**Solid Freeform Fabrication 2019: Proceedings of the 30th Annual International Solid Freeform Fabrication Symposium – An Additive Manufacturing Conference**
**Reviewed Paper**

# APPLICATIONS OF SUPERVISED MACHINE LEARNING ALGORITHMS IN ADDITIVE MANUFACTURING: A REVIEW

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## Abstract

Additive Manufacturing (AM) simplifies the fabrication of complex geometries. Its scope has rapidly expanded from the fabrication of pre-production visualization models to the manufacturing of end use parts driving the need for better part quality assurance in the additively manufactured parts. Machine learning (ML) is one of the promising techniques that can be used to achieve this goal. Current research in this field includes the use of supervised and unsupervised ML algorithms for quality control and prediction of mechanical properties of AM parts. This paper explores the applications of supervised learning algorithms - Support Vector Machines and Random Forests. Support vector machines provide high accuracy in classifying the data and is used to decide whether the final parts have the desired properties. Random Forests consist of an ensemble of decision trees capable of both classification and regression. This paper reviews the implementation of both algorithms and analyzes the research carried out on their applications in AM.

## Introduction

Additive Manufacturing is a process of fabricating a component in a layer by layer manner directly from 3D CAD models by melting or sintering polymers or metal alloys using different energy sources such as laser, electron beam, arc, etc. This technology has broadened its applications in producing end-use parts because of the advantages such as the ability of fabricating complex geometries, use of diverse materials, and capacity of achieving desired mechanical properties [1].

To achieve perfect structural integrity is the basic requirement in fabricating any end use part. The Generation of defects in the part during the process results in wastage of time, money, and material. Additive manufacturing faces major challenges in in-situ defect detection and process control. Machine learning (ML) methods offer an opportunity to detect the defects in real time, which prevents material wastage and reduces the efforts for trial and error. Machine learning, which is seen as a subset of artificial intelligence, consists of algorithms which build a mathematical model based on sample data, known as 'training data', in order to make predictions or decisions on unknown 'test data' without being explicitly programmed to perform the task.

Among different types of machine learning algorithms, supervised learning algorithms are used for classification and regression purposes. In this algorithm, the training data set contains one or more inputs and labeled desired outputs. A mathematical model is built on this data and is executed in the following steps. First, the model is trained to learn a mapping function from input

to output using a training data set so that the function can predict the output for new data input. Next, the performance of the model is checked by generating predicted labels of the testing data. Last, the model is cross-validated for performance evaluation in terms of accuracy, precision, recall, etc. Output variable for classification problems is categorical, whereas regression problems have continuous real output variables [2].

There are different supervised learning algorithms. This work reviews and analyzes the applications of two supervised ML algorithms- support vector machine and random forests. These algorithms were chosen as they represent the majority of research carried out using supervised learning algorithms. Neural networks were excluded to limit the scope of this review.

## Supervised Machine Learning Algorithms

### *Support Vector Machine*

Support Vector Machine (SVM) is one of the powerful supervised machine learning algorithms which can be used for classification as well as regression.

In classification problems, this algorithm is used to find a decision boundary which can properly separate unseen data into two or more categories with the help of training data.

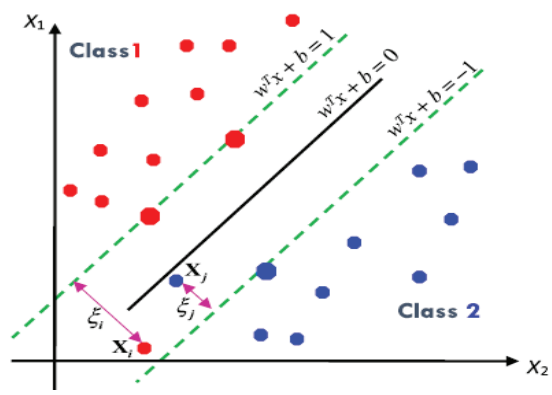


Figure 1: Classification of linearly separable data by support vector machine algorithm [2]

