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An Intelligent Hybrid Manufacturing System for FDM Surface Defects Monitoring with Industry 4.0

Fahim Al-Rashid Chowdhury[1], Pervez Hossain[1], SM Rahaman[1], Md Shihab Shakur[2], M. Azizur Rahman[1,3], Md. Shahnawaz Bhuiyan[1]*

[1] Department of Mechanical & Production Engineering, Ahsanullah University of Science & Technology, Dhaka-1208, BANGLADESH

[2] Department of Industrial & Production Engineering, Bangladesh University of Engineering & Technology, Dhaka-1208, BANGLADESH

[3] McMaster Manufacturing Research Institute (MMRI), Department of Mechanical Engineering, McMaster University, Hamilton, ON L8S4L7, Canada

ABSTRACT

Additive manufacturing (AM) and machining in a single machine colloquially known as Hybrid manufacturing help to produce customized and complex products without assembling including greater design freedom and reduced material wastage. A CNC-based grinding mechanism is introduced in the same system to overcome those defects and enhance the quality. To increase productivity and improve product surface quality, evolving additive manufacturing demand and finishing subtractive processes must be combined on the same platform. For the additive manufacturing method, Fused Deposition Modeling (FDM) has been employed, and a grinding operation can be performed for surface finishing. A camera module is used to capture surface images for defect detection such as stringing, rashing, and surface cracking after the AM process. Convolutional Neural Network (CNN) is applied to the captured image for the defect detection process. If the CNN analysis reveals any surface defects, a grinding operation will be performed on the surface for better surface quality. The architecture has provided a platform to collect data from the image captured by the camera module for evaluating and identifying surface defects using CNN. CNN model provided 89% accuracy for surface defects detection. As a result, the CNC grinding operation can be done on that particular surface of the product for smoothing the partially roughened surfaces. Therefore, this study demonstrates to improve the surface quality, reduce cycle time, set up time reduction & improve the product's sustainability. The proposed approach of a hybrid manufacturing system also provides a basic framework to increase efficiency, reduce downtime, increase efficiency, improve end part consistencies of the product as a consequence of post-processing & defect detection in the same system, and enable I4.0

Keywords: Surface quality, Grinding operation, Hybrid manufacturing, Convolutional neural network, Sustainability.

1. Introduction

Manufacturing industries have become fixated on preoccupied on delivering products with greater quality, cheaper prices, and quicker turnaround times over the last few decades. The main goals of sustainability in Additive Manufacturing are minimal material wastage, less post-processing, and very low costs even for manufacturing complex items [1]. Therefore, manufacturing technology brought new opportunities and instruments to translate innovative thoughts into viable production approaches. The Fourth Industrial Revolution (4IR) utilizes artificial intelligence, IoT, cloud computing, AM, Big data, and Cyber-Physical Systems (CPS) to digitally share information and can transfer data from digital to physical through AM technologies [2]. One of the foundations of the advanced manufacturing process is the AM due to the layer-by-layer complex part fabrication capability. AM methods include vat polymerization, stereolithography, material extrusion, binder jetting, sheet lamination, and so forth. Fused Deposition Modeling (FDM) 3D printing is a material extrusion-based additive manufacturing (AM) process. FDM technique can produce designs with detailed and optimized geometries, resulting in components with improved strength-to-weight ratios and lower weights. However, making a higher-quality product in FDM might be problematic at times because to faults such as stringing, rashing, surface cracking, etc. Furthermore, dimensional control in AM is difficult because to issues like as ghosting, bed levelling, non-homogeneous temperature, nozzle clogging, and so on [3]. The additive and subtractive manufacturing (SM) processes alone are amazing; but, the combination of AM and SM, known as hybrid manufacturing, opens a whole new level of innovation in product manufacture [4]. When it comes to producing more sophisticated parts with higher flexibility and precision in a relatively short production time, hybrid manufacturing has a lot of space for growth. Hybrid manufacturing may create items with complicated design aspects that would otherwise be impossible to achieve through traditional machining techniques. The relationship of hybrid manufacturing combining AM and SM can be illustrated in Fig. 1. Combining AM and SM will bridge the gap by eliminating the negatives of the two methods enabling the user to better part quality. Therefore, the following research question can arrive from the discussion:

RQ1: How to detect the defects from FDM-produced parts?

*Corresponding Author Email Address: shihabshakur2016@gmail.com

RQ2: How to reduce the FDM defect by applying the SM process?

