DEVELOPMENT OF UNDER EXTRUSION DATASET USING MODIFIED GCODE IN ADVANCE MANUFACTURING OF FDM 3D PRINTER

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To my beloved parents, thank you.

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ABSTRACT

Failures in 3D printers are common in the manufacturing industry, leading to wastage of materials and time. This thesis addresses the challenge of automatically detecting under-extrusion failures in Fused Deposition Material (FDM) 3D printers using training techniques. Existing studies primarily focus on stringing failure detection, disregarding the impact of extrusion rate on printer failures. Under-extrusion failures can result from insufficient extrusion speed, low melting temperature, nozzle blockage, or worn-out extruder gear, rendering printed models unusable. To overcome this issue, a training method based on the YOLOv5 models are proposed. A dataset comprising 2400 images is created by modifying and augmenting 200 under-extrusion samples. Raspberry Pi and a camera are employed to gather data on under-extrusion samples in real-time. The YOLOv5x model is trained on Google Colab, offering enhanced precision, recall, and mean average precision (mAP) compared to previous models. The experimental results demonstrate the effectiveness of the YOLOv5 training models in detecting under-extrusion failures. The YOLOv5x model achieves 99% precision, 100% recall, and 99% mAP, outperforming other models. This research contributes to the intelligence of 3D printers by reducing waste materials and time lost due to failed prints. Furthermore, the proposed training approach can be extended to identify other types of 3D printing failures.

ABSTRAK

Kegagalan pada pencetak 3D adalah perkara biasa dalam industri pembuatan, menyebabkan pembaziran bahan dan masa. Tesis ini mengatasi cabaran mengesan automatik kegagalan bawah ekstrusi pada pencetak 3D menggunakan teknik latihan. Kajian sedia ada tertumpu pada pengesanan kegagalan meregang, mengabaikan impak kadar ekstrusi terhadap kegagalan pencetak. Kegagalan bawah ekstrusi berlaku disebabkan kelajuan ekstrusi tidak mencukupi, suhu lebur rendah, penyumbatan nozel, atau gear ekstruder haus, menyebabkan model yang dicetak tidak dapat digunakan. Untuk mengatasi isu ini, kaedah latihan berdasarkan model YOLOv5 dicadangkan. Set data yang terdiri daripada 2400 imej dibangunkan dengan memodifikasi dan meningkatkan 200 sampel bawah ekstrusi. Raspberry Pi dan kamera digunakan untuk mengumpulkan data pada sampel bawah ekstrusi secara masa nyata. Model YOLOv5x dilatih di Google Colab, menawarkan ketepatan, kenangkabalan, dan min purata yang lebih baik berbanding model-model sebelum ini. Keputusan eksperimen menunjukkan keberkesanan model-model latihan YOLOv5 dalam mengesan kegagalan bawah ekstrusi. Model YOLOv5x mencapai ketepatan 99%, ingatan semula 100%, dan min purata 99%, melebihi prestasi model-model lain. Kajian ini memberi sumbangan kepada kecerdasan pencetak 3D dengan mengurangkan pembaziran bahan dan masa yang terbuang akibat cetakan yang gagal. Selain itu, pendekatan latihan yang dicadangkan dapat diperluas untuk mengenal pasti jenis kegagalan pencetakan 3D yang lain.

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LIST OF SYMBOLS AND ABBREVIATIONS

AM	Additive Manufacturing
FDM	Fused Deposited Material
3D	Three Dimensional
ME	Material Extrusion
CNN	Convolutional Neural Network
PID	Proportional Integral Derivative
FFF	Fused Filament Fabrication
IMMS	Inertial Machine Monitoring System
IMU	Inertial Measurement Unit
SVM	Support Vector Machine
IoT	Internet of Things
BLOB	Binary Large Object
HC	Hypercolumn
CCD	Charged-coupled Device
GigE	Gigabit Ethernet
GPU	Graphic Processing Unit
cuDNN	Cuda Neural Network
DIoU	Distance Intersection over Union
GIoU	Generalized Intersection over Union
ReLU	Rectified Linear Unit
SE	Squeeze and Excitation
SSD	Single shot Detector
BiFPN	Bidirectional Feature Pyramid Network
SIoU	Splicing Intersection over Union
CA	Coordinate Attention
mAP	Mean Average Precision

