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# Machine Learning Applications In Metal Additive Manufacturing: A Review

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***ABSTRACT:*** *Additive Manufacturing (AM) technologies areextremely widespread due to their procedures have proved their capacity to generate intricate forms and are used on a diverse range of materials. Industrial applications can develop cracks, keyhole defects, net form issues, and more during and after manufacture. This is a result of the many phenomena that take place during printing. It has been demonstrated that the Finite element method can accurately predict mechanical properties, as well as shape, size, and microstructure.This numerical model optimizes process parameters and forecasts distortions, shapes, residual stresses, as well as thermal histories. They also help to better understand how to improve processes. Nonetheless, numerical modelling that is used for AM still faces a variety of difficulties. In actuality, multi-physical simulations are slow and require simplifying assumptions. This causes a discrepancy between computed and experimental outcomes. Machine learning (ML), another viable technology, has advanced due to machine computing capacity. This can complement and even replace previous methods. It has been called a technical progress accelerator in various fields but is still a novel approach in the field of metal. This review presents ML applications inAM metallic components. In addition, themost prevalent AM techniques for metals, both the thermal as well as the microstructure model of metal parts produced by AM are analyzed, explained, and contrasted.*

***KEYWORDS:*** *Additive manufacturing, direct energy deposition, thermal model, microstructure model, machine learning.*

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## I. INTRODUCTION

Additive manufacturing (AM) remainsa relatively new technique that can be applied in the production of three-dimensional objects in industrial settings. AM is used in many industries, especially for complex design and low-volume production. The repetitive deposition of thin material layers, by a computer model, is how AM components are fabricated [1]. AM parts are made by melting the material with focussed energy and then rapidly consolidating it. The severe thermal gradients, non-uniform expansion, and contraction of the material may have a major effect on the functionality of the printed component throughout the thermal cycle. [2]. AM can build complex shapes without moulds, reducing part count [3]. AM parts can be made from steel, titanium, and nickel alloys, which are employed in aerospace and healthcare. AM can create complex geometries, but the production process is complicated and many factors affect component quality. The microstructure of the metal plays a significant role in its characteristics and can significantly affect how it behaves mechanically[4].The durability and strength of metal are affected by the size of the dendrites and grains inside the metal, as well as the microsegregation of intermetallic compounds and phases[5].

The AM technique's settings and the material used will define the microstructure's appearance. The approach and parameters will depend on the metallic AM technique used.Directed energy deposition (DED) and powder bed fusion (PBF) are two primary approaches utilized in the additive manufacture of metals [6]. The digital files serve as the starting point for both of these procedures. After that, the computer-aided design files for the three-dimensional object are sectioned off into sheets, and the information is sent to the printing machine. The granules are melted in layers in the next step. In every loop, a powder layer with a predetermined thickness is applied to a substrate. After this, a source of heat is raster-scanned throughout the powder layer to heat it. When the powder is heated, it melts and forms a bond with either the base or the layer that was previously melted. After the platform has been lowered, the operation will begin again.In DED operations, the feedstock can be either wire or powder, and the heat source can be either a laser, an electron beam, or electricitywhile PBF uses a laser or electron beam [7]. Melting feedstock near or on the substrate creates a layer. Fig. 1 illustrates a few examples of both laser-PBF and laser-DED configurations.

