Process Parameter Optimization of Additively Manufactured Parts using Intelligent Manufacturing

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Declaration

I certify that this research work titled *"Process Parameter Optimization of Additively Manufactured Parts using Intelligent Manufacturing"* is my work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged/referred to.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. The thesis is also according to the format given by the university.

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Copyright Statement

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Abstract

Additive manufacturing is an essential element in the manufacture of machinery. Over the years, researchers have planned to innovate with new ideas for improving laminated molding techniques. This article aims to optimize process parameters. Several machine-learning techniques were used to solve the problem, but they were tedious and time-consuming. The Azure ML database was used to mitigate these errors. This gave similar results without writing a massive line of code. The motivation of this thesis is to improve the tensile strength of objects by optimizing process parameters. Above all, the printer selection was made on a per-order basis. SLA and FDM printers are a hot topic in today's laminated modeling, so a detailed literature review was conducted. FDM printers are used for research work because SLA printers are costly, and the print quality is good. Tensile strength was evaluated in relation to infill density, infill pattern, layer height, and the number of perimeter walls. After measuring the force of each part, the data was uploaded to the Azure ML portal, a linear regression model was applied, a prediction engine was built, and multiple input parameters were defined to forecast different tensile strength values on the web to extend the service model.

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List of Abbreviations

Here is the list of abbreviations used in this thesis:

ABS	Acrylonitrile Butadiene Styrene
AI	Artificial Intelligence
AM	Additive Manufacturing
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
API	Application Programming Interface
ASTM	American Society for Testing and Materials
CAD	Computer Aided Design
CCD	Central Composite Design
CPS	Cyber Physical Systems
DIW	Direct-Ink Writing
DLP	Digital Light Processing
DMLS	Direct Metal Laser Sintering
DSS	Decision-Support System
ECS	Environmental Control Systems
FDM	Fused Deposition Modeling
HPDC	High Pressure Die-Casting
IoT	Internet of Things
ISO	International Organization for Standardization
LOM	Laminated Object Manufacturing
ML	Machine Learning
MEI	Mining Environment Index
MLP	Multi-Layer Perceptrons
PCA	Principal Component Analysis
PETG	Polyethylene terephthalate glycol
PLA	Polylactic Acid
PLC	Programmable Logic Controller
RFID	Radio Frequency Identification

RSM	Response Surface Methodology
SLA	Stereolithography
SLS	Selective Laser Sintering
STL	Standard Triangle Language
SVM	Support Vector Machines
TD	Twitter Dataset
TPU	Thermoplastic Polyurethanes
UAM	Ultrasonic Additive Manufacturing
UCM	Underground Coal Mines
USB	Universal Serial Bus
UTM	Universal Testing Machine

CHAPTER 1 : INTRODUCTION

The work in this thesis is presented in four parts. The first part deals with exploring AM and its connectivity types. The second is research on the IoT for AM. The third part uses big data for AM. The fourth part described azure ML for process parameters optimization. This study aimed to find a solution that combines all aspects to achieve optimized process parameters for good tensile strength of parts.

1.1 Scope, Background and Motivation

Additive manufacturing is a broad field with many uses. In this article, we explored layered modeling techniques and used the IoT and big data research to derive datasets. There are various methods for AM. The most important technologies today are SLA and FDM printing. As SLA printers are a new field of laminated molding, it offered high quality printed matter at a high price. FDM printers, on the other hand, are extremely resilient. Various methods for linking to IoT are also being considered. The goal was to leverage the Azure ML database to investigate how different prediction approaches create different outcomes. Linear regression is an effective tool for providing results on how output parameters depend on different input parameters. A web service has been deployed that utilizes the API keys used by Python for the IoT.

1.2 Additive Manufacturing (AM)

Additive manufacturing is a broad area with several applications. Typical uses include ducting ECS, unique aesthetic aircraft interior components, rocket engine components, combustion bushings, composite instrumentation, fuel tanks, and so on. 3D printing produces intricate, high-strength items. ISO/ASTM 52900:2015 [1] defines and establishes terminologies used in AM methods, *"applying the principle of additive profiling and thus producing 3D physical geometry by adding continuous material addition"*. Sintering is one of three types of AM processes that involves heating materials without liquefying them to create composites of extremely high quality. Full melting of metals by direct laser sintering is another AM technique. A third method, called SLA, makes hard ceramic components using ultraviolet radiation that can set a maximum temperature limit. The term "Binder Jet" refers to a few AM procedures that use the x, y, and z axes to apply layers. Ceramics, metals, and polymers are just a few of the materials that can be deposited using directed energy deposition. In this procedure, a laser arc is employed. A specified substance is ejected or deposited through a heated nozzle during material extrusion which is another type of AM. Electron beams are used to melt the powder. Sheet metal rolling has his two types: LOM and UAM. UAM uses ultrasound to weld various parts, and LOM manufactures raised parts. Another method is barrel polymerization, which creates the part using the liquid in the barrel. The last form is directional arc, which draws its power from arc welding. The automobile sector has long been a pioneer in AM, and now there are prospects for it to earn more from its adoption. Complex designs can be optimized with the help of additional manufacturing components, which also boosts material efficiency. There are also system-wide benefits. Processes in supply chains and logistics can also be optimized. Adefuye et al. [2] gave an overview of sand casting techniques in Nigeria and it is stated that Nigerian sand casting mills typically transition from the low-tech sand casting practices they were working on to high-tech, additive sand casting procedures that were profitable. They came to the decision to go entirely to manufacturing. The researchers also described the various varieties of 3D printers shown in Table 1-1.

	SLA	FDM	SLS	LOM	DLP
Applications	Ideal for form testing. The best method for producing water-resistant materials	Ideal for prototypes. Applications for personal usage	Ideal for practical items with a wide range of applications. Suitable for objects with complicated shapes. Chemical and heat resistant.	Excellent for nonfunctional prototypes.	Like SLA
Overall Accuracy	The most precise printing procedure	Process that is precise and dependable	Not very accurate	Dimensional accuracy is slightly lower.	High Accuracy
Material Options	ABS Materials that are semi-flexible ABS for high temperatures	Thermoplastic materials	Nylon Glass-Filled Nylon	Paper Plastic Metal	Like SLA
Finish Options	Outstanding surface finish	Standard Finish	Standard Finish	Wood like characteristics and can be treated similarly	Good finish High resolution
Post-Processing Requirement	Post-processing is required to remove the support structure.	Post-processing is required to remove the support structure.	There is no need for a support structure, and post-processing is minimal.	Polishing Painting	Requires Post processing

Table 1-1 Comparison of the different types of 3D printing technology (modified from Adefuye et al. 2019)

Charlez et al. [3] demonstrated these advantages, the reasons interest is increasing, and the prospects for integrated metal-based and polymer-based AM in the conventional vehicle manufacturing process chain. Different automotive parts were produced using the inkjet multi-material platform. Figure 1.1 shows the illustration of Inkjet printer.

