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Machine Learning-Based Image processing for on-line Defect Recognition in Additive Manufacturing

Dr. Ajay.P[1] , Dr.B.Srilatha[2], Kassie Jemberu Abebe[3], Feleke Worku Tadesse[4] and Mesfin Tura Bizuneh[5]

[1]Research Scholar, Department of Electronics and Communication Engineering,

Anna University,Chennai, India.

[2]Assistant Professor, Department of Electronics and Communication Engineering, Sri Sairam College of Engineering, Bangalore, Karnataka, India

[3,4,5] Lecturer, School of Mechanical and Industrial Engineering, Institute of Technology,

Debre Markos University, Debre Markos, Ethiopia – 269.

Abstract

Quality control in manufacturing relies heavily on the identification of product flaws. This research examines the most up-to-date machine-learning algorithms for finding defects. To begin, we organise product flaws such as electrical components, pipelines, welds, and textiles into distinct groups and subgroups. Second, the features, strengths, and weaknesses of modern mainstream methodologies and machine-learning methods for flaws are explained. In the third section, we review and examine the use of ultrasonic testing and other technologies for flaw identification by concentrating on technique and experimental findings. Various ML algorithms are compared and assessed for their performance in different sorts of AM tasks. Finally, a number of possible future study avenues have been outlined.

Keyword: Machine Learning, Additive manufacturing, Defect Recognition, (AM), Metal defects, Quality inspection, Deep learning, Convolutional neural network (CNN), Defect classification

1. Introduction

The field of additive manufacturing (AM) has seen tremendous expansion in the last several years. A product's complicated geometry and many materials may be easily manufactured using the layer-by-layer manufacturing method. Material sales in the business grew at an all-time high of 41,9 percent in 2018, led by metals. Growth of more than 40% every year over the last five years has been shown in the current annual Wohler's Report. This shows the need to create solutions that are more suited for large production rather than fast prototyping, as shown by this increase [1]. AM offers a lot of promise in the medical profession, especially for unique designs, aerospace, and automotive for lightweight construction and functionally vital components created locally at remote sites. There are still concerns about component quality that are delaying the complete use of AM technology in these domains, although There are a number of applications where in-situ and real-time process monitoring is essential, especially with metal powder.

Internal holes, pits, abrasion and scratches may be found in mechanical items manufactured in complicated industrial processes owing to design flaws and machine manufacturing equipment failures, as well as unfavourable working circumstances. Products may also be susceptible to corrosion and fatigue since they are used on a regular basis. People and their safety are put at risk because of these flaws that raise expenses, limit product service life, and result in a massive amount of waste. It is thus essential for firms to have the ability to identify faults in order to enhance the quality of their produced items without negatively impacting their output [2]. When it comes to fault identification, automated systems are clearly superior than manual methods. Furthermore, it can operate with great accuracy and efficiency even when placed in an unfavourable environment. It is possible to cut production costs, increase production efficiency and product quality, and build the groundwork for the intelligent transformation of the manufacturing sector via research on defect-detection technologies [3]. As a result, a large number of academics have examined technologies and applications connected to defect detection in order to give references for the implementation and investigation of defect detection technology. Lalit Mohan Kandpal, for example, is an expert in the field of pharmaceutical product fault identification. For example, infrared and other spectral technologies may be used to detect cancer. Xianghua Xie uses computer vision and image processing methods to identify surface defects in produced items. Xianghua Xie Image processing-based surface defect detection in industrial applications demands great real-time performance, according to previous research[4]. Defect-detection techniques routinely employed in the manufacture of textile textiles were studied by researchers from the viewpoint of the textile industry's development of defect detection methods. It's common practise to deploy thermal imaging technology in a variety of industrial settings. The work of I. Jorge Aldave focuses on the comparison of findings acquired with commercially available non-experimental IR technologies in order to offer benchmarks for cameras in the area of non-destructive defect detection. Modern industry and academics are focusing on defect-detection technologies. For the time being, researchers are still working on identifying and classifying different kinds of product flaws [5]. They also need to identify and classify the most common forms of product flaw detection methods. Research status of key technologies both locally and internationally has not yet been summarised or reviewed.

Figure 1 shows how electrical components, pipelines, welding components, and textile materials all have similar faults. As a result, it describes and evaluates the current state of deep-learning technology for defect detection and its applications, in order to offer a reference for both theory and practical application.