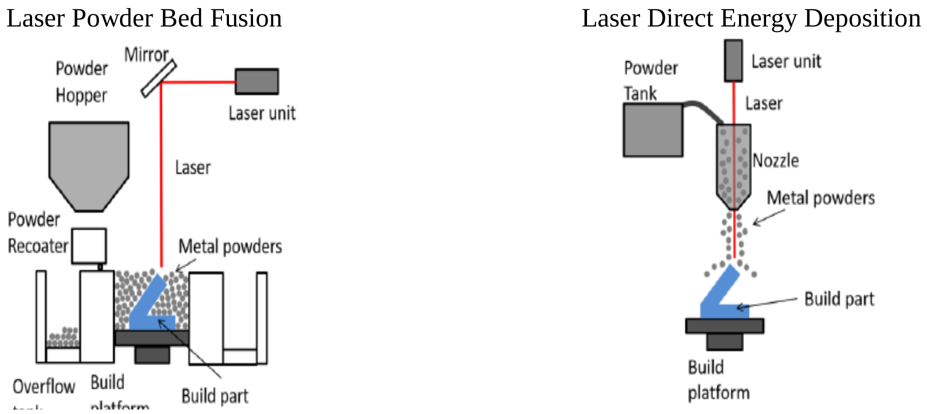


**Fig**. 1 Schematic diagram of laser powder bed fusion and laser direct energy deposition configurations [8].

Although both techniques layer the part, there are major differences between them. Layers must be piled in one direction because PBF machines can only operate on three axes. DED machines with 5+ axis settings can generate layers in any direction if the part and tool head don't conflict. Hence, AM can repair and print parts more efficiently with DED. This review presents ML applications in Metal AM parts. In addition to some of the most prevalent AM processes for metals, followed by modelling of metallic parts in AM with their comparison. The remaining parts of this chapter are laid out in the following format. In Sect. 2, we explain in more detail both thermal modelling and modelling of microstructure in the direct energy deposition method of additive manufacturing. In addition,the comparison with the numerous models used in terms of their degrees of precision and length scales,and justify how the models are chosen and coupled. In Sect. 3, we classify ML used for AM. In Sect. 4, we show the applications of ML for metal AM in terms of the prediction of mechanical behaviour and optimization of AM process parameters. Section 5 summarizes our main findings and enumerates future work.

## II. MODELLING IN METAL ADDITIVE MANUFACTURING

The various microstructure models, highlighting the model's boundary conditions as well as the assumptions it makes are summarized in Fig. 2.

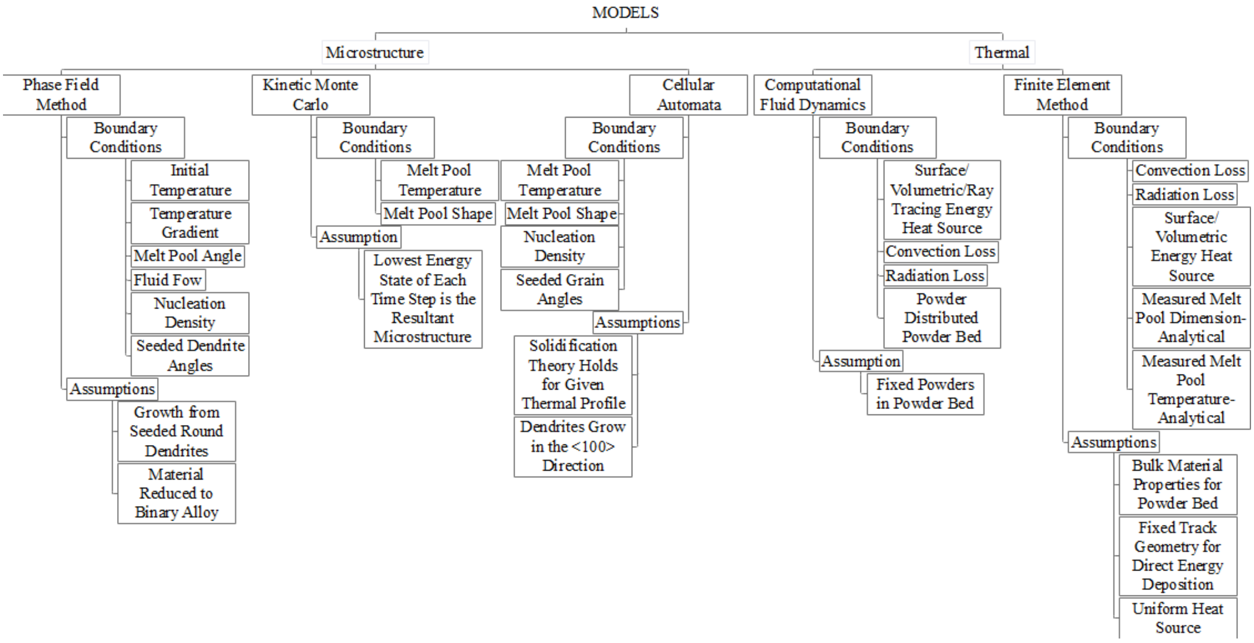


**Fig. 2.** Schematic representation of microstructure and thermal models along with their respective boundary conditions and assumptions.

### a. Thermal Modelling in Direct Energy Deposition Additive Manufacturing

The thermal models that are utilized in conjunction with the microstructure models are discussed.