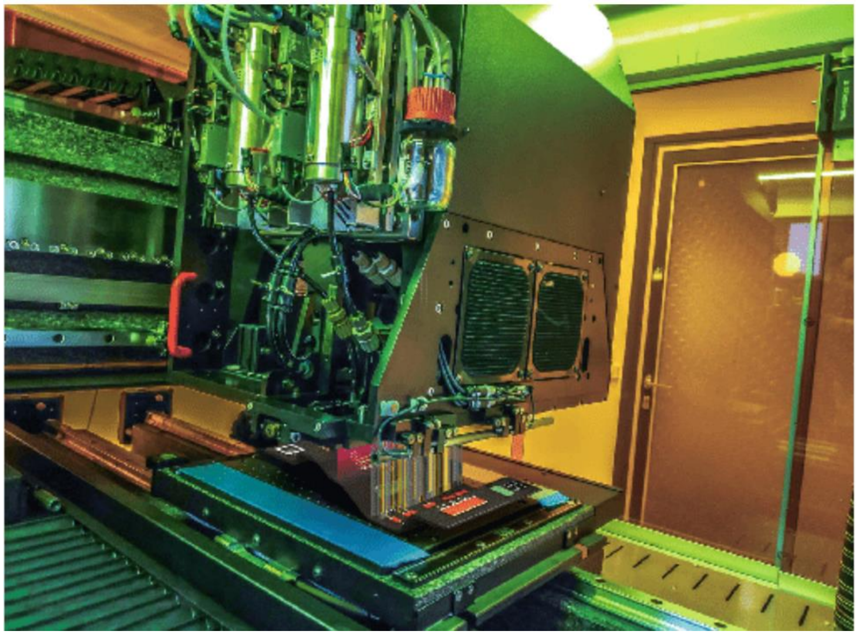

Figure 1.1 Illustration of an on-demand multi-material inkjet printing platform with fully functional 3D printed object (Charlez et al. 2022)

B-Blakey-Milner et al. [4] gave a thorough review of metal clad forming in the aerospace sector (based on industry/popular and technical literature). It provides the current state of the art and outlines the most significant application situations as well as the economic and technical benefits of the appropriate additives produced in these applications. For each application situation depicted in Figure 1.2, these insights highlighted problems and possible possibilities in metal laminate modelling.

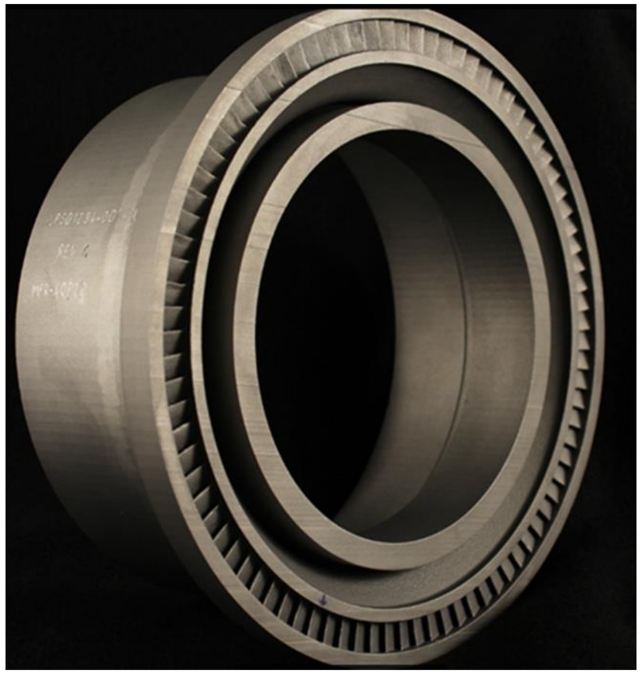

Figure 1.2 Additive Manufacturing Demonstrator Engine Liquid Oxygen (LOX) Turbopump Stator Courtesy : NASA (Blakey-Milner et al. 2021)

Salmi [5] examined the available additive molding techniques. Although, to a lesser extent, the material is also employed in medical and dental applications. ISO/ASTM has established classes for this procedure. Powder bed fusion, material extrusion, VAT photopolymerization, material injection, binder injection, film lamination, and directed energy storage were used to classify AM medical applications. Implants were manufactured employing focused energy collecting based on the findings. Laminated sheet metal models are seldom used in medical implants. Powder bed melting, material extrusion, and VAT photopolymerization were all employed in all categories. Material injection was not utilised for implants or biomanufacturing, and adhesive nozzles were not used for medical devices, equipment, or components. Thermoplastics, photopolymers, and metals like titanium alloys were the most widely used materials. Some medical implants constructed were shown in Figure 1.3

