep neural networks. In *2018 19th IEEE International Conference on Mobile Data Management (MDM)*, pages 125–134. IEEE, 2018.
- Sagnik Basumallik, Rui Ma, and Sara Eftekharijad. Packet-data anomaly detection in pmu-based state estimator using convolutional neural network. *International Journal of Electrical Power & Energy Systems*, 107:690–702, 2019.
- Yasuhiro Ikeda, Kengo Tajiri, Yuusuke Nakano, Keishiro Watanabe, and Keisuke Ishibashi. Estimation of dimensions contributing to detected anomalies with variational autoencoders. *arXiv preprint arXiv:1811.04576*, 2018.
- Dan Li, Dacheng Chen, Lei Shi, Baihong Jin, Jonathan Goh, and See-Kiong Ng. Mad-gan: Multivariate anomaly detection for time series data with generative adversarial networks. *arXiv preprint arXiv:1901.04997*, 2019.

- Aaron Randall Tuor, Ryan Baerwolf, Nicolas Knowles, Brian Hutchinson, Nicole Nichols, and Robert Jasper. Recurrent neural network language models for open vocabulary event-level cyber anomaly detection. In *Workshops at the Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.
- Rui Maia. Multivariate temporal data analysis for vessels behavior anomaly detection. 2017.
- Andrea Dal Pozzolo, Olivier Caelen, Reid A Johnson, and Gianluca Bontempi. Calibrating probability with under-sampling for unbalanced classification. In *Computational Intelligence, 2015 IEEE Symposium Series on*, pages 159–166. IEEE, 2015.
- Yuwei Cui, Chetan Surpur, Subutai Ahmad, and Jeff Hawkins. A comparative study of htm and other neural network models for online sequence learning with streaming data. In *Neural Networks (IJCNN), 2016 International Joint Conference on*, pages 1530–1538. IEEE, 2016.
- JTA Andrews, N Jaccarda, TW Rogers, T Tanaya, and LD Griffina. Anomaly detection for security imaging.
- Mohammad Sabokrou, Mohsen Fayyaz, Mahmood Fathy, et al. Fully convolutional neural network for fast anomaly detection in crowded scenes. *arXiv preprint arXiv:1609.00866*, 2016a.
- Mohammad Sabokrou, Mohsen Fayyaz, Mahmood Fathy, and Reinhard Klette. Deep-cascade: cascading 3d deep neural networks for fast anomaly detection and localization in crowded scenes. *IEEE Transactions on Image Processing*, 26(4):1992–2004, 2017.
- Asim Munawar, Phongtharin Vinayavekhin, and Giovanni De Magistris. Spatio-temporal anomaly detection for industrial robots through prediction in unsupervised feature space. In *Applications of Computer Vision (WACV), 2017 IEEE Winter Conference on*, pages 1017–1025. IEEE, 2017.
- Wei Li, Guodong Wu, and Qian Du. Transferred deep learning for anomaly detection in hyperspectral imagery. *IEEE Geosci. Remote Sensing Lett.*, 14(5):597–601, 2017b.
- Meina Qiao, Tian Wang, Jiakun Li, Ce Li, Zhiwei Lin, and Hichem Snoussi. Abnormal event detection based on deep autoencoder fusing optical flow. In *Control Conference (CCC), 2017 36th Chinese*, pages 11098–11103. IEEE, 2017.
- Gaurav Tripathi, Kuldeep Singh, and Dinesh Kumar Vishwakarma. Convolutional neural networks for crowd behaviour analysis: a survey. *The Visual Computer*, pages 1–24, 2018.
- Jacob Nogas, Shehroz S Khan, and Alex Mihailidis. Deepfall–non-invasive fall detection with deep spatio-temporal convolutional autoencoders. *arXiv preprint arXiv:1809.00977*, 2018.
- Yong Shean Chong and Yong Haur Tay. Abnormal event detection in videos using spatiotemporal autoencoder. In *International Symposium on Neural Networks*, pages 189–196. Springer, 2017.
- Ali Khaleghi and Mohammad Shahram Moin. Improved anomaly detection in surveillance videos based on a deep learning method. In *2018 8th Conference of AI & Robotics and 10th RoboCup Iranopen International Symposium (IRANOPEN)*, pages 73–81. IEEE, 2018.