For linear classification of n-dimensional data into two classes, a hyperplane with (n-1) dimensions is generated. Figure 1 shows the linear classification of two-dimensional data. Hyperplane for this case is a line which is defined as,

$$w^T x + b = 0, \tag{1}$$

Where, 'w' is (n-1) dimensional vector in the direction normal to the hyperplane and 'b' is a bias term. The essential condition to reduce the possible error in data separation is that the hyperplane should be at the maximum distance from the closest data points of each of the classes. Since it is a supervised machine learning algorithm classes are labelled as (y = +1) and (y = -1) and data distributed in two classes lies either on the left of (y = +1) or on the right side of (y = -1). Therefore, two boundaries, to ensure the data separability, can be defined as given in equation 2:

$$w^T x + b = \left\{ \geq 1, \begin{matrix} for\ y_i = 1 \\ for\ y_i = -1 \end{matrix} \leq -1, \right\} \tag{2}$$

And the optimal hyperplane lies in between these two boundaries. The distance between these boundaries is called margin. To find the best hyperplane margin should be maximized using equation 3. [2]

$$d(w, b;\ x) = \frac{|(w^T x + b - 1) - (w^T x + b + 1)|}{||w||} = \frac{2}{||w||} \tag{3}$$

In case the data is not linearly separable due to some similar features, training data in the original input space (x) is transformed into a higher dimensional feature space φ(x) using a kernel function.

$$(x) \rightarrow \varphi(x) \tag{4}$$

This conversion from input to feature space provides the ability to generate a linear hyperplane in the feature space as shown in Figure 2.

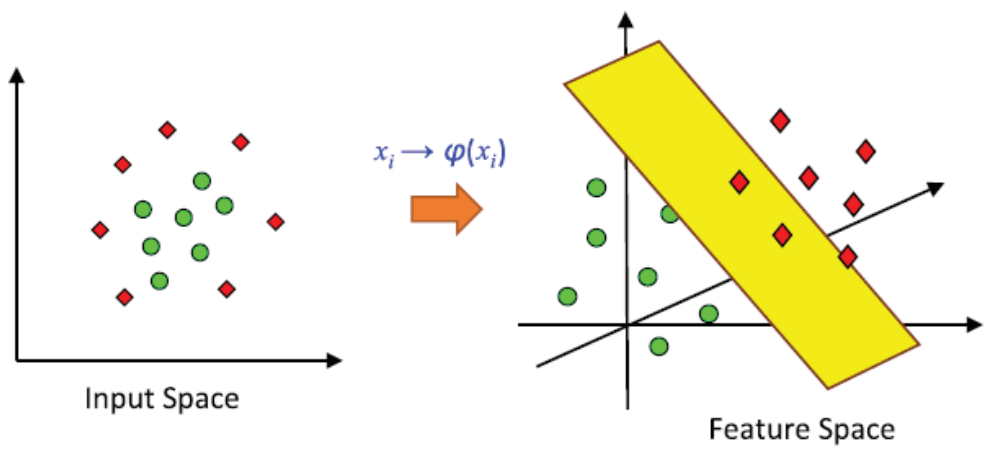


Figure 2: Conversion from the input space to feature space [2]

The hyperplane, in this case, maximizes the margin and minimizes the classification error function. Kernel functions used for different classifiers are as shown in Table 1. [2]

| **Type of Classifier** | **Kernel function used** |
|---|---|
| Linear | $K(x_i, x_j) = (x^T_i\, x_j)\ \rho$ |
| Complete polynomial of degree ρ | $K(x_i, x_j) = (x^T_i\, x_j + 1)\ \rho$ |
| Multilayer perceptron | $K(x_i, x_j) = \tanh(\gamma\, x^T_i\, x_j + \mu)$ |
| Gaussian RBF | $K(x_i, x_j) = \exp(-[\|\|x_i - x_j\|\|^2]\ /2\sigma^2)$ |
| Dirichlet | $K(x_i, x_j) = \sin((n+1/2)\ (x_i - x_j))\ /2 \sin((x_i - x_j)/2)$ |
| Sigmoid | $K(x_i, x_j) = \tanh(\alpha\ (x_i \cdot xi) + \vartheta)$ |

Table 1: Types of the SVM classifier

When input and output data are defined in the training step, SVM determines the Lagrange multipliers. Non-zero values of the Lagrange multiplier determine the support vector which in turn determines the margin of each class to generate optimal hyperplane (decision function).