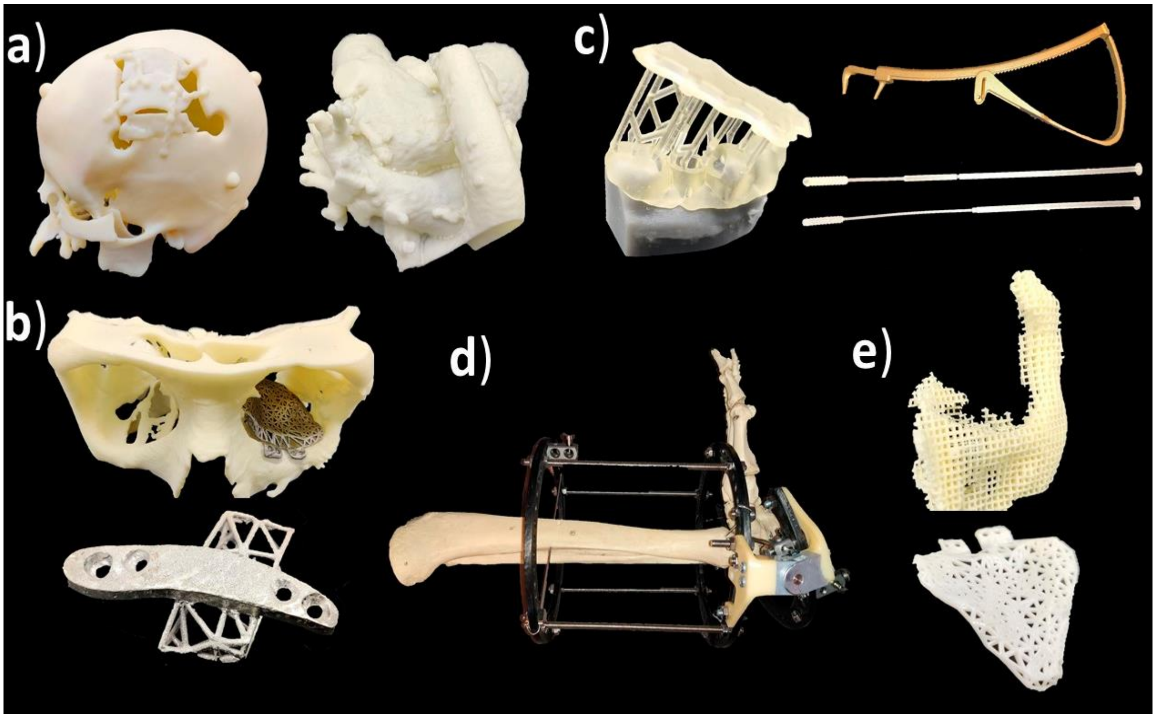

Figure 1.3 (a) Medical models; (b) implants; (c) tools, instruments and parts for medical devices; (d) medical aids, supportive guides, splints and prostheses; (e) biomanufacturing (Salmi, 2021)

1.3 Internet of Things (IoT)

Nowadays, everyone is talking about the IoT. On the IoT, numerous computers or processors are linked together and send data autonomously. In many ways, Bluetooth is like this. Some people can effortlessly transfer their data to another nation thanks to the IoT. The IoT offers a wide variety of possible applications in the commercial world. Real-time data monitoring and tracking will help the researchers link their company to the cloud more effectively. Some applications include enhancing customer satisfaction, reducing costs and time, boosting employee productivity, and boosting earnings. The IoT is a brand-new arena where researchers can study the field of AM. As a result, lead times can be shortened, and product quality can be raised. Bandyopadhay et al. [6] investigated the IOT's cutting edge and emphasized its most critical technological influences. Applications, difficulties, and potential future study areas in this field. Additionally, it compares and explains various academic and commercial definitions of IoT from various points of view. The framework was shown in Figure 1.4. Finally, a few crucial future IoT research areas were identified and briefly explained.

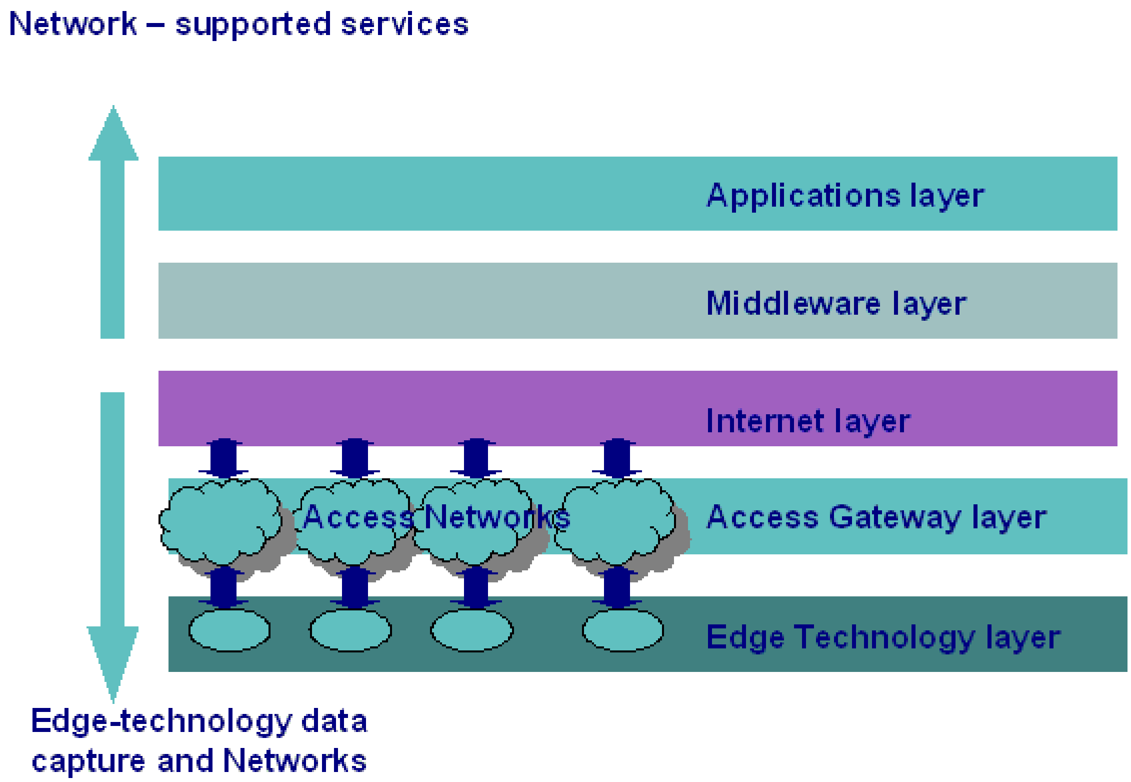

Figure 1.4 Layered architecture of Internet of Things (Bandyopadhyay et al. 2011)

1.4 Big Data

Big data is an area that enables efficient exploration, extraction, or management of overly extensive or complex data indexes that must be programmatically managed through processing applications and routine data management. Big Data includes data from stock exchanges, social networks, etc. Different processes perform different tasks, such as storing measurement data, raw materials, mechanical parts, evaluation information, mechanical tests, and representations. In AM, many parameters influence the final process, and optimizing them requires a large data frame to optimize the data efficiently. Grant controlled approval rights to regulatory, audit, and approval workflows. From montage interactions to tryouts, keep one's family's data and identities updated. Implement/mechanize cycles as representations of real devices and information. Stay informed throughout the support lifecycle. It provides primary data for creating an audit plan. It seeks to thoroughly review the big data literature from the last four years and highlight the leading big data problems, applications, resources, and tendencies. To achieve this goal, Rodriguez-Mazahua et al. [7] analyzed and categorized 457 articles on big data. This overview provides practitioners and researchers with relevant information about big data research, key application trends in various technology areas, and a summary of big data tools for reference. Figure 1.5 shows 5V of big data.