- Huan Yang, Baoyuan Wang, Stephen Lin, David Wipf, Minyi Guo, and Baining Guo. Unsupervised extraction of video highlights via robust recurrent auto-encoders. In *Proceedings of the IEEE international conference on computer vision*, pages 4633–4641, 2015.
- Zhengying Chen, Yonghong Tian, Wei Zeng, and Tiejun Huang. Detecting abnormal behaviors in surveillance videos based on fuzzy clustering and multiple auto-encoders. In *Multimedia and Expo (ICME), 2015 IEEE International Conference on*, pages 1–6. IEEE, 2015.
- Matheus Gutoski, Nelson Marcelo Romero Aquino, Manassés Ribeiro, André Engênio Lazzaretti, and Heitor Silvério Lopes. Detection of video anomalies using convolutional autoencoders and one-class support vector machines.
- Dario D’Avino, Davide Cozzolino, Giovanni Poggi, and Luisa Verdoliva. Autoencoder with recurrent neural networks for video forgery detection. *Electronic Imaging*, 2017(7):92–99, 2017.
- Dario Dotti, Mirela Popa, and Stylianos Asteriadis. Unsupervised discovery of normal and abnormal activity patterns in indoor and outdoor environments. In *VISIGRAPP (5: VISAPP)*, pages 210–217, 2017.

- M Sabokrou, M Fathy, and M Hoseini. Video anomaly detection and localisation based on the sparsity and reconstruction error of auto-encoder. *Electronics Letters*, 52(13):1122–1124, 2016b.
- Hanh TM Tran and DC Hogg. Anomaly detection using a convolutional winner-take-all autoencoder. In *Proceedings of the British Machine Vision Conference 2017*. Leeds, 2017.
- Mahmudul Hasan, Jonghyun Choi, Jan Neumann, Amit K Roy-Chowdhury, and Larry S Davis. Learning temporal regularity in video sequences. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 733–742, 2016.
- Lucas Pinheiro Cinelli. *ANOMALY DETECTION IN SURVEILLANCE VIDEOS USING DEEP RESIDUAL NETWORKS*. PhD thesis, Universidade Federal do Rio de Janeiro, 2017.
- Waqas Sultani, Chen Chen, and Mubarak Shah. Real-world anomaly detection in surveillance videos. *Center for Research in Computer Vision (CRCV), University of Central Florida (UCF)*, 2018.
- Dan Chianucci and Andreas Savakis. Unsupervised change detection using spatial transformer networks. In *Signal Processing Workshop (WNYISPW), 2016 IEEE Western New York Image and*, pages 1–5. IEEE, 2016.
- Weixin Luo, Wen Liu, and Shenghua Gao. Remembering history with convolutional lstm for anomaly detection. In *Multimedia and Expo (ICME), 2017 IEEE International Conference on*, pages 439–444. IEEE, 2017a.
- Itamar Ben-Ari and Ravid Shwartz-Ziv. Attentioned convolutional lstm inpainting network for anomaly detection in videos. *arXiv preprint arXiv:1811.10228*, 2018.
- Akash Singh. Anomaly detection for temporal data using long short-term memory (lstm), 2017.
- Weixin Luo, Wen Liu, and Shenghua Gao. A revisit of sparse coding based anomaly detection in stacked rnn framework. *ICCV, Oct*, 1(2):3, 2017b.
- Xu-Gang Zhou and Li-Qing Zhang. Abnormal event detection using recurrent neural network. In *Computer Science and Applications (CSA), 2015 International Conference on*, pages 222–226. IEEE, 2015.
- Xing Hu, Shiqiang Hu, Yingping Huang, Huanlong Zhang, and Hanbing Wu. Video anomaly detection using deep incremental slow feature analysis network. *IET Computer Vision*, 10(4):258–265, 2016.
- Yong Shean Chong and Yong Haur Tay. Modeling representation of videos for anomaly detection using deep learning: A review. *arXiv preprint arXiv:1505.00523*, 2015.
- Mahdyar Ravanbakhsh, Enver Sangineto, Moin Nabi, and Nicu Sebe. Training adversarial discriminators for cross-channel abnormal event detection in crowds. *arXiv preprint arXiv:1706.07680*, 2017a.