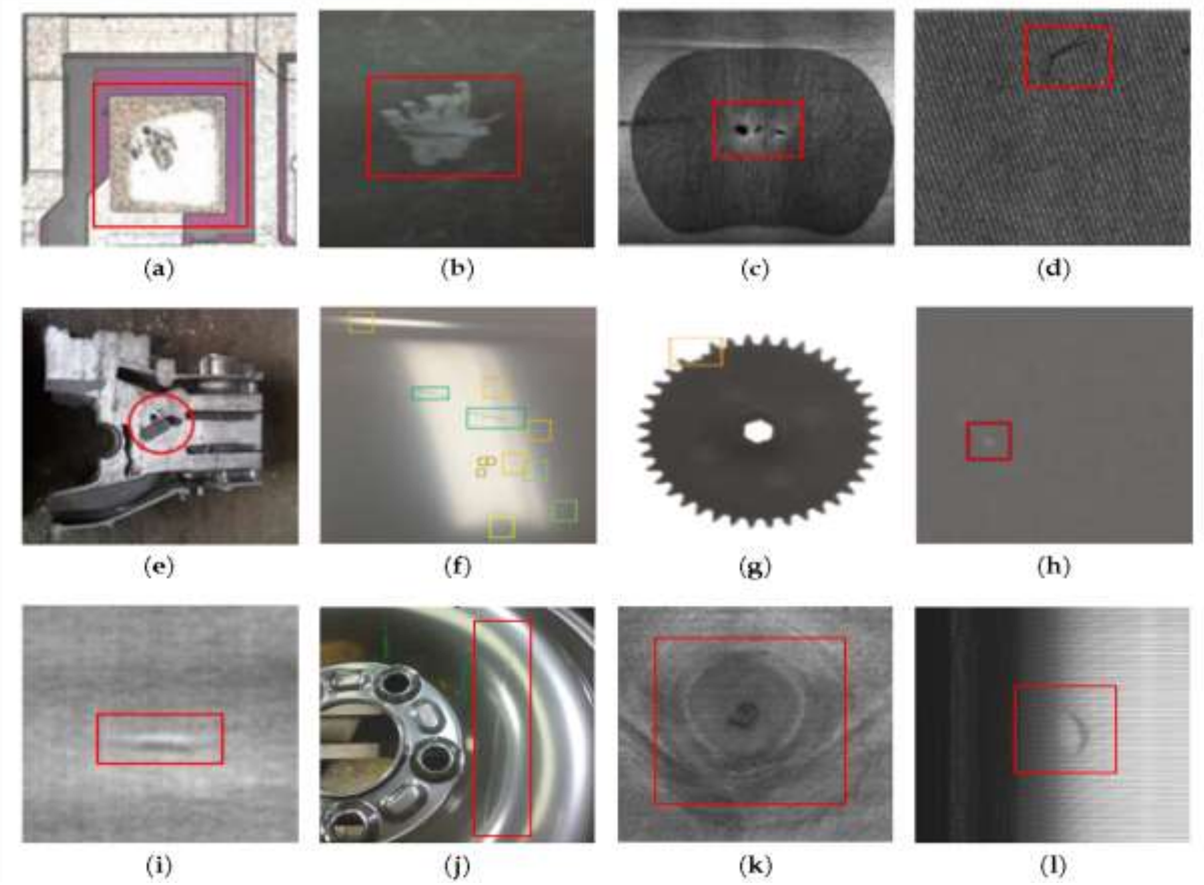

Figure 1. Defects in different areas: (a) metallization peeloff of electronic components. (b) pipeline corrosion. (c) defective with gas pore. (d) defect bigknot of textile materials. (e) shrinkage and porosity defect of Casting. (f) defects in green, yellow, orange bounding box are scratch, cratering, hump, respectively in carbody. (g) Lack defect of gear. (h) light leakage defect on mobile screen. (i) Convexity defect in aluminum foil. (j) Scratch defect of the wheel hub. (k) Branch defect of wood veneer. (l) Bubble defect of tire sidewall .

2. Literature Review

Products' surface and interior faults are the primary focus of product defect-detection technologies. Spot, pit, scratch, colour variation, and flaw on product surface are all examples of defects that may be detected with defect detection technology. Internal fault detection, hole detection, and crack detection are the most common methods for detecting internal defects. Products may be tested for quality by using a variety of approaches, such as deep learning and magnetic powder as well as ultrasonic and machine vision [6].

