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SURVEY

A Review of Deep Learning-Based Anomaly Detection Strategies in Industry 4.0 Focused on Application Fields, Sensing Equipment, and Algorithms

ADRIANO LISO, ANGELO CARDELLICCHIO, COSIMO PATRUNO, MASSIMILIANO NITTI, PIERFRANCESCO ARDINO, ETTORE STELLA, AND VITO RENÒ
Institute of Intelligent Industrial Technologies and Systems for Advanced Manufacturing, National Research Council of Italy, 70126 Bari, Italy
Corresponding author: Angelo Cardellicchio (angelo.cardellicchio@stiima.cnr.it)

ABSTRACT Anomaly detection is a topic of interest in several areas, ranging from Industry 4.0 to Energy Management, Smart Agriculture, Cybersecurity, and Bioinformatics. In a wide sense, detecting anomalies implies finding samples generated within a process that differs from its standard data generation mechanisms. Identifying these samples is extremely important for a variety of reasons, depending on the specific application and scenario, ranging from the minimization of production costs to maintaining the required safety standards. As such, the increasing availability of wide networks of sensors that yield large amounts of data characterizing the processes under observation allowed the large adoption of deep learning techniques, which proved worthy of attention due to their capability of identifying anomalies with large precision, accuracy and reproducibility. Consequently, there is an extensive need to consolidate research results to provide a common framework to understand the topic and ensure a common foundation to establish future research trends. To respond to this need, this work systematically reviews the state of the art of anomaly detection in Industry 4.0, evaluating gaps in the current knowledge and proposing future directions of interest. To pursue this objective, three main dimensions have been considered: the scenario where the anomaly detection methodologies were applied, the sensing equipment used to gather data characterizing the underlying process, and the algorithm employed to properly interpret the phenomena. The study was conducted following the PRISMA protocol, which allowed the identification of a relevant selection of papers by extracting a meaningful dataset of 78 papers of interest. The analysis highlighted the diffusion of autoencoders in several configurations and application scenarios, highlighting their effectiveness and flexibility for anomaly detection.

INDEX TERMS Anomaly detection, autoencoders, Industry 4.0.

I. INTRODUCTION

Anomaly detection refers to the problem of finding samples that differ from the normal distribution of data instances. Several factors, including system failures, human errors, malicious operations, or natural environmental changes, can cause anomalies. Thus, anomaly detection is essential in decision systems, as it reduces risks and costs associated with these unexpected events and, in some instances, can even prevent the failure of the critical parts of a system. In recent years, various fields and applications have widely used anomaly detection techniques. Examples include detection

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systems for precision agriculture and life monitoring of plants [1], [2], [3], fault detection in energy forecasting [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], real time fault detection in smart manufacturing [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], crack detection and structural monitoring [53], [54], [55], [56], [57], [58], [59], [60], environmental monitoring [61], [62], [63], [64], [65], [66], [67], [68], anomaly detection for vehicles and intelligent transportation systems [69], [70], [71], [72], fault detectors for radar and hyperspectral data [73], [74], [75], [76], and bioinformatics [77], [78], [79].

Most legacy fault detectors or monitoring systems were based on traditional signal processing and analysis, with sensors that raise the alarm when readings exceed a threshold, usually manually set by domain experts. However, as the processes involved in these use cases become larger and more complex, traditional, handcrafted methods proved inadequate for proper modelling of the behaviour of the system.

Meanwhile, several concurring factors were introduced with the advent ofIndustry 4.0. First, wide networks of cheaper and more efficient sensors were deployed in real-world scenarios, thus providing larger quantities of data to characterize the processes under investigation. Finally, the improvements in the computational power in centralized servers and edge devices allowed the development, training, validation, and deployment of models with high representational capabilities. Consequently, the research community shifted its focus from traditional methods towards automatic learning techniques, exploiting the improved representational capability provided by machine learning (ML) and, more recently, deep learning (DL) models to deal with processes characterized by large amounts of complex data. As such, there is a need to consolidate the vast amount of methods, approaches, and results achieved by the research community, providing practitioners with a common ground upon which novel ideas, models and techniques can be developed.

To fill this gap, this work aims to review anomaly detection techniques applied to industrial scenarios. Research articles were read thoughtfully and selected following the PRISMA [80] protocol. Specifically, three main factors were first identified as the driving aspects leading innovations in the anomaly detection field. Then, three research questions were crafted, each dealing with one of the identified factors. From this background, a set of 78 papers was carefully selected and analyzed.

The remainder of this work is structured as follows. In Section II, the three main factors leading the review work, namely application areas, data sources, and algorithms, are analyzed. Section III describes the methodology used to perform literature research for this review according to PRISMA principles. Then, Section IV recaps the results of this review research, giving a deeper and more technical discussion of the most relevant algorithms and techniques used in most of the selected research papers. Finally, Section V concludes the paper, giving future works perspectives.

II. BACKGROUND

Anomaly detection is paramount in several active research areas, such as Industry 4.0, energy management, cybersecurity, and healthcare. Given the strategic value of these applications, the scientific community has provided several advancements over the last few years, particularly by exploiting the power of deep learning methodologies. The selected contributions can be characterized and compared by three different factors on the base.

A. FIRST FACTOR: APPLICATION AREA

The first factor on which the research in the anomaly detection area focused was the application area of the proposed detection method. Interestingly, most of the works are focused on three main areas of interest, that is, *smart manufacturing*, *energy management*, and *structural and environmental monitoring*. This is strictly related to the strategic relevance of these applications:

- *Smart manufacturing*: Real-time detection of anomalies in smart manufacturing, either on the production line or on the outcome, can help in cost reduction and waste mitigation from production lines, therefore improving the environmental impact and the sustainability of the manufacturing process.
- *Energy management*: Forecasting energy production and assessing anomalous consumption peaks can help identify losses in smart grids or possible misuse from malevolent users.
- *Structural and environmental monitoring*: Interpreting anomalous trends and spikes allows maintainers and decision-makers to quickly adapt to changes and critical situations. For example, maintainers can use anomaly detection systems to identify ongoing degradation in reinforced concrete infrastructures like bridges. Another example is when an anomalous trend is shown for specific environmental variables, which decision-makers can use to define policies to mitigate risks.

Let us mention that several works are also related to cybersecurity, medical applications, intelligent transport systems, and agriculture. However, this review did not consider these specific fields, as the discussion will focus on Industry 4.0-related challenges.