- B Boghossian and J Black. The challenges of robust 24/7 video surveillance systems. 2005.
- Nico Görnitz, Marius Kloft, Konrad Rieck, and Ulf Brefeld. Toward supervised anomaly detection. *Journal of Artificial Intelligence Research*, 46:235–262, 2013.
- Alistair Shilton, Sutharshan Rajasegarar, and Marimuthu Palaniswami. Combined multiclass classification and anomaly detection for large-scale wireless sensor networks. In *Intelligent Sensors, Sensor Networks and Information Processing, 2013 IEEE Eighth International Conference on*, pages 491–496. IEEE, 2013.
- Vilen Jumutc and Johan AK Suykens. Multi-class supervised novelty detection. *IEEE transactions on pattern analysis and machine intelligence*, 36(12):2510–2523, 2014.
- Sangwook Kim, Yonghwa Choi, and Minho Lee. Deep learning with support vector data description. *Neurocomputing*, 165:111–117, 2015.
- Sarah M Erfani, Mahsa Baktashmotlagh, Masud Moshtaghi, Vinh Nguyen, Christopher Leckie, James Bailey, and Kottagiri Ramamohanarao. From shared subspaces to shared landmarks: A robust multi-source classification approach. In *AAAI*, pages 1854–1860, 2017.
- Erxue Min, Jun Long, Qiang Liu, Jianjing Cui, Zhiping Cai, and Junbo Ma. Su-ids: A semi-supervised and unsupervised framework for network intrusion detection. In *International Conference on Cloud Computing and Security*, pages 322–334. Springer, 2018.

- Pramuditha Perera and Vishal M Patel. Learning deep features for one-class classification. *arXiv preprint arXiv:1801.05365*, 2018.
- Gilles Blanchard, Gyemin Lee, and Clayton Scott. Semi-supervised novelty detection. *Journal of Machine Learning Research*, 11(Nov):2973–3009, 2010.
- Riley Edmunds and Efraim Feinstein. Deep semi-supervised embeddings for dynamic targeted anomaly detection. 2017.
- Hossein Estiri and Shawn Murphy. Semi-supervised encoding for outlier detection in clinical observation data. *bioRxiv*, page 334771, 2018.
- Xiaowei Jia, Kang Li, Xiaoyi Li, and Aidong Zhang. A novel semi-supervised deep learning framework for affective state recognition on eeg signals. In *Bioinformatics and Bioengineering (BIBE), 2014 IEEE International Conference on*, pages 30–37. IEEE, 2014.
- Jindong Gu, Matthias Schubert, and Volker Tresp. Semi-supervised outlier detection using generative and adversary framework. 2018.
- Samet Akcay, Amir Atapour-Abarghouei, and Toby P Breckon. Ganomaly: Semi-supervised anomaly detection via adversarial training. *arXiv preprint arXiv:1805.06725*, 2018.
- Mohammad Sabokrou, Mohammad Khalooei, Mahmood Fathy, and Ehsan Adeli. Adversarially learned one-class classifier for novelty detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3379–3388, 2018.
- Asimena Dimokranitou. *Adversarial autoencoders for anomalous event detection in images*. PhD thesis, 2017.
- Naomi S Altman. An introduction to kernel and nearest-neighbor nonparametric regression. *The American Statistician*, 46(3):175–185, 1992.
- Tin Kam Ho. Random decision forests. In *Document analysis and recognition, 1995., proceedings of the third international conference on*, volume 1, pages 278–282. IEEE, 1995.
- Kenji Kira and Larry A Rendell. The feature selection problem: Traditional methods and a new algorithm. In *Aaai*, volume 2, pages 129–134, 1992.
- Ningxin Shi, Xiaohong Yuan, and William Nick. Semi-supervised random forest for intrusion detection network, 2017.
- Bing Zhu, Wenchuan Yang, Huaxuan Wang, and Yuan Yuan. A hybrid deep learning model for consumer credit scoring. In *2018 International Conference on Artificial Intelligence and Big Data (ICAIBD)*, pages 205–208. IEEE, 2018.