#### i. Finite element method

The finite element method (FEM) has been integrated with a variety of other microstructure models. In most cases, these simulations are performed on extremely large volumes that include a great number of tracks and layers. When compared to PBF models, simulation for DED has some unique characteristics. It is necessary to continue adding material while the heat source is being moved. This is performed in FEM models by positioning inert components close above the substrate; these components become active as the temperature rises.This serves as a depiction of the metal that is being fed into the melt pool as it is being added. For an element to be considered dead or inactive, its thermal conductivity must be reduced to nearly zero. This ensures that the element's temperature will not shift. When it comes to obtaining correct temperature profiles and melt depths, meshing for FEM plays a significant role. The hexahedral element is widely utilized because it offers improved precision and is capable of functioning effectively with simulations that make use of simple geometry.

#### ii. Computational fluid dynamics

To collect data on the geometries of the track and the melt pool as well as the temperature profiles over time, computational fluid dynamics-CFD techniques, more notably the finite volume method-FVM, have been utilized. The Navier-Stokes equation is effectively solved through the application of FVM methods.This allows for the simulation of AM effects such as vaporization and the Marangoni effect. Because of this, more precise predictions can be made regarding the geometry of the melt pool as well as the temperature distribution within the pool[9]. When the number of partial differential equations that need to be solved grows, the amount of computing power that is necessary also grows. The vast majority of FVM models are only capable of simulating one melt track in three dimensions [10].In DED processes, the CFD-discrete element method approach has also been employed. This technique takes into account, not just the interactions with the melt pool, but also gas flow, powder flight, and heating but the simulation's detail increases operational costs.Although CFD can produce more realistic tracks, there is little published literature on its application to DED procedures.Another one of the CFD methods that are used to connect with microstructure models is called the lattice Boltzmann Method (LBM). LBM represents the flow of fluid by solving discrete Boltzmann equations, as opposed to the Navier-Stokes equation, which describes the flow of fluid.This is because LBM is more accurate. While LBM can model powder distribution in addition to fluid flow and evaporation,FVM needs to be coupled with a discrete element approach to be able to simulate powder distribution. Although CFD models are capable of simulating a wide variety of physical processes, the simulation is restricted to only a few short tracks due to the complexity of the models and the small cell sizes used which can be improved. The FEM models make a lot of assumptions, resulting in a reduction in their accuracy but an increase in the size of the domain, which allows it to support a greater number of longer tracks and more layers.

**b. Modellingof Microstructure in Direct Energy Deposition Additive Manufacturing**

The following microstructure models will be discussed: Cellular Automata (CA), Kinetic Monte Carlo (KMC), as well as Phase Field Modelling (PFM). Both CA as well as KMC models are considered mesoscale models because they simulate a large number of grains by focusing largely on the total size of the grains as well as their aspect ratio [8]. The PFM is a micro-scale model since it simulates sub-grain level, which allows it to obtain the concentration of solutes, precipitates, and dendrite shape [11]. In addition to this, it can simulate several grains at the same time by applying multi-phase field models. Microstructure modelling necessitates the use of thermal models since these models supply the microstructure model with the necessary inputs of temperature,rate of cooling, and temperature gradient respectively. A more accurate determination of the rate of cooling and the temperature gradient can lead to an improvement in the microstructure's predictability. Fig.3 presents a chart that contrasts with the different models concerning both their length scales and their degrees of precision. Because of the reduced length scale, the required simulation time step is also less, which results in a significant increase in the amount of data collected [12]. Models with greater accuracy typically have a greater number of variables and equations to solve, which necessitates the utilization of a greater quantity of processor resourcesIn most cases, the size that can be accurately simulated by a model is constrained by its accuracy, which in turn is a function of the length scales and time steps used in the model.Two different approaches can be taken when it comes to linking the combining the microstructure model with the macro thermal model[13]. The models might be weakly connected, which means that the thermal model will be simulated first, and then the thermal history can be utilized as an input to the microstructure model [9]. Another approach is to tightly couple the two models and run them both at the same time in such a way that the data is exchanged and the models interact with one another. Although heavily coupled simulations have the potential to produce more accurate results, they take significantly more time to run.

