

# Application of Artificial Intelligence in Additive Manufacturing- A Review

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## Abstract

Additive manufacturing is technique of producing a 3D object layer by layer. This is different from a conventional machining operation. In a conventional machining, a component is made by removing chips from the raw material. Additive manufacturing is also called 3D printing. 3D printing has the advantage in that it can produce any complicated 3D object. 3D printing has been deployed in food industries, chemical industries, aeronautical industries, healthcare industry, etc. Many researchers have been working in the recent past on additive manufacturing. In this research work an attempt has been made to explore the usefulness of artificial intelligence (AI) in additive manufacturing. AI enabled Additive manufacturing results in significant cost reduction. Though many researchers have been working in the area of AI not many researchers have focused in detail on the applicability of AI in the area of additive manufacturing. In this context, the findings of current research work assume special significance. The research findings from the current research work provide future directions which are useful not only for academicians but also for practitioners interested in pursuing further research.

## Keywords

Industry 4.0, AM, Artificial Intelligence, Smart manufacturing, Additive manufacturing

## 1. Introduction

Artificial intelligence, a technique by which computer connected devices mimic human intelligence. Applications of Additive manufacturing (AM) applications is found currently in food, chemical, aerospace, automotive and healthcare industries. The biggest benefit of 3D printing is that even complex objects can be made as per customer requirements. It is better suited for low volume production as of today. The stages in additive manufacturing are 3D model preparation, component prototyping and component production. The objective of prefabrication stage is to figure out whether it is technically possible and feasible to print a given 3D model. Artificial intelligence enabled 3D printing /or AM is also called smart manufacturing. The smart manufacturing would result in improved productivity.

## 2. Literature Review

An attempt has been made in the following paragraphs to bring out the usefulness of the AI in additive manufacturing.

### 2.1 Printability

Printability shows the ease with which a 3D object can be made by 3D printing (Telea and Jalba 2011). In theory, any 3-dimensional object can be made by additive manufacturing. The scope of 3D printing is limited by the component geometry. Applicability of 3D-printing is also restricted by the type of material. Selection of 3D printing is decided by the amount of time available for product manufacture. Lu (2016) has proposed an algorithm for measuring the printability of any 3D object. That is by using this method, it is possible to find out whether any given object can be produced by 3D printing or not. The method consists (Figure 1) of a module for feature extraction, using machine learning and another module for managing 3D-printer. This method calculates the printability by looking into cost, size and time. So, printability measure is very useful in production environments. This would help in decision making.

## 2.2. Improving Efficiency in Pre-fabrication

Today's customer requirements necessitate production of products having complex geometrical features. The more the complex the product is the more time is required in performing slicing of the object. Slicing basically stores the information about the tool path movement. This is similar to the cutter location data generation in a CNC machining. Just like how CL data is used in CNC machining for moving the cutting tool in the required path, similarly the slicer data is used by the 3D printer for moving the printer head in producing a 3D object. This constitutes the prefabrication phase. Researchers have been using AI in improving the efficiency in slicing operation (Kulkarni et al. 2000).

Adaptive slicing algorithm proposed by Gregori et al. (2014) was computationally very efficient. John C et al. (2016) developed a implied slicing algorithm. The main objective of using AI in slicing algorithm is to make it computationally more efficient. Though many researchers have been working on improving the efficiency of slicing algorithms, still much more work needs to be done with regard to reducing the computational time and possibility of using parallel computation. With the advent of Industry 4.0, especially Big-data, parallel computing has become a necessity as the implementation of AI require huge computational infrastructure. Literature shows that researchers have proposed methods consisting of two processors for speeding up of pre-fabrication in 3D printing.