G-code	Geometry Code
Esteps	Extruder Steps
RPN	Region Proposal Network
R-CNN	Region-based Convolutional Neural Network
VGG-16	16-layer version of Visual Geometry Group Nets
DCNN	Deep Convolutional Neural Network
BB	Bounding Boxes
CSP	Cross Stage Partial
PANet	Path Aggregation Neural Network
FC	Fully Connected
SGD	Stochastic Gradient Descent
BCE	Binary Cross Entropy
PASCAL VOC	PASCAL Visual Object Classes
COCO	Common Object in Context
RAM	Random Access Memory
HDD	Hard Disk Drives

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CHAPTER 1

INTRODUCTION

1.1 Research Background

The industrial term for 3D printing is additive manufacturing (AM), which is a computer-controlled technique that builds three-dimensional products by depositing materials in layers. 3D printing is widely used in industries such as manufacturing, medicine, and other industries. Numerous studies have been conducted on 3D printers because of its expanding applications. The speed, low prototyping costs and flexibility of 3D printers make it superior compared to conventional methods such as mould processing.

The 3D printing technology of fused deposited material (FDM) has progressed to such a point that it cannot be made only with several materials and requires the incorporation of a variety of technologies. The material extrusion technique is one of the most extensively utilized 3D printing procedures due to the low cost and wide variety of materials that can be used. Nonetheless, during printing operations, defects in the printed model are often undetected. The printers will simply continue the printing job while ignoring any defects on the printed model. For FDM 3D printers to be used productively in industry, there are still issues that need to be resolved, despite the fact that the core technology is already established several years ago [1]-[3].

There are numerous types of failures in 3D printing and one of them is under-extrusion as shown in Figure 1.1. This type of failure occurs due to multiple reasons such as insufficient extrusion speed, low melting temperature of the filament during printing, partial blockage of the nozzle, or a worn-out extruder gear. Extrusion failures may result in undesirable layer gaps, missing layers, and even holes in the printed objects, making the models unusable. Currently, most off-the-shelf 3D printers often lack a dedicated system for intelligently tracking and monitoring the printing process. Even if there are potential faults in the print, 3D printers are programmed to continue printing the assigned part until all layers are completed [4].

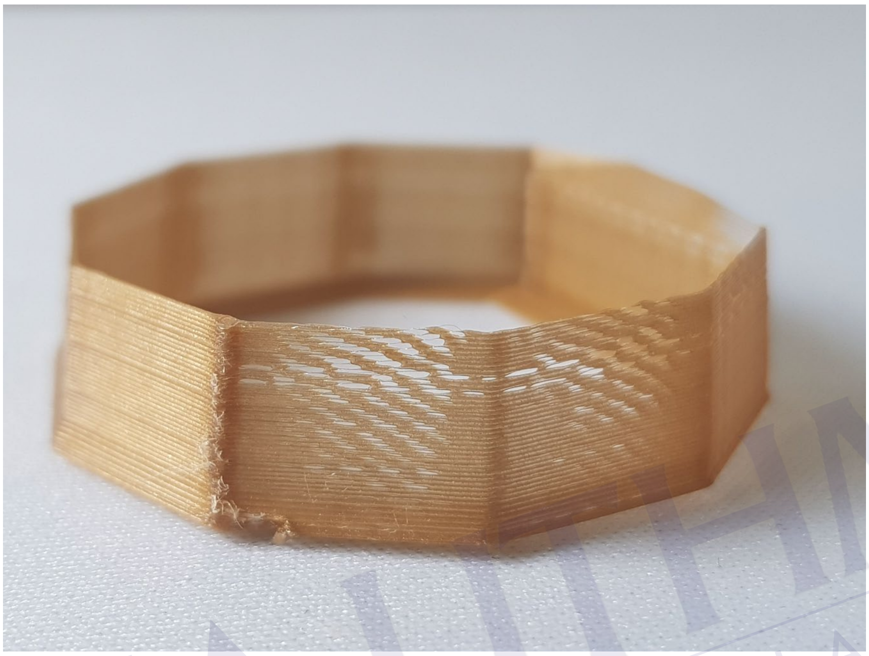

Figure 1.1: Under extrusion failure in Ultimaker 3D printer [5]

In the worst-case scenario, print failures may affect and destroy the entire machine. Under normal circumstances, the 3D printing process must be restarted, and the failed materials are usually discarded, which result in the consumption of time and materials [6]. To prevent such issues, it is imperative for the human operator to periodically monitor the printing process manually, which can be a burdensome task.