- Evan Racah, Christopher Beckham, Tegan Maharaj, Samira Ebrahimi Kahou, Mr Prabhat, and Chris Pal. Extremeweather: A large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events. In *Advances in Neural Information Processing Systems*, pages 3402–3413, 2017.
- Hao Wu and Saurabh Prasad. Semi-supervised deep learning using pseudo labels for hyperspectral image classification. *IEEE Transactions on Image Processing*, 27(3):1259–1270, 2018.
- Mark Kliger and Shachar Fleishman. Novelty detection with gan. *arXiv preprint arXiv:1802.10560*, 2018.
- Tyler Tian Lu. Fundamental limitations of semi-supervised learning. Master’s thesis, University of Waterloo, 2009.
- Natali Ruchansky, Sungyong Seo, and Yan Liu. Csi: A hybrid deep model for fake news detection. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 797–806. ACM, 2017.
- Ryan J Urbanowicz, Melissa Meeker, William La Cava, Randal S Olson, and Jason H Moore. Relief-based feature selection: introduction and review. *Journal of biomedical informatics*, 2018.
- Sarah Erfani, Mahsa Baktashmotlagh, Masoud Moshtaghi, Vinh Nguyen, Christopher Leckie, James Bailey, and Ramamohanarao Kotagiri. Robust domain generalisation by enforcing distribution invariance. In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence*, pages 1455–1461. AAAI Press/International Joint Conferences on Artificial Intelligence, 2016b.

- Ruobing Wu, Baoyuan Wang, Wenping Wang, and Yizhou Yu. Harvesting discriminative meta objects with deep cnn features for scene classification. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1287–1295, 2015b.
- Andrew M Saxe, Pang Wei Koh, Zhenghao Chen, Maneesh Bhand, Bipin Suresh, and Andrew Y Ng. On random weights and unsupervised feature learning. In *ICML*, pages 1089–1096, 2011.
- Pierre Baldi. Autoencoders, unsupervised learning, and deep architectures. In *Proceedings of ICML workshop on unsupervised and transfer learning*, pages 37–49, 2012.
- Varun Chandola, Varun Mithal, and Vipin Kumar. Comparative evaluation of anomaly detection techniques for sequence data. In *Data Mining, 2008. ICDM'08. Eighth IEEE International Conference on*, pages 743–748. IEEE, 2008.
- Pradeep Dasigi and Eduard Hovy. Modeling newswire events using neural networks for anomaly detection. In *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers*, pages 1414–1422, 2014.
- Davide Abati, Angelo Porrello, Simone Calderara, and Rita Cucchiara. And: Autoregressive novelty detectors. *arXiv preprint arXiv:1807.01653*, 2018.
- Bo Zong, Qi Song, Martin Renqiang Min, Wei Cheng, Cristian Lumezanu, Daeki Cho, and Haifeng Chen. Deep autoencoding gaussian mixture model for unsupervised anomaly detection. 2018.
- Takaaki Tagawa, Yukihiro Tadokoro, and Takehisa Yairi. Structured denoising autoencoder for fault detection and analysis. In *Asian Conference on Machine Learning*, pages 96–111, 2015.
- Dan Xu, Elisa Ricci, Yan Yan, Jingkuan Song, and Nicu Sebe. Learning deep representations of appearance and motion for anomalous event detection. *arXiv preprint arXiv:1510.01553*, 2015.
- Simon Hawkins, Hongxing He, Graham Williams, and Rohan Baxter. Outlier detection using replicator neural networks. In *International Conference on Data Warehousing and Knowledge Discovery*, pages 170–180. Springer, 2002.
- Dan Zhao, Baolong Guo, Jinfu Wu, Weikang Ning, and Yunyi Yan. Robust feature learning by improved auto-encoder from non-gaussian noised images. In *Imaging Systems and Techniques (IST), 2015 IEEE International Conference on*, pages 1–5. IEEE, 2015.
- Yu Qi, Yueming Wang, Xiaoxiang Zheng, and Zhaohui Wu. Robust feature learning by stacked autoencoder with maximum correntropy criterion. In *Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on*, pages 6716–6720. IEEE, 2014.
- Raghavendra Chalapathy, Aditya Krishna Menon, and Sanjay Chawla. Robust, deep and inductive anomaly detection. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 36–51. Springer, 2017.