B. SECOND FACTOR: SENSING EQUIPMENT

The second factor worth highlighting in this review is the sensing equipment selected for data acquisition, mainly because it lets us discuss what hardware and enabling technologies researchers focused on over the last few years. There is a strict connection between the hardware choice and the application area, so this factor mainly depended on the specific operating context: for example, data acquired in the context of energy management systems were usually gathered directly from the SCADAs or PLCs connected to the generator (e.g., a wind turbine). In other instances, data were gathered using cameras operating in different domains, such as visible or hyperspectral cameras. It is also worth noting that if the work mainly focused on developing algorithms concerning a specific application domain, researchers used data synthesized via generative methods or acquired from publicly available datasets.

C. THIRD FACTOR: ALGORITHMS

The third and last factor on which research focused was the algorithms used for anomaly detection purposes. Most selected works used machine learning (ML) or deep learning (DL) approaches to implement the task. In that sense, the application and the data source led to selecting the specific algorithm. For example, in energy management, forecasting energy production over different periods can be the basis for evaluating an anomaly behavior of a certain generator (e.g., a slow decay in energy production by a wind turbine). Hence, most researchers focused on tools specific to time series prediction, such as linear predictors (e.g., ARIMA models and their variants) or predictors based on deep neural networks, such as Recurrent Neural Networks (RNNs). Another example was the visual inspection of manufactured samples, looking for defects and anomalies. In this case, researchers relied on traditional image processing techniques and DL tools, such as Convolutional Neural Networks (CNNs), to better exploit visual cues embedded in the acquired data.

III. METHODOLOGY

Given the three factors reported in the previous section, that refer to specific research dimensions, the methodology described hereafter was followed to systematically identify the most relevant works that refer to anomaly detection. This section describes the steps of the research method used in this systematic review, according to the PRISMA [80] protocol.

A. RESEARCH QUESTIONS

First of all, the study focused on investigating the three relevant factors chosen and described in the previous section, aiming to understand better their influence on the research works of the last years. In particular, the following three specific research questions were formulated in a 1 : 1 relationship with the relevant factors and then used as the basis of this systematic review:

- *About application fields - RQ1*: Which application fields mainly involved anomaly detection approaches under the general framework of Industry 4.0?
- *About sensing equipment - RQ2*: What sensing equipment is generally used to capture relevant data for anomaly detection purposes?
- *About algorithms - RQ3*: Which are the most relevant algorithms and techniques used to extract and predict the meaningful features for anomaly detection in different application fields?

As the literature analysis was designed over the PRISMA protocol [80], there was the need to define a *literature search strategy*, starting from a series of *inclusion and exclusion criteria*, followed by a *quality assessment*, which finally led to *data extraction*. All these steps will be described in the next paragraphs.

B. LITERATURE SEARCH STRATEGY

The first step for defining the literature search strategy was to gather studies on anomaly detection by performing an extensive literature search on the Scopus database for the following reasons:

1) First, using more than one database for a literature search does not necessarily guarantee a positive impact on the research outcome. Using several databases may lead to duplicate papers and low-quality or non-relevant ones.
2) Second, Scopus is recognized as a high-reliability database for scientific literature. Hence, high-quality papers can be effectively found.

C. INCLUSION AND EXCLUSION CRITERIA

The papers have been selected by a combined inclusion/exclusion test starting from a first query that joined the keywords *anomaly*, *detection*, *deep*, *learning* using the AND logic operator. The research dates back to 2023 and produced a total of 5398 results. Then, after selecting only papers published after 2017 in international journals and written in English, 59% papers were filtered (2209/5398 papers remained). Since the goal of this review is to summarize those proposed approaches that have had a relevant impact on the scientific community, in accordance with the mentioned research questions, only papers from journals classified as Q1 at least once in the last years have been kept in the dataset. To this end, the "Scimago Journal & Country Rank" has been used to identify the information about the journals' best quartile, namely "SJR Best Quartile". Hence, Q2, Q3, and Q4 papers were discarded, resulting in 514 remaining papers. Among these, papers with several citations smaller than the first quartile of the correspondent publication year were also excluded, resulting in 381 papers. All 381 abstracts have been read to label each paper with its corresponding application field. Review papers have been discarded to avoid redundant reporting of overlapping contributions. About 23% of these papers relates to cybersecurity: different intrusion detection systems are proposed for detecting anomalous behaviors in video surveillance or for self-defending from threats hiding behind the huge growth of network traffic in domains such as IoT, 5g networks, smart grids, Industrial Control Systems. Another 15% of these papers relates to medical applications such as medical image analysis (with data from X-ray and magnetic resonance), ECG anomaly detection, daily human activity recognition, etc. A relevant

TABLE 1. Exclusion criteria.

#	Exclusion criterion
1	Articles not written in English
2	Articles that are reviews
3	Articles that do not refer to anomaly detection
4	Articles published in journals with under-threshold impact factors (based on SJR quartiles)
5	Articles concerning anomaly detection in fields unrelated to Industry 4.0

TABLE 2. Inclusion criteria.

#	Inclusion criterion
1	Articles are written in English
2	Research articles
3	Articles refer to anomaly detection with deep models
4	Articles published in journals with high impact factors (based on SJR quartiles)
5	Articles concerning anomaly detection in Industry 4.0

number of authors try to detect anomalies in data coming from wearable sensors, fitting in a hybrid domain that is middle-way between the previous two, that is, the Internet Of Medical Things. Being interested in real industrial case studies where data from a huge variety of sensors is needed for automation, papers that refer to these fields have not been considered. Rather, the focus was shifted towards fields such as Smart Manufacturing, Energy Forecasting, Structural health and environmental monitoring, or Intelligent transportation systems, which all together constitute the 25% of the 381 papers, namely 95 papers. So, more general purposes, even if they still refer to anomaly detection, have not been considered. The exclusion criteria are summarized in Table 1, while the inclusion ones (dual of the previous ones) are reported in Table 2.

Finally, table 3 highlights the process used to complete the data extraction step from the Scopus database. The process is described in terms of subsequent steps performed on the selected 95 papers. Hence, the paper analysis has been extended, going more deeply into detail about the three research questions and how the authors identified, modelled, and solved the problem to filter the papers critically. After further evaluating the relevance of the selected works with respect to the RQ implemented in the review, a final number of 77 papers remained.