In wet magnetic particle detection, the magnetic powder is dissolved in a liquid (oil or water) before being analysed for magnetic fields. The external magnetic field attracts the magnetic powder, which identifies the position of faults. The liquid medium is recyclable and offers a high sensitivity for moisture detection[7]. Dry Using magnetic powder testing, defects may be detected by attaching magnetic powder directly to the magnetised workpiece. Large castings, welding components, and other items that aren't good candidates for wet detection might benefit from this technique's local examination for flaws. Using an external magnetic field and a continuous magnetic particle detection approach, flaws in a magnetic solution or powder may be found. The external magnetic field flaws may be seen using this approach. Precision in Magnetic powder testing may be affected by elements such as roughness and profile of the test piece, geometrical features of defects, the chosen magnetization process, and the quality of operators. Osmosis testing's sensitivity is affected by a variety of elements, including the imaging reagent, the osmotic fluid's performance, the operator's skill level, and the presence of flaws. Coil type and material, as well as the test piece's surface profile, affect eddy current detection accuracy[8]. Ultrasonic testing results are influenced by the angle formed by the faulty surface and the propagation path of ultrasonic sound waves. Detection of defects is easier if the angle is vertical, since the signal returns is strong. When the angle is horizontal, the signal is faint, making it simple to identify a leak. As a result, in order to minimise leakage detection, the proper detection sensitivity and associated probe must be used. Projection direction, probe efficacy, sound contact quality, and instrument operating frequency all play a role in ultrasonic testing.

The primary components of machine vision detection are picture capture, defect detection and classification, and categorization of defects. Machine vision is extensively utilised because it is rapid, accurate, non-destructive, and inexpensive. The colour, texture, and geometric aspects of an item are used by machine vision to identify an object. The complexity of image processing is determined by the quality of the picture capture. As a result, the precision and efficiency with which a problem may be detected and classified depend directly on the quality of the image processing method. Using image processing, the deep-learning approach is also a defect-detection tool used to identify relevant characteristics in large datasets [9].These two types of defect-detection methods have their merits, yet it's clear that both methods have their limitations. Detection technologies employed in the past are quite targeted. There are specific benefits to using Osmosis testing technology over other general techniques for discovering faults in extremely permeable and non-porous materials, for example. In most conventional detection techniques, human help is necessary to finish the work because of the high cost of equipment development and the difficulty of adapting it due to the limited lifespan and manufacturing precision of the equipment. Automated defect identification relies heavily on machine vision and deep learning, which have become the most popular in recent years because of their adaptability and lack of need on human aid.

Traditional defect detection approaches give better outcomes and cheaper costs, but still depend on a substantial quantity of learnt data to drive model updates and increase the accuracy of inspections[10]. Object identification, intelligent robots, saliency detection, sound event detection in parking garages, sound event detection for smart city safety, UAV blade problem diagnostics, and other disciplines have seen significant advancements in deep-learning technologies. Multi-layered convolutional neural networks underlie deep learning. Attribute categories may be better understood in abstract ways like edge and shape by combining low-level characteristics to generate a high-level representation of attribute categories or features As a result, many scientists are experimenting with deep-learning technologies in the hopes of improving product quality by detecting defects earlier. Convolutional neural network (CNN), auto encoder neural network, deep residual neural network, complete convolution neural network, and recurrent neural network are all examples of these types of neural networks [11].

The neural network-based product flaw detection tool. In the auto encoder network, the coding and decoding steps are the most important. For feature extraction, the input signal is transformed into coding signal; in the decoding step, the feature information is transformed into a reconstruction signal, and then the reconstruction error is reduced by modifying the weight and bias to identify defects. What sets autoencoder networks apart from most other machine learning algorithms is that the autoencoder network's primary purpose is to learn features instead of categorization. It can also learn on its own, and its mapping is quite nonlinear. Segmenting complicated background and foreground areas using nonlinear metrics may be learned by the system. Deep residual neural network technique for product flaw identification [12]. Using the convolutional neural network, the deep residual network adds a residual module on top of it. The residual network is straightforward to optimise and may be improved by increasing the network depth, which increases the accuracy. Generative Adversarial Networks, for example, The extraction capability grows with network depth, however the activation function may diverge easily. As network structure grows, so does the number of residual layers, but the output and input dimensions of convolution layers in the residual unit remain constant. The activation function is then used to decrease loss by optimising this process.

neural network with full convolution A link between any two nodes in any two adjacent levels is what is referred to as a completely connected layer. There will be a lot more weight values in a fully connected neural network, which implies the network will take up a lot more memory and computations. The feature map created by the convolution layer is mapped into a fixed-length feature vector during the construction of the fully connected neural network. If an image is large enough, the full convolution neural network accepts it and uses the deconvolution layer to sample the feature map of the last convolution layer, so that a prediction can be generated for each pixel while still retaining the spatial information in the original input image, and finally classify pixel-by-pixel the feature map.