Addressing the research question, the study scops the following research objectives:

RO1: To develop an intelligent hybrid manufacturing system for detecting visual defects.

RO2: To conduct hybrid manufacturing if any visual defect is produced on the surface.

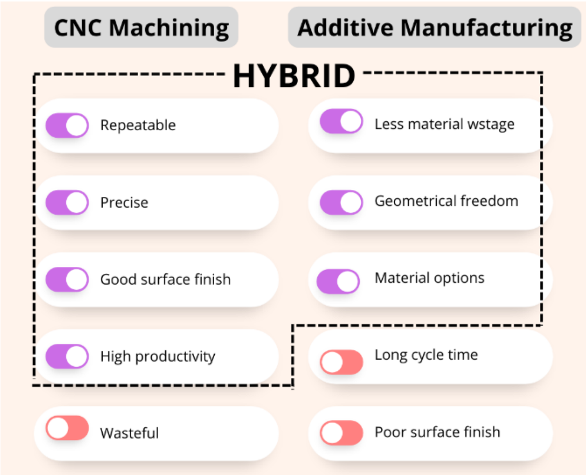


Fig.1 Advantages of Hybrid Manufacturing

To complete the research objectives, a convolutional neural network (CNN) is applied for detecting visual defects. If any defect occurs, the hybrid system activates the CNC milling operation autonomously on the surface of the product by smoothing the partially roughened surfaces.

The following articles deal with the literature review in section 2 to show the background of the work. Then the proposed framework and experimental setup are presented in section 3 and 4 respectively. After that the result and practical and managerial implications are presented in sections 5 and 6 respectively. Finally the conclusion porsion is added in section 7.

2. Literature Review:

The term "Industry 4.0" refers to a collection of technologies that help increase the productivity and responsiveness of the industrial system. I4.0 commonly referred to as smart manufacturing, is built on information technology-driven industrial systems [5]. Industry 4.0 has revolutionized traditional manufacturing by leveraging the development of digital technology. However, there are other difficulties, including checking the status and location of goods, data-driven manufacturing, and real-time monitoring and management of the production processes [5]. Some of the common components of the I4.0 revolution include the Internet of Things, cyber-physical systems, additive manufacturing, big data, machine learning, and robotics [2]. The fundamental idea behind the FDM manufacturing technique is to simply melt the raw material and mold it to create new forms [6]. There are numerous reasons for this, including plastic oozing out of the nozzle as the extruder moves to a new location, resulting in stringing [7]. Rashing occurs between the layers because adhesion did not occur properly, which is usually caused by a low printing temperature. For that, the layers adhere well, but a difference in temperature between different sections of the part printing due to design requirements causes it to deform, which can cause some layers to separate, and thus thermal shrinkage causes some rashing on the layer's surface [8]. layer thickness and printing time are inversely proportional, increasing layer thickness gives less printing time but in turn, the surface roughness becomes which will produce fatigue in the surface, and thus creaking happen. Researchers have discovered a variety of methods to enhance the mechanical properties of printed objects. Artificial Intelligence (AI) is applied in AM to create intelligent service-oriented manufacturing processes for the industry [9]. The aim to automate intellectual processes traditionally performed by humans is referred to as AI [10]. Combining artificial intelligence (AI) and three-dimensional (3D) printing technology may improve performance by lowering the possibility of mistakes and enabling automated manufacturing [11]. For example, CNN based cyber-physical system can be an effective way to produce better FDM parts with optimized process parameters [12].

In the I4.0 era, a plethora of hybrid manufacturing systems have been commercially disclosed, with some of them currently being made available as new combined machines from machine tool manufacturers or as retrofit options onto existing platforms [13]. The hybridization of manufacturing processes is intimately linked to the implementation of the industry 4.0 strategy [14]. A range of hybrid techniques have been developed as a result, helping to overcome some of the limitations that still remain by fusing 3D printing with procedures [15]. Every manufacturing method has benefits and drawbacks, and it is best suited for specific materials and purposes. Even while additive manufacturing, often known as 3D printing, has advanced significantly since its beginnings, it still has limitations, including a small selection of available materials, a lack of manufacturing accuracy, a poor surface polish, the need for post-machining, etc. Combining additive and subtractive processes is possible due to their complementarity [16]. Two options present themselves in this situation: (i) a hybrid technique, and (ii) subtractive post-processing and AM. Study and research are needed for the first one and the second panorama, in which each operation is independent of the others, is commonly employed. The traditional method of reaching that tighter tolerance—CNC milling, turning, etc.—lacks flexibility when confronted with challenging geometries. Combining AM with the traditional subtractive approach can close the gap by removing the drawbacks of each technique, giving the user the best of both worlds, as seen in Fig 2.