- Shuangfei Zhai, Yu Cheng, Weining Lu, and Zhongfei Zhang. Deep structured energy based models for anomaly detection. *arXiv preprint arXiv:1605.07717*, 2016.
- Olga Lyudchik. Outlier detection using autoencoders. Technical report, 2016.
- Weining Lu, Yu Cheng, Cao Xiao, Shiyu Chang, Shuai Huang, Bin Liang, and Thomas Huang. Unsupervised sequential outlier detection with deep architectures. *IEEE Transactions on Image Processing*, 26(9):4321–4330, 2017.
- Rishabh Mehrotra, Ahmed Hassan Awadallah, Milad Shokouhi, Emine Yilmaz, Imed Zitouni, Ahmed El Kholy, and Madian Khabisa. Deep sequential models for task satisfaction prediction. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 737–746. ACM, 2017.
- Qinxue Meng, Daniel Catchpoole, David Skillicorn, and Paul J Kennedy. Relational autoencoder for feature extraction. *arXiv preprint arXiv:1802.03145*, 2018.
- Mostafa Parchami, Saman Bashbaghi, Eric Granger, and Saif Sayed. Using deep autoencoders to learn robust domain-invariant representations for still-to-video face recognition. In *Advanced Video and Signal Based Surveillance (AVSS), 2017 14th IEEE International Conference on*, pages 1–6. IEEE, 2017.

- Wallace E Lawson, Esube Bekele, and Keith Sullivan. Finding anomalies with generative adversarial networks for a patrolbot. In *CVPR Workshops*, pages 484–485, 2017.
- Valentin Leveau and Alexis Joly. Adversarial autoencoders for novelty detection. 2017.
- Jinwon An and Sungzoon Cho. Variational autoencoder based anomaly detection using reconstruction probability. *Special Lecture on IE*, 2:1–18, 2015.
- Suwon Suh, Daniel H Chae, Hyon-Goo Kang, and Seungjin Choi. Echo-state conditional variational autoencoder for anomaly detection. In *Neural Networks (IJCNN), 2016 International Joint Conference on*, pages 1015–1022. IEEE, 2016.
- Ashish Mishra, M Reddy, Anurag Mittal, and Hema A Murthy. A generative model for zero shot learning using conditional variational autoencoders. *arXiv preprint arXiv:1709.00663*, 2017.
- Markus Goldstein and Seiichi Uchida. A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data. *PloS one*, 11(4):e0152173, 2016.
- Jerone TA Andrews, Thomas Tanay, Edward J Morton, and Lewis D Griffin. Transfer representation-learning for anomaly detection. *ICML*, 2016b.
- Vincent Vercruyssen, Wannes Meert, and Jesse Davis. Transfer learning for time series anomaly detection. *IAL ECML PKDD 2017*, page 27, 2017.
- Kang Li, Nan Du, and Aidong Zhang. Detecting ecg abnormalities via transductive transfer learning. In *Proceedings of the ACM Conference on Bioinformatics, Computational Biology and Biomedicine*, pages 210–217. ACM, 2012.
- Ibrahim Almajai, Fei Yan, Teofilo de Campos, Aftab Khan, William Christmas, David Windridge, and Josef Kittler. Anomaly detection and knowledge transfer in automatic sports video annotation. In *Detection and identification of rare audiovisual cues*, pages 109–117. Springer, 2012.
- PM Ashok Kumar and V Vaidehi. A transfer learning framework for traffic video using neuro-fuzzy approach. *Sādhanā*, 42(9):1431–1442, 2017.
- Peng Liang, Hai-Dong Yang, Wen-Si Chen, Si-Yuan Xiao, and Zhao-Ze Lan. Transfer learning for aluminium extrusion electricity consumption anomaly detection via deep neural networks. *International Journal of Computer Integrated Manufacturing*, 31(4-5):396–405, 2018.
- Bernardino Romera-Paredes and Philip Torr. An embarrassingly simple approach to zero-shot learning. In *International Conference on Machine Learning*, pages 2152–2161, 2015.
- Richard Socher, Milind Ganjoo, Christopher D Manning, and Andrew Ng. Zero-shot learning through cross-modal transfer. In *Advances in neural information processing systems*, pages 935–943, 2013.