Support vector machine needs smaller amounts of training data. Also, it is robust against the error of models and has a higher computational efficiency compared to other supervised algorithms. Due to these advantages, it has various applications in various problems such as text classification, pattern recognition, etc.

***Applications of SVM in Additive Manufacturing***

In additive manufacturing, the SVM algorithm have been demonstrated in the following areas:

1. Defect Detection:

Additively manufactured components often have defects such as the incomplete fusion of the powder, porosity, cracks, inclusions, etc. These defects have a strong impact on the mechanical properties of the component. Porosity is one of the defects of major concern [3]. The existing porosity detection techniques are either visual based or simulation-based or based on post-manufacturing characterization. Vast research has been carried out on in-situ porosity detection using various sensors. Support vector machine provides great accuracy in in-situ porosity detection. Table 2 shows that it is used to classify the builds in two classes as defective or flawless using the input data from different sensors such as a high-speed camera, IR camera, pyrometer, etc. The following can be used as input data and class labels for training SVM model.

| **Sr. No** | **Input data** | **Modification in SVM/Kernel used** | **Class labels** | **Ref.** |
|---|---|---|---|---|
| 1. | Layer wise Images | Ensemble classifier | Anomalous/ nominal | [4] |
| 2. | RGB values of images at a checkpoint | Increasing no. of checkpoints | Bad/good | [6] |
| 3. | Surface flatness | | Flat/ Non-flat | [9] |
| 4. | Thermal History | Linear, Gaussian, Polynomial Kernel | Normal/abnormal | [5] |

Table 2: Applications of SVM in defect detection

Different measures are taken in order to improve the performance of SVM in terms of accuracy. In [4], A linear SVM ensemble classifier fuses visual information extracted from high-resolution layerwise images of build surface in PBF process captured from eight different sources. This classifier is trained using the labels ‘anomalous’ and ‘nominal’ automatically acquired from the post-build CT scans. An ensemble classifier combines the outputs from individual classifiers which enables multiple in-situ sensor modalities to be utilized for quality assessment. In this work, multiple images collected under different lighting conditions for each layer serve as sensor modalities to increase the accuracy of the model to 85% compared to the accuracy of 65% if individual classifiers are used.

[5] Develops a methodology for DLD process based on functional principal component analysis (FPCA) to extract key characteristics from melt pool thermal images by converting them to morphological model. Using different supervised learning algorithms, data is classified into ‘normal’ and ‘abnormal’ melt pool labels acquired via X-ray Tomography. To classify the data

using SVM, linear, polynomial and Gaussian kernel functions are used. SVM provides the highest value of the accuracy measure (28.32%) in correctly predicting abnormal data points. Also, it is found that the polynomial kernel function provides superior performance compared to other kernels. The method carried out in this study can be applied to other processes such as PBF or EBM, which have similar energy- material interaction.

Another study, [6], uses SVM to detect any possible defects occurring during the FDM process. In this study, the algorithm classifies the parts as 'good' or 'bad' using the images taken at specific check points through the automated image capturing process. For training the model, section averages (of RGB values) of the images calculated at checkpoints are loaded as input to the vectors of training models. The method is capable of detecting both completion failure defects such as filament running out or printing stopped in the mid-progress and structural or geometrical defects.

2. Fault diagnosis:

The precision of 3D printing is influenced by many factors. One of the most important factors is the health of a 3D printer. Hence it is necessary to monitor the condition of components of 3D printer. SVM can be efficiently used for the fault diagnosis of 3D printers. A study [7] on fault diagnosis of delta 3D printer proposes Transfer support vector machine (TSVM) technique which is first of its kind. Figure 3 shows that in this hybrid approach, after preprocessing the attitude signals, data is divided into source domain and target domain. Next, cross-domain features are extracted from a source domain labeled-data and target domain unlabeled-data by performing transfer component analysis. Later SVM is used for classification using this new data as training data. This technique can better distinguish different fault conditions.