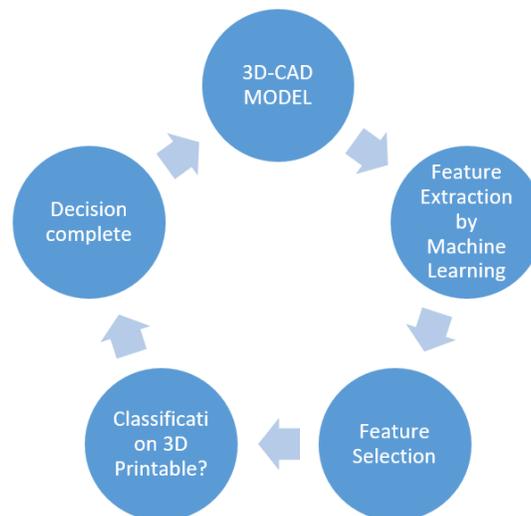


Figure 1 Working principle of a Printability checker

## 2.3 Service-oriented architecture-SOA

Many researchers have proposed methods that makes use of Service oriented architecture (SOA) during 3D object manufacturing (Mell and Grance 2009, Tao et al. 2011, Hassan 2011, Hassan 2009, Da Silveira et al. 2001). Nowadays company's use manufacturing as a service. This technique requires cloud infrastructure. In this technique, instructions for part fabrication are given through the cloud and the actual component/ or part will be produced by 3D printing at the other end of the cloud. Thus, SOA would help implementing smart manufacturing. This has both variety and volume flexibility. Hence very useful in meeting customer demand. In SOA based architecture (Figure 2) manufacturing process can be controlled from different geographical regions. Both starting and stopping of 3D printing is possible through cloud. Figure 1 shows how different cyber physical systems (CPS 1 to CPS 6) interact using service-oriented architecture using cloud infrastructure. This would help companies to work on collaborative mode. Customer on-demand feedback is possible through cloud. Corrective actions are possible through cloud by taking inputs from the users.

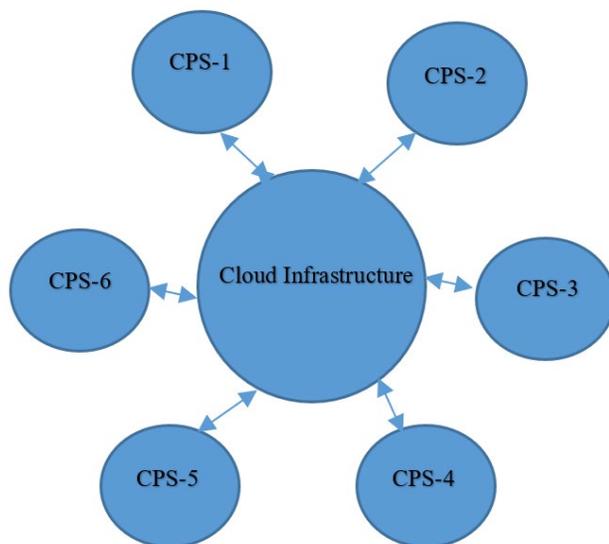


Figure 2 Working principle of service-oriented architecture

## 2.4 Defect detection and classification

Many researchers have studied products produced from additive manufacturing and have concluded that they may have several types of defects.

### 2.41 Types of defects

Porosity defect in AM fabricated product is detrimental. This defect would result in product failure, when the product becomes operational. Researchers have observed overall porosity from 1% to 5% in AM fabricated products. Researchers have demonstrated that the shape of the pores as well as the orientation of the pores and the size of these pores may lead to product failure. Porosity types - (i) Lack of fusion (LOF) porosity (ii) Gas porosity.

In correct selection of process parameters during AM would result in LOF defects. Yadroitsev et.al. (2007) have observed that optimizing the hatch distance porosity in AM products may be minimized. They employed a laser spot size (SZ) of 70  $\mu\text{m}$  and (HW) hatch width of 120  $\mu\text{m}$  for minimum porosity. Detailed study on the effect of hatch distance on porosity was made by Mireles et.al. (2015).

During additive manufacturing when there is a gas entrapment, would result in gas pores. Ng et.al. (2009) have done extensive analysis of gas pores and have concluded that it is impossible to eliminate gas pores in AM products. However, the AM products may have gas pores to the extent of 0.7%. Sercombe et.al. (2008) have studied gas-pores formation and have concluded that these pores would act like crack propagation centers.