Thus, real-time quality control remains a significant challenge in 3D printing. Automatic detection of defects during the printing process can effectively minimise the waste of material and time . Integrating stages into the printing process can trigger an alarm to pause or stop the printing process, allowing corrective measures to be implemented to avoid reprinting of model parts.

1.2 Problem Statement

Despite the fact that FDM 3D printers have the ability to easily fabricate real parts in a shorter period and at a lower cost compared to traditional manufacturing methods, they still lack the intelligence required to detect and identify failures in the printed model during the printing process. Instead, the printers will simply continue printing while totally ignoring even the most significant defects in the printed model. In the worst-case scenario, these failures can potentially affect and damage the entire machine. Under normal circumstances, the 3D printing process must be restarted, and the failed materials are usually discarded. In order to avoid this issue, it is necessary for the human operator to periodically monitor the printing process manually, which can be a burdensome task. This approach results in inefficient use of human resources, especially for large printing farms that can fit up to 300 3D printers at a time [7]. However, a significant amount of time, investment and energy usage is excessively wasted as unplanned machine downtime, which costs industrial manufacturers approximately RM 233 billion annually. Equipment failures account for 42% of this cost, with energy charges contributing more than RM 46 billion in context of reliability importance of industrial manufacturing [8].

1.3 Objectives

The objectives of this research is to investigate a deep learning approach for detecting under-extrusion failures in the advanced additive manufacturing of FDM 3D printers. The subsequent objectives of this study were:

a) To obtain a dataset of under extrusion failures of FDM 3D printing.
b) To design detection algorithm to identify 3D printing failures based on deep learning approach using YOLOv5 models.

1.4 Scopes of Study

The scopes of the research were outlined as follows:

a) The failure dataset consisted of 2400 augmented samples derived from 200 samples of 3D printed material with intended under-extrusion condition and samples that were sets below 10cm.
b) The failure detection was based on vision system using a high quality camera with a 4K resolution that focused on detecting under-extrusion conditions.
c) The research involved training YOLOv5 models on the dataset and evaluating their performance using various metrics. YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x were used for training and detecting under-extrusion datasets. Each of these models represents a different variant of the YOLOv5 architecture, characterized by varying sizes and complexities. These variants are designed to handle different scales and complexities of objects in the input data. By utilizing these different YOLOv5 models, the research aimed to explore and compare their performance in accurately identifying under-extrusion instances, employing various evaluation metrics to assess their effectiveness.
d) Google Colab was utilized as a data training and model evaluation platform. The use of Google Colab GPU runtime accelerated the training process. The trained models, logs and figures were saved on Google Drive for further analysis.
e) Results comparisons are in terms of training performance of YOLO models architecture and image sizes which are 600,1200, and 2400 images. The total number of images determined based on the size and diversity of the dataset being used. A larger dataset with more diverse samples can provide more robust and generalizable results.

1.5 Research Contributions

a) This study focused on under-extrusion failures, which were chosen due to their significant impact on the quality of 3D printed objects. By intentionally modifying the code of printed samples to produce under-extrusion failures at a 40% rate of filament extrusion, ready-to-use under-extrusion datasets were created. These datasets served as a foundation for the research, supporting performance analysis and deep learning algorithm design.

b) In order to collect samples continuously, an automatic system was built by utilizes a Raspberry Pi 4 to automate the process of sample collection and data acquisition. By adding instructions to the 3D printer and webcam, the system can continuously gather data without manual intervention, reducing the time and effort required for collecting samples and evaluating data.

c) This automated system made a fundamental contribution to the technology of 3D printing failure detection by helping to minimise downtime and the waste of filament in 3D printing. Errors can now be spotted online and corrected at an early stage. Datasets are gathered and analysed so that the system can be improved in future works by deploying it in a more stable environment. Interface and algorithms from this system can be implemented in cloud-based manufacturing as it will provide datasets to others.

d) This research focused on the development of a system for automated data acquisition and failure detection in 3D printing. This is a valuable contribution to the field as it has the potential to minimize downtime and waste in 3D printing processes. The use of YOLOv5 for object detection is a key component of this system, allowing for accurate and efficient failure detection.