A visual representation of the protocol followed throughout this review work is shown in Figure 1, where the main topic addressed in this paper is represented in blue on top. From it, column-wise details about the three research questions and the subtopics analyzed are represented using a different colour scheme depending on their granularity: green for the questions and yellow for the subtopics.

TABLE 3. Recap of the subsequent steps performed on the selected papers.

#	Step	Outcome
1	Paper reading	Yes/No (already performed)
2	Research question assessment	The clear description of the research question and the evaluation of whether the paper fits or not in the three RQ of this review
3	Type of article	Problem identification
4	Study outcomes	Short description of study outcomes
5	Critical assessment	

TABLE 4. Recap of the distribution of the paper based on their application area.

Application area	% of papers
Agriculture	5.3
Energy forecasting	22.4
Smart manufacturing	38.2
Structural health monitoring	9.2
Anomaly detection	7.9
Environmental monitoring	6.6
Intrusion detection systems	3.9
Vehicles anomaly detection	6.6

IV. RESULTS AND DISCUSSION

This section is dedicated to describing the results of the review of the selected papers, with a subsequent discussion about the relevant aspects that could be useful to answer the research questions posed critically. To perform this task, the section starts with a quantitative description of the selected works based on different grouping strategies, mainly related to the application area and algorithms/techniques exploited by the researchers. It is worth highlighting the following considerations:

- Table 4 shows the most relevant application areas the selected works consider. As it can be seen, most of the works are related to either the *Smart manufacturing* or the *Energy forecasting* application areas. This is mainly related to the high relevance of these topics in current society, whose main focus is improving the smart manufacturing system's overall throughput, reducing costs, and preserving the environment.
- Looking at Table 5, where a recap of the distribution of the paper based on the type of algorithm used is shown, more than 50% of the papers considered implement either an autoencoder or a convolutional neural network, suggesting that the core of the subsequent description and discussion will be based on these approaches.

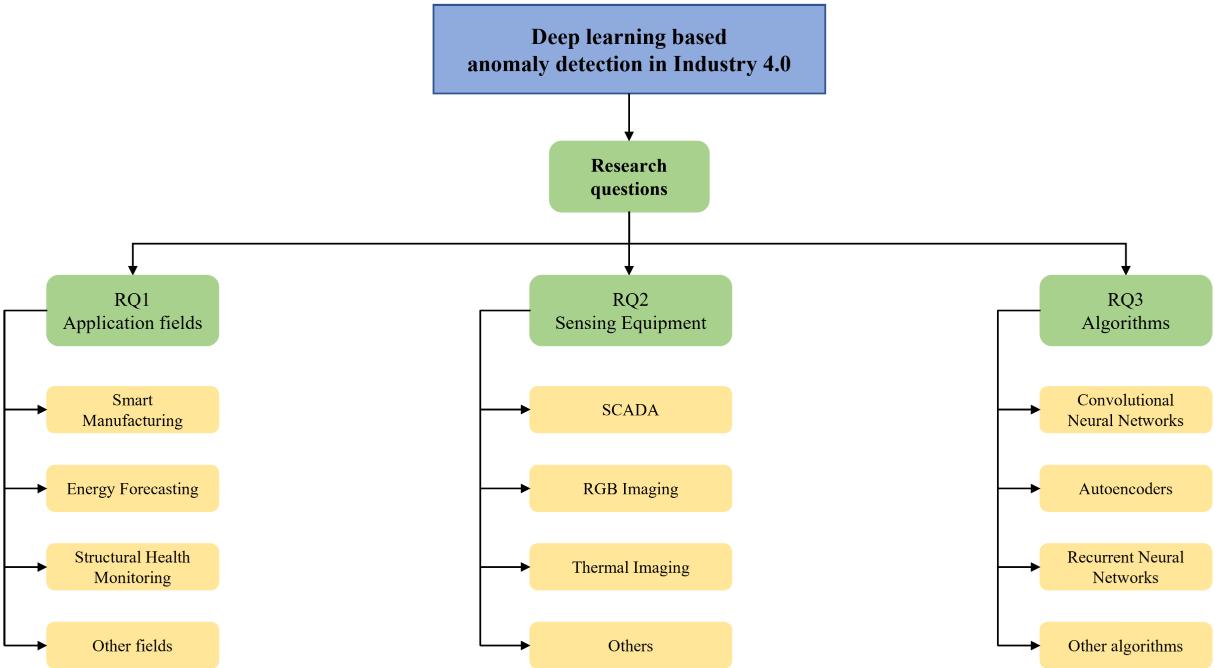

FIGURE 1. Visual representation of the scheme followed during the review. Starting from the topic of interest (i.e., deep learning anomaly detection in Industry 4.0), three research questions concerning application fields, sensing equipment, and algorithms led to identifying relevant works selected following the PRISMA protocol.

TABLE 5. Recap of the distribution of the paper based on the type of algorithm used.

Algorithm type	% of papers
Autoencoders	27.5
Artificial Neural Networks	4.9
Clustering	4.9
Convolutional Neural Networks	29.4
Generative Adversarial Networks	2
Recurrent Neural Networks	15.7
Graph Neural Networks	1
Support Vector Machines	4.9
Attention mechanism	3.9
Proprietary algorithms	1
Other ML/DL approaches	4.9

- In almost all selected papers, the datasets consist of time series (usually acquired by SCADA systems) or images, with only a few of them using higher dimensional data.

For this reason, in the next paragraphs, a brief description of an autoencoder will be first given, followed by its declination on time series data and images, and finally, highlighting the combined approach of autoencoders coupled with other kinds of networks.

A. BRIEF RECAP OF AUTOENCODERS

An autoencoder is an artificial neural network consisting of two parts: an encoder, which maps input data to a lower-dimensional representation called latent space, and a decoder, which restores encoded data to its original size. During the training phase, the autoencoder learns to encode an input sample and decode it, minimizing reconstruction errors. The encoder and the decoder show a symmetric structure with multiple layers that reduce and enlarge the input. Each layer is followed by an activation function that introduces the non-linearity in the model. The bottleneck structure of an autoencoder makes it particularly useful for dimensionality reduction and nonlinear feature learning with an unsupervised approach. In the anomaly detection context, where the number of anomalous samples is usually much smaller than normal ones, such a neural network is used to identify the salient features that allow the decoder to reconstruct normal encoded samples with small reconstruction errors while failing to reconstruct abnormal inputs. The general scheme of an autoencoder is shown in Figure 2.