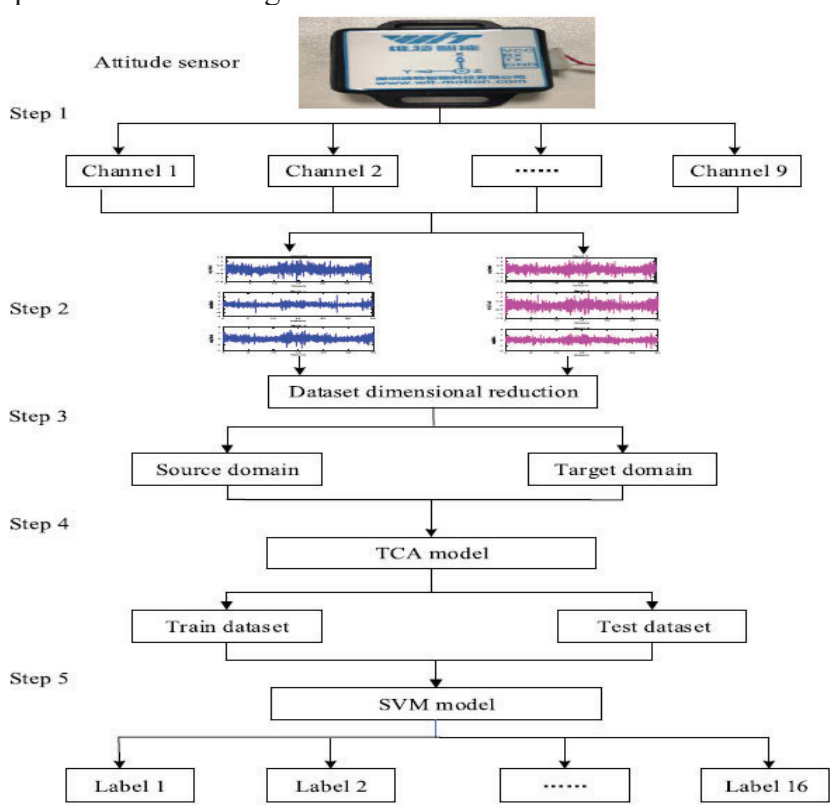

Figure 3: Flowchart for Transfer Learning [7]

Another study [8] employs the least square support vector machine (LS-SVM) for the fault diagnosis modelling. Micro-electro-mechanical systems (MEMS) based attitude sensors are used for attitude monitoring. As shown in Figure 4, data is collected in 12 different condition patterns and fed to the LS-SVM model. The model achieves the highest accuracy of 94.44% in this case of nonlinear multi-classification issue.