1.6 Thesis Outline

The structure of this thesis was organised in the following manner. Chapter 1 discussed the background and context of this research, including the identification and discussion of problems in the 3D printing process. The research objectives, contributions, publications and awards throughout the research timeline were also presented. Chapter 2 reviewed relevant literature to review the research within existing concepts and identify areas for future research. Chapter 3 explained the methodology, detailing the data gathering with a focus on continuous data collection of under-extrusion failures. And the results were presented in Chapter 4. Chapter 5 discussed the research findings, limitations and future research opportunities.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

FDM 3D printing technology has been used as a swift and accurate prototyping method in recent years. FDM is one of the most adopted methods in 3D printers because it uses relatively simple machineries and provides various material selections [9]. The main application of 3D printing is in the industrial and manufacturing sectors [10]. Previously, 3D printing machines were mainly implemented for the rapid manufacturing of plastic prototypes [11]. Even though 3D printing has marginally reduced prototyping and manufacturing cost with lesser amount of time; however, some failures are common and universal when using the FDM system. Such failures are clogged nozzle, invasion of foreign substances, material deformation and collapse of printed model due to various reasons [12]. All these failures are unforeseeable and difficult to detect, thus resulting in waste of time, money and energy power consumption. A failure detection method which was introduced in 2014 by several researchers had adopted optical inspection by using 2D laser triangulation scanner [13]. However, the problem was that high surrounding temperature during 3D printing process hindered the operation of optical sensors. A patent was previously filed which proposed a capacitive detector as it can operate within a high temperature. Nevertheless, it can only detect clogging or potentially clogging status but not the condition of the printed model [14]. Other researchers have also proposed a method to detect various deposition statuses in the FDM process [15]. Recently, a monitoring system was developed to identify FDM machine failures based on the inertia of machine [16]. Nevertheless, all the suggested methods were not able to give early detection of failures in the printed model. There have been a number of techniques described to enhance fault diagnosis performance through deep learning methods. One of the recently discovered techniques is machine learning method that has been applied to industries for identifying failures in FDM 3D printing. Such algorithms require a huge amount of computer power for large volumes of data, especially for image data. For instance, [17] makes it impossible to respond to errors in a timely manner since calculations take longer than the duration of a single printing shift. Advanced computation and analysis techniques are needed in order to continuously analyse this high dimensional and high frequency data [18]. The advancement of machine learning in this area has enormous potential. The commonly used deep learning technique, which is a specialised subset of machine learning, has performed well in classifying parameters and modulation recognition tasks. This method has been effectively applied in these areas. Most of the current applications give little thought to the amount of data being used. Real historical data for modulation recognition may be lacking in practice. Therefore, training recognition models with modest amounts of data is preferable. The performance of deep learning models depends on having enough data, presenting a significant challenge [19].

For example, [20] designed a deep learning system that would classify the most recent image of an unfinished 3D printed part in order to identify failure in the 3D printing process. The total average accuracy of this system is 70%. This demonstrates that majority of the printing errors can be identified by this algorithm, thus helping to reduce waste produced by uncontrolled printing of faulty parts. [21] also employed a convolutional neural network (CNN) to construct a monitoring system for a 3D printer specifically for the error of warping. The algorithm concentrates exclusively on the important area in the bottom corners of the printed object, where the error is predicted to guarantee the best possible monitoring of the warping error. They tested the results using various geometries and achieved an accuracy of 97% using the suggested technique.

[22] proposed a system which included a digital microscope for real-time image capture, a high precision image classification algorithm to track the progress of the printing process, and a proportional, integral, derivative (PID) controller for closed-loop control. They demonstrated how well the system can detect the types and severity of errors as well as how a feedback control method can be used to perform process parameter adjustments to minimize defects. In a subsequent article, [23] an image-based closed-loop quality control system was created for fused filament

fabrication (FFF), which is a common AM method. A proposed image diagnosis-based feedback quality control approach was used in conjunction with a customised online image acquisition system to execute this system. With the use of online automated machine parameter modification, the typical quality difficulties can be effectively and efficiently mitigated. Their case studies using a real FFF platform demonstrated the usefulness and applicability of the suggested method. Additionally, other reviews were discussed in this chapter, including previous findings and methods.