Sequence data is fed into a recurrent neural network in a chain fashion, with all cyclic units coupled in a similar fashion [13]. The CNN model uses convolution and pooling operations to extract feature information from input layer test samples. The convolution process on the CNN is replaced by the recurrent convolution operation in the recurrent neural network. A key distinction is that the recurrent neural network processes the samples' features using recurrent convolution, rather than pooling layer operation, following the recurrent operation to extract input layer features.

3. Application Status of Defect-Detection Technology

It is common practise in manufacturing to utilise non-destructive product defect detection in which multiple algorithms may be analysed to understand and enhance the algorithms. Here, we use a mix of conventional flaw detection and additional techniques to monitor the application's health. Defect detection techniques and their accompanying performance data or summaries are shown in Figure 2 for non-destructive defect detection.

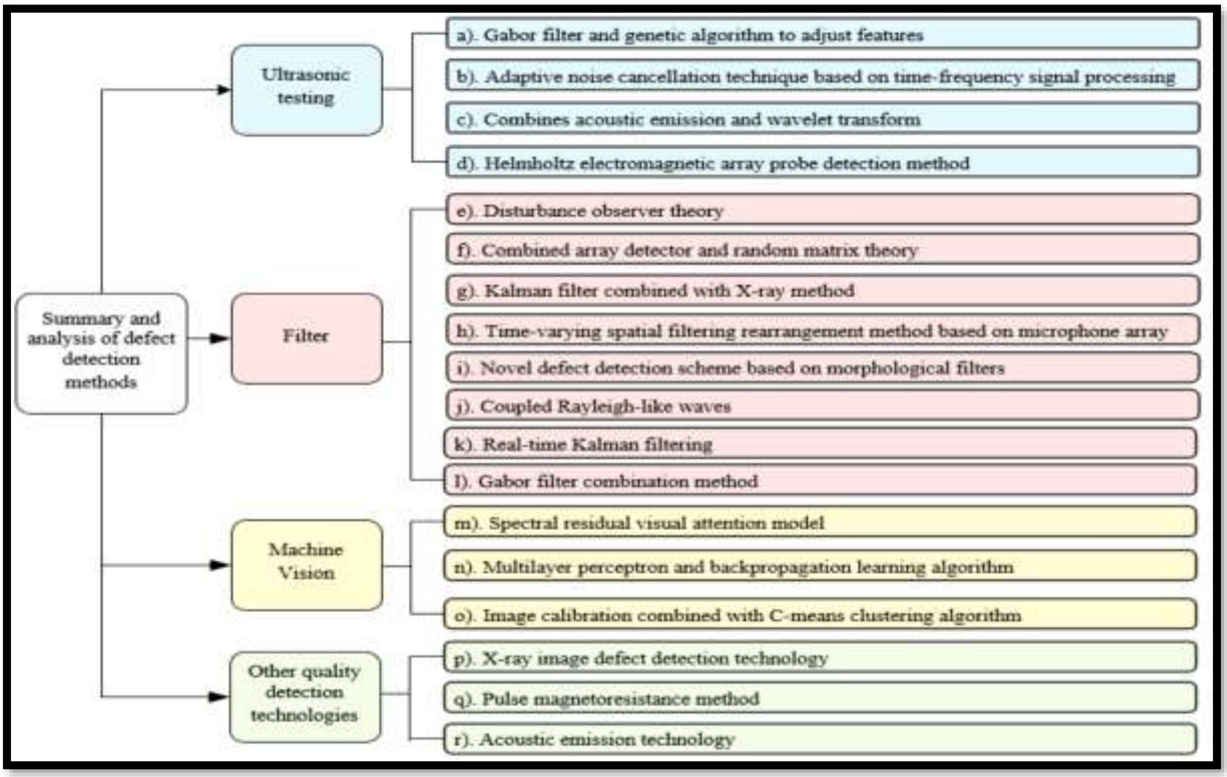

Figure 2. Summary and analysis of defect-detection methods.