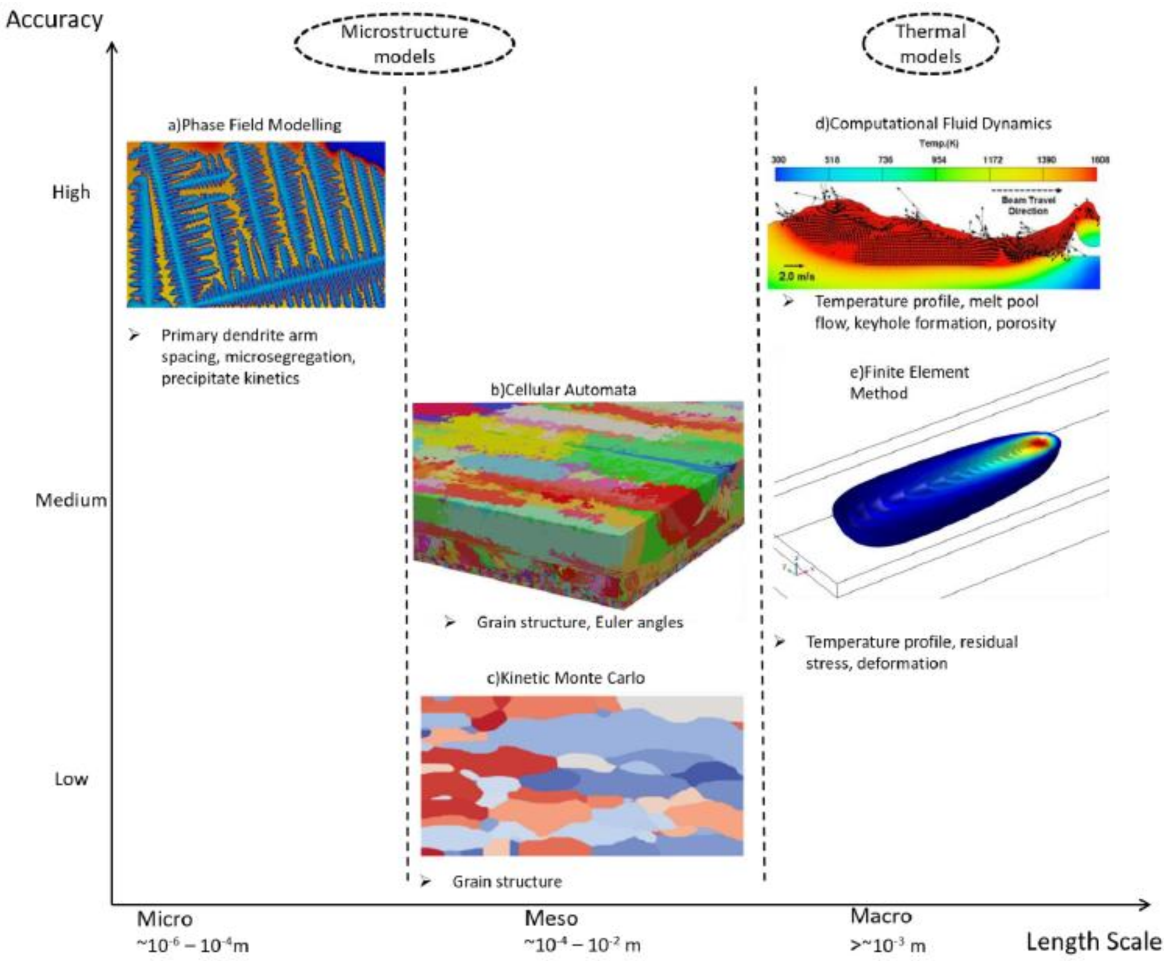


Fig. 3. Schematic diagram that compares several models regarding length scale and accuracy [8].

**c. Comparison of the Techniques used to Model Microstructure**

In most cases, CFD models are only able to simulate a single melt track, however, FEM models can take into consideration multiple melt tracks at the same time. Whereas CA and KMC models can replicate the entire grain structure, PFM models can only simulate a small number of dendrites. In contrast to the other models, the PFM not only generates realistic dendritic structures but also takes into account the distribution of solutes among the dendrite arms.Both KMC and CA models ignore details such as the concentration of solutes and the morphology of dendrites. Information such as the grain width and aspect ratio can be obtained from either model. One key distinction is that CA models take into account the crystallographic development direction that is most liked by metals. As the preferred direction and the direction of the temperature gradient both influence the direction in which the crystal grows and the rate at which it grows, the grain size and aspect ratio that the KMC calculates may not be accurate. To determine the rate of solidification in the favoured dendritic crystallographic direction, CA makes use of the theory of solidification, which results in CA models having a higher level of accuracy than KMC models.