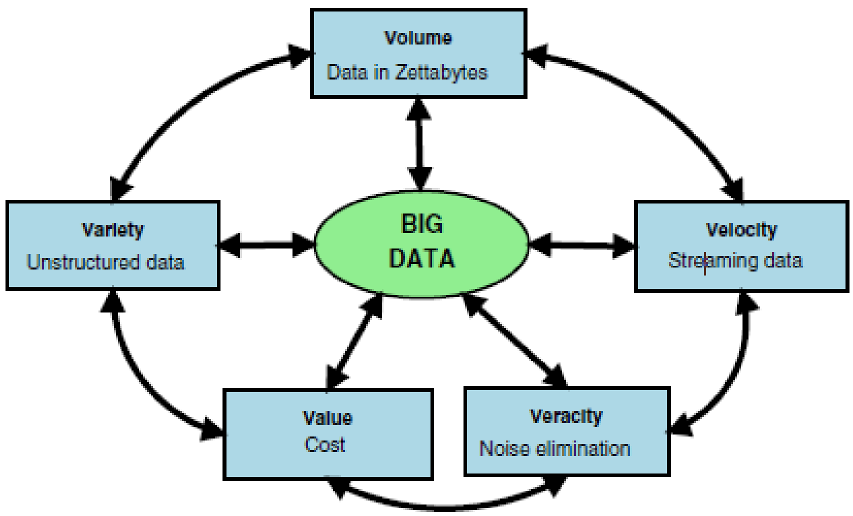

Figure 1.5 The 5V model that currently defines Big Data (Rodriguez-Mazahua et al. 2016)

1.5 Azure Machine Learning

Azure ML is a cloud administrator for accelerating and managing the lifecycle of AI projects. AI professionals, information researchers, and architects can participate in everyday workflows such as model training and submission, ML Operations monitoring, and more. Models developed in open-source frameworks like PyTorch, TensorFlow, or sci-kit-learn can also be used, or anyone can build their models in Azure ML. The ML Operations appliance helps with model validation, retraining, and redeployment. Raza et al. [8] discussed activity awareness areas for patients, the elderly, or the general public. This study's findings can also be used to telemedicine. They also applied various ML algorithms to achieve reasonably accurate activity detection. Microsoft Azure ML Studio and benchmark datasets were used to build and evaluate ML models. Additionally, an activity detection web service was developed using Microsoft Azure ML Studio. It helps developers and researchers tackle activity detection. Figure 1.6 and 1.7 shows methodologies.

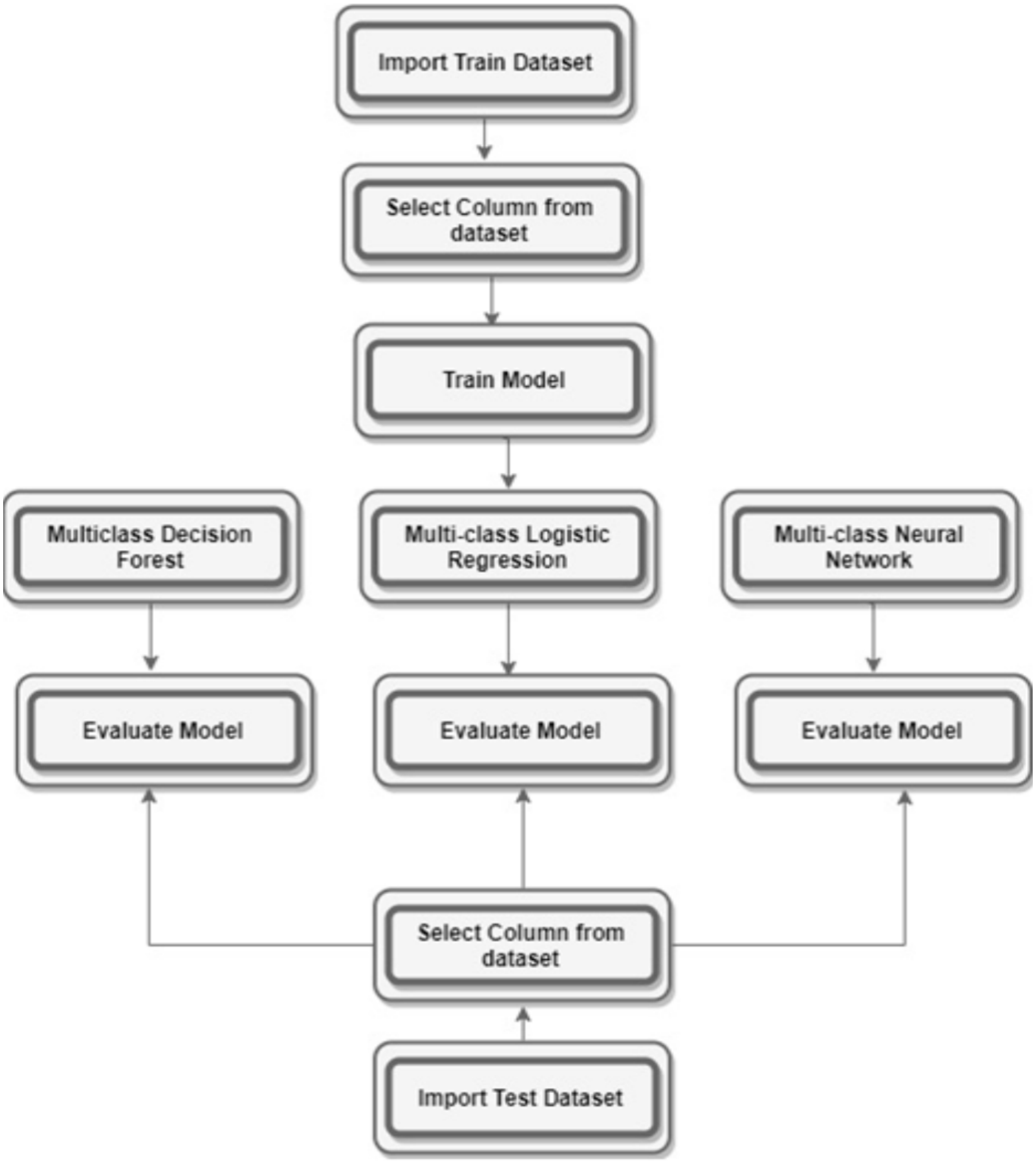

Figure 1.6 Development and evaluation of model (Raza et al. 2021)

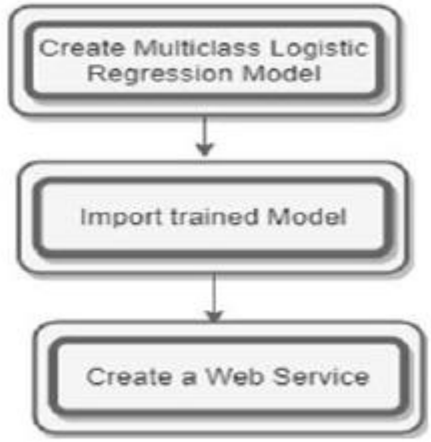

Figure 1.7 Web Services (Raza et al, 2021)

Regression Optimization is a strategy for improving procedure supervised set points at the network or institutional scale that can be managed by combining AI and optimization approaches in a single foundation. Gogtay et al. [9] discussed about different types of regression analysis techniques in Table 1-2.