Defects in the sample's internal structure are often detected using ultrasonic defect detection techniques. That's why ultrasonic performance is the most important outcome. The results reveal that ultrasonic defect-detection systems offer the benefits of quick detection speed and easy operability. In addition, they have a unique ability to identify faults in the product's interior structure and substance, as well as its size [14]. When it comes to workpieces that have complex structures and poor detection efficiencies, this approach isn't ideal. Because of the nonlinear connection between defect location and signal reception time, ultrasonic methods are particularly poor at identifying flaws on the sample's top surface. This causes the defect to be located close to the direct pass wave end.

To a greater extent, the "trailing" phenomena of a direct pass wave signal on a map is more definite the more densely distributed the product's true location .

4. Machine Learning for Defect-Detection

It is possible to utilise machine learning (ML) to analyse massive volumes of data in real time. ML architectures have evolved over the last several decades as increasingly powerful computers have become available. Non-linear correlations in big datasets may be discovered using ML approaches. Supervised learning, semi-supervised learning, and unsupervised learning are all types of machine learning methodologies. Two stages of training are included in supervised methods: You need to categorise each piece of data into one of two categories: acceptable and unacceptable. Next, the labelled data is used to train the machine learning network. Prior to understanding how to utilise it, the user must be able to recognise and name the problems. In an unsupervised technique, no data are labelled before analysis [15]. Algorithms try to find errors by themselves. Using both supervised and unsupervised methods at the same time is referred to as semi-supervised. In other words, the ML algorithm makes use of both labelled and unlabeled data when making predictions.

4.1 Convolutional neural networks

Computer vision issues are increasingly being solved with convolutional neural networks. Convolutional neural networks are the newest deep-learning approaches for image identification. Based on the multi-layered structure of genuine brain regions in the visual cortex, convolutional neural networks have demonstrated outstanding achievements in many very complicated application situations.

For picture recognition, traditional ML techniques divide the problem into two parts. An method like HOG SURF or HOUP may be used in the initial phase of feature engineering in order to extract meaningful data representations from raw picture data. A machine-learning algorithm attempts to discover a pattern that links a-priori produced data representations to a target variable in the second stage, known as classification. Feature engineering is required for the algorithm to learn these patterns [16]. This is especially true when it comes to manually extracting the required data representations.

The combination of these two stages is what sets convolutional neural networks apart from traditional ML techniques in computer vision. Because of this, features that are relevant to the classification results are automatically pulled from the feature engineering process. Unnecessary information is automatically filtered out. Therefore, convolutional neural networks are able to transform raw input, such as pixel data from pictures, into more meaningful data representations, the so-called feature maps, which in turn enable the categorization. For example, a nose in face recognition may be represented by these feature maps.

4.2 General convolutional neural network architectures

There are several common convolutional neural network designs. Image processing takes place within the context of a three-dimensional array. The convolutional layers turn the original input into feature maps by applying many tiny filter kernels to the picture array. Since the filter matrices cover the whole picture, as illustrated in Figure 3, the spatial information is preserved. Non-linearity functions such as ReLU, batch normalisation layers, convolutional layers, and pooling layers are then applied to these feature maps. Convolutional neural networks are able to automatically extract meaningful feature representation with fully connected layers from the raw picture and optimise them to represent particular target classes by merging numerous convolutional, activation, batch normalisation, and pooling layers.

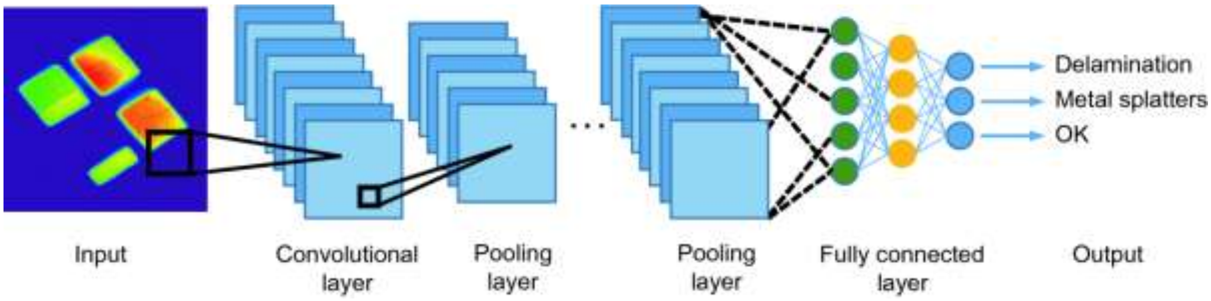

Figure.3. typical convolutional neural networks include numerous blocks of convolutional layers followed by pooling and then one or more fully connected layer for classification at the conclusion of the network.