A commonly used variant of the standard, undercomplete autoencoder is the *variational autoencoder*, which attempts to map the provided input onto a distribution in the latent space instead of a single point. The working scheme of the variational autoencoder is reported in Figure 3.

B. AUTOENCODERS FOR TIME SERIES

Time series data comprises sequential observations collected at regular intervals. Different authors use time series data coming from SCADA systems, which stand for "Supervisory Control and Data Acquisition", even if, in some cases, scientists and engineers do not rely on such systems but prefer

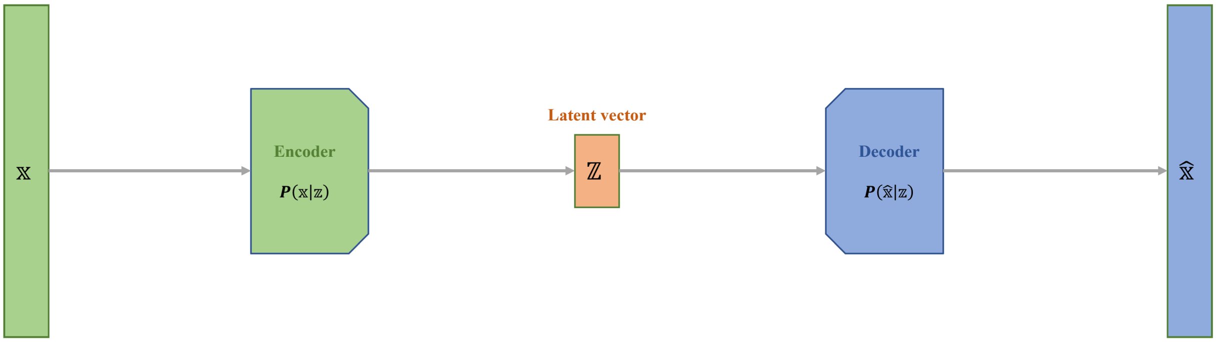

FIGURE 2. Working scheme of an autoencoder. The network is composed of an encoding part, which actively compresses the input X, a latent space Z, and a decoder, which attempts to reconstruct the input X.

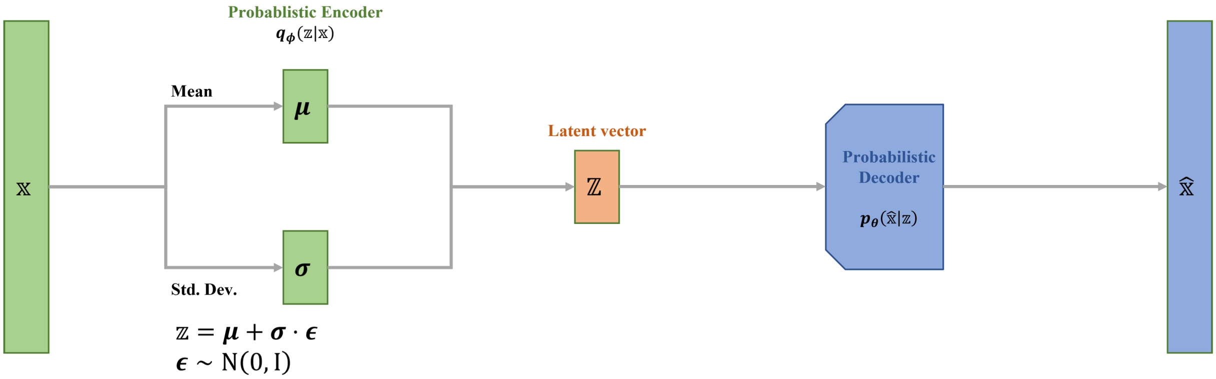

FIGURE 3. Working scheme of a variational autoencoder. A variational autoencoder differs from a standard autoencoder in the sense it projects X onto a distribution in the latent space Z.

to directly sample data from the industrial plant or, more generally, from the field.

However, a SCADA system is generally used in industrial control systems (ICS) to monitor and control processes, machinery, and infrastructure in various fields such as manufacturing, energy, and transportation. For this review, the works involving SCADA systems are interestingly related to the fault detection of wind turbines and are included in the "energy forecasting" domain. This monitoring system is installed by default on modern wind turbines and ensures a cost-effective solution for operators without additional measurement devices. Some key parameters typically monitored by SCADA include wind speed and direction, power output, rotor speed, and temperatures across different parts (gearbox, generator, and bearings) of the turbine. These data can be used to assess fault events, the health state of components, and for wind prediction, following a data-driven approach that exploits machine learning techniques and neural networks. This approach is more suitable and efficient than model-based methods, which use explicit system dynamic models and control theories to generate predictions and residuals for fault detection and isolation. In this context, the first comparison between different works concerns processing raw data from SCADA. In [7], for example, authors first normalize signals such that they have vanishing mean and unitary variance, then apply zero-phase component analysis (ZCA) to decouple them from each other and obtain zero covariance. The ZCA is an algorithm closely related to PCA which transforms the vector x_t, whose components are the values of the signals selected from SCADA at time t, into $x_t^{ZCA} \equiv \Sigma^{-1/2} x_t$, where Σ is the estimated covariance matrix. Then, an autoencoder, consisting of fully connected layers, is fed with whitened vectors of signals from the normal operational conditions at different timestamps and reconstructs the input. Since the bottleneck structure of the autoencoder forces it to learn only the most important features of the training data, anomalous test signals deviating from normal ones show large reconstruction errors and can be classified as faults. In this case, the reconstruction error, which is evaluated as mean-squared distance between input signal x_t^{ZCA} and reconstructed output $\hat{x}_t^{ZCA}$, is the Mahalanobis distance $\mathrm{MD}(x_t, \hat{x}_t)$ between original sample x_t and $\hat{x}_t \equiv \Sigma^{1/2} \hat{x}_t^{ZCA}$:

$$(x_t^{ZCA} - \hat{x}_t^{ZCA})^2 = (x_t - \hat{x}_t)^T \Sigma^{-1} (x_t - \hat{x}_t) = \mathrm{MD}(x_t, \hat{x}_t). \tag{1}$$

The threshold on the reconstruction error, which distinguishes between normal and abnormal behaviour, is calculated by averaging across signals. The authors also propose a post-processing step on output signals in the time domain consisting of a smoothing technique called exponentially weighted moving average (EWMA). This additional step enables the procedure to capture even small shifts in the average signal without triggering alarms for big but rarely occurring spikes overwhelming the threshold.