## III. CLASSIFICATIONS OF MACHINE LEARNING FOR ADDITIVE MANUFACTURING

Machine Learning (ML) is a method that is used in artificial intelligence. It is a technique that enables a machine to train automatically how to generate predictions even though it has not been explicitly coded to do so.The goal of ML is to accomplish a task through the processes of learning and analyzing data from a given dataset [14].The field of ML can be partitioned into three distinct subfields: reinforcement, supervised, and unsupervised learning respectively. Throughout the process of reinforcement learning, the model can involve in conversation with its environments to acquire knowledge and select those behaviours most likely to result in the highest possible rewards [15]. In supervised learning, the algorithm discovers associations among features of interest by utilizing unlabeled data to train itself, while in unsupervised learning, the algorithm learns from training data that has been labelled to assist in the prediction of outcomes. The development of an ML system necessitates careful consideration during the process of selecting an acceptable ML algorithm [16]. This is because the correctness of the outcome is significantly impacted by the algorithm used. No one algorithm can solve all of a problem’s complexities because each algorithm offers its own set of benefits when applied to a particular setting.

The following are some categories that can be used to classify the most common ML techniques used in mechanical engineering: regression, classification and clustering,and estimation [17]. In particular, regression, classification and clustering algorithms are the ones that are used the most when attempting to predict material properties [18]. The primary operations of ML can be broken down into the following categories: the compilation of data, the selection of descriptors and algorithms, the forecasting of models, and the implementation of the models Fig. 4 depicts various ML techniques that are often used to solve challenges encountered in Engineering.The gathering of experimental data, the prediction of desirable qualities, and the experimental validation of those predictions are the three stages that make up a full cycle of predicting the mechanical properties and behaviour of a structural component. The utilization of a prediction model is the key concept behind the prediction of the behaviour of materials and mechanical properties. Both numerical simulation and ML deal with models, hence they are related to one another.Although during simulation, the precise values of the inputs to the random variables are unknown; yet, the modelling itself is known with utmost precision, while in ML, the model being trained on is unknown before the training process begins, however, the inputs are known. The incorporation of simulation into ML can be carried out with applications in the fields of engineering and natural science.To be more specific, the results that were obtained from simulations can be included in a wide variety of ML elements (e.g., training data, algorithm, and final hypothesis). Enhancing the accuracy of the training data is the most typical approach taken when incorporating the findings of simulations into ML [19]. For example, the findings of the simulation were utilized as training data to predict mechanical strength. ML algorithms can learn from their prior numerical findings. Both experimental data and the results of numerical simulations can be used as data sources for MLsystems.

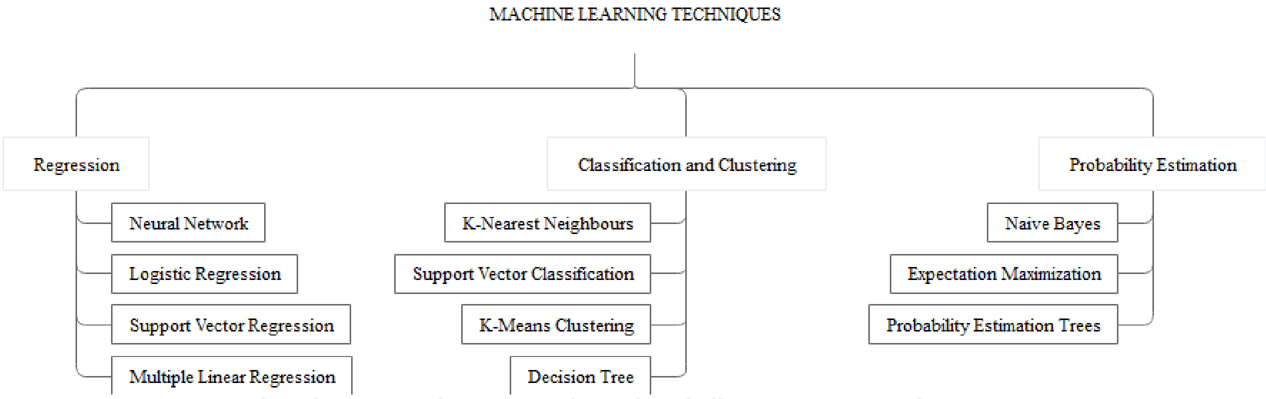


Fig. 4. Machine learning techniques used to solve challenges encountered in engineering.

