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Applications Of Supervised Machine Learning In FDM Manufacturing: A Review

Naveen Kumar Suniya[1] , Abhisek Gour[2]

[1]Department of Production and Industrial Engineering, Jai Narain Vyas University, Jodhpur, India.

[2]Department of Computer Science and Engineering, Jai Narain Vyas University, Jodhpur, India.

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Abstract

Additive manufacturing (AM), also commonly known as 3D Printing, has emerged as a revolutionary technique for manufacturing components having complex geometries. Fused Deposition Modelling (FDM) is one of the most commonly used methods in additive manufacturing due to multiple factors namely, availability of compatible materials, design ease, reduced wastage etc. However, FDM-based additive manufacturing suffers from some critical issues such as increased build time, need for the support structure, lower mechanical strength, sub-optimal dimensional accuracy, surface roughness etc. In recent times, researchers have attempted to improve these output characteristics and overcome some of these limitations with the help of computational intelligence-based methods. Specifically, supervised machine learning-based techniques have proven to be quite useful in model design, quality evaluation as well as in-situ monitoring. This paper explores and outlines opportunities for such applications and reports specific learnings published over the past few years. Analytical insights into the selection of ML models, model training, and current challenges have been presented to guide further research and experimentation in this interdisciplinary area.

Keywords

FDM, Machine Learning, Artificial Neural Network, Review, In-situ monitoring.

Introduction

The Fused Deposition Modelling (FDM) is the most preferred additive manufacturing technique for manufacturing components requiring complex geometrical structures. Fused Deposition Modelling (FDM) builds 3D parts directly from corresponding CAD models through the successive deposition of layers of a thermoplastic material that fuses to manufacture the components or parts layer over layer (Moradi et al., 2020).

FDM process uses a 3D printer which consists of a print platform (also called build platform), a print bed, an extrusion head & nozzle and a thermoplastic material spool (Penumakala et al., 2020). The temperature-controlled extrusion head is fed with thermoplastic modelling material that is heated to a semi-molten state. The head extrudes and deposits the filament with precision in ultrathin layers. The system builds the desired model, layer by layer, depositing the thermoplastic material in a bottom-up approach. Consequently, the design freedom offered by the FDM process is reported to be significantly higher as compared to the traditional methods of manufacturing (Delli et al., 2018). A schematic diagram of the FDM manufacturing process is presented in Fig. 1.

In FDM-based manufacturing, no specialized tools are required except the 3D printer for pre-build or post-build processing which takes away the hassle of tool availability and reduces limitations to the functional aspects of model design (Sood et al., 2010). However, the fused deposition modelling process currently faces challenges in maintaining the output characteristics of the fabricated parts mainly due to extrusion irregularities.

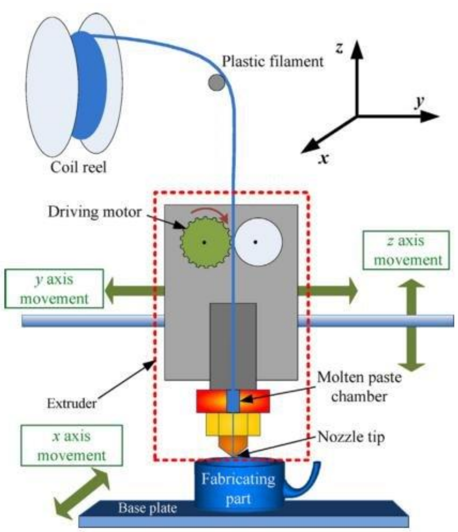

Figure 1 Schematic of the FDM manufacturing process [43]

The quality of the components manufactured through FDM is dependent on multiple process parameters including Air Gap, Build Orientation, Extrusion Temperature, Infill Density, Infill Pattern, Layer Thickness, Print Speed, Raster Width, Raster Orientation, Filament Material, etc. Generally, these parameters are manually determined by skilled professionals based on given requirements.

Moreover, it becomes imperative to achieve desired constraints on the output characteristics to consider FDM as an alternative approach to traditional manufacturing techniques. Some output parameters which are often sought to be important in the literature (Dey & Yodo, 2019; Vyavahare et al., 2020) are mentioned below-

a) Surface Finish / Roughness,
b) Dimensional Accuracy,
c) Tensile Strength,
d) Compressive Strength,
e) Material Usage,
f) Build Time etc.