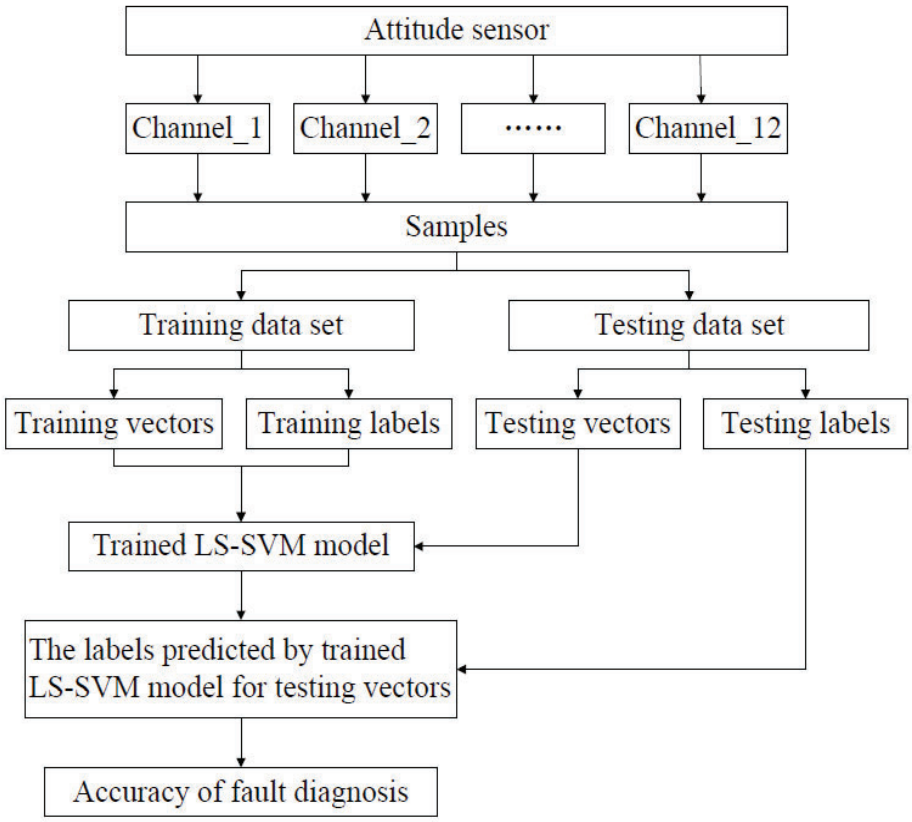


Figure 4: Flowchart for LS-SVM method [8]

3. Process maps:

In addition to the sign of the decision function, its value plays an important role. [9] Has found that the value of decision function has a physical meaning which can be considered to generate a process map for the additive manufacturing process. This study uses SVM to classify the parts built by the EBM process in two classes 'Flat' or 'Non-flat'. According to the study, the probability of obtaining an AM part with a flat surface increases as the value of the decision function increases. It is assumed that surface flatness reflects the energy balance between the input energy and energy loss and is related to internal defect generation. Thus, the value of decision function can be interpreted as a measure of porosity generation. This method uses a small amount of data to determine the process window and can be used to optimize the process parameters.

***Random Forests***

Random forests are another supervised machine learning method used to build predictive models for both classification and regression problems. Random forest algorithm uses an ensemble of randomly generated decision trees to arrive at the best possible answer.

Figure 5 depicts a typical decision tree. Decision tree creates a model to recursively subdivide the data. The aim while choosing every single division in the decision tree, starting from the root node, is to maximize the amount of information gain obtained by that division. Information gain is calculated by finding out the Gini impurity or the entropy gain for that division. Gini impurity is basically the probability (P) of incorrect classification of the $i^{th}$ class. Gini impurity for each node with 'k' classes can be found out using the following equation:

$$Gini\ impurity = \sum_{i=1}^{k} 1 - (P(i))^2 \tag{5}$$

The algorithm, starting from a root node, keeps dividing recursively until a leaf node is formed as shown in Figure 5. The node is called a leaf node if a predefined termination condition is met or the information gain from that division is zero. This algorithm works well with a completely different scale features, or a mix of the binary and continuous feature. However, the model tends to overfit and provides poor generalization performance [10].

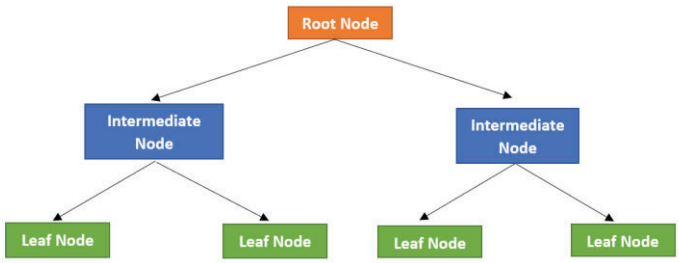


Figure 5: Decision Tree

Random forests address this problem by creating an ensemble of decision trees. As shown in Figure 6, every random forest is built using two methods- bootstrap aggregating (bagging) and random subspace method. In bagging, bootstrap datasets are created which have the same size (n) as the original data set. The no. of these bootstrap datasets is the same as the no. of trees (B) in random forest. These datasets are created from random resampling of data with-replacement due to which datasets can have duplicate entries as well as missing entries. This process is called bagging. Next, to create a decision tree/ classifier, 'm' sub features are randomly selected out of 'M' possible features in the bootstrapped dataset. In most cases, $m=\sqrt{M}$. This is called a random subspace method.