Ser	Type of Regression	Dependent Variable and its nature	Independent Variable and its nature	Relationship between variables
1	Simple Linear	One, continuous, evenly spaced	One, Continuous, evenly spaced	Linear
2	Multiple Linear	One, Continuous	Any number of two or more, whether continuous or categorical	Linear
3	Logistic	One, binary	Any number of two or more, whether continuous or categorical	Not necessarily linear
4	Polynomial (logistic) [multinomial]	Non-binary	Any number of two or more, whether continuous or categorical	Not necessarily linear
5	Cox or proportional hazards regression	Time to an event	Any number of two or more, whether continuous or categorical	Is not often linear

Table 1-2 Regression Analysis (modified from Gogtay et al. 2017)

CHAPTER 2 : LITERATURE REVIEW

The operation of additive manufacturing and its possible applications have been the subject of extensive study. This article, however, gives a general overview of the various AM processes and how various methods were utilized to retrieve data from the printer, transfer it to the cloud, and use it. Complex issues are simple to tackle, thanks to big data. There were established many phases where various subjects were covered. The topic of various AM techniques is also covered. The IoT will be handled with additive manufacturing techniques in the next phase. The discussion of big data and its potential to enhance AM will come next. Azure ML will be introduced in the following phase to assist with process parameter optimization. After doing a gap analysis based on the first four parts, offered different solutions.

2.1 Additive Manufacturing (AM)

Babu et al. [10] stressed the significance of versatile research, including robotics and automation, process control, characterization of microstructure and characteristics at different sizes, and key computational tools to cope with all of these difficulties. A revolutionary technology for scaling additive structural material fabrication to greater sizes (>1 m) and increased productivity (5-20 kg/h) while preserving mechanical performance and geometric flexibility was also described. Rajaguru et al. [11] offered a comprehensive study review of several AM techniques, combination of digital pretreatment technologies, and product-based process design. Shortening development, manufacturing time, and model creation were all highly contentious topics. Some application-related materials were supplied with Rapid Manufacturing details and features. Bikas et al. [12] discussed various laminated modeling techniques. Current research requires planning manufacturing strategies for laminate structures through interactive systems, examining empirical strategy approaches, and identifying research gaps. The authors had no material influence on this method. The study described how the laminate modeling framework was implemented. Guessasma et al. [13] provided a critical look at the optimal design and shows limitations, advantages, and opportunities for improvement of AM. This review emphasized the design restrictions of AM and the variations that might develop between virtual and actual designs. These distinctions were investigated using 3D imaging techniques to detect processing errors. The phrase "optimal design" guidelines were generated from 3D structural information. Chen et al. [14] described before to summarize the state of AM technology, its potential uses, and its development trajectory. Following the production process, the researchers concentrated on a few essential AM concepts and particular methodologies. The research also examined current issues with AM technology, its difficulties, and potential future directions. This research aimed to offer suggestions for the path AM technology could take in emerging nations. Jose et al. [15] studied the materials and methods applied to AM. A large majority of systems for AM still needed controllers or some local control for variables (like temperature), which rendered them prone to mistakes. In addition to providing an overview of various AM technologies, this study also explained how AM is used in various industries, including aerospace, electronics, the arts, and biomedicine, and gave instances of industrial and academic endeavors to improve AM control systems. Eventually, the researchers addressed workloads for further research and emphasized the advantages of employing closed-loop control in AM. Mellor et al. [16] performed a case study of a business that intends to dominate the market for SLS components and technical advancements in AM. Additionally, it was demonstrated that HPDC technology lowers the cost per assembly as production rises, but that cost for SLS remains constant. 42 was the breaking point. They had the drawback of only being used in case studies, which allowed for the future definition of new frameworks by academics. Ahmed et al. [17] discussed dimensional distortion and improved dimensional quality. The authors discussed how dimensional quality improves when using specific laser disassembly methods. Five arrangements were made with different methods: fixed height and length, variable height and length, heat treatment, artificial aging, and fixed measurement as shown in Figure 2.1. Height affected repeatability, but the length did not significantly affect dimensional change. Heat treatment and simulated ageing did not increase dimension and strain quality, which are inversely related to thickness. It was accomplished in a single step.

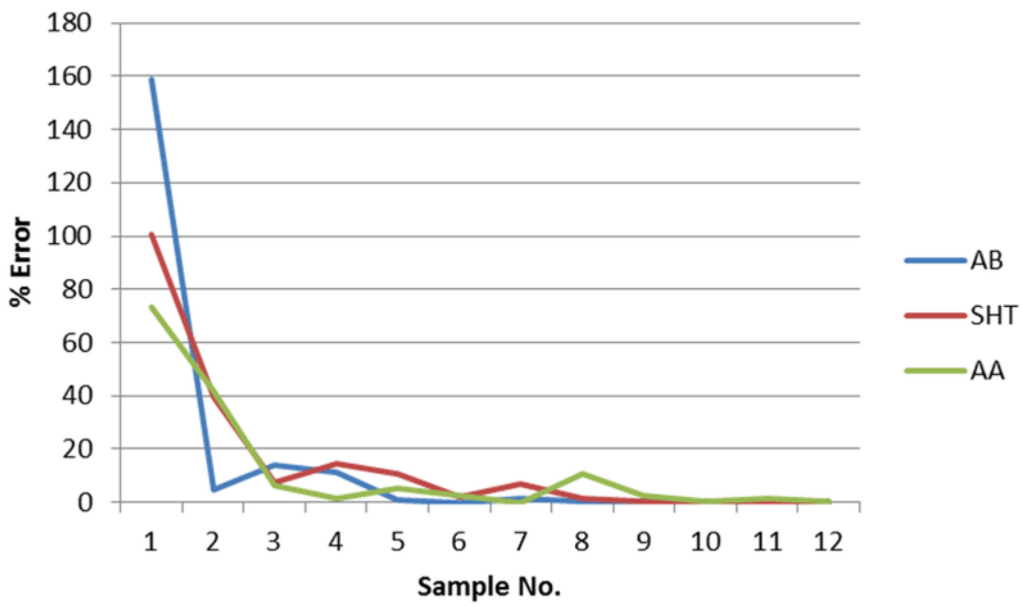

Figure 2.1 % Error in sample length and height comparison in As-Built (AB), Solution Heat Treatment (SHT), and Artificial Aging (AA) conditions (Ahmed et al. 2019)

Majeed et al. [18] furthermore explained how selective laser melting changed wall thickness to alter Alsi10Mg hardness. A suitable environment was employed to evaluate the thin-walled samples. Thickness was soon proportionate to hardness. The hardness was 137.3 HV for a component that was 5 mm thick. Between 0.5 and 1.0 mm in thickness, hardness decreased. In the future, a different printing method can be used to examine wall thickness, influencing hardness which is shown in Figure 2.2.