2.2 Previous Research on Failure Detection of 3D Printing

Inertial Machine Monitoring System (IMMS) was developed for automated failure detection in a high-end machine, especially in a 3D printer [24]. This system consists of two types of sensors which have been proven to be qualified for equipment failure detection. Microphones are used in this system to detect failures by using sound vibration monitoring. A microphone is used to record the moving noise of switchblades during the operation of railway infrastructure. Statistical Features are used to detect and classify three failure scenarios with an accuracy exceeding 94.1%. Microphones are also used for acoustic processing for joint fault diagnosis of legged robots. Microphone-based approaches mainly focus on sound in the high-frequency spectrum. This system is configured with a network of inertial measurement units (IMUs). To record real-world performance data, a linear axis 3D printer was equipped with 36 IMMS sensor modules. The sensors were placed in 3D-printed holders and epoxy-glued on the machine as shown in Figure 2.1.

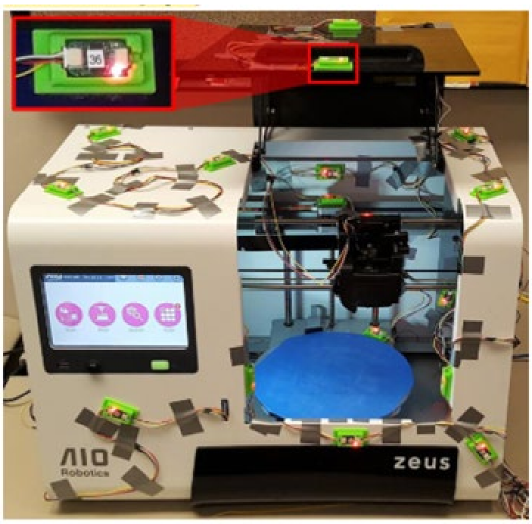

Figure 2.1: Sensor module location on FDM 3D printer [24]

Based on the research, two scenarios were tested: (1) data from all 36 sensors and (2) data from four sensors. Three sensors were attached to moving machine components (X, Y and Z axis) while one sensor was placed on the inner metal case. In scenario (1), the Coarse Gaussian Kernel had the best performance with a 27.3% error rate among all support vector machine (SVM) classifiers. The feedforward neural network was reported to achieve similar results. In scenario (2), the overall error performance of SVM and neural network showed an improvement. This indicated that sensors attached to moving machine components alone were not sufficient to properly classify all failure scenarios. Table 2.1 reports the result of the error performance based on different classifiers.

Table 2.1: Error performance based on classifier [24]

Classifier (with statical features)	**Error Performance**	
	(1) All Sensors	(2) Moving Parts
Random Guess	90.90%	90.90%
SVM – Linear Kernel	37.30%	36.40%
SVM – Quadratic Kernel	38.20%	36.40%
SVM – Fine Gaussion Kernel	38.20%	36.40%
SVM – Cubic Gaussion Kernel	90.90%	71.80%
SVM – Medium Gaussion Kernel	45.50%	36.40%
SVM – Coarse Gaussion Kernel	27.30%	45.50%
Feedforward Neural Network	27.30% ± 0.8% 20 Neutrons	38.20% ± 4.5% 91 Neutrons

IMMS has showed that inertial sensor networks can be successfully used to reliably detect and classify 10 different machine failures or states of degraded operation. With an increasing number of Internet of Things (IoT) sensors on the manufacturing floor, predictive maintenance of industrial equipment guarantees higher efficiency and productivity. By providing valuable failure classification and early detection of machine degradation, IMMS can contribute to the development of smart monitoring systems to help in minimising machine downtime.

Previously, consumer-grade video cameras with video analysis software were used and mounted onto a Makerbot Replicator 2X 3D printer [25]. OpenCV Version 3.0 and the Python API are used in this system as this software provides recent algorithms for image detection, manipulation and recognition. To detect errors from

REFERENCES

[1] Mellor, S., Hao, L., & Zhang, D. (2014). Additive manufacturing: A framework for implementation. International Journal of Production Economics, 149, 194–201. https://doi.org/10.1016/j.ijpe.2013.07.008

[2] Ituarte, I. F., Coatanea, E., Salmi, M., Tuomi, J., & Partanen, J. (2015). Additive Manufacturing in Production: A Study Case Applying Technical Requirements. Physics Procedia, 78, 357–366. https://doi.org/10.1016/j.phpro.2015.11.050

[3] Ford, S., & Despeisse, M. (2016). Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. Journal of Cleaner Production, 137, 1573–1587. https://doi.org/10.1016/j.jclepro.2016.04.150

[4] Delli, U., & Chang, S. (2018). Automated process monitoring in 3D printing using supervised machine learning. 26, 865–870. https://doi.org/10.1016/j.promfg.2018.07.111

[5] "R/3dprinting - anyone know what's up with my Cura Tree supports? looks like underextrusion... (CR-10 // 200°C nozzle, 60°C bed // 120mms print speed // 0.2mm layer height)," reddit. [Online]. Available: https://www.reddit.com/r/3Dprinting/comments/g2gzxt/anyone_know_whats_up_with_my_cura_tree_supports/. [Accessed: 11-Jan-2023].