### 2.42 Defect identification and classification by using Artificial Neural Networks

Earlier much of the information processing including logical reasoning was processed by human brain. Many researchers (Principe et al. 2000) started mimicking human brain by making use of computers. This has given the Artificial Neural Network (ANN). In ANN (Figure 3), input layer will have set of nodes. Data from external environment or external devices will be received by this input layer. The input layers will calculate weighed data and will be passed onto the hidden layers. These hidden layers also consist of set of nodes. The hidden layers will process the weighed data received from input layer before sending them to output layer. The output layer also consists of set of nodes. The output layer will send the transformed values to the end user.

The process of computing optimum weights by the input layer is called training of the ANN. When a comparison is made between the output of ANN with that of expected output, it is called supervised learning. For the first iteration, weights are set to random values. So that less deviation is observed between actual and expected results. The process is repeated and many iterations are made.

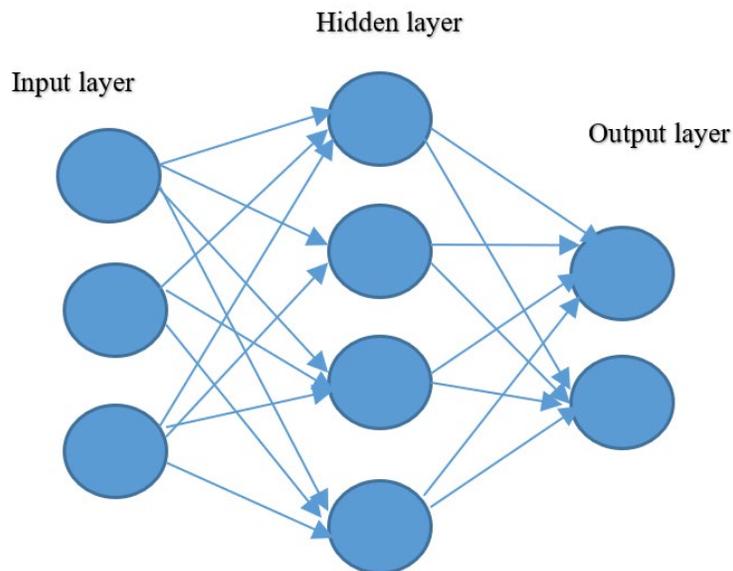


Figure 3 Artificial Neural network

At the time of training the network, input as well as output data are made available to the given network. The amount of time taken for training of a network varies from problem to problem. As and when a network approaches pre-defined performance target, training is said to be complete. No more training is required for the network. At this stage, the network can be employed for testing with data obtained outside trained data samples. If ANN gives satisfactory results during this stage this means that the network has learnt the general patterns of the application.

## 2.5 Real-time build control

Researchers have shown that by controlling molten metal, scan speed, and layer thickness it is possible to control the quality of the manufactured product. Thus, quality of the AM manufactured product can be controlled by real time build control. For performing Real-time build control involves three inputs: 3D object geometry, Training data set, Executing free form deposition. Machine learning is employed for exercising real-time build control (Edward et al. 2018).

## 2.6 Predictive maintenance

By performing timely and routine maintenance, service life of a machine tool may be extended. Preventive maintenance is done as per pre-defined schedule. Whereas, in the case of break down maintenance, maintenance of a machine tool is done only after a failure. With the advent of advanced technologies such as sensors, new, cost-effective and intelligent condition monitoring systems have been developed. These systems are used for performing condition-based maintenance system of machine tools. With the advent of sensors, real time data on process variables is made available to knowledge-based models. These models are used for predicting the remaining life of machine tools. Thus, AI/ machine learning is used for preventing un anticipated machine breakdowns and thereby enhancing the machine availability and quality of the manufactured product. Yam et al. (2001) have proposed a system which consists of - Condition monitoring of the machine, fault diagnosis and prediction machine deterioration. By using such systems would help in estimating the remaining useful life of the equipment. This will also help in selecting appropriate maintenance policy for the machine.