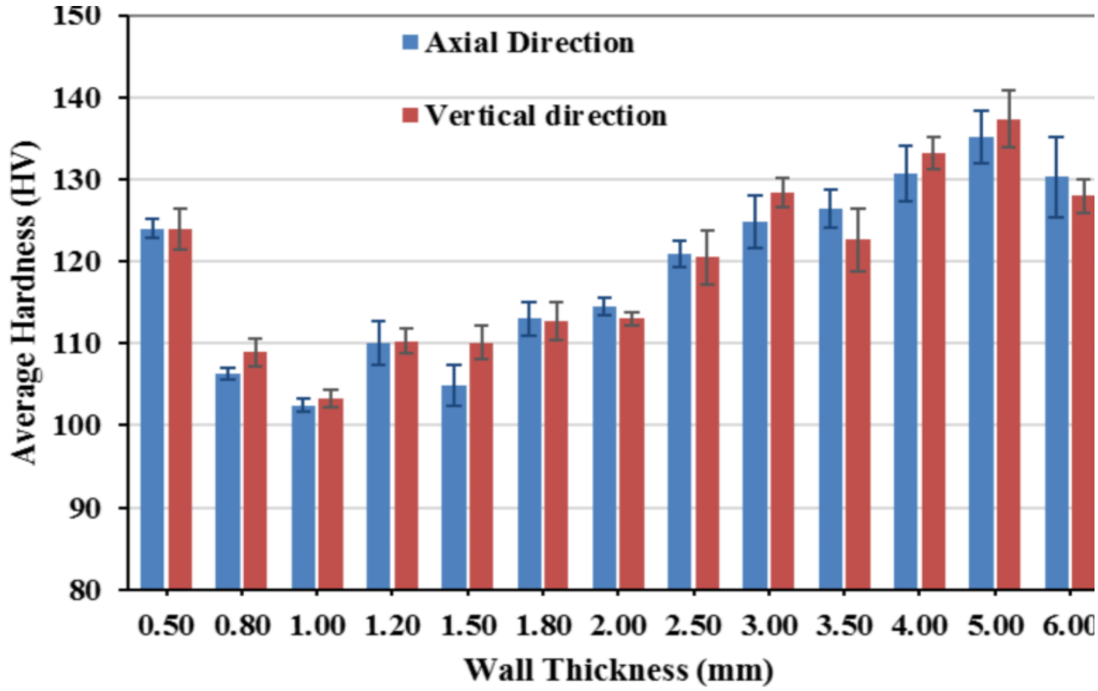

Figure 2.2 Comparison of the average axial and vertical direction hardness of thin-walled and bulk samples of AlSi10Mg alloy (Majeed et al. 2019)

Msallem et al. [19] described the dimensional accuracy of various published printers. The authors described the dimensional stability of the mandible, which holds it in place. They printed 50 replicas using five different printing techniques. They found that selective laser fusion was more accurate but the most accurate in creating fused filaments—different printing techniques using different materials. Figure 2.3 showed the results of the trueness.

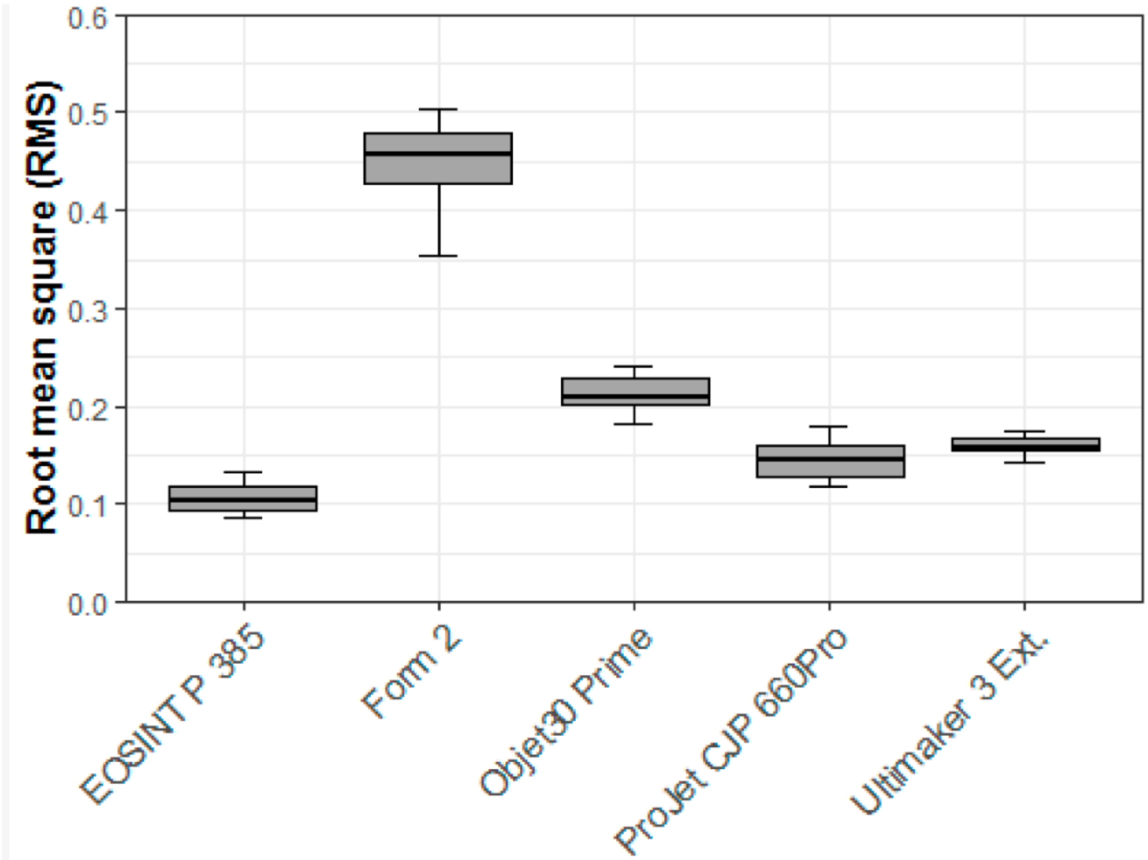

Figure 2.3 Box plot demonstrating trueness RMS (mm) values by 3D printer type (Msallem et al. 2020)