The ImageNet Large Scale Visual Recognition Competition has been a major factor in the development of convolutional neural networks (ILSVRC). The ImageNet computer vision competition is one of the most challenging and fascinating. ImageNet's winning design has inspired many of today's most advanced algorithms, from simple stacks of layers like AlexNet and VGG to more complex structures like Inception, ResNet, Xception and MobileNetV2.

Other trends in defect-detection technology include the growing dominance of machine learning approaches, which are currently employed in all product defect detection domains. Surface defect detection and interior fault diagnosis are the two primary subcategories of defect-detection technology. In surface defect detection, deep-learning image processing technology is used to classify and locate product defects in images, whereas in internal fault diagnosis, digital signals in the time or frequency domain are used to diagnose problems in rotating parts such as bearings. This is similar to 'Auditory' detection. In our research, we discovered that the defect-detection complex worked better and extracted more features.

AM applications are shown in Figure.4 with their associated ML subcategories. Supervised learning is the most common kind of machine learning application in the area of AM.

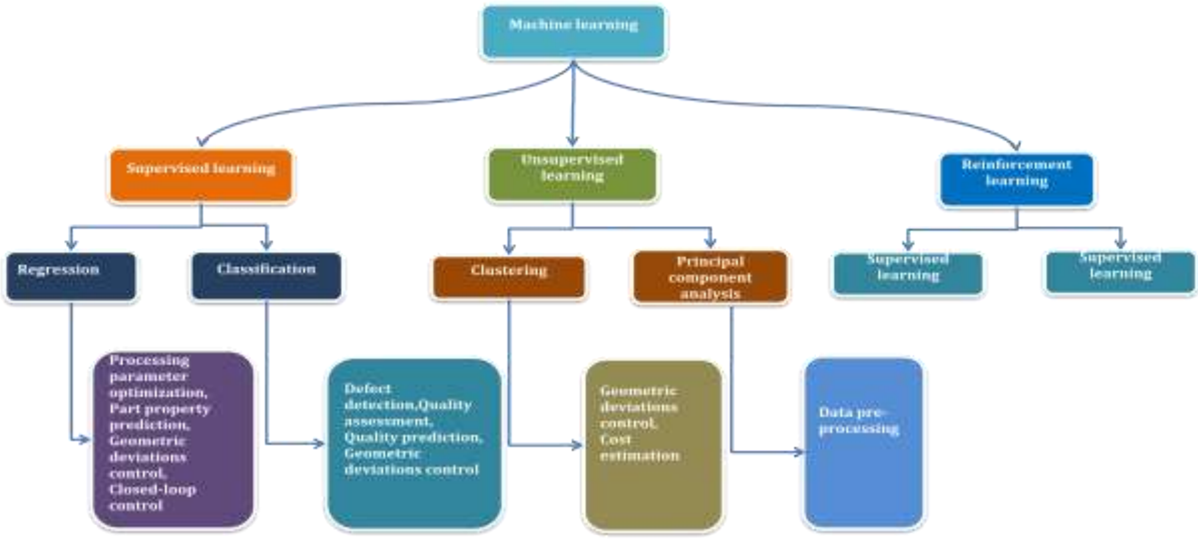

Figure .4. Taxonomy of ML applications in AM field.

supervised learning, unsupervised learning, and reinforcement learning are all examples of machine learning tasks. It is shown in Figure.4 that the ML taxonomy is matched to the AM applications shown in the figure. There are numerous input-output pairings in the training set, and each data point is labelled with an output YY. XX1, XX2,...,XXnn characteristics that may have an impact on an input's output are included in each vector. A quality evaluation (excellent or terrible) is an example of a target classification, and the associated ML category is classification. Another example is regression, which is a target parameter such as porosity and tensile strength. Unlike supervised learning, in unsupervised learning, each input data point does not have an associated output. Typical examples of unsupervised learning include clustering, where all data is grouped together based on similarity. When it comes to self-driving cars and board games like chess, reinforcement learning (also known as kinesthetic learning) teaches participants how to optimise a numerical reward signal by mapping events to actions. Figure 1 depicts a few examples of AM applications and the ML categories they fall under. Supervised learning is the most common kind of machine learning application in the area of AM.