Apart from these part characteristics, there are some operational parameters such as power consumption, affordability, maintenance cost of 3D Printers, etc. which also influence the adaptability of FDM-based manufacturing approaches. It has been observed that finding the right set of values for all these process parameters requires the deployment of multivariate optimization strategies in the design process. Fortunately, machine learning algorithms have proven to be quite efficient in such cases.

This study provides an overview of existing work on the applications of machine learning algorithms in the selection, optimization, and prediction of such important characteristics. Starting with some brief details about commonly used machine learning methods, also potential areas to apply machine learning in the field of FDM have been outlined. Further, a literature survey of various experiments carried out by researchers and the most important insights have been reported.

Machine Learning Algorithms

Machine Learning (ML) is commonly referred to as a subset of Artificial Intelligence. Generally, machine learning can be identified as the process of extracting useful information from the raw data (Baumann et al., 2018). Most ML algorithms try to find the most significant features in any given dataset based on their statistical and probabilistic relationship with the assessed outcomes. Such information or knowledge can then be utilized for the optimization of the underlying system.

In the past few years, ML techniques are being extensively used as an effective tool for modelling and simulating scientific phenomena, mechanical properties, engineering processes, and different material behaviors in the field of mechanical engineering (Moradi et al., 2020). In the context of fused deposition modelling, applied machine learning involves creating and evaluating models that are capable of understanding the relationships between input process parameters and the respective part characteristics.

Generally, the system has to be trained first on a subset of the data in order to derive useful information. This is commonly known as the learning phase (Baumann et al., 2018). There are different approaches of learning which can be classified into supervised learning and unsupervised learning.

Supervised Learning:

As the name suggests, supervised learning takes place under supervision or with a strategy to correct the learning process for achieving the desired output. For supervised learning, some input and their corresponding results are given to the system. The system then tries to establish the relationship between the given input and the corresponding output. This developed relationship aims to predict the output for a set of input that was not used during the learning process (Jian et al., 2020).

Unsupervised learning:

In unsupervised learning, the learning takes place even if the target output is not available. The system tries to discover and develop a relationship for a set of data without specification (input/ output) (Jian et al., 2020).

Considering the use cases of machine learning techniques in FDM manufacturing, supervised learning models are relatively more useful and it is evident from the literature as well (Yi et al., 2019; Jin et al., 2019). Some of the most commonly used algorithms are Linear Regression, Naïve Bayes, Random Forests, K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN). A brief overview of some of these algorithms is presented here.

A. Naïve Bayes:

Naïve Bayes algorithm uses a maximum likelihood-based probabilistic approach to solve both classification and regression problems (Abdulrahman et al., 2020). Naïve Bayes algorithm uses the posterior probabilities of known data samples and prior probabilities of the known classes in the training dataset to determine the likelihood of all data samples for each possible class. The calculated likelihood is then used to compute the predicted probability of class membership for any unknown data sample. A threshold mechanism is then deployed to classify the input samples into one of the n output classes.

B. K-Nearest Neighbor Algorithm:

KNN is a supervised ML algorithm that is more suitable for classification but has been used for regression problems as well. In KNN, the parameter 'K' is a positive integer that denotes the number of nearest neighbors participating in finding the closest class for a given data sample. The algorithm classifies the data samples based on the majority of the k nearest neighbors. Several distance metrics have been used to determine the similarity/distance between data samples in the KNN algorithm. Manhattan/City Block Distance, Euclidean Distance, Hamming distance, Minkowski Distance and Chebychev Distance are some commonly used distance metrics for calculating the distance between two data points (Nurul et al., 2017). Sensitivity to noise can be decreased by reducing 'K' and the decision boundary can be smoothened with a larger value of 'k' (at the cost of higher computational complexity) (Mehla et al., 2020). An illustration of the KNN Algorithm is given in Fig. 2.