- Yongqin Xian, Bernt Schiele, and Zeynep Akata. Zero-shot learning-the good, the bad and the ugly. *arXiv preprint arXiv:1703.04394*, 2017.
- Kun Liu, Wu Liu, Huadong Ma, Wenbing Huang, and Xiongxiang Dong. Generalized zero-shot learning for action recognition with web-scale video data. *arXiv preprint arXiv:1710.07455*, 2017.
- Jorge Rivero, Bernardete Ribeiro, Ning Chen, and Fátima Silva Leite. A grassmannian approach to zero-shot learning for network intrusion detection. In *International Conference on Neural Information Processing*, pages 565–575. Springer, 2017.
- Jinghui Chen, Saket Sathe, Charu Aggarwal, and Deepak Turaga. Outlier detection with autoencoder ensembles. In *Proceedings of the 2017 SIAM International Conference on Data Mining*, pages 90–98. SIAM, 2017.
- Martin Ester, Hans-Peter Kriegel, Jörg Sander, Xiaowei Xu, et al. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Kdd*, volume 96, pages 226–231, 1996.
- V Sreekanth, Andrea Vedaldi, Andrew Zisserman, and C Jawahar. Generalized rbf feature maps for efficient detection. 2010.
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.

- Guiqin Yuan, Bo Li, Yiyang Yao, and Simin Zhang. A deep learning enabled subspace spectral ensemble clustering approach for web anomaly detection. In *Neural Networks (IJCNN), 2017 International Joint Conference on*, pages 3896–3903. IEEE, 2017.
- François de La Bourdonnaye, Céline Teulière, Thierry Chateau, and Jochen Triesch. Learning of binocular fixations using anomaly detection with deep reinforcement learning. In *Neural Networks (IJCNN), 2017 International Joint Conference on*, pages 760–767. IEEE, 2017.
- Yuan Zuo Ke Pei Geyong Min Chengqiang Huang, Yulei Wu. Towards experienced anomaly detector through reinforcement learning. *The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18)*, 2016.
- S Kanarachos, J Mathew, A Chronos, and M Fitzpatrick. Anomaly detection in time series data using a combination of wavelets, neural networks and hilbert transform. In *IISA*, pages 1–6, 2015.
- Jürgen Schmidhuber. Deep learning in neural networks: An overview. *Neural networks*, 61:85–117, 2015.
- Yoshua Bengio et al. Learning deep architectures for ai. *Foundations and trends® in Machine Learning*, 2(1):1–127, 2009.
- Paul J Werbos. Backpropagation through time: what it does and how to do it. *Proceedings of the IEEE*, 78(10):1550–1560, 1990.
- Huichu Zhang, Yu Zheng, and Yong Yu. Detecting urban anomalies using multiple spatio-temporal data sources. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(1):54, 2018f.
- Sangmin Lee, Hak Gu Kim, and Yong Man Ro. Stan: Spatio-temporal adversarial networks for abnormal event detection. *arXiv preprint arXiv:1804.08381*, 2018.
- MÁTÉ SZEKÉR. Spatio-temporal outlier detection in streaming trajectory data, 2014.
- Laisen Nie, Yongkang Li, and Xiangjie Kong. Spatio-temporal network traffic estimation and anomaly detection based on convolutional neural network in vehicular ad-hoc networks. *IEEE Access*, 6:40168–40176, 2018.
- Ethan W Dereszynski and Thomas G Dietterich. Spatiotemporal models for data-anomaly detection in dynamic environmental monitoring campaigns. *ACM Transactions on Sensor Networks (TOSN)*, 8(1):3, 2011.
- Hoifung Poon and Pedro Domingos. Sum-product networks: A new deep architecture. In *Computer Vision Workshops (ICCV Workshops), 2011 IEEE International Conference on*, pages 689–690. IEEE, 2011.
- Seyed Mahdi Rezaeina, Ali Ghodsi, and Rouhollah Rahmani. Improving the accuracy of pre-trained word embeddings for sentiment analysis. *arXiv preprint arXiv:1711.08609*, 2017.
- Marwa Naili, Anja Habacha Chaibi, and Henda Hajjami Ben Ghezala. Comparative study of word embedding methods in topic segmentation. *Procedia Computer Science*, 112:340–349, 2017.