[6] Kim, C., Espalin, D., Cuaron, A., Perez, M. A., Macdonald, E., & Wicker, R. B. (2015). A study to detect a material deposition status in fused deposition modeling technology. 779–783

[7] J. Průša, "Three hundred 3D printers in one room: A quick look to our printing farm," Original Prusa 3D Printers, 10-Feb-2018. [Online]. Available: https://www.prusaprinters.org/a-quick-look-to-our-printing-farm/.[Accessed: 19-Apr-2019]

[8] Dow Jones & Company. *How Manufacturers can achieve top quartile performance?*. The Wall Street Journal https://partners.wsj.com/emerson/unlocking-performance/how-manufacturers-can-achieve-top-quartile-performance/ [Accessed: 19-Apr-2019].

[9] Delli, U., & Chang, S. (2018). Automated Process Monitoring in 3D Printing Using Supervised Machine Learning. Procedia Manufacturing, 26, 865–870. https://doi.org/10.1016/j.promfg.2018.07.111

[10] W. Associates, Wohlers Report: 3D Printing and Additive Manufacturing State of the Industry. 2019.

[11] R. Luganson, "Artificial Intelligence in 3D Printing: Real-time 3D printing control control," Arcada University of Applied Sciences, 2018.

[12] J. Kerns, "Moving 3D Printing from Prototyping to Production," 2018. .

[13] C. Kim, D. Espalin, A. Cuaron, M. A. Perez, E. Macdonald, and R. B. Wicker, "A Study to Detect a Material Deposition Status in Fused Deposition Modeling Technology," 2015 IEEE Int. Conf. Adv. Intell. Mechatronics, pp. 779–783, 2015.

[14] M. Faes et al., "Process Monitoring of Extrusion Based 3D Printing via Laser Scanning," Proc. PMI 2014 Conf., 2014.

[15] T. P. Paul and J. Samuel Batchelder, "Capacitive detector for use in extrusion-based digital manufacturing systems," U.S. Patent 8 222 908, 2012..

[16] J. Windau and L. Itti, "Inertial Machine Monitoring System for automated failure detection," 2018 IEEE Int. Conf. Robot. Autom., pp. 93–98, 2018

[17] M. Moretti, A. Rossi, and N. Senin, "In-process monitoring of part geometry in fused filament fabrication using computer vision and digital twins," Additive Manufacturing, p. 101609, Sep. 2020. [Online]. https://linkinghub.elsevier.com/retrieve/pii/S2214860420309817

[18] S. S. Razvi, S. Feng, A. Narayanan, Y.-T. T. Lee, and P. Witherell, "A Review of Machine Learning Applications in Additive Manufacturing," in Volume 1: 39th Computers and Information in Engineering Conference. Anaheim, California, USA: American Society of Mechanical Engineers, Aug. 2019, p. V001T02A040. [Online]. Available:

https://asmedigitalcollection.asme.org/ings/IDETC-CIE2019/59179/naheim,%20California,%20USA/1069728

[19] Njoku, J. N., Caliwag, A., & Lim, W. (2021). Efficient Deep Learning Model for Data-Limited Modulation Recognition. Training, 32, 64QAM.