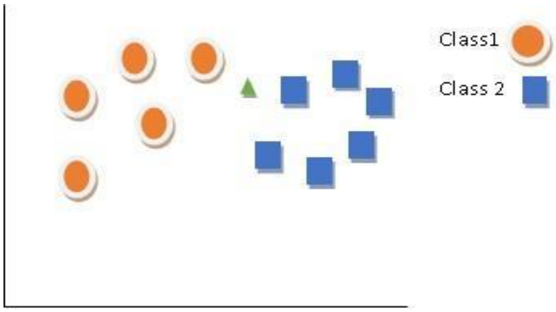

Figure 2 An illustration of the KNN algorithm

C. Support Vector Machines (SVM):

SVM is a simple yet powerful machine learning tool to classify linear as well as non-linear data. For linear data distribution, SVM aims to determine the best hyperplane between two classes by maximizing the orthogonal support vectors between decision boundary and closest data points as illustrated in Fig. 3. In the case of nonlinear distribution, SVM uses a method called "Kernel Trick" to find two (or more than two) hyperplanes to classify the underlying dataset. SVM algorithm requires a smaller number of training data and offers higher computational efficiency when compared to other supervised ML techniques (Joshi et al., 2019).

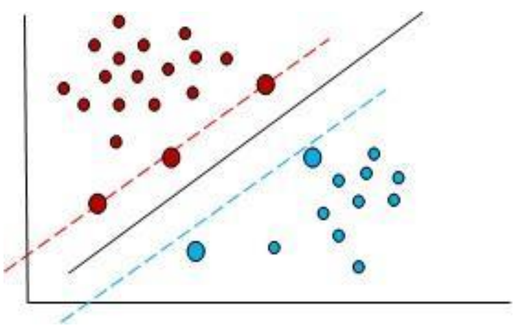

Figure 3 Illustration of a decision boundary identified by a linear SVM

D. Random Forest:

Random Forest is a supervised machine learning algorithm proposed by Briemen (Molero et al., 2020). The algorithm is based on the concept of Decision Trees. Traditionally, a decision tree is implemented as a binary tree structure where each node denotes a classification decision based on the entropy offered by the respective feature. However, non-binary trees have also been used by several researchers for various classification purposes. A Random Forest divides a multi-class classification problem among several decision trees and uses aggregation techniques to produce the final output (Jhu et al., 2019). Bootstrap Aggregation (also known as Bagging) and Random Subspace methods are two such examples often used by researchers. Due to their flexibility, random forests can handle hundreds of variables without excluding any variable (Molero et al., 2020).

E. Artificial Neural Networks (ANN):

ANNs have proven to be a very efficient and effective technique to apply the principles of Machine Learning in most real-world problems with diverse input data characteristics (Abdulrahman et al., 2020). ANNs are based on the human brain model and try to simulate how information is processed by a human brain. A perceptron acts as an artificial neuron and an ANN architecture is composed of multiple layers of these perceptrons. Each perceptron computes a weighted sum of input signals and uses a transfer function to pass the collected information to the perceptrons in the next layer. Every ANN architecture contains an input layer, one or more hidden layers and an output layer (Abdulrahman et al., 2020). Transfer functions used at the output layer determine the type of output generated by the ANN (Agatonovic-Kustrin & Beresford, 2000). An illustration of a basic ANN architecture is shown in Fig. 4.

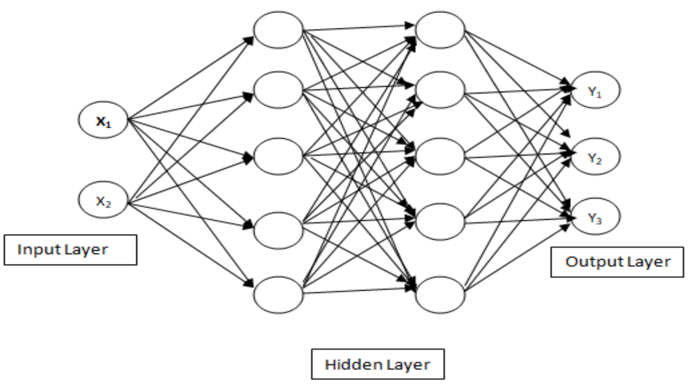

Figure 4 Architecture of an Artifical Neural Network

Optimizing FDM Processes using ML Algorithms

As discussed earlier, FDM-based manufacturing involves several process parameters which can be tuned to impact the output quality and operational aspects of the manufacturing process.