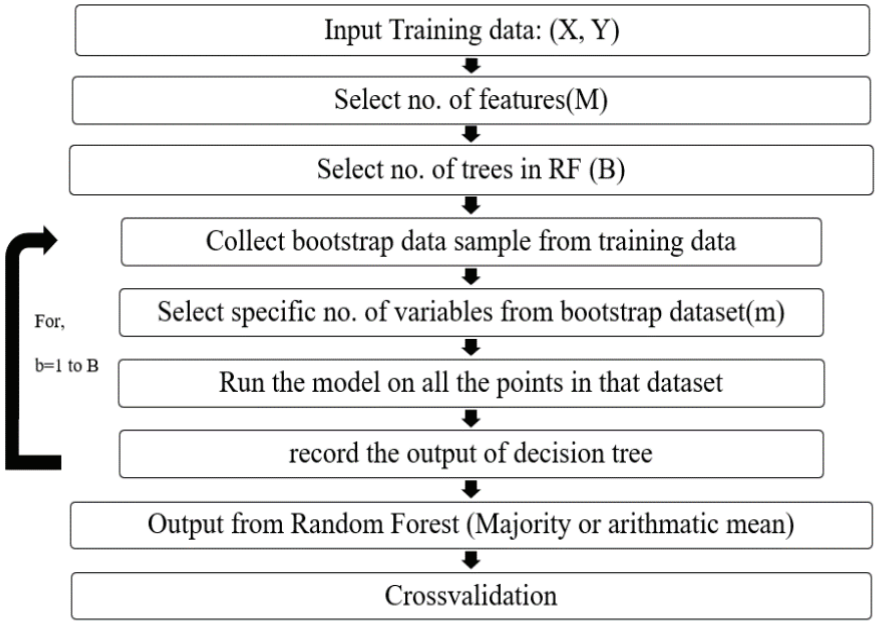


Figure 6: Flowchart of the Random Forest Algorithm

For a random sample ($X_b$, $Y_b$), for b= 1 to B, bagging and feature selection are carried out B times and a classification or regression tree is trained to have B possible outcomes. The output of the random forest is either the majority of the outputs from all decision trees for classification problems or the arithmetic mean of the outputs of all decision trees for regression problems.

Accuracy of random forests can be controlled by choosing the right number of features that are selected and correct depth for decision trees. Since each decision tree works on a different dataset due to bootstrap sampling, this ensemble method decreases the chances of overfitting [11]

### *Applications of Random Forests in Additive Manufacturing*

Being one of the most accurate learning algorithms, random forests algorithm has applications in defect detection, defect prediction which improves the part quality as well as helps in detecting the cyber physical attacks in additive manufacturing.

1. Surface Roughness Prediction

In [12] the algorithm is used to train the model that predicts surface roughness of the parts produced by the FDM process. The study applies feature level fusion process for feature extraction from multiple sensor data such as the temperature of the table and extruder, vibrations of table and extruder, etc. to combine them into a single feature vector. This vector is input to the model which by using regression trees predicts the value of surface roughness. Also, models with individual sensor inputs are also generated. However, sensor fusion proves to be a more accurate method with the lowest cross validation error of 5.91%.

2. Detection of attacks on cyber-manufacturing systems

[13] attempts to use a vision-based system to detect intentional attacks on additive manufacturing processes, employing random forests algorithm. Due to malicious attacks on AM

systems, final products can result in defective infills without affecting the exterior and consequently can produce malicious defective parts without any warning. Random forest is used to accurately classify the in-process images parts as defective and non-defective in order to detect the anomalies during the process.


Figure 7: Procedure for image classification using the random forest algorithm

Figure 7 shows the general procedure for image classification for detecting malicious attacks based on grayscale values of the images, mean, STD deviation, and no. of pixels with a grayscale value above a certain threshold are used as the input features for the random forest algorithm. For accurate feature extraction anomaly detection techniques are embedded with a random forest method which is proved to be advantageous as the detection accuracy is increased almost by 5% [14].