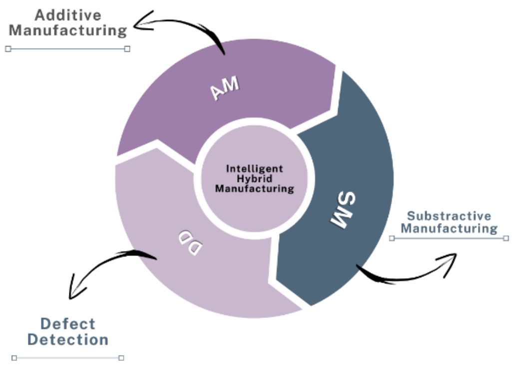


Fig. 2 An Intelligent Hybrid Manufacturing System

FDM process can be made more customers driven by applying neural networks to predict data under an intelligent cyber-physical system [17]. Convolutional neural networks

(CNN) are a kind of feedforward neural network. The best learning algorithms for comprehending visual content are CNNs, which have demonstrated excellent performance in tasks involving image segmentation, classification, detection, and retrieval [18]. CNN uses numerous layers of convolution and pooling structures to successfully find deep semantic information embedded in images, as opposed to standard artificial features and deep learning methods [19]. CNN has been used as a significant deep-learning model for image classification in the AM process in recent times. For example, CNN can be applied for detecting the warping problem in the FDM process [20]. Moreover, CNN can be applied in the in situ microstructure inspection in the laser AM process [21]. However, the application of CNN to make hybrid manufacturing intelligent is still fragmented. From that perspective view, a framework to build an intelligent hybrid manufacturing system has been developed. The CNN analysis will take an image from the surface of the FDM printed part and take the image of the surface. If the output is bad, then the hybrid system activates CNC operation autonomously thus reducing time and material waste. CNC grinding operation for enhancing the surface of the product by smoothing the partially roughened surfaces. The usage of hybrid manufacturing is applied to turn the 3D printing process accurate, versatile, more effective, and efficient.

3. Framework for Intelligent hybrid manufacturing system:

The construction of a digital CAD model and its translation to stereolithographic (STL) file format is the first step in the FDM process. After every layer is generated, the slicer figures out the instructions with the settings that suit the needs and desired quality as a G-code file. The nozzle should be heated until the desired temperature is attained. The material is supplied into the extrusion head, melted in the nozzle, and then layer by layer placed on the platform before cooling and solidifying. The building platform will be lowered, and a new layer will be deposited if one layer is finished. The process will be continued until the part is finished. The image analysis is performed in four steps: image procurement, preprocessing, feature extraction & classification. If the CNN analysis from the images does not detect any defects, the 3D fabrication will be continued. However, if any kind of defect is found, from CNN image analysis, the CNC grinding operation will be carried out on the product surface. However, the process was limited to the flat and top surfaces only. The CNC grinding wheel cutter will perform a grinding operation for the finish cut to get a better surface finish and get rid of any visual defects. The CNC finish machining is implemented to ensure the desired accuracy by eliminating the effects of the star resulting from the deposition of a certain layer. FDM hybrid in CNC allows the machine to switch between the two processes without the use of an additional actuation system, reducing mechanism complexity and the time it takes to determine the cutter’s absolute location relative to the FDM part for subsequent machining. Finally, the hybrid machining is finished. The whole framework is illustrated in Fig. 3.

Convolution Neural Network structure is used to detect the defects. The CNN is performed layer by layer, the input layer, the convolutional layer, and the output layer. The main aim of this layer is feature extraction. CNN is easier to train with fewer connections and fewer parameters, and the learned features tend to be shift invariant. Raw image data has been used to train the CNN Model. The data set was 250*250 pixels in size. Maintaining the same pixel is a recommended practice. The general component of model training is data splitting. The ratio of splitting was 75/15/10 (75% for training, 15% for validation, and 10% for testing), as shown in the chart diagram is shown in the following Table 1.