In this section, a detailed analysis of some notable research works using ML algorithms for optimization of various process parameters as per the desired system characteristics is presented.

A. Detecting defects in the FDM printed parts

FDM process uses incremental manufacturing technique which is prone to various process anomalies including printer running out of the filament, mid-progress stopping of the printer (which can be caused by multiple reasons such as electricity break down or manual intervention etc.), structural or geometrical defects, impact on the thermal properties of filament due to environmental conditions and so on.

To solve such issues, Delli et al. (2018) proposed a methodology to check the quality of the printed part by integrating a digital camera with the system and application of image processing and supervised machine learning algorithms on captured images. Images of parts in semi-finished condition are taken at several critical stages of the printing process according to the geometry of the parts. Based on the identification of critical checkpoints in the part geometry, the printing process was paused at these checkpoints to take the images. These images were fed for processing and early detection of defects. ABS and PLA printed parts were used for demonstration. This method is reported to detect both finished failure defects as well as mid-progress structural or geometrical defects. However, pausing the printing process to take images of a semi-finished part at multiple checkpoints increases the build time of the process. This method also suffers from the limitation of the orientation of the camera viewport. In their experimentation, images were taken from top view only, and therefore, the proposed method can detect the defects on the horizontal plane only.

Similarly, during the fabrication process, under and over extrusion can happen at any point due to various anomalies. To overcome this problem, Jin et al. (2019) developed a real-time monitoring and autonomous correction system. It was proposed to modify 3D printing parameters iteratively and adaptively using a feedback loop and deep learning strategies. The proposed system consists of two parts: a CNN-based classification module that identifies under/over extrusion and an in-situ real-time monitoring and refining module which updates the Print Speed, Flow Rate, and Nozzle Height parameters of the 3D printer to achieve desired results. Python-based modules were designed to update these printing parameters through an open-source 3D printer-controller GUI.

Liao et al. (2019) observed various problems in the 3D printers including motor stall, nozzle blockage, squeeze slip of extrusion motor, bearing failure, etc., and developed a fault diagnosis system through sensors and high-speed cameras. The proposed approach was able to identify fault type and fault location during the printing process.

B. Predicting Mechanical Properties of the printed parts

The tensile strength of the printed parts depends majorly on the physical properties of the filament used, thermal configuration of the printing process, printing patterns, etc. Various attempts have been made by the researchers to establish relationships between these parameters and the tensile strength of the printed parts in different scenarios.

For example, Zhang et al. (2020) investigated the relationship between the mechanism of the layer-by-layer printing process and resulting product quality by utilizing the attention mechanisms of long short term memory (LSTM) networks for Fused Deposition Modelling. The research established a data-driven model to predict the tensile strength of the printed part by measuring the temperature with variation in the machine settings.

Sood et al. (2010) proposed an ANN-based model where the input layer had five neurons - one each for layer thickness, air gap, orientation, raster angle and raster width; and the output layer had four neurons representing tensile strength, flexural strength, impact strength, and compressive strength. Tan sigmoid activation function was used for all layers except the output layer (which used a linear activation function). The Levenberg-Marquardt algorithm was used for training purposes for faster throughput and Bayesian Regularization was used for better generalization. Lastly, based on the predicted values of the ANN model, the Bacterial-Foraging Optimization Algorithm (BFOA) was deployed to suggest input process parameters for improving the overall strength of the printed parts.

Pazhamannil et al. (2020) developed a model to predict the tensile strength of printed parts using ANN. Three parameters viz. nozzle temperature, layer thickness, and infill speed were chosen as the independent variables to the model. Tensile strength of PLA printed part as per design of experiments was experimentally investigated and data collected through these experiments were used to train the ANN model to predict the tensile strength.

Ali et al. (2019) presented the application of ML techniques for the prediction of dynamic mechanical properties of parts. Raster angle, build orientation, air gap, and the number of contours were used as independent variables and the natural frequency as the target variable. An integrated system of signal conditioner, data acquisition unit, and the Lab View software to obtain natural frequency readings. The excitement of the test specimen was implemented by clamping it and striking it while an accelerometer was attached to it. Natural frequency of different specimen was recorded using I-optimal design of experiments strategy and an ANN model was trained to predict the natural frequency. It was concluded that goodness of fit between the predicted values obtained from the ANN model and the experimental values can be observed with an overall R^2 value of 99.96%.