Eckart Uhlmann et al. (2018) and Jardine et al. (2006) have designed the necessary steps, for identifying clusters, from sensors data. The steps are - SLM equipment data obtained through the sensor, Pre-processing of data, and Cluster-based analysis and evaluation. The results are used for subsequent preventive maintenance of SLM machine.

## **2.7 Material Waste reduction**

In additive manufacturing a 3D object is produced, layer by layer, from first layer to the last layer, incrementally. Thus, 3D-printing of objects with overhang is not possible (Leary et al. 2014). In order to overcome this limitation, parts with overhang need proper supports. But the problem here is that these supports will have to be removed through post processing, after manufacturing. This will add up to the cost of manufacturing. Hence, many researchers have been working in minimizing the support and hence the wastage. One more factor that requires researcher's attention is the part orientation. Because, proper orientation will bring huge savings in reducing support. Many researchers observed the relationship between part orientation and support (Pham et al. 1999, Frank et al. 1995, Strano et al. 2013, Das et al. 2017, Morgan et al. 2016).

Many researchers have tried by using cheaper material for providing support. The scheme followed here is that once the manufacturing of the component gets over support material is dissolved.

Hopkins et al. (2009), have used acrylic co-polymers as support material. By this way, the support can be taken out easily. Acrylonitrile butadiene styrene material was used for 3D printing by using support painted with polylactic acid (Domonoky et al. 2017). The component when immersed in isopropyl alcohol and potassium hydroxide the support will be removed. Ni, F et al. (2017) has explored by using polyvinyl alcohol as a support material (because it dissolves in water) in 3D printing process.

## **2.8 Minimizing Energy Consumption**

Additive manufacturing process consumes more energy than traditional machining process (Table 1). Though many researchers have been working on additive manufacturing, very little focus is given regarding energy consumption by AM process. 3D printing is performed either by SLS or FDM.

In SLS process, laser light is used as a heat source. During the process, laser light is moved over metal powder which is evenly spread on metal platform. During the process, the laser, is moved as per the CAD model in incremental fashion. This will cause sintering of the metal powder. This forms a layer of the 3D object. After the first layer is formed, roller is used for spreading metal powder evenly and then the entire process is repeated. The SLS process, is carried out by many researchers (Mansour and Hague 2003) by using various types of polymers such as ceramic materials polyester, metals, etc.

In SLS process energy is consumed not only for the processing but also for performing non-value adding activities. Energy required for processing depends upon how much material is to be fused while building the 3D object. In addition to processing, energy is also consumed while moving piston, re-coater arm and heating. Researchers have demonstrated that processing consumes about 56% of the energy. This clearly shows that significant amount of energy is consumed in performing various non-value adding activities. Thus, in future much attention is required from researchers in minimizing the energy consumed in performing non-value adding activities. This would be a significant value addition.

The following factors contribute to the process energy requirement for sintering the material powder Lu (2016) observed that absorptivity of parent material, the average intensity of the laser, scanning speed of the laser and the spot diameter of the laser add up to the processing energy consumption. Main limitation of the additive manufacturing process is that it consumes more energy than the traditional machining process. Thus, much research is required in this direction in making the AM process eco-friendly.

Table 1 Comparison between different manufacturing processes

Manufacturing process	Specific Energy consumption (KWH/Kg)	Reference
Turning	9.8 (Brass)	Kara and Lee (2011)
	7.0 (Mild steel)	Kara and Lee (2011)
Milling	6.8(Mild steel)	Kara and Lee (2011)
Injection molding	1.47	Duflou et.al. (2012)
SLS	29.83-40.09	Luo et.al. (1999)
FDM	23.08-163.69	Luo et.al. (1999)

### 2.9 Spare parts manufacturing

Whenever an automobile goes down or become non-operational spare parts-bearings, brakes, handle etc. are required. Spare parts requirement arises, whenever a component is broken or worn-out. In a conventional set-up a inventory of spare parts is kept. This would help in meeting the spare parts requirements of the customer quickly. This way of maintaining inventory of spare parts in a company has the risk of under stock or excess stock. By keeping less inventory of spare parts would result in spare parts not reaching the customer on-time. Thus, keeping under stock will cause customer dissatisfaction. Thus, in understock scenario, the company will lose its reputation. Similarly, keeping excess stock will result in high inventory carrying cost.