[20] Zhang, Z., Fidan, I., & Allen, M. (2020). Detection of material extrusion in-process failures via deep learning. Inventions, 5(3), 1–9. https://doi.org/10.3390/inventions5030025

[21] Saluja, A., Xie, J., & Fayazbakhsh, K. (2020). A closed-loop in-process warping detection system for fused filament fabrication using convolutional neural networks. Journal of Manufacturing Processes, 58, 407–415. https://doi.org/10.1016/j.jmapro.2020.08.036

[22] Liu, C., Roberson, D. M., Kong, Z. J., Roberson, D., & Kong, Z. (2017). Textural Analysis-based Online Closed-Loop Quality Control for Additive Manufacturing Processes Real-time process monitoring for advanced manufacturing View project Modeling, synthesis, and diagnosis for large and complex manufacturing systems View project Textural Analysis-based Online Closed-Loop Quality Control for Additive Manufacturing Processes. https://www.researchgate.net/publication/316171394

[23] Liu, C., Law, A. C. C., Roberson, D., & Kong, Z. (James). (2019). Image analysis-based closed loop quality control for additive manufacturing with fused filament fabrication. Journal of Manufacturing Systems, 51, 75–86. https://doi.org/10.1016/j.jmsy.2019.04.002

[24] Windau, J., & Itti, L. (2018). Inertial Machine Monitoring System for automated failure detection. 2018 IEEE International Conference on Robotics and Automation (ICRA), 93–98.

[25] Baumann, F., & Roller, D. (2016). Vision based error detection for 3D printing processes. MATEC Web of Conferences, 59, 3–9. https://doi.org/10.1051/matecconf/20165906003

[26] Lyngby, R. A., Wilm, J., Eiriksson, E. R., & Nielsen, J. B. (2017). Dimensional Accuracy and Surface Finish in Additive Manufacturing ,. March 2019.

[27] Lin, G., Liu, K., Xia, X., & Yan, R. (2022). An Efficient and Intelligent Detection Method for Fabric Defects based on Improved YOLOv5. *Sensors*, *23*(1), 97. https://doi.org/10.3390/s23010097

[28] Kim, M., & Kim, Y. (2022). Parcel Classification and Positioning of Intelligent Parcel Storage System Based on YOLOv5. *Applied Sciences*, *13*(1), 437. https://doi.org/10.3390/app13010437

[29] Wang, D., Zhang, M., Sheng, D., & Chen, W. (2022). Bolt Positioning Detection Based on Improved YOLOv5 for Bridge Structural Health Monitoring. *Sensors*, *23*(1), 396. https://doi.org/10.3390/s23010396

[30] YARTINZ. NPU-BOLT. Available online: https://www.kaggle.com/datasets/yartinz/npu-bolt (accessed on 20 November 2022).

[31] Xu, B., Cui, X., Ji, W., Yuan, H., & Wang, J. (2023). Apple Grading Method Design and Implementation for Automatic Grader Based on Improved YOLOv5. *Agriculture*, *13*(1), 124. https://doi.org/10.3390/agriculture13010124

[32] Tian, Z., Huang, J., Yang, Y., & Nie, W. (2023). KCFS-YOLOv5: A High-Precision Detection Method for Object Detection in Aerial Remote Sensing Images. *Applied Sciences*, *13*(1), 649. https://doi.org/10.3390/app13010649

[33] Cheng, G.; Han, J. NWPU VHR-10 Dataset. [EB/OL]. Available online: https://github.com/chaozhong2010/VHR-10_dataset_
coco (accessed on 1 November 2022).

[34] UCAS-AOD Dataset. [EB/OL]. Available online: https://hyper.ai/datasets/5419 (accessed on 1 November 2022).

[35] Long, Y.G. RSOD Dataset. [EB/OL]. Available online: https://github.com/RSIA-LIESMARS-WHU/RSOD-Dataset- (accessed on 1 November 2022).

[36] Song, Q., Li, S., Bai, Q., Yang, J., Zhang, X., Li, Z., & Duan, Z. (2021). Object detection method for grasping robot based on improved yolov5. *Micromachines*, *12*(11). https://doi.org/10.3390/mi12111273

[37] Connor, S.; Taghi, M.K. A survey on Image Data Augmentation for Deep Learning. J. Big Data 2019, 6, 60. [CrossRef]

[38] CR-6 SE 3D printer. creality. (n.d.). Retrieved January 4, 2023, from https://www.creality.com/products/cr-6-se-3d-printer

[39] Ltd, R. P. (n.d.). Buy a Raspberry Pi 4 Model B – Raspberry Pi. Buy a Raspberry Pi 4 Model B – Raspberry Pi. Retrieved January 4, 2023, from https://www.raspberrypi.com/products/raspberry-pi-4-model-b/

[40] Logitech BRIO Webcam with 4K Ultra HD Video & HDR. (n.d.). Logitech BRIO Webcam With 4K Ultra HD Video & HDR. Retrieved January 4, 2023, from https://www.logitech.com/en-my/products/webcams/brio-4k-hdr-webcam.html

[41] Mathworks, “What is Deep Learning?” 2019. [Online]. Available: https://www.mathworks.com/discovery/deep-learning.html. [Acc essed: 19-Apr-2019].