Polylactic acid (PLA) is one of the most used materials in 3D printing due to its affordable cost and deformation properties. Moradi et al. (2020) enhanced the producibility of PLA-based parts using fused filament fabrication and machine learning techniques. The research claimed to improve the toughness and reduce the production cost of the FFF printed tensile test samples while not compromising the desired part thickness. To achieve these results, an ANN-based modelling process was proposed. In the proposed approach, the response surface method (RSM) was used to prevent idle printing samples. Further, a combination of Genetic Algorithms and ANN (GA-ANN) was used to develop an accurate estimation for toughness, part thickness, and production cost based on input variables specifically, layer thickness (LT), infill density (ID), and extrusion temperature (ET). Researchers reported that the technique improved the modelling accuracy by about 7.5% for toughness, 11.5% for part thickness, and 4.5% for production cost in comparison with ANN only. 70 percent of the total data was considered as training data for ANN and 30 percent data was used as testing data. First hidden layer initiated with 10 neurons and continued up to 16 neurons with an increment of 2 neurons.

Barrrionuevo & Ramos-Grez (2020) investigated the effect of layer thickness, infill density, and raster angle on the yield strength of wood composite filament-timber fill fabricated by FDM. A hybrid machine learning tool, named ANFIS (Adaptive Neuro-Fuzzy Inference System), was implemented to determine the optimal value of the considered factors to achieve maximum yield strength. Maximum yield strength was reported at high layer thickness with 100% infill density and 90^0 raster angle parallel to the load direction. It was reported that the proposed model performed well even with lesser training data.

Kam et al. (2018) investigated the effect of machine vibration on the mechanical properties of PETG printed parts. 18 specimens were printed using different orientation angles and printing speeds. Vibration amplitudes were measured in the x, y, and z axes. It was reported that the vibration of the extruder and build platform affects the mechanical properties of printed parts significantly.

C. Predicting the Surface Roughness of printed parts

Due to the layer-by-layer manufacturing process in FDM, surface roughness becomes a critical characteristic to assess the quality of manufactured parts. Fortunately, the same can be improved with the appropriate selection of process parameters.

For example, Boschetto et al. (2013) built a neural network to model the surface roughness of 3D printed parts on the basis of chosen layer thickness and deposition angle. They used Levenberg- Marquardt's (LM) algorithm to train the network. The trained network proved to be useful in obtaining a FDM roughness model that was proposed to be effective at all ranges of deposition angle.

Later, Barrios & Romero (2019) compared various decision tree-based models including C4.5, Random Tree and Random Forest for predicting the roughness of 3D printed parts made from polyethylene terephthalate glycol (PETG). Layer height, temperature, printing speed, print acceleration and flow rate were used as independent variables and surface roughness as the target variable. Authors used the ‘L27’ orthogonal array methodology for designing of experiments. It was concluded that the Random Tree variant shows better results in predicting the surface roughness of 3D printed parts.

Some researchers also attempted to use embedded sensing components to improve the surface roughness of printed parts. For example, Wu et al. (2018) developed a sensing system to monitor the health of the FDM process with the help of a random forest-based model that predicts the surface roughness in real time. The proposed model showed promising results in predicting the surface roughness with high accuracy after analyzing the experimental data.

Similarly, Li et al. (2019) proposed a data-driven approach for the prediction of surface roughness. Various sensors incl. thermocouples, accelerometers, and infrared thermal sensors were used to collect the temperature and vibration data during the FDM process. An ensemble algorithm was proposed to train the prediction model. Sensor-based monitoring data were used to extract the features in the time and frequency domain. A subset of these features was used to improve the prediction accuracy and computational efficiency. The validation of the prediction model was carried out by the monitoring data extracted from a set of FDM tests conducted on a fused filament fabrication (FFF) machine.