Industries, nowadays, make use of machine learning enabled 3D printing for spare parts manufacturing. For the supply of spare parts to automobile and defense sectors. Machine learning based technologies would help in predicting the life of an equipment. Thus, it is possible to help in knowing when the equipment is going to fail and how many sparts are required. 3D printing would manufacture that many spare parts and deliver at the right time. Thus, spare parts can be made available at right time and this would make the customer happy. This would also result in unexpected equipment failure and the resulting downtime. This would enhance the brand image of the manufacturer. Spare parts manufacturer will have reduced cost in logistics, reduced inventory cost, if he is close to the customer.

### 2.10 Security enhancement and intruder detection

Security based solutions can be of two types- prevention-based methods and detection-based methods. Prevention-based methods use encryption and authentication as means of protecting against possible attacks. Detection based methods are used when prevention methods fail. The detection methods are classified as follows-Signature detection Anomaly detection and Hybrid methods.

An attempt has been made in the following paragraphs to elaborate challenges and present the intruder detection architectures used in the 3D printing.

With the advent of Industry 4.0, attempts were made to integrate industrial systems with communications technologies has resulted in increased security threats. Providing security to the cyber-physical system involves an integrated approach involving various security systems. Cyber-physical systems will come under dual attacks- Denial-of-service attack (DoS) and Deception attacks. In DoS, type of attack, the attacker blocks the services of a device either temporarily or permanently to the Internet. A deception attack is also known as a false data attack. Here, the attacker injects false data into the target node. This may result in instability of the cyber-physical system or sometimes performance degradation. In a cyber-physical system (Figure 4), sensors will collect data and will be sent through a

communication network, without any human intervention. The intent of such a system is to control a heterogeneous swarm of cyber-physical systems by artificial intelligence. Norman (2012) developed a solution for a distributed access control system by using an expert system. Nowadays, swarm intelligence algorithms are made an integral part of a control system (Perez et al., 2018).

Desnitsky et al. (2016) have proposed a scheme for detecting intruders in the case of cyber-physical systems. The scheme includes designing the protected embedded system. A good example given here is the indoor security system. The solution proposed here selects the best combination of security components depending upon the optimization problem. In this method, after identifying functional and non-functional requirements, optimum number of components are determined and then figuring out harmful effects on the device based on testing. The author also claims that the method can be tweaked for managing a group of devices for shielding of the area under consideration.

*Types of attack detection methods:*

**A Denial-of-service attack:** Detection is the first and foremost step in the fight against such attacks. Literature has reported using machine learning techniques for protecting cyber-physical systems. These techniques are known as data-based approaches.

*Signature-based method.*

Signature-based attacks try to identify the attack signatures with that of others employing separating normal traffic from that of a fake one (Buczak et al. 2017, Kaur et al. 2017).

To conclude many researchers have been working in the design and development of intruder detection systems for enhancing safety in many domains/ applications. However, there are many challenges and many areas remain untouched. The chapter provides opportunities and future direction in the area of intruder detection, for the interested researchers and practitioners.

*Anomaly-based method.*

This technique tries to detect normal patterns in a dataset and thereby identifies intrusion. This method requires less memory than that of a signature-based method for detecting intruders. This is because this technique does not require any signature storage. This technique of intruder detection is capable of dealing with unknown attacks.