Huang et al. [20] discussed the influence of laminate modeling on society. The researchers examined the cultural impact of additives, also known as lamination or lamination, from a particular angle. It was more environmentally friendly and offered the medical field several advantages. Guo et al. [21] also described some techniques used for hierarchical modeling. The authors elaborated on the main actions, entities, or uses of present AM revolutions and presented future research needs for this innovation. New research related to schemes, materials, new instruments, computerized displays and controls, biomedical applications, and energy was needed for greater industrial acceptance. Usability implementations needed to be improved to make the AM transformation accessible and standard innovation. Vayre et al. [22] suggested a building system for laminated modeling. In evaluating criteria for material assembly of metal parts, the authors analyzed the manufacturability and requirements of these cycles. At this point, planning strategies should be recommended and represented by model revisions. The author needs to address this issue in the overview directly, but researchers should consider using assemblies instead of single or less obvious parts from different cycles. This can be done using models of the parts used to describe the assembly. Horn et al. [23] talked about developing laminated modeling production to accelerate the company's product improvement. The author introduced some cutting-edge applications, focusing on critical advances that facilitated the assembly of laminated build parts. The question of how contract manufacturing and assembly subsidies affect the economy, supply chain organizations, and, surprisingly, the climate remains unresolved. Thome [24] detailed the use of SLA printers in the manufacture of microfluidic devices. The researchers produced microfluidic devices using a Formlabs SLA printer. Numerous difficulties appeared. Tank resin got misted because of ongoing use. The intended width was less than all channels made of spheres, rectangles, and cylinders, while the designed height was more than all channels. With 3D printers, researchers can accomplish more and improve the manufacturing process. To understand 3D printers, one needs to understand the materials used. Lang et al. [25] described additive molding for manufacturing ceramic materials by multi-material injection performed by database process control technology. Weighting factors influencing droplet shape were identified and optimized through a practical design. ML can also be used for future work. Shahrubudin et al. [26] discussed this topic. In addition to using polymers, ceramics, and composites, 3D printing also uses metals like cobalt and aluminum alloys. Applications in many disciplines were also covered in this research. Future studies will enable researchers to examine various 3D printer kinds and the materials needed for each type. Due to the towering price of the framework, researchers can use parallel programming to enhance the model. Jaiswal et al. [27] developed an idea that would provide layer modeling complete control. The researchers enhanced the architectural qualities of materials with functional degradation. The researchers produced a test model. Several case studies with various outcomes were also taken into consideration. Lovo et al. [28] published his work on printers with digital optical processing. The researchers of this study investigated both top-down and bottom-up DLP approaches and offered laboratory testing for their investigation. With measured luminance energy density values of 208.4 lm*s/mm and 264.1 lm*s/mm for white and black resins, respectively, the results were extremely close to FDM, and printing rates were quick, exceeding 300mm3. Researchers will be able to create printers in the future that are at least as quick as DLP. Mantada et al. [29] discussed how varying geometric tolerances impact different 3D printer times. The author covered several variables that impact 3D printer accuracy. The princinples of SLA and FDM printers were given in Figure 2.4 and 2.5. The findings demonstrate that the printer's geometric tolerances grew from the first to the fourteenth day, but they stayed constant from the fourteenth to the eighty-fourth day.

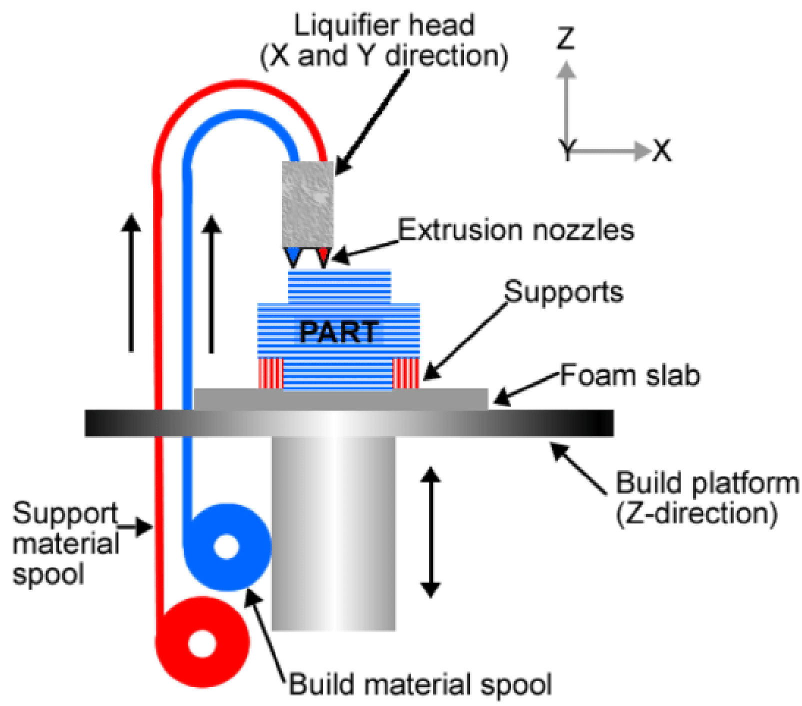

Figure 2.4 The principle of FDM method (Mantada et al. 2017)