- Edgar Altszyler, Mariano Sigman, Sidarta Ribeiro, and Diego Fernández Slezak. Comparative study of lsa vs word2vec embeddings in small corpora: a case study in dreams database. *arXiv preprint arXiv:1610.01520*, 2016.
- Tobias Schnabel, Igor Labutov, David Mimno, and Thorsten Joachims. Evaluation methods for unsupervised word embeddings. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 298–307, 2015.
- Christophe Bertero, Matthieu Roy, Carla Sauvanaud, and Gilles Trédan. Experience report: Log mining using natural language processing and application to anomaly detection. In *Software Reliability Engineering (ISSRE), 2017 IEEE 28th International Symposium on*, pages 351–360. IEEE, 2017.
- Amir Bakaroy, Vasiliy Yadrntsev, and Ilya Sochenkov. Anomaly detection for short texts: Identifying whether your chatbot should switch from goal-oriented conversation to chit-chatting. In *International Conference on Digital Transformation and Global Society*, pages 289–298. Springer, 2018.
- Robert Bamler and Stephan Mandt. Dynamic word embeddings. *arXiv preprint arXiv:1702.08359*, 2017.
- Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

- Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 27*, pages 2672–2680. Curran Associates, Inc., 2014a. URL <http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf>.
- Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014b.
- Alireza Makhzani, Jonathon Shlens, Navdeep Jaitly, Ian Goodfellow, and Brendan Frey. Adversarial autoencoders. *arXiv preprint arXiv:1511.05644*, 2015.
- Lucas Deecke, Robert Vandermeulen, Lukas Ruff, Stephan Mandt, and Marius Kloft. Anomaly detection with generative adversarial networks. 2018.
- Mahdyar Ravanbakhsh, Moin Nabi, Enver Sangineto, Lucio Marcenaro, Carlo Regazzoni, and Nicu Sebe. Abnormal event detection in videos using generative adversarial nets. In *Image Processing (ICIP), 2017 IEEE International Conference on*, pages 1577–1581. IEEE, 2017b.
- Aksel Wilhelm Wold Eide. Applying generative adversarial networks for anomaly detection in hyperspectral remote sensing imagery. Master’s thesis, NTNU, 2018.
- Vít Škvára, Tomáš Pevný, and Václav Šmídl. Are generative deep models for novelty detection truly better? *arXiv preprint arXiv:1807.05027*, 2018.
- Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.
- Yoon Kim. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*, 2014.
- Ronald J Williams. Complexity of exact gradient computation algorithms for recurrent neural networks. Technical report, Technical Report Technical Report NU-CCS-89-27, Boston: Northeastern ..., 1989.
- Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*, 2014.
- Karl Pearson. Liii. on lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 2(11):559–572, 1901.
- Cheng-Yuan Liou, Jau-Chi Huang, and Wen-Chie Yang. Modeling word perception using the elman network. *Neurocomputing*, 71(16-18):3150–3157, 2008.
- Cheng-Yuan Liou, Wei-Chen Cheng, Jiun-Wei Liou, and Daw-Ran Liou. Autoencoder for words. *Neurocomputing*, 139:84–96, 2014.
- Graham Williams, Rohan Baxter, Hongxing He, Simon Hawkins, and Lifang Gu. A comparative study of rnn for outlier detection in data mining. In *Data Mining, 2002. ICDM 2003. Proceedings. 2002 IEEE International Conference on*, pages 709–712. IEEE, 2002.
- Chong Zhou and Randy C Paffenroth. Anomaly detection with robust deep autoencoders. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 665–674. ACM, 2017.
- Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *Journal of machine learning research*, 11(Dec):3371–3408, 2010.
- Kazi Nazmul Haque, Mohammad Abu Yousuf, and Rajib Rana. Image denoising and restoration with cnn-lstm encoder decoder with direct attention. *arXiv preprint arXiv:1801.05141*, 2018.
- Jonathan Masci, Ueli Meier, Dan Cireşan, and Jürgen Schmidhuber. Stacked convolutional auto-encoders for hierarchical feature extraction. In *International Conference on Artificial Neural Networks*, pages 52–59. Springer, 2011.