An autoencoder-based approach is also followed in [4]. Still, in this case, the autoencoder is composed of multiple Restricted Boltzmann Machines (RBMs), and the signals do not undergo a complex pre-processing step, only normalized in the [0, 1] interval. The reconstruction error of each sample is still estimated as the mean squared distance between the input vector of selected features and its reconstructed output. Unlike the previously described work, a non-stationary adaptive threshold is set based on extreme value theory. In the other two selected works, [5] and [10], the anomaly detection task is confined to the pre-processing step. At the same time, the final goal is essentially the prediction of the signals of interest. The pre-processing consists of smoothing data by resampling over an appropriate period and removing outliers, exploiting a manual approach and the Isolation Forest (IF) algorithm. Feature engineering is performed to select relevant features from SCADA parameters, and a time series of correspondent signals is used to train a model for forecasting purposes. In both works, authors compare two models for the prediction task: in the first, XGBoost and LSTM are used, and in the second, GRU and LSTM. XGBoost and GRU outperform the LSTM regarding computational cost and forecasting accuracy

C. AUTOENCODERS FOR IMAGES

Among papers whose datasets consist of images, the most used technique is generally based on exploiting CNNs. On the other hand, different works also introduce an encoder-decoder structure to identify anomalies in an end-to-end fashion or as a part of a bigger detection system. In most cases, the model is trained with normal samples, and pixel-wise anomaly maps are generated: each pixel presents an anomaly score responsible for the binary classification (normal or anomalous) of the pixel once an appropriate threshold is fixed. Different strategies are finally applied to find an overall anomaly score and a second threshold to classify the image, or a patch of the image, as normal or not.

In [53], the authors follow this approach to detect defects in concrete structures. The dataset consists of images of cracks acquired with an RGB camera. Then, multi-scale patches are extracted and fed to an autoencoder composed of several convolutional layers. The input samples are augmented via different types of geometric transformations (flipping and rotations) to enhance the learning process of invariant features. The number of channels of each layer is doubled during the encoding phase to augment the representation of the encoded features. Before transforming and storing feature representations in the code, the feature maps are flattened and down-sampled by a fully connected layer to render good coherences between features. During the decoding phase, the reverse mapping is obtained by concatenating transposed convolutional layers with several channels, each halved at every step. The mean-squared error (MSE) is used as the loss function, and the anomaly maps are constructed by computing the pixel-wise squared difference between the inputs and outputs. The maximum anomaly score between pixels is extracted for each patch, and a threshold is set as the average of the maxima between all patches. A patch containing a pixel with an anomaly score above the threshold is classified as anomalous.

A similar strategy is pursued in [52]. In this case, the dataset consists of photos of printed circuit boards (PCBs) acquired by an RGB camera. The approach assumes that PCB is shown from an overhead view. Then, the images undergo a registration step based on SIFT features and the RANSAC algorithm to correct planar distortions (the 3D appearance of the components is not considered). As before, an autoencoder presenting an architecture similar to the one previously described is fed using only anomaly-free patches extracted from the images. To improve network generalization, each input image is corrupted by randomly masking out rectangular regions, forcing the model to consider more of the image context when extracting features. The proposed loss function combines the pixel-wise MSE between the ground truth of the input of the autoencoder and its reconstructed output and the content loss, defined as the squared and normalized distance of the feature representations (extracted by a second network, VGG19, pre-trained on the ImageNet dataset) between the reference image (ground truth) and the reconstruction. The content loss function considers structures formed by the relations between pixel neighbourhoods, while the MSE one assumes that pixels are not correlated. Finally, each pixel is classified as normal or anomalous based on its anomaly score and a threshold that maximizes the geometric mean, a combination of the true positive rate and false positive rate. In the specific work, an image with more than 10 anomalous pixels is then classified as anomalous.

Authors of [2] exploit a similar loss content function, also using a VGG19 network as a starting point, calling it perceptual loss, not during the training phase but to generate anomaly maps and detect unknown objects in pictures acquired by cameras on board of autonomous agricultural vehicles. Performances of a vanilla autoencoder, a vector quantized variational autoencoder (VQ-VAE), a denoising autoencoder (VAE), and a semisupervised autoencoder (SSAE) are compared. VQ-VAE combines VAEs with vector quantization to obtain a discrete latent representation. The encoder output is mapped to the nearest embedding vector from the shared discrete embedding space. The decoder uses the corresponding embedding vector as input. VAE tries to reconstruct an input corrupted with noise by minimizing the MSE between the reconstructed output and the non-corrupted input. A synthetic dataset is used to train the model and make it able to remove anomalies. A dataset containing abundant normal images and a relatively small percentage of anomalous samples is used for the SSAE. In this last case, the

MSE loss function is modified with the so-called max-margin term, which keeps the reconstruction error of abnormal pixels above an experimentally fixed threshold, assuming that the ground truth mask is available. For each model, the anomaly map is generated as a relative perceptual L1 loss between the input image of the autoencoder and the reconstructed image. The threshold on the anomaly score of each pixel is fixed by maximizing the intersection over union (IoU) with the ground truth. The threshold on the total anomaly score of an image, calculated as the percentage of pixels above the previous threshold value, maximizes the F1 score on the test set.