To study the effect of different learning algorithms on prediction performance, Molero et al. (2020) tried ten different algorithms to predict the surface roughness of the parts printed with Polylactic Acid (PLA) material. Input data collected through 27 horizontal (XY) and 27 vertical (XZ) specimens were supplied as input to different models. Machine Learning algorithms like Bayesian Networks, Naïve Bayes, Multilayer Perceptrons (ANN), Logistic Regression, SVMs, KNN, K-Star, Decision Tree variant J48 (C4.5), Logistic Model Trees & Random Forests were used to train the respective models. Based on their experimentation, they concluded that Multi-Layer Perceptrons and Logistic Model Trees performed better in predicting the surface roughness of printed parts.

D. Machine learning algorithms for in-situ monitoring

Many researchers have attempted implementation of various strategies to carry out in-situ monitoring of the manufacturing process. Saluja et al. (2020) developed a prediction model to detect warping of printed parts using a Convolutional Neural Network during the fabrication process. They proposed to capture an image of sample corners every two seconds by modifying original G-codes. In addition to this, a script was designed to extract, resize and grayscale the corners of the samples from the captured raw images. These processed images were fed to a CNN model and then trained to predict warping. Their initial experiments were not promising but after experimenting with different architectures and activation functions, they reported the validation mean accuracy of 98% while using the Leaky-ReLU activation function.

Kim et al. (2018) used two accelerometers and acoustic emission (AE) sensors to develop a data-driven monitoring system. For modelling, the data was collected at a large scale under healthy as well as faulty process conditions. Root Mean Square (RMS) values from these collected data samples were used as training data for training an SVM algorithm. This research concluded that by the use of such a monitoring system, the wastage of material and energy consumption can be reduced due to the prevention of faulty manufacturing.

Similarly, Wu et al. (2015) applied an acoustic emission technique to identify normal and abnormal states of FDM machines. SVM with the radial basis function kernel was implemented to identify the state. Liu et al. (2018) used an acoustic emission sensor to diagnose the fault in FDM. The efficiency to identify the machine state was improved significantly using reduced feature space dimension.

Kantaros & Karalekas (2013) identified the effect of layer thickness and deposition orientation on the magnitude of residual strains developed due to solidification. An optical sensor with a short Fiber Bragg Grating (FBG) was embedded at the mid-plane of a prismatic specimen to record the residual strains developed at the end of the FDM process. It was concluded that residual strains measured for 0^0 direction, where beads are along the long dimension of the specimen lower than the other directions.

E. Predicting Power Consumption in the FDM Process

The manufacturing industry contributes to a large part of energy consumption and therefore, over the last few decades, sustainability of energy is sought for action in the adoption of new manufacturing processes (Yang & Liu, 2020).

Yi et al. (2019) implemented a Random Forest (RF) based algorithm to simulate and predict the energy consumption in the FDM process. For the training of proposed ML models, power data with a 1-second sampling rate was captured during the printing process. To be precise, data on the consumption of power for the training of the model and for inference was also collected. Further, G codes for different input variables (i.e. print speed, moving position, or extrusion of materials) along with collected power data were used as input, and power consumed for different input values was used as the target variable of the model. The collected data was split into a 70:30 ratio. A hybrid combination of five variants of the Random Forest algorithm namely, gradient boosting regressor (GBR), light gradient boosting machine (LGB), Bagging Regressor (BGG), RF Regressor (RFR), and eXtreme gradient boosting model (XGB) was trained. The trained hybrid model was labelled as the RF simulator. This research concluded that the proposed model is a powerful tool for developing energy simulation of the FDM process. The XGB shows the best training quality at the validation stage of the training and the LGB model shows the highest average prediction accuracy in the experimental comparison for this case.

Alternately, Yang & Liu (2020) provided a flexible and modular modelling method for output indicators such as manufacturing time, energy, and material consumption based on path planning code and machine characteristics. It predicts an accurate consumption from arbitrary manufacturing at the pre-manufacturing phase and allows users to customize the machine parameters to reduce the consumption. Model precision was validated by performing the test of two design models with different parameters.

F. Improving the Geometrical Structure of the printed parts

The dimensional accuracy of printed parts is heavily dependent on extrusion settings of the printer such as layer thickness, infill speed, nozzle temperature, etc. as well as the thermal properties of the material used.

Deswal et al. (2019) tried to establish the relationship between these parameters and optimize them for improving the preciseness of the FDM process. Two-hybrid machine learning models incl. GA-ANN (Genetic Algorithm - Artificial Neural Networks) and GA-RSM (Genetic Algorithm - Response Surface Method) were used for training and optimization. They concluded that GA-ANN outperformed GA-RSM in estimating all the dimensions (length, width, and thickness).