## Summary and Conclusion

The support vector machine algorithm works by generating a hyperplane that can divide the data into two or more classes. The hyperplane generated needs to be tuned in order to perfectly classify the data. This algorithm is successfully used for detecting part defects, diagnosing faults in 3D printers and generating process maps. The accuracy of this algorithm can be increased using different methods for converting input data from the input space to feature space such as transfer component analysis, combining data from multiple sensor modalities etc.

Random forest algorithm proves to be another powerful classifier. It reduces the chances of overfitting and can be used in additive manufacturing as it can work with missing data and does not require scaling. It has been used in research on surface roughness prediction as well as in detecting malicious defects caused by the attacks on cyber manufacturing systems. Accuracy of this algorithm depends upon the no. of decision trees used and no. of levels of each decision tree.

This review shows that, in additive manufacturing, machine learning basically has been applied for defect detection and prediction purposes. Table 3 summarizes the applications of SVM and RF in different additive manufacturing processes for different purposes.

| Aim | Process | Material | ML technique | References |
|---|---|---|---|---|
| Defect Detection | FDM, PBF | ABS, PLA, Stainless steel | SVM | [6], [4] |
| Surface topology | FDM, EBM | PLA, CoCr Alloy | RF, SVM | [12], [7] |
| Porosity Prediction | DLD | Ti-6Al-4V | SVM | [5] |

| | | | | |
|---|---|---|---|---|
| Fault Diagnosis in 3D printers | FDM | | SVM | [7], [8] |
| Cyber Attack Detection | FDM | | RF | [13], [14] |

Table 3: Summary of applications of ML in AM

Figure 8 shows the areas of the applications of both algorithms. While selecting an algorithm for any application there are different parameters that should to be taken into consideration. The input dataset, the method of data preprocessing as well as training the model, dataset taken as ground truth, computation power of the system, the time required for computation are some of the parameters. Thus, the choice of the algorithm is highly application specific which makes it difficult to compare between the two algorithms. For example, as shown in Figure 8, the only common area of research, under the scope of this review, which uses both SVM or RF is regarding the surface topology of the AM parts. However, the performance of both algorithms cannot be compared as SVM is employed for classification and RF is used for regression purpose.

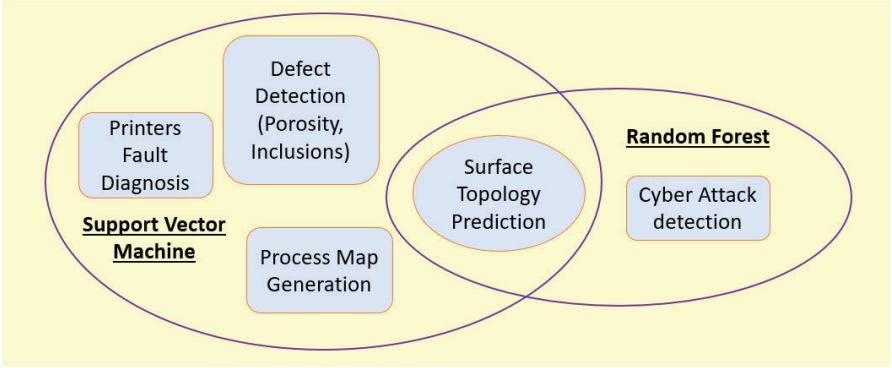


Figure 8: Areas of application of ML algorithms

More research is required in the metal AM processes as till now the majority of studies were conducted on the applications of SVM and RF in various fields of the FDM process. Within the scope of this review, it can be stated that SVM is preferred in comparison to RF. This review is limited to the study of only two supervised learning algorithms. Within the scope of the review, both algorithms prove to be highly accurate in the classification of parts as defective and non-defective. This makes them eligible for the application of detecting the generation of defects in real time.