A high-level look at the classification of ML in AM. The manufacturing of an AM-based product can be broken down into four primary categories: the design phase, the act of printing itself, the stage after processing, also known as post-processing, and the part assessment stage [20]. Fig. 5 illustrates the most important aspects of these phases and shows how various ML approaches can be utilized at each stage.The AM process begins with the creation of a computer-aided design model and the AM printed parts' inspection concludes the processing chain.

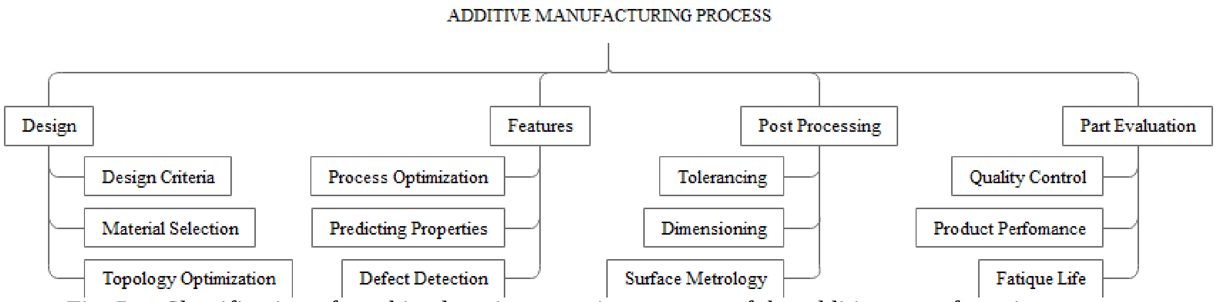


Fig. 5. Classification of machine learning to various aspects of the additive manufacturing process.

## IV. APPLICATION OF MACHINE LEARNING FOR ADDITIVE MANUFACTURING

AM uses MLfor process optimization, mechanical behaviour prediction, and defect identification. They typically use ML to tune AM settings with property requirements.

### a. Application of Machine Learning for Prediction of Mechanical Behaviour.

Although there are techniques, like finite element analysis, which have the potential to predict the development of the thermal field at each given point, these techniques are likely to experience severe disparities with the research results from the experiment as a result of the simplifying assumptions used [21]. Previous research efforts have investigated whether or not it is possible to use ML techniques to anticipate the evolution of a thermal field at every given position in the structural components [18].In this section of the review, the primary emphasis is placed on the application of ML approaches to the study of the development of the thermal field and its influence on the functionality of components that have been printed. Since the parameters of the printing process can have a substantial impact on the functionality of additively made parts, it is helpful to optimize and predict these printing parameters to improve the performance of components.

Metallic bonding is predominant in both metals and alloys made from them. A variety of procedures make it possible to exert influence over the microstructure and atomic arrangement of material. Because the material's microstructure has such a significant impact on its properties, a broad concept is required to properly evaluate the particular microstructural feature that is under investigation. Understanding the links between microstructure and mechanical characteristics is essential for maximizing the mechanical performance of metallic components. This comprehension is linked to the connection that exists between the microstructure and the mechanical properties of the material.A description of the microstructure for engineering materials includes the types of phases that are present, and their grain size, as well as a breakdown of the structure, as well as the shape and size distributions of the grains. The ultimate qualities of the material are, in many instances, determined by the microstructural characteristics of the material, such as point defects, dislocations, as well as grain size are extremely important components. [22]. The impact that a material's microstructure has on its properties is analyzed and summarized in Table 1.