While printing objects through FDM in a layer-by-layer fashion, it is equally important to plan support structures when building certain objects. By optimizing process parameters, the distance between two facets can be maximized to reduce the need for support structures. Jiang et al. (2019) investigated the effect of process parameters on printable bridge length (PBL) with the help of Back Propagation Neural Networks (BPNN). BPNN along with the orthogonal design of experiments was used to predict the non-linear relationship between PBL and various process parameters, specifically, bridge length, print speed, print temperature, and cooling fan speed. The BPNN model was trained to predict the deformation of the bridge. They found that the longest PBL can be increased as cooling fan speed increases, print speed decreases, and print temperature decreases.

Comparative Analysis

A brief comparative analysis of these studies is presented in Table 1. It can be observed that Artificial Neural Networks (ANNs) appear more often in the literature as compared to other ML algorithms. Similarly, most of these studies focus on improving either mechanical properties or surface roughness of the printed components. Many algorithms have utilized a combination of Genetic Algorithms as an optimization strategy along with machine learning approaches to find the best input parameters for the desired results.

Table 1. Comparative Analysis of various ML Approaches in FDM Manufacturing

S. No.	Title	Author(s)	ML Algorithm Used	Target Parameters
1.	Automated process monitoring in 3D printing using supervised learning	Delli et al. (2018)	Support Vector Machine (SVM)	Manufacturing Defects
2.	Modeling, analysis, and optimization of dimensional accuracy of FDM-fabricated parts using definitive screening design and deep learning feedforward artificial neural network	Mohamed et al. (2021)	Artificial Neural Network (ANN)	Dimensional accuracy
3.	Enhancing 3D Printing Producibility in Polylactic Acid Using Fused Filament Fabrication and Machine Learning	Moradi et al. (2020)	ANN & ANN-GA (Genetic Algorithms)	Toughness, Part Thickness, Production Cost
4.	Energy simulation of fused deposition modelling using machine learning approach	Yi et al. (2019)	Hybrid Random Forest Algorithm	Energy Consumption
5.	Attention mechanism incorporated Deep learning for AM part quality	Zhang et al. (2020)	LSTM (Deep Learning)	Tensile strength
6.	Autonomous in-situ correction of fused deposition modelling printers using computer vision and deep learning	Jin et al. (2019)	ANN	Over extrusion/ Under extrusion
7.	Surface roughness prediction in fused deposition modelling by neural networks	Boschetto et al. (2013)	ANN	Surface Roughness
8.	Analysis and prediction of printable bridge length in fused deposition modelling based on backpropagation neural network	Jiang et al. (2019)	ANN	Printable Bridge Length (PBL)
9.	A Hybrid ANN-BFOA Approach for Optimization of FDM Process Parameters	Sood et al. (2010)	ANN	Mechanical Strength
10.	The fabrication of long carbon fiber reinforced polylactic acid composites via fused deposition modelling: Experimental analysis and machine learning	Hu et al. (2021)	Gaussian Process Model	Mechanical Properties

11.	Predictive modelling of surface roughness in fused deposition modelling using data fusion	Wu et al. (2019)	Random Forests, SVM Regression, Ridge regression, Least absolute Shrinkage, and Selection Operator	Surface Roughness
12.	Natural frequency prediction of FDM manufactured parts using ANN	Ali et al. (2019)	ANN	Natural Frequency (Mechanical Property)
13.	Prediction of the tensile strength of polylactic acid fused deposition models using artificial neural network technique	Pazhamannil et al. (2020)	ANN	Tensile Strength
14.	A closed-loop in-process warping detection system for fused filament fabrication using convolutional neural networks	Saluja et al. (2020)	CNN	Warping (Defect) Detection
15.	Modelling and analysis of significant process parameters of FDM 3D printer using ANFIS	Yadav et al. (2020)	ANFIS (Adaptive Neuro-Fuzzy Inference System)	Tensile Strength
16.	Detecting first layer bond quality during FDM 3D printing using discrete wavelet energy approach	Khattab et al. (2014)	Discrete Wavelet Transform	First-layer Bond Quality
17.	Modelling and parametric optimization of FDM 3D printing process using hybrid techniques for enhancing dimensional preciseness	Deswal et al. (2019)	ANN-GA, ANN, ANN-RSM	Dimensional Accuracy
18.	Decision Tree Methods for Predicting Surface Roughness in Fused Deposition Modeling Parts	Barrios & Romero (2019)	C4.5 Trees, Random Trees, Random Forest	Surface Roughness