4.3 ML Applications in AM

ML is a tool for manipulating data. There are several forms of data that may be used in the PSP relationship chain, as shown in Figure.5. Processing parameters and processed resulting data are separated into two words in the commonly used PSP relationships when referring to the concept of "processing" in this context. As you can see from these data, there are many connections between them, including but not limited to the following: (1) The processing parameters, such as extruder temperature (ME), laser power (L-PBF), printing speed, and layer thickness, have a significant impact on structure, quality, and performance; (2) the designed shape plays a critical role in printing cost and geometric deviation; and (3) the in situ image has a significant impact on printing speed and layer thickness. ML models may generate inferences based on this data if a dataset is used to train them that contains at least two kinds of related data in the PSP connection chain. This is the standard approach for putting ML models into action.

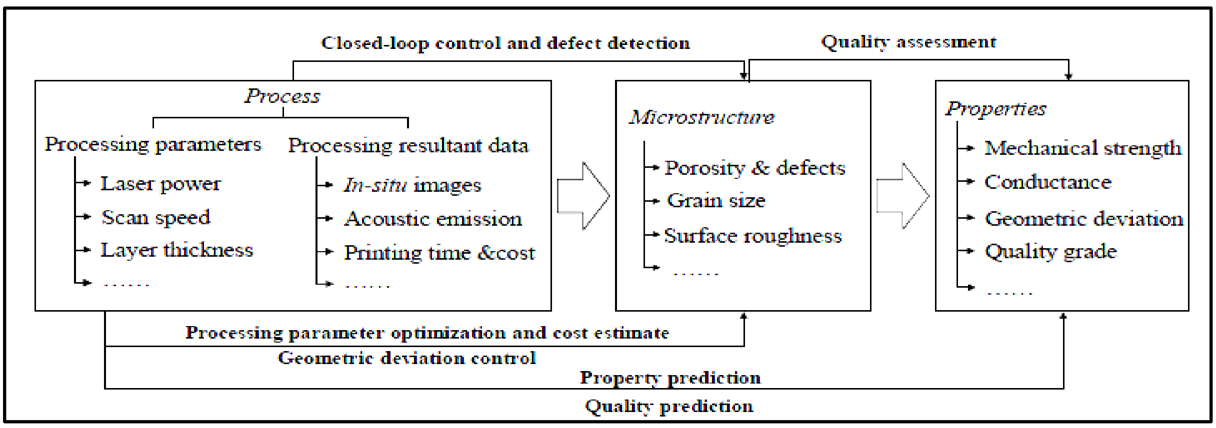

Figure 5. The process-structure-property relationship chain in additive manufacturing.

Figure 6 depicts a method for detecting Ti-6Al-4V defects in the L-PBF process that makes use of pictures as input. Geometric characteristics are retrieved from each thermal picture and utilised to train the ML models for images that have been classified as porous or non porous. To identify defects, Zhang et al. used SVM using photos taken in the field as input. This three-group classification problem results in a 90.1 percent accuracy rate for SVM, even though CNN performs better (92.8 percent accuracy). Using AE as input, Ye et al. used SVM for fault identification, which necessitated the extraction of features like pictures. SVM (98,01 percent accuracy) surpassed the deep belief network in this binary classification task (95.87 percent). The F1 score of Gobert et alimproved .'s SVM model for defect identification using CT image layers is 0.62. Overall, SVM is an excellent choice for classifying data.