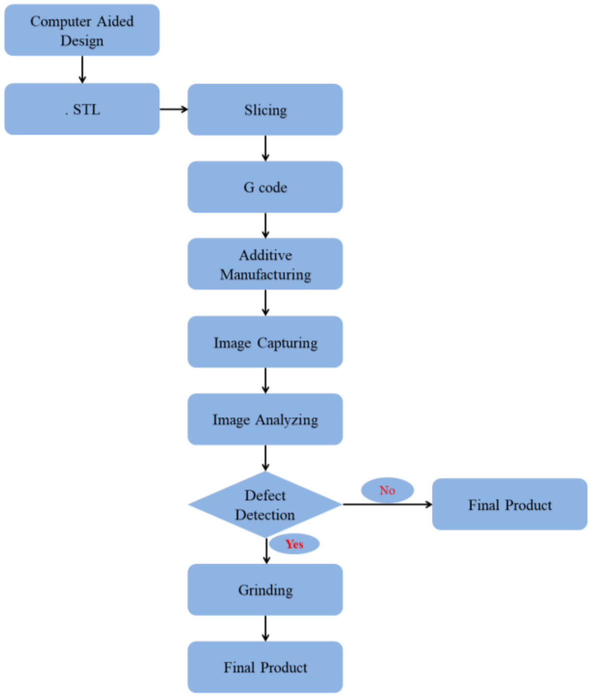
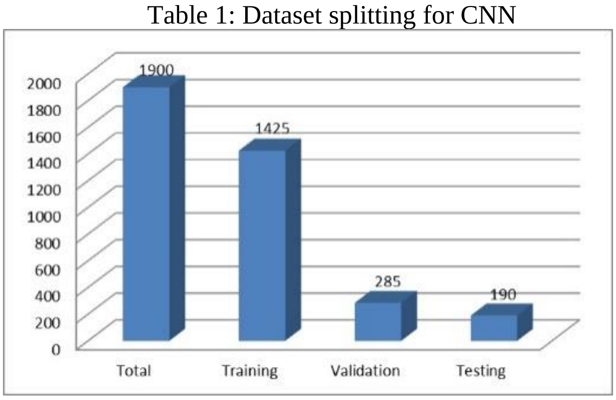


Fig. 3 Proposed hybrid manufacturing process

Table 1: Dataset splitting for CNN



The networks do not contain any pre-learned features, which will be produced when the networks are trained on a picture set. The colored image set is created by printing 15 FDM parts in various shapes and the image is taken from different angles. The data set was 64*64 pixels in size. Before any additional layers are added, the image is first placed in the input layer. The convolutional layer with 128 kernels and a combination of a 3x3 matrix and ReLu activation extract features. Then, operations like 2 stridings, padding, and max-pooling layer using a 3x3 matrix were carried out. A dense layer made up of 256 neurons is applied, and 15% of them drop out at random. Utilizing the Adam optimizer, the learning rate was 0.0001, and the Sparse Categorical cross entropy was employed as the loss function. The batch size was 32, and there were 100 epochs. The fully connected layers are shown in Fig. 4.

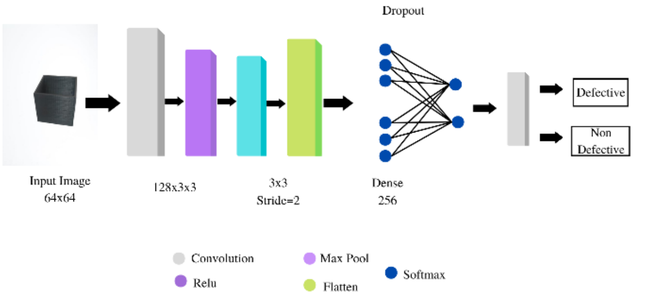


Fig. 4: Architecture of convolutional neural network

4. Experimental setup

To fulfill the proposed methodology, a hybrid manufacturing machine is setup for this study, shown in figure 5 with the the Specifications below:
AM Technology: FFF (Fused Filament Fabrication)
SM technology: CNC grinding
Nozzle Diameter: 0.4mm
Print Bed Type: Glass
Printing Speed: normal 20-180mm/s
Filament Diameter: 1.75mm
File Format: STL
Slice Software: Cura, Simplify3D
Printing Precision: ±0.1mm
Power Supply Input: 24V/3.4A/ 50Hz
Bed Temperature: ≤110℃
Machining Motor: 12 V brushed motor
Cutting tool: Abrasive grinding wheel