A modification of a VAE is introduced in [81] to detect underwater unknowns with dynamic undersea backgrounds. In a VAE the encoder maps a point $\bar{x}$ in the original space to the conditional probability $p_e(z|\bar{x})$, describing the distribution of encoded variable z in the latent space when the point $\bar{x}$ is picked up in the original space, while the decoder maps a point $\bar{z}$ sampled from $p_e(z|\bar{x})$ to the conditional probability $p_d(x|\bar{z})$, describing the distribution of decoded variable x conditioned by $\bar{z}$. During the training phase, a VAE models the encoding and decoding conditional distributions by maximizing the probability that the reconstructed output $\hat{x}$, sampled from $p_d(x|\bar{z})$, is equal to $\bar{x}$. In a vanilla autoencoder, $p(z)$ is supposed to be apriori known (generally, it is represented by the standard multivariate normal distribution). Since it is related to the conditional distributions through Bayes' theorem, it serves as a regularization term, encouraging the VAE to learn a structured and well-behaved latent space. The mentioned modification regards the latent distribution, which is not supposed to be known, but it is estimated by an autoregressive network. The latent vectors reformed by this network, composed of fully connected and masked fully connected layers, consider context information under dynamic sea background by considering the sequence dependencies in encoded space. The anomaly map, calculated at the patch level, contains two contributions: one from the patch reconstruction between the input and decode image and one from the similarity between an encoded vector and its reformed counterpart. Since the model is trained on normal samples, anomaly images containing unknown objects show a higher total anomaly score.

So far, approaches based on the definition of anomaly scores, with a threshold separating normal and anomalous samples, have been discussed. Nevertheless, clustering algorithms can also be implemented to detect anomalies directly in the latent space without considering the reconstruction error. An example of this approach is given by [69], where the goal is to detect anomalies in urban environments (like pedestrians on the road) based on stereovision acquisitions. A deep autoencoder is trained on V-disparity maps of mostly free scenes (using the cross-entropy as loss function), and flattened encoded training samples are classified in the latent space via the KNN algorithm, which is commonly used when the collected data are non-Gaussian distributed or cannot be linearly separable. Unlike clustering algorithms such as K-means, training a KNN algorithm does not require any prior assumption on the underlying data structure. During the test phase, the KNN scheme separates inliers from outliers by computing the distance of each encoded test sample from its k-nearest encoded training samples. The structure of the autoencoder makes sure that the distance between an abnormal sample (i.e., a scene with an obstacle) and its k-nearest neighbour normal training samples is larger than the distance between a normal sample (i.e., obstacle-free scene) and its k-nearest neighbour normal training samples. The threshold T on the distance is set according to the 3-sigma rule, that is:

$$T = \mu_D + 3\sigma_D, \tag{2}$$

In the previous equation, μ_D and σ_D are the mean and standard deviation of KNN distances under obstacle-free cases. In this case, anomaly detection is obtained by clustering the encoded representations of data samples to separate the set of normal samples, which should fall in a particular region of the latent space, from the anomalous ones, which should be characterized by out-of-region feature vectors.

Another example of the application of a clustering algorithm in the latent space is given by [29], where the authors provide a framework to process images of the melt pool acquired during Laser Powder Bed Fusion, which is an additive manufacturing process where laser power is applied to fuse the spread powder and fabricate industrial parts layer by layer. Here, an autoencoder composed of convolutional layers produces encoded representations of melt pool images, flattened and fed to an agglomerative clustering algorithm to annotate data as normal or anomalous. Then, anomalous data are discarded, and the autoencoder is retrained using normal samples only. Hotelling's and Shewhart's control charts are used to monitor the deep flattened representation vectors and the variance of residuals (the reconstruction error between flattened decoded and input images), respectively. The control limits on these two charts are set based on statistical analysis and used to decide if a real-time process is out of control (if both statistics fall inside the control limits, the process is considered in control).

D. AUTOENCODERS COMBINED WITH NEURAL NETWORKS

Depending on the purposes, some authors combine an encoder-decoder structure with other neural networks to form a larger segmentation and anomaly detection framework. This is, for example, the case of [40], where images from metallography are inspected to segment impurities (inclusions originated from outside the sample like oxide particles added to the melt before solidification or precipitates formed from the sample itself) and grains (adjacent domains in the sample where atoms are arranged in a specific crystallographic orientation). Impurities, appearing as dots in the image, are segmented by a U-Net-inspired architecture consisting of convolutional layers organized in an encoder-decoder symmetric structure with skip connections between specular encoding and decoding layers. Skip connections allow the model to learn deep semantic information while preserving high-resolution information that might get lost during down-sampling and up-sampling. A VGG-16 neural network (composed of 13 convolutional layers followed by 3 fully connected layers) pre-trained on the ImageNet dataset is used as the encoder. Since the model is trained on small patches, a high-overlap sliding window technique is used to segment impurities on the whole image while averaging the overlapping pixels among the segmented windows to help in noise reduction. Once segmented, impurities are filled by a generative inpainting network to resemble a full metallographic scan without such defects. At this point, another U-Net model provides for the segmentation of grains. Finally, two kinds of anomaly scores are assigned to classify segmented impurities as normal or anomalous: spatial anomaly measure, based on a version of kNN properly modified to account for how much an object is distant from its neighbours and how large it is compared to them and shape anomaly measure, based on autoencoder. In this case, however, the use of the autoencoder is different: it is trained in a supervised manner to reconstruct not the input but a specific target image, which in the case of a normal sample is the sample itself, while in the case of an abnormal sample is a blank image. The authors find a larger reconstruction error, representing the shape anomaly score, than training the autoencoder in a semisupervised manner with only normal impurities.

In [15], an autoencoder that fits in a pipeline for detecting faulty solar panels in photovoltaic (PV) power plants is presented. The dataset consists of thermal and RGB images of 6 PV power plants acquired by unmanned aerial vehicles (UAV) equipped with infrared and RGB cameras under various flight conditions. As a first step, orthophotos for both kinds of images are generated and then aligned. Then, solar panels in the images are segmented by a mask region-based convolutional neural network (Mask R-CNN) architecture, and anomalies (mostly hotspots, appearing as high-intensity blobs in thermal images) are detected by an adapted version of Faster R-CNN. Thermal images undergo normalization and are augmented via geometrical and appearance-based transformation. Once an anomaly is detected, the goal of the autoencoder, which is trained to replicate the most salient features of a healthy solar panel from an RGB photo, is to detect the principal cause of the anomaly by inference on the correspondent RGB image based on a threshold on the reconstruction error. If the RGB image does not show any peculiarity, it may indicate that the cause is a deeper physical failure. The ground truth bounding box for each anomaly is manually annotated with the help of simple linear iterative clustering (SLIC), and a threshold set to 0.5 on the IoU between the predicted and true bounding box determines if the prediction is a true or false positive.