Table 1. The influence of microstructure on the qualities of the parts.

| Qualities | Influence of Microstructure |
|---|---|
| Mechanical (tensile strength, ductility, hardness, etc.) | High |
| Electrical (electrical conductivity, etc.) | Low |
| Thermal (dimensional stability, melting point, etc.) | Low |
| Chemical (corrosion resistance, surface tension, etc.) | Low |

Mechanical stresses such as tensile, compressive, and shear have a direct influence on the microstructure of metallic structural elements, as well as the integrity of the metal itself. The consolidation behaviour of the pieces can be significantly affected by microstructural alterations. There are a wide variety of potential microstructures that may be found in metal materials. Depending on the dynamic loading, any one of these microstructures could result in macrostructural damage and, as a direct consequence, restrict the lifetime of the material. Therefore, the investigation of microstructures is a very significant matter. Various methods of characterization have been put to use over time to investigate part microstructures. Recent research that was published in [23] analyses how the postprocessing of AM-printed objects affects their microstructure as well as their thermal characteristics. There is a correlation between a number of the material's microstructural characteristics and its mechanical qualities. For example, grain size, texture, phase transitions, as well as the volume percentage, shape, and size of particles. It is crucial to highlight that ML approaches have been successfully applied to forecast certain behaviours, features, and fatigue lifetimes of the AM-printed components. PDF and DED are the two processes of AM that see the most extensive application and are used for printing metal products. PBF is a multi-step process that may be broken down into two independent sub-processes: electron beam melting (EBM) and selective laser melting (SLM). DED techniques can either utilizewire arc, electron beam, or Laser as the source of heat. Table 2 presents techniques of ML used in a variety of applications within the domain of AM.

Table 2. Techniques of machine learning applied across a variety of AM domains.

| AM Techniques | Metal | ML Methods | Drive | Ref. |
|---|---|---|---|---|
| SLM | Steel | MLP | The varied stages at which the condition of melting can be found. | [24] |
| SLM | AlSi10Mg | SVM | An analysis of the qualities possessed by the AM powder | [25] |
| EBM | CoCr alloy | SVM | The development of flowcharts for various processes. | [26] |
| DED | Cu | MLP | Theoretical modelling of the bead's three-dimensional geometry. | [27] |
| Laser DED | Steel | BPNN, LS-SVM | Predict the depositing height of printed parts | [28] |
| DED | Steel | SVM | Prediction of the exactitude of the building construction process. | [28] |

### b. Application of Machine Learning for Optimization of Additive Manufacturing Process Parameters.

The past few years, it has seen a significant rise in the number of times that AM has been used in the building and construction industry; therefore, optimizing this procedure has been of utmost importance, and it has been a focus of our effort. As a result of this, ML was recently applied to optimize the printing parameters of a cement-based substance using a 3D printer. They developed a mathematical model to examine the diffusion mechanism of the substance throughout the extrusion process. In addition, they made use of a support vector machine that was built using the ML technique to examine the effects that different parameters had on the flow process [29]. The network was trained on experimental data, and the results of the proposed method demonstrated that the deformation of the print filament is not related to the viscosity of the plastic being used. Despite this, the printing speed along with the yield strength of the material stress does have significant impacts, most notably on the distortion of the produced filament. Various process parameters play important roles in determining the quality of printed parts as well as their overall performance when components are fabricated utilizing AM processes.

As a direct consequence of this, the effects of these characteristics have been the subject of investigation, even though experimental methodologies require a significant investment of both time and money. The capabilities of ML approaches were demonstrated when compared to other available options for optimizing AM parameters [30]. To predict the depth of the melt pool that was produced by the laser powder-bed fusion process, a Gaussian process-based model was utilized [31]. For this, scan rate, as well as laser power, were regarded to be input variables, while experimental data collected from the printed 316 stainless steel were utilized. The accuracy of the model's predictions was analysed, and the results indicated that the model had a reasonable overall performance. This was shown by the fact that the model's mean absolute error was not unreasonably high. During the process of PBF, an elevated lens was utilized to construct an imaging system that can detect the information of both the melt pool, plume, as well as spatter, and this was done to ensure the safety of the process as shown in Fig. 6. The characteristics were determined to be extracted based on a better understanding of the process so that they could be fed into the typical ML method. To provide further context, a convolution neural network model was applied in the process of locating quality anomalies, and also the results showed that the system had an efficiency of 92.7% in terms of location of quality [32].The morphology of the melt pool, which includes properties like geometry, continuity, as well as homogeneity, has a considerable bearing on the final product's quality when it is printed using the DED method. Therefore, in regard, ML was utilized to make predictions regarding the height of the melt pool width as well as depth in several DED processes. ML was applied in more recent work to the construction of a data-driven model and the prediction of the temperature of the melt pool that was employed in the DED process.