19.	Use of Data Mining Techniques for the Prediction of Surface Roughness of Printed Parts in Polylactic Acid (PLA) by Fused Deposition Modeling (FDM): A Practical Application in Frame Glasses Manufacturing	Molero et al. (2020)	Bayesian Networks, Naïve-Bayes, ANN, Logistic Regression, SVM, KNN, KStar, J48 (C4.5), LMT, Random Forest	Surface Roughness
20.	Surface Roughness Prediction in Additive Manufacturing Using Machine Learning	Wu et al. (2018)	Random Forest	Surface Roughness
21.	Prediction of surface roughness in extrusion-based additive manufacturing with machine learning	Li et al. (2019)	Classification and Regression trees (CART), Random Vector Functional Links (RVFL), Ridge Regression (RR), SVM Regression, Random Forest, AdaBoost	Surface Roughness

Conclusion and Future Directions

The present research attempts to provide an understanding of the ongoing efforts in finding applications of machine learning in Fused Deposition Modelling. It can be observed that many researchers are exploring traditional machine learning and optimization algorithms to establish relationships between process parameters, part characteristics, and operational factors. However, most of these attempts are limited to classical statistical approaches such as ANOVA, SVMs, Decision Trees, ANNs, etc. However, these approaches have shown promising results in the prediction of the part characteristics specifically, tensile strength, surface roughness, toughness, etc. It can be observed that many studies have tried to use neural network-based architectures in conjunction with genetic algorithms for deriving optimal values of input parameters for the desired target performance.

Most of the studies that tried to investigate the impact of various process parameters on output quality have reported significantly high prediction accuracy (generally above 90%). However, in some applications such as in-situ monitoring of manufacturing quality, researchers have reported several limitations in the work carried out. For example, Jin et al. (2019) observed that while predicting the abnormal extrusion events with visual methods, the quality of the dataset plays a major role in the achieved accuracy. Delli et al. (2018)

highlighted that their approach could identify defects in the horizontal plane of manufacturing and required pausing the printing process which could have been avoided by installing the camera on the print head or using multiple cameras. It has also been observed that gathering images from different angles and focusing on the boundary images can further improve the usability of such in-situ monitoring systems. Moreover, most of the input parameters analyzed by the researchers can be observed to have a direct impact on the output quality. However, some higher-order process parameters such as acceleration and deceleration of the nozzle motion, vibration of the print bed, thermal properties of the material used, etc. have not been investigated in much detail.

Surprisingly, only a very few studies have attempted to use the relatively newer machine learning approaches such as Random Forests, Ensemble Methods, etc., or deep learning approaches such as Convolutional Neural Networks, Long Short-Term Memory (LSTM), Generative Adversarial Networks (GANs), etc. For example, Zhang et al. suggested that further improvements in the tensile strength can be achieved by utilizing deeper neural networks and carrying out precise hyperparameter tuning of the trained model. There is also a greater scope for conducting investigations on hybridized techniques used in the FDM process in the near future as some hybridized techniques provide better results as compared to any individual approach.

Further, very few studies have attempted to investigate the holistic inclusion of machine learning approaches in the industrial manufacturing context. For example, utilizing such investigations on improving the design of 3D printers, printer health monitoring, identification of newer printing materials, preventive maintenance of 3D printers, etc., and validation of such findings in the industrial environments is yet not explored in sufficient detail.

To conclude the discussion, it can be observed that a significant amount of research is being carried out for using ML techniques in FDM manufacturing processes. Yet more interdisciplinary attempts towards utilizing advanced sensor systems, computer vision, and machine learning approach in finding new use cases for FDM manufacturing such as repairing broken parts, improving the degree of freedom to achieve multi-plane printing, in-situ identification of structural defects, elimination of support structures, multi-part printing, etc.

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