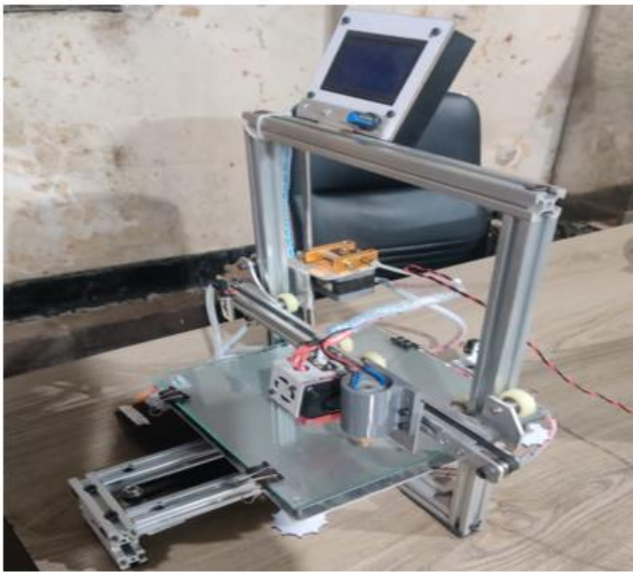


Fig. 5 Hybrid Manufacturing Machine

In the Hybrid machine setup, a DC motor, abrasive cutting tool, and extruder for FDM fabrication are used. The direct current (DC) motor is a type of electric machine that converts electrical energy into mechanical energy, applied in milling operation for rotational of mill cutter. A tool holder is added to the machining component that secures the extruder and end mill cutter. The end mill cutter is capable of cutting in all directions. End mills rotate to cut in a horizontal or lateral (side to side) direction, which only cut the material vertically and straight down. There is a 0.4mm nozzle, the melted filament comes out during the printing process. The nozzle is attached to the extruder which is the printer's most important component. It is made up of two major parts. The material is pushed into the cold end by a motor. The hot end, on the other hand, is where the filament is melted and pushed out. The fabrication is done on the top of the bed. The surface of the bed allows the plastic filament to adhere to it during the printing process. A flat, level print bed is required for a 3D printer to properly create the layers of material in filament form that make up a 3D-printed item. The Hybrid setup is illustrated in Fig. 6.

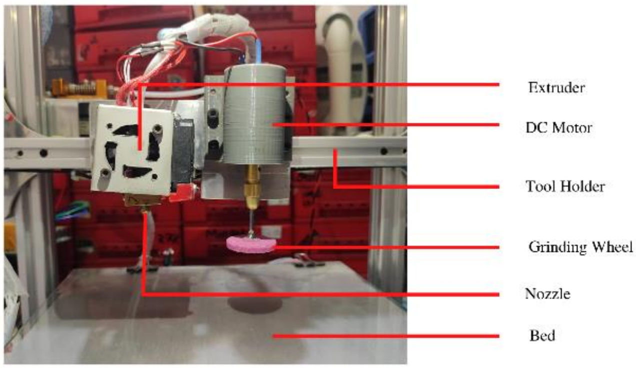


Fig.6 Hybrid machining setup

5. Result and discussion

The purpose of training a model is to construct a collection of weights and biases that, on average, result in moderate losses across all samples. Any model that predicts a larger loss is considered less accurate. The model performance graph was constructed for 100 epochs and is shown in Fig. 7 below. This figure is separated into two graphs that exhibit the accuracy and losses of the model against the epoch. According to the graph, the CNN model train accuracy was 89%. There is no overfitting or underfitting problem here. With increasing epoch numbers, training and validation accuracy are increasing and losses are decreasing. As the loss decreases, CNN demonstrates its potential for work. Because of small data volumes or the same type of data, there are fluctuations in accuracy and loss.