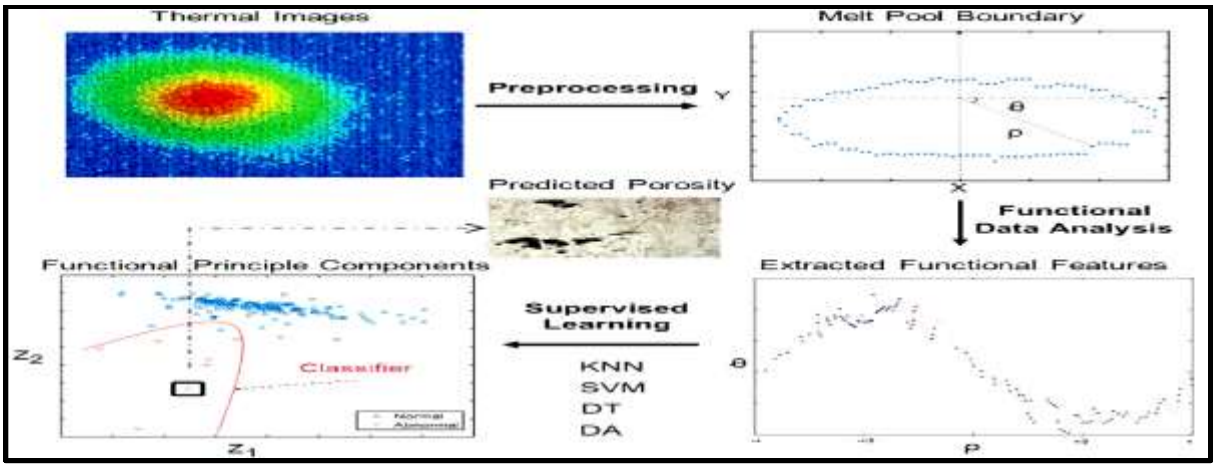

Figure 6. The procedure from thermal images (input) to porosity predictions (output) of Ti-6Al- 4V in L-PBF process.

Figure 7 shows the multi-scale CNN they built. Convolution is used in the NN to transmit visual information. Shen et al. used a voxel grid as a geometric input feature and achieved an overall F1 score of 0.95 utilising CNN for geometric error correction. There are several methods for classification jobs in the AM area, however NN is a complicated yet powerful model. NN may be used in a wide range of classification problems.

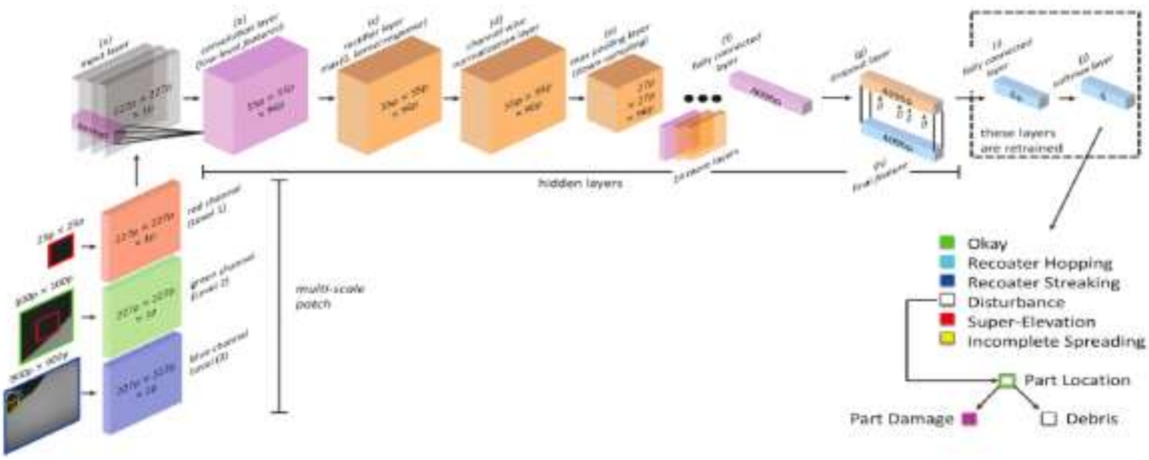

Figure 7. The flowchart of multi-scale CNN in defect detection in L-PBF process using multiplematerials.

5. Conclusion

There are two types of learning tasks that may be accomplished using ML in the AM field: supervised and unsupervised. Regression, classification, clustering, and PCA are all presented, as well as several common methods, and the performance of certain prominent algorithms is evaluated for each individual job. Research in this area should focus on these topics: Even though machine learning (ML) has been around for decades, its applications in additive manufacturing (AM) have only just come to light. Optimization of processing parameters, property forecasts, defect detections, geometric deviation controls, quality forecasts and evaluations are just a few of the many applications available. ML models may first understand the relationship between processing parameters and properties using existing data, so that they can give suggestions for improving these parameters. For the second, after training, ML models are able to anticipate geometric deviations and provide suggestions on how to correct them. When it comes to coping with real-time photos and auditory emissions from printing processes, ML models excel. According to a map of process parameters, microstructure, and properties, only a small portion of the available data has been used so far. Research in this early stage of the area will focus on using new data collecting techniques, investigating more ML applications, and building better algorithms.

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