[42] A van de Sande, K. E., R Uijlings, J. R., Gevers, T., & M Smeulders, A. W. (n.d.). *Segmentation as Selective Search for Object Recognition*.

[43] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. E. Reed,C. Fu, and A.C. Berg. SSD: single shot multibox detector. In Computer Vision ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part I, pages 21–37,2016. [Online]. Available: https://arxiv.org/abs/1512.02325[55]

[44] Bas, J., Preston, H., & Moiseyev, L. (2020). OctoPlus: 3D Printing Error Detection System. In Design Review Report.

[45] Luque, A. L., Rodríguez, J. M. J., Donoso, J. L. C., & Feito Higueruela, F. R. (2018). Advances for 3D printing: Remote control system and multi-material solutions. Computer Science Research Notes, 2802(May), 160–163. https://doi.org/10.24132/CSRN.2018.2802.20

[46] Shinde, Y., Madaki, R., & Nadaf, S. (2008). IoT based 3D Printer. International Research Journal of Engineering and Technology, 1015. www.irjet.net

[47] G. Jocher. ultralytics /yolov5 [Online]. Available: https://github.com/ultralytics/yolov5

[48] G.Jocher. BCE With LogitsLoss [Online]. Available https://pytorch.org/docs/master/generated/torch.nn.BCEWithLogitsLoss.html #bcewithlogitsloss

[49] C.-Y. Wang, H.-Y. M. Liao, Y.-H. Wu, P.-Y. Chen, J.-W. Hsieh, and I.-H. Yeh, "CSPNet: A new backbone that can enhance learning capability of CNN," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*, 2020, pp. 390-391.

[50] Liu, S., Qi, L., Qin, H., Shi, J., & Jia, J. (2018). Path Aggregation Network for Instance Segmentation. http://arxiv.org/abs/1803.01534

[51] K. Wang, J. H. Liew, Y. Zou, D. Zhou, and J. Feng, "Panet: Few-shot image semantic segmentation with prototype alignment," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2019, pp. 9197-9206.

[52] Jacob, S.; Nelson, J. How to Train YOLOv5 on a Custom Dataset. 2020. Available online: https://blog.roboflow.com/how-totrain-yolov5-on-a-custom-dataset/ (accessed on 21 September 2021).

[53] Glenn Jocher. 2020. Available online: https://github.com/ultralytics/yolov5 (accessed on 21 September 2021).

[54] Bell, S., Zitnick, C. L., Bala, K., & Girshick, R. (n.d.). Inside-Outside Net: Detecting Objects in Context with Skip Pooling and Recurrent Neural Networks.

APPENDIX A

LIST OF PUBLICATIONS

i) M. L. Liwauddin, M. A. Ayob and N. Rohaziat, "Continuous Data Collection of Under Extrusion in FDM 3D Printers for Deep-Learning Dataset," 2022 IEEE 5th International Symposium in Robotics and Manufacturing Automation (ROMA), 2022, pp. 1-6, doi: 10.1109/ROMA55875.2022.9915693.

ii) M. L. Liwauddin, M. A. Ayob and N. Rohaziat "YOLOv5 Models Comparison of Under extrusion Failure Detection in FDM 3D Printing," 8th IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS2023) (Accepted)

APPENDIX B

VITA

The author was born on September 18th, 1995, in Johor Bahru, Malaysia. He went to SMK Taman Daya for secondary education. He pursued his diploma of Microelectronic Engineering in Universiti Malaysia Perlis (UniMAP) in 2013. He then enrolled B.Eng. (Hons) in Electronic Engineering in 2016. Upon receiving his bachelor's degree, he continued his study in Master of Electrical Engineering in 2020. During his study, he was appointed as Graduate Research Assistant (GRA) under Faculty of Electrical and Electronic Engineering (FKEE). Besides, he is currently a member of the Institute of Electrical and Electronic Engineering (IEEE). In addition, he authored proceeding papers published in the 2022 IEEE 5th International Symposium in Robotics and Manufacturing Automation (ROMA) and 8th IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS2023), which is indexed with SCOPUS.