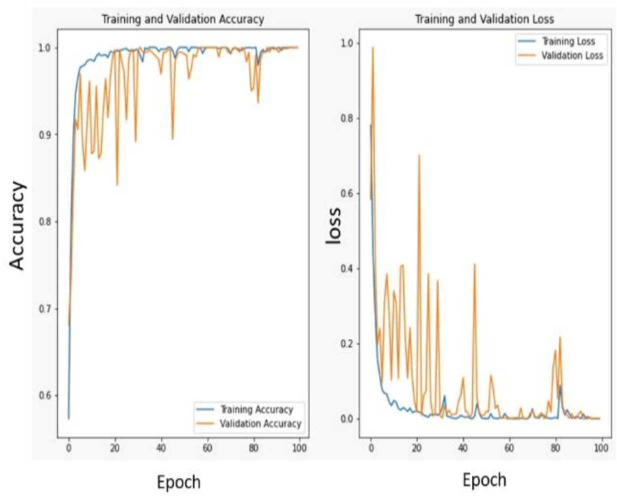


Fig. 7 Accuracy and loss curve of CNN

The model can detect defective and non-defective surfaces for the identification of surface defects such as rashing and stringing after being deployed, shown in fig. 8. As it is a supervised model, it detects non-defected surfaces in numerous circumstances. The model's performance will be more accurate in the future when it is trained with additional data. To address this issue, further work on unsupervised models can be conducted.

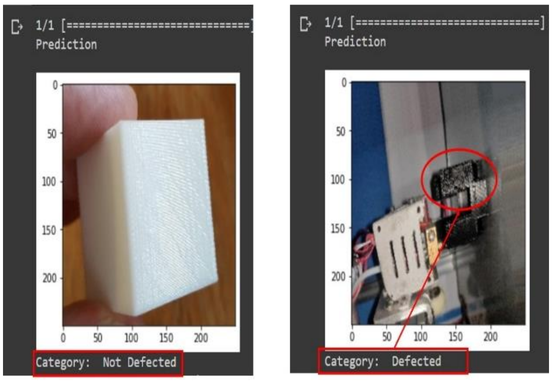


Fig.8 Actual scenario after deploying the model

6. Practical and managerial implications

Hybrid manufacturing enables the machine to switch between additive and subtractive processes without the need for an extra actuation system and also decreases mechanism complexity. When compared to subtractive or additive machining alone, this proposed architecture will provide several advantages such as the usage of a constant or fixed component coordinate system allows for easy switching between additive and subtractive operations, as well as the use of multiple CNC machines cutting tools such as milling, drilling, and grinding, etc. After the AM process, a camera module is utilized to take surface pictures for defect identification such as stringing, rashing, and surface cracking. The system offers a framework for collecting data from camera module images for analyzing and recognizing surface flaws using CNN. Therefore, the primary uniqueness of the study is how successfully the hybrid manufacturing system incorporates intelligence. The study can benefit practitioners of industry in understanding the relevance of hybrid manufacturing systems to increase productivity and improve the surface quality of printed products. The hybrid manufacturing machine can pave the way for certain benefits such as decreased material waste, higher flexibility, enhanced efficiency, shorter process times, and reasonably high-quality products. AM or machining technology is not a new industry technology. However, combining both additive and subtractive processes for more demanding engineering applications opens up a wide range of new possibilities. Practitioners can understand how technology (HM) can be infiltrated the present manufacturing sector structures on a broad scale. In the long run, industries can replace traditional manufacturing with hybrid manufacturing in circumstances where the desired product's production volume is small, flexibility is poor, processing times are long, and the ability to quickly adapt production needs are the fundamental variables that a company needs to consider. In a nutshell, the study would help to provide a roadmap for researchers and practicing engineers to improve their understanding of hybrid manufacturing which provides a fundamental foundation for increasing efficiency, reducing downtime, improving product end part consistency as a result of post-processing and defect detection in the same system, and enabling I4.0.

7. Conclusions

The initial purpose of developing hybrid manufacturing processes is to increase productivity, improve product surface quality, and evolve FDM process demand and finish on an individual platform. Convolution Neural Network (CNN) to autonomously learn how to monitor product surface, makes the processes simpler and easier. CNN has the potential to apply in hybrid manufacturing to become an intelligent process. Such an approach can be an enabler of hybrid machining workstations which includes rapid process times, flexibility, sustainability, and high-quality fabrication. However, there are some shortcomings in this work. The data set was small and insufficient data resulted in lower accuracy in CNN. The future recommendation is to add a KNN filter so that the defecting part can be clustered into various classes. The surface roughness before and after the grinding operation can be evaluated with mathematical and statistical model. Moreover, skilled personnel are required to overview such operations. Some close loop sensor can add more value in the work. The machine grinding operation can be perform on the flat surfaces only, it would be great if such system can be developed on contour point to point surfaces. However, the potential of CNN in hybrid machining to become intelligent cannot be denied and more extensive research is required in Additive manufacturing. All these processes will satisfy various Industry 4.0 needs, including customization, efficiency, quick delivery, and waste reduction, and it is essential for bringing 4IR.

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