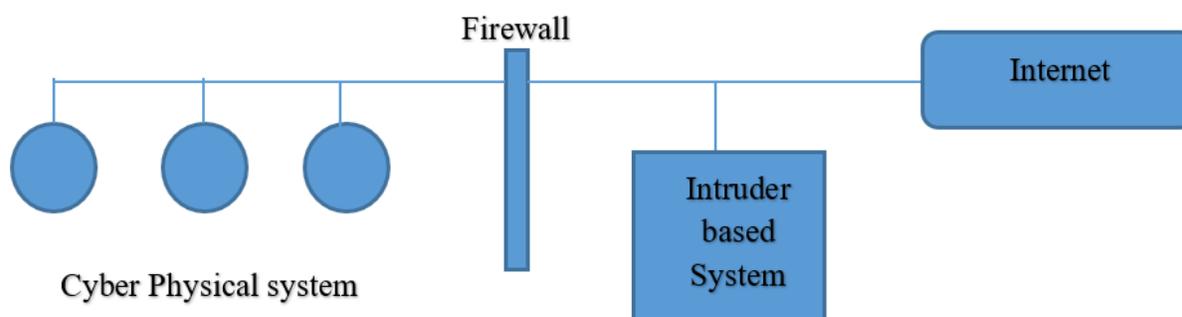


Figure 4 Intruder Detection System (IDS)

Though many researchers have been working on enhancing the security of cyber-physical systems (CPS) in smart manufacturing companies, providing security to CPS is a dynamic problem and requires continuous research for protecting a company's CPS. What was observed from the literature is that the cyber-attacks happening each time is greatly different. This will add up to the complexity dimension of the problem. Also, the vulnerability of a cyber physical system may vary from company to company. This makes the problem even more difficult.

Intruder detection systems (IDS) consist of different types of sensors (e.g., microwave sensors, electric field sensors, infra-red sensors, etc.) for detecting intruders as well as isolating the system from the outside. Earlier intruder detection systems are designed in such a way that they required human intervention. These systems are limited by the capability of human operators. With the advent of vision systems, many researchers have started solving intruder detection systems and have successfully demonstrated intruder detection, classification, and tracking. Many researchers have used both optical and thermal cameras for acquiring images for subsequent processing by intelligent

intruder detection systems. This is because optical cameras have the difficulty in detecting intruders during night times and also when the intruder is camouflaged.

#### Camera system

Literature has reported using thermal camera having a field of view of 35 mm and having 640X512 resolution. It was also reported of using an optical camera -SAMSUNG SCO-2120R optical camera, in addition to thermal camera (Figure 5). Literature has also reported using of a network video server fitted with IP filtering function for joining to a network.

The camera is controlled by a pan-tilt device equipped with 3500 and a tilt range of rotation (300-800). In order to overcome tangential distortion due to manufacturing process, Zhang (2000) proposed a calibration algorithm. In his research work, 26 chess board images are taken from different perspectives for Camera calibration. In his research, camera calibration algorithm computes distortion coefficients using the chess board images. Then these coefficients are used for correcting camera distortion using OpenCV function (Bradski et al. 2008).