Reference [8] resumes, in a sense, the approaches followed by the last described papers, since it compares mask R-CNN and UNet neural network (together with LinkNet and a feature pyramid network (FPN)), still for anomaly cells detection in PV power plant. In particular, after the normalization of the dataset, the neural network EfficientNet is used as the backbone feature extractor, while UNet, LinkNet, and FPN as segmentation networks, which output an overall mask containing all the anomalous cells. Although UNet achieves the best results in terms of IoU, the authors underline the capability of Mask R-CNN to solve multiple tasks:

- Generation of a bounding box and its class label for each detected anomaly;
- Segmentation of the image at the instance level means that objects among the same class are clustered as different entities.

To compare the result of Mask R-CNN with other models, all the anomalous predicted cells are finally merged into one overall mask. Moreover, the authors also compare the performance of Mask R-CNN in three different cases:

- training the network from scratch;
- pre-training the network on the Microsoft Common Objects in the Context dataset (MS-COCO), then retraining all layers;
- pre-training on the MS-COCO dataset, then retraining only the layers of the head section (the classifier section);

showing that the best results are obtained in the third case.

E. DISCUSSION AND CHALLENGES

Finally, it is worth highlighting some of the most relevant challenges posed by using autoencoders for anomaly detection in industrial scenarios. Let us note that the scope of some of these challenges is not limited to this specific topic but can also be applied to other kinds of deep learning models, even the new ones.

Let us first focus on generic issues that have to be addressed by all deep learning models. At first, there is the problem of dealing with *local minima*. Specifically, most deep learning models are trained using *parameters learning*, which involves minimizing a loss function by solving an optimization problem via a gradient descent algorithm. While effective, these algorithms are inherently affected by the possibility of falling into a local minima, providing a solution based on sub-optimal parameters. In other words, gradient descent algorithms update the network's current parameters according to the slope of the current solution of the loss function; ideally, this could be approached as a convex problem with a single global minimum, which would also define the desired set of parameters. However, in real and more complex cases, the loss function could not be globally convex and show several local minima, meaning that when the optimization reaches one of these points, it will stop upgrading the model's parameters, undermining the representational capabilities of the learning algorithm. To partially cope with this issue, several solutions were proposed. First, advanced gradient descent algorithms, such as SGD [82] or Adam [83], introduce stochasticity, which helps the optimizer escape from local minima. Furthermore, falling in a local minimum could also be avoided by adopting other techniques, such as variable learning rate and hyperparameter tuning.

Another challenge that must be considered is related to overfitting and generalization. Specifically, the optimization procedure described before "adapts" the values assumed by the model's parameters during training to minimize the loss function *mainly on training data*. Furthermore, it is not guaranteed that a neural network is capable of *generalization*, providing the same degree of accuracy when processing data it was not trained on. To deal with this issue, domain experts may use different approaches, but the most common working pipeline involves the following steps:

- *Selecting a proper dataset*, that is, a dataset able to provide as many perspectives as possible on the phenomena under investigation.
- *Splitting the dataset*, using a certain percentage (usually $70-80\%$) of the data to train the model while the rest to validate and test its performance.

In the case of anomaly detection, the main problem to be solved could be represented as implementing a one-class model based on the observations of a certain phenomenon in *good operating conditions* so that the model itself could identify anomalous situations, capturing a comprehensive dataset becomes a crucial step. The second step is dataset splitting, which involves a randomized selection of the data samples to provide to the model during training, mainly to avoid biases related to subsets of data acquired under common and specific conditions. To further stress this randomization, k-fold cross-validation is often also used: data are first split into k folds, on which the model is trained separately, and, finally, results are merged via a specific strategy.

As for the issues specific to the application of autoencoders for anomaly detection, one of the most relevant is the lack of generalization capability of models trained on specific aspects of the application scenario. For example, the model trained in [7] was trained from data provided by a single turbine in a farm and validated accordingly. As different turbines may present several differences, for example, in weight, span, underlying technologies, or even orientation, the generalization capabilities of the trained model were not guaranteed. This was also the case for several other proposals, such as the anomaly detector on PCBs proposed in [52] or the work in [2].

Another challenge arisen from the review was the need to establish a baseline for improvements achievable by process optimization and hyperparameters tuning, such as [29]. Specifically, by gathering data of proper quality and using algorithms which take into account optimization procedures that involve the automatic tuning of parameters (e.g. the number of layers in the autoencoder, the number of neurons per layer, the size of the latent space, the optimization function, etc...), the reconstruction capabilities anomaly detection performance can vastly improve.

TABLE 6. Results achieved by autoencoders for anomaly detection.

Reference	Application area	Metric	Value
[18]	Energy forecasting	RMSE	27.43
[23]	Smart manufacturing	MSE	0.0044
[49]	Environmental	RMSE	2.980
[2]	Agriculture	F_1	85.91%
[3]	Agriculture	F_1	99.42%
[9]	Energy forecasting	F_1	93.50%
[13]	Energy forecasting	F_1	91.90%
[25]	Smart manufacturing	F_1	82.30%
[33]	Smart manufacturing	F_1	95.70%
[34]	Smart manufacturing	A	87.70%
[36]	Smart manufacturing	F_1	84.46%
[38]	Smart manufacturing	AUC	89.00%
[41]	Smart manufacturing	F_1	99.80%
[42]	Smart manufacturing	AUC	96.10%
[45]	Smart manufacturing	F_1	90.3%
[52]	Smart manufacturing	F_1	81.10%
[53]	SHM	F_1	65.87%
[54]	SHM	F_1	89.58%
[59]	SHM	AUC	99.93%
[66]	Environmental	F_1	81.35%
[69]	Vehicles	AUC	91.00%
[72]	Vehicles	R^2	$\geq 99.00\%$
[73]	Environmental	F_1	$\geq 84.00\%$

Using autoencoders may also lead to several improvements over classic ML techniques. This may be quantified in the first place using common metrics such as accuracy, precision, and recall: most of the works analyzed in this review demonstrate higher performance when autoencoders and DL methods are compared with classic ML approaches. Moreover, in several cases, the use of DL also allows for improved processing speed, such as [5] and [10] demonstrated when GRUs were compared with LSTMs and classic time series modelling approaches, therefore allowing for real-time implementation of the anomaly detector. Finally, the representational capabilities of autoencoders can be further extended, hinting not only at the rise of an anomaly but also at the nature behind the fault that likely caused it, effectively providing a way for domain experts to properly address potentially critical events, such as theorized by the authors in [7].