**References:**

1. Gao, W., Zhang, Y., Ramanujan, D., Ramani, K., Chen, Y., Williams, C. B., … Zavattieri, P. D. (2015). *The status, challenges, and future of additive manufacturing in engineering. Computer-Aided Design, 69, 65–89.*doi:10.1016/j.cad.2015.04.001
2. Gholami, Raoof, and Nikoo Fakhari. "Support Vector Machine: Principles, Parameters, and Applications." *Handbook of Neural Computation*, 2017, pp. 515–535., doi:10.1016/b978-0-12-811318-9.00027-2.
3. Kim, Felix H, and Shawn P Moylan. "Literature Review of Metal Additive Manufacturing Defects." 2018, doi:10.6028/nist.ams.100-16.

4. Gobert, Christian, et al. "Application of Supervised Machine Learning for Defect Detection during Metallic Powder Bed Fusion Additive Manufacturing Using High Resolution Imaging." *Additive Manufacturing*, vol. 21, 2018, pp. 517–528., doi:10.1016/j.addma.2018.04.005.
5. Khanzadeh, Mojtaba, et al. "Porosity Prediction: Supervised-Learning of Thermal History for Direct Laser Deposition." *Journal of Manufacturing Systems*, vol. 47, 2018, pp. 69–82., doi:10.1016/j.jmsy.2018.04.001.
6. Delli, Ugandhar, and Shing Chang. "Automated Process Monitoring in 3D Printing Using Supervised Machine Learning." *Procedia Manufacturing*, vol. 26, 2018, pp. 865–870., doi:10.1016/j.promfg.2018.07.111.
7. Guo, Jianwen, et al. "Fault Diagnosis of Delta 3D Printers Using Transfer Support Vector Machine With Attitude Signals." *IEEE Access*, vol. 7, 2019, pp. 40359–40368., doi:10.1109/access.2019.2905264.
8. He, Kun, et al. "Intelligent Fault Diagnosis of Delta 3D Printers Using Attitude Sensors Based on Support Vector Machines." *Sensors*, vol. 18, no. 4, 2018, p. 1298., doi:10.3390/s18041298.
9. Aoyagi, Kenta, et al. "Simple Method to Construct Process Maps for Additive Manufacturing Using a Support Vector Machine." *Additive Manufacturing*, vol. 27, 2019, pp. 353–362., doi:10.1016/j.addma.2019.03.013.
10. Breiman, Leo. *Machine Learning*, vol. 45, no. 1, 2001, pp. 5–32., doi:10.1023/a:1010933404324.
11. Müller Andreas Christoph, and Sarah Guido. *Introduction to Machine Learning with Python: a Guide for Data Scientists*. Oreilly Et Associates Inc, 2016.
12. Wu, Dazhong, et al. "Surface Roughness Prediction in Additive Manufacturing Using Machine Learning." *Volume 3: Manufacturing Equipment and Systems*, 2018, doi:10.1115/msec2018-6501.
13. Wu, Mingtao, et al. "Detecting Malicious Defects in 3D Printing Process Using Machine Learning and Image Classification." *Volume 14: Emerging Technologies; Materials: Genetics to Structures; Safety Engineering and Risk Analysis*, 2016, doi:10.1115/imece2016-67641.
14. Wu, Mingtao, et al. "Detecting Attacks in CyberManufacturing Systems: Additive Manufacturing Example." *MATEC Web of Conferences*, vol. 108, 2017, p. 06005., doi:10.1051/matecconf/201710806005.

**Appendix:**

1. Meanings of symbols from Table 1

| Symbol | Classifier | Kernel Function | Meaning |
|---|---|---|---|
| $x_i$ | All | All | One input data point in 'n' dimensions |
| $x_j$ | All | All | Another input data point in 'n' dimensions |
| $\rho$ | Polynomial | Polynomial | Degree of polynomial |

| | | | |
|---|---|---|---|
| $\gamma$ | Multilayer Perceptron | Hyperbolic tangent | Slope of tanh function |
| $\mu$ | Multilayer Perceptron | Hyperbolic tangent | Intercept constant of tanh function |
| $\sigma$ | Gaussian | Gaussian | Width of the Gaussian distribution |
| $\alpha$ | Sigmoid | Hyperbolic tangent | Weight for sigmoid function |
| $\vartheta$ | Sigmoid | Hyperbolic tangent | Bias for sigmoid function |