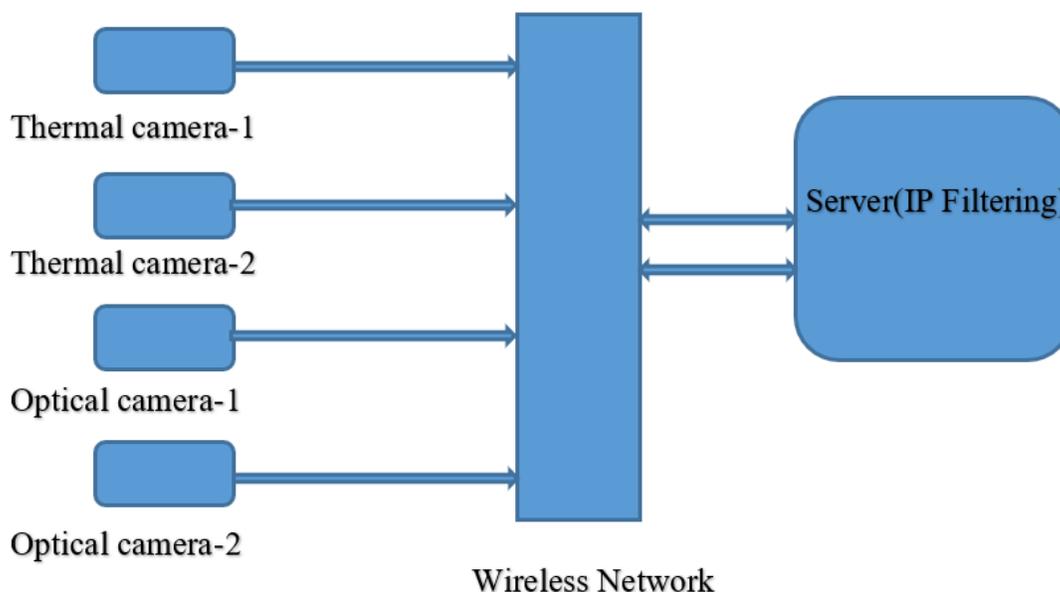


Figure 5 Camera network with thermal and optical cameras

#### Virtual Fence(VF)

It is a virtual line (Figure 6) that differentiates system or protected area from surroundings. A virtual fence is setup by using a spline curve. The control points of spline curve is setup by using the coordinates given by the operator. The operator normally uses a GUI for feeding the coordinates.

The cubic spline function connecting two points  $(x_i, y_i)$  and  $(x_{i+1}, y_{i+1})$  is given below.

$$P(x) = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i \quad (1)$$

Intrusion detection is very much significant in surveillance system. It is capable of identifying moving objects entering into pre-warning area defined by VF. The system is also capable of detecting moving objects in real time.

During intruder detection, the moving object is classified as humans or animals. Researchers have used deep learning for classifying moving objects. The Convolution Neural Network (CNN) is also a type of deep learning algorithm. CNN does learn from the coefficients of the convolution filter uses relevant features for classifying images. Seung One researcher has proposed a CNN based intruder detection algorithm for classifying moving objects. In their research work, they used six convolution layers. The detection algorithm extracts feature that are unique for a given image. They used a training image database of 10 class of human intruders as well as wild animals. The training database consisted of 5000 images in each class. Thus, there were 50000 images. Most of the intruder detection is done using OpenCV 3.0 library.

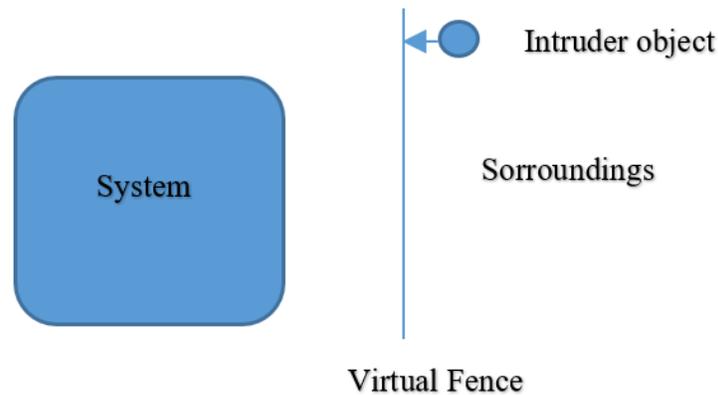


Figure 6 Virtual Fence with intruder object

One researcher has implemented a virtual fence utilizing a graphical user interface. A virtual fence will differentiate areas under surveillance from external areas. One research work (Jia et al., 2014) has been reported to have identified the moving objects in the background by using a convolution neural network (CNN). The researcher also tried to classify moving objects as either animal or intruder. The IDS are normally designed in such a way that whenever an intruder is detected while crossing the virtual fence, an alarm is prompted. It was reported in one research work that Virtual fence was implemented as a spline curve with set of control points defined using a graphic user interface by an operator. In another research, deep learning was used for classifying moving objects, estimation of pose recognition of different actions, recognition of different scenes and speech recognition. Deep learning was implemented using a computer-based model consisting of many layers. Particle filters are used for intruder tracking. Particle filter is a simulation-based technique. It uses Bayesian type of probability distribution. It gives good results not only for linear but also for non-linear environments.