A summary of the results of the work that used autoencoders for anomaly detection is provided in Table 6. Due to the wide variety of results in application areas, evaluation metrics, considered datasets, and experimental procedures, it is important to underline that Table 6 only provides a *synthetic* summary, highlighting only the most relevant metric computed by the authors with regards to the scope of this survey.

V. CONCLUSION AND PERSPECTIVES

This paper presented a review of deep learning-based anomaly detection strategies that are applied to industrial scenarios. The literature strategy search and the subsequent paper analysis (designed over the PRISMA protocol) have been guided by three different factors under analysis: i) the application area of the papers – i.e., their operating context; ii) the sensing equipment used – i.e., the datasets and the strategies used to capture data from the field in real scenarios; iii) the algorithms used to process the high amounts of data that today are straightforwardly available at relatively low costs. In brief, the three factors are related to the applications, hardware, and software used in real scenarios in the last years, suggesting the three research questions formulated in this review paper. From the literature analysis, it is possible to critically evaluate the research trends about applied anomaly detection, which result in best practices to be also further investigated as soon as new technologies and instruments become available in the near future. Even if all the reviewed papers based their analysis and consequent results on the effective use of machine/deep learning techniques, they are focused on solving a problem usually formulated on specific data, making a high customization of the proposed algorithms. Given the fact that more computational resources will likely be available to the large public in the future, the capability of exploiting innovative approaches using artificial intelligence should be encouraged, for example, investigating the cross-domain application of anomaly detection models, acting as the commonly used pre-training of large convolutional neural network models in computer vision.

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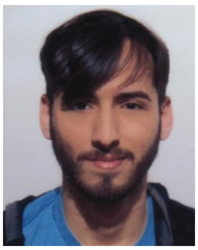
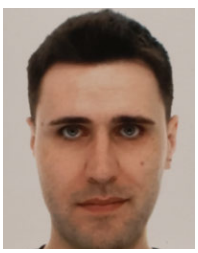
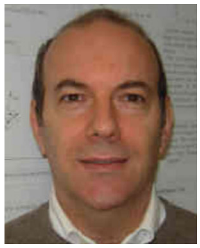


ADRIANO LISO was born in Bari, Italy, in 1993. He received the master's degree in physics from Università degli studi di Bari Aldo Moro, defending the thesis "Collective Effects in the Electromagnetic Emission of Two Quantum Emitters in Different Dimensions." He is currently pursuing the National Ph.D. degree in robotics and intelligent machines with Università di Genova. His research project regards the application of deep models to detect anomalies in Industry 4.0. He carries on all his activities with CNR-STIIMA.

ANGELO CARDELLICCHIO was born in Taranto, Italy, in 1985. He received the master's degree in computer engineering and the Ph.D. degree in electrical and information engineering from Politecnico di Bari, in 2019. His Ph.D. thesis on "Smart Sensor Systems for Environmental Monitoring: Implications and Applications." His professional experiences range from web and mobile development to data analysis in the energy, environmental, vulnerability, and industrial domains. He has been with the Institute of Intelligent Industrial Technologies and Systems for Advanced Manufacturing, National Research Council of Italy, since 2021. He has also been a Contract Professor with the University of Bari and the University of Foggia. He is currently a Contract Professor with Politecnico di Bari. He has authored several contributions to international peer-reviewed journals, conferences, and book chapters.



COSIMO PATRUNO was born in Putignano, Italy, in 1988. He received the bachelor's and master's degrees in automation engineering from Politecnico di Bari, Italy, in 2010 and 2013, respectively. From May 2013 to January 2022, he cooperated with the National Research Council (CNR) as a Research Fellow. Since February 2022, he has been a permanent Researcher with STIIMA-CNR. He has authored several contributions to international peer-reviewed journals, conferences, and book chapters. His research interests include 3D data analysis, signal and image processing, computer vision, machine learning, and perception systems for robotics.



MASSIMILIANO NITTI was born in Bari, Italy, in 1968. He received the degree in computer science from the University of Bari. From 1996 to 2000, he worked with the Research and Development Department, Mermec S.p.A., where he developed railway diagnostic systems. From 2000 to 2007, he worked with IESI-CNR as a Research Technician. Since 2007, he has been with STIIMA-CNR, as a Researcher. His research activity concerns image processing, robotics and 3D reconstruction from images. He develops image acquisition and processing systems from both a hardware and software point of view. He thus gained direct experience in the railway, sports, industrial, medical, and agricultural sectors. He has experience in parallel and distributed computing, fast code execution using different tools, both with the use of SSE2, SSE3 processor instructions, and through the use of GPU or FPGA. He is responsible for numerous collaborations between STIIMA-CNR and industries for the development of pre-competitive systems.

PIERFRANCESCO ARDINO was born in Bari, Italy, in 1993. He received the master's degree in computer science and the Ph.D. degree in information and communication technology from Università degli Studi di Trento, in 2023. His Ph.D. thesis on "Exploring Deep Generative Models for Structured Object Generation and Complex Scenes Manipulation." He is currently a Research Fellow with CNR-STIIMA. His interested in computer vision applications including image and video processing and generative AI.

ETTORE STELLA was born in Bari, Italy, in 1960. He received the Laurea degree in computer science from the University of Bari Aldo Moro, Italy, in 1984. He has been working with the National Research Council of Italy, Bari, since 1987, where he has been the Research Director, since 2010. He was a Contract Professor with the Telecommunications Engineering Faculty, University of Basilicata, Italy, from 2004 to 2009. He was the co-author of international patents. He is the co-author of more than 150 papers in international journals, book chapters, and proceedings of international conferences. His professional experiences are in computer vision, robotics, industrial automation, and high-performance computing.

VITO RENÒ was born in Bari, Italy, in 1988. He received the master's degree (Hons.) in computer engineering and the Ph.D. degree in electrical and information engineering from Politecnico di Bari, in 2011 and 2017, respectively. His master's thesis on "Computer Vision and Robust Background Modeling." His Ph.D. thesis on "3D Modeling, Reconstruction And Analysis of Environments Assisted by Multi-Sensorial Data Processing." He is currently a Researcher with CNR-STIIMA. He is involved in research activities in the fields of computer vision and pattern recognition. He is the co-author of more than 70 scientific papers and one international patent. Deeply curious and enthusiast about artificial intelligence, with a pinch of multi-disciplinary and synergic applications.

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