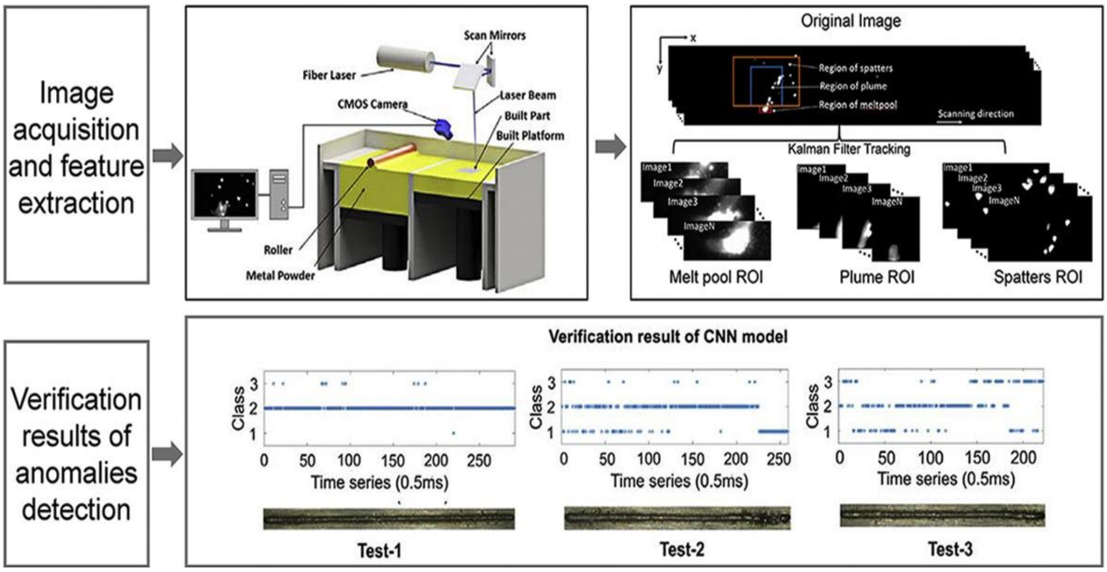

Fig. 6.Specifics regarding the design of the powder bed fusion process monitoring[33].

Precisely, they made use of two different ML strategies known as Extreme Gradient Boosting, and Long Short-Term Memory. Both of these algorithms are very scalable and particularly effective when it comes to evaluating time-series data. Also, to this, a superalloy composed of Ni was utilized in the production of thin-walled test coupons, as well as the measurement of the temperature of the melt pool within each layer [34]. The findings that were collected demonstrated that both ML algorithms made highly accurate predictions regarding the temperature of the melt pool.Similarly, in [35], ML was used in the DED process to identify links between both the input parameters of the laser metal deposition technique and the final geometrical parameters of the pieces that were produced. This linkage was sought to improve the efficiency of the laser metal deposition process. This correlation was sought to improve the quality of the parts. This was done to improve the quality of the printed part. The results of the experiments were factored into the training process for the artificial neural network, which was carried out in two stages. According to the results that were obtained, Neural network-based ML is capable of providing an accurate estimation of the processing parameters that are necessary to print an item made of metal that has a specific geometry.

## V. CONCLUSION

The applications using ML in the field of AM are discussed in depth in this review article. The paper discusses the most prevalent metal AM processes and their applications. The thermal and microstructural modelling of metallic parts and their comparison are also examined. With AM data, ML linkages between processes, structures, and properties can be easily created in any direction. ML has been shown to exploit AM processes and improve AM production predictability. In general, ML has had a beneficial impact on the possibilities of extending AM adoption and boosting its value proposition.While ML has been evolving for several decades, the applications of ML in AM sector have only been identified for some years. ML has improved AM adoption and value, its applications in AM have just been discovered in recent years, despite its decades-long development. The following is the proposed direction for future study. These applications include property prediction, quality prediction and evaluation, defect discovery, and geometric deviation control. ML models will predict geometry variation depending on the supplied geometry and recommend ways to adjust for geometric inaccuracy after training. Yet, this process-microstructure-property map has not utilized all of its data. As a result, thisnew research area will focus on data collection and algorithm development.

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