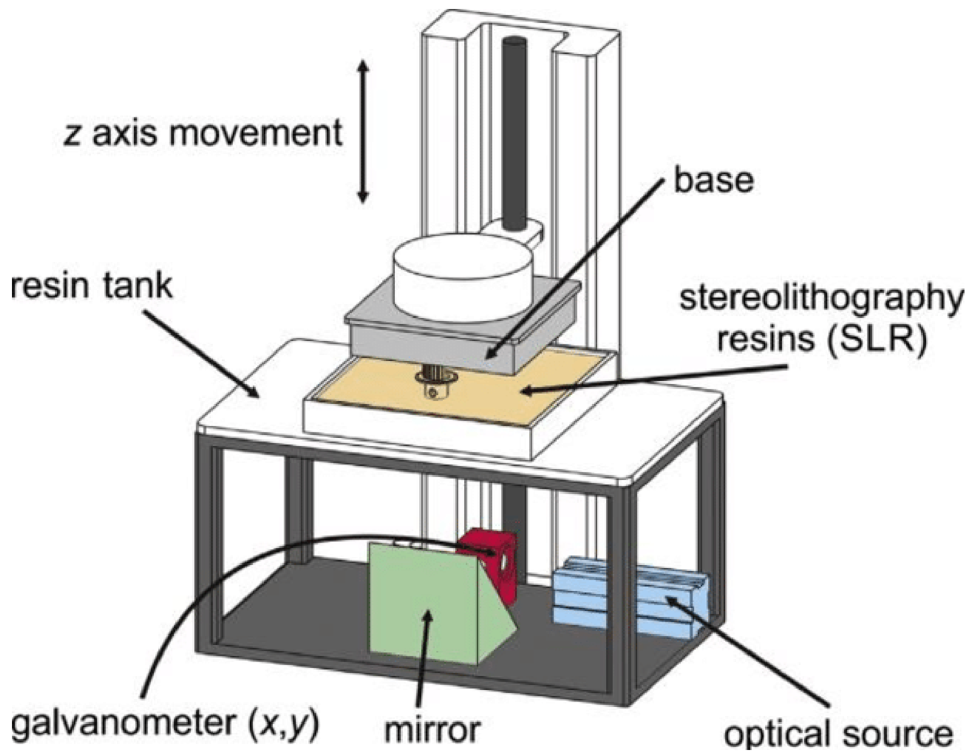

Figure 2.5 The principle of SLA method (Mantada et al. 2017)

Printing composites with moderate mechanical performance is now possible thanks to recent advancements in AM technology. Li et al. [30] gave a summary of composite AM methods. The mechanical characteristics of fiber-reinforced composites made employing cutting-edge AM techniques, both discontinuous and unending, were the focus. The deformation mechanism was briefly explained as well. The upcoming tasks were also offered advice. FDM and modified FDM composites typically outperformed SLS, DIW, and SLA composites in terms of tensile strength and modulus. ABS is an industrial thermoplastic widely used in FDM technology. Samykano et al. [31] analyzed the effects on the mechanical characteristics of acrylonitrile, three primary processing parameters, including layer height, raster angle, and infill density. The assessment findings directly illustrated the variables considered while measuring the mechanical quantities. The superlative parameters for the 3D printing with ABS were discovered to be 80% infill density, 0.5mm layer thickness, and 65° raster angle using response surface methods to validate trial data and forecast future test outcomes. Toughness (energy absorption) was measured as 31.57 MPa, 774.50 MPa, 19.95 MPa, 0.094 mm/mm, and 2.28 Jm-3, respectively. Tensile strength was also measured. The response surface approach was applied to anticipate ABS train features and forecast ideal conditions quantitatively. Srinivasan et al. [32] indicated that the two most crucial variables are layer thickness and infill density. As the process conditions for printed components vary based on the application, mechanical qualities like tensile strength and hardness are crucial. By adjusting the three process parameters such as infill density, infill pattern, and layer thickness, the experimental tests of FDM printed components made of ABS material were done. Response criteria included tensile strength and hardness. RSM and CCD were used to study experiments. Desirability analysis was used to optimize. Sumalatha et al. [33] explained the Taguchi technique's ability to demonstrate the link between many qualities and aspects. Current research addresses the boundaries of interactions such as layer thickness, fill thickness and printing speed. In this study, they planned to investigate the impact of interaction limits on various execution limits. Mechanical properties (structural strength), manufacturing time, and the unpleasant surface can be tracked with fewer test runs. Taguchi's research program was used to save costs and a period of trial and error. Using ANOVA, the true meaning of process limits was determined. Signal-to-noise ratios were used, and significant limits were recommended for ideal results and ideal limit settings.

2.2 Internet of Things (IoT)

Barbosa et al. [34] presented a solution for establishing a connection between the IoT and layered modeling. The author used Beacon software, the energy-efficient Bluetooth standard. Beacon technology connects the Wi-Fi to the printer and provides the necessary information about various parameters that allow the user to control Wi-Fi with the phone. The method suggested is shown in Figure 2.6.

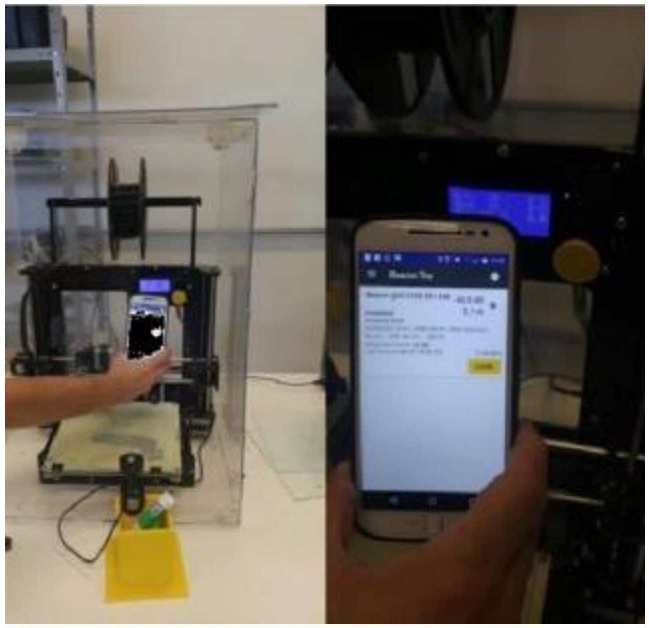

Figure 2.6 Architecture of the proposed system (Barbosa et al. 2017)

Arumugan et al. [35] described IoT applications for industrial objects in laminated modeling and how they can be helpful in manufacturing. In particular, the authors confirmed that many countries spent more on IoT in 2020 than in 2015. The advantage of the IoT was that all applications could be digitally controlled and managed remotely. This study covers areas such as the challenges faced by the Association of Industrial IoT Experts, the awareness of the challenges faced by the association's resources in implementing industrial IoT in organizations, and ongoing feasibility completion level investigations. Additional evaluations have been made. After executing IIoT. Agron et al. [36] described how to connect the IoT to SLA printer surveillance via ANN. Monitor the oxygen level of the SLA printer that has become an issue. The final score was 96%. For future advances in the check program, researchers need to distinguish the worldview using state-of-the-art AI computing and PC vision innovations that enhance the check program's honesty. To understand the IoT, one must understand how the programming language should be applied to a system. Nandi et al. [37] discussed this. The author's goal was to adopt a programming language and discuss how to print CAD models. There are various steps, such as generating an STL file with G code and printing it. Different algorithms are presented, and different results are produced. In the future, if hardware inaccuracies occur, the printer will need to add padding in this direction automatically. There were many applications for AM, but they needed to connect to the IoT with online access. Andrade et al. [38] proposed such a procedure. The author used Octoprint software to connect an IoT and a 3D printer for online access. The software informs the user of the basics of how the printer prints, the temperature, etc. There is no programmed framework for fiber materials, with the drawback of no accounting system and other requirements specific to the printer. The framework is shown in Figure 2.7. Trading and moving out of printed parts can eliminate these disadvantages in the future.