One of the objectives of Intruder detection is to increase the accuracy of intruder identification. In order to address the limitations of IDS, a researcher has proposed intelligent intruder identification system that improves the reliability and efficiency of intrusion identification in nuclear power plants. This scheme uses two-cameras and deep learning technologies for tracking intruder behavior detection.

### 3. Conclusion

Additive manufacturing process as of today is limited by the geometrical feature, type of material, and the time requirement. Many researchers have been working in evaluating the suitability of a product to be made by 3D printing. Researchers have proposed a printability algorithm which suggests whether a component is to be produced by 3D printing or traditional methods by looking at several factors such as feature, material, time, etc. There is a scope for extending the applicability of 3D printing for other materials as well.

Tool path generated by the slicer algorithm is very much similar to that of CNC machine program. Slicing algorithm specifies the path along which the printer head of a 3D machine should move, while manufacturing a product. The efficiency of the 3D printing process depends to a large extent on the slicing algorithm. Many researchers have been working on improving the efficiency of the slicing algorithm. There is a wide scope for further research in this topic.

Training of the network (ANN) required large number of samples or training data. The efficiency of training ANN, depends upon the number of parts in the data set. Larger the samples higher will be the prediction rate. Quality of samples are also very important. Training is said to be complete when the network is capable of making predictions to the user defined accuracy levels. The problem with this type of training ANN is that it will consume lot of time. Thus, there is a wide scope for reducing the time required for training ANN without compromising the quality and accuracy of predictions.

Many researchers have started working on condition-based maintenance of machine tools. These methods make use of artificial intelligence and machine learning techniques. These techniques would help in preventing the unanticipated equipment failure and the subsequent downtime. Online machine diagnostic systems have to be more robust. This would help in enhancing the machine availability, the product quality and subsequently enhancing the customer satisfaction. Online machine diagnostics requires further research for making it more robust.

One of the limitations of additive manufacturing is that components with overhang requires support and this would result in wastes and would increase the cost of manufacturing. Many researchers have explored the effect of orientation of component on support volume requirements. They had used AI based techniques for minimizing the waste of material. This aspect of AM is still in infancy and further research is required in the time to come.

Additive manufacturing process consumes more energy than conventional machining process. Thus, additive manufacturing processes are not energy efficient. Thus, further research is required in making the additive manufacturing more energy efficient. This would also reduce the cost of manufacturing. This would extend the scope of additive manufacturing process. Additive manufacturing process also generates billions of small particles during manufacturing a product, if these particles when inhaled would cause harmful effects.

Machine learning based methods have been proposed by many researchers for performing the predictive maintenance of machine tools. These methods would help in accurately predicting the remaining useful life of machine tool. This would help in reducing the machine down time. This would also help in estimating for spare parts requirements. So that, the spare parts would be ready before the machine fails and thus reduce the machine downtime.

Application of AI in additive manufacturing is still in infancy and further research is required in (i) reducing the energy consumption by additive manufacturing (ii) increasing the productivity during additive manufacturing (iii) increased use of AI in additive manufacturing for reducing manufacturing cost (iv) increased accuracy in predicting the remaining life of machine tool (v) minimizing defects during additive manufactured products.

Though many researchers have been working on enhancing the security of cyber-physical systems (CPS) in smart manufacturing companies, providing security to CPS is a dynamic problem and requires continuous research for protecting a company's CPS. What was observed from the literature is that the cyber-attacks happening each time is greatly different. This will add up to the complexity dimension of the problem. Also, the vulnerability of a cyber physical system may vary from company to company. This makes the problem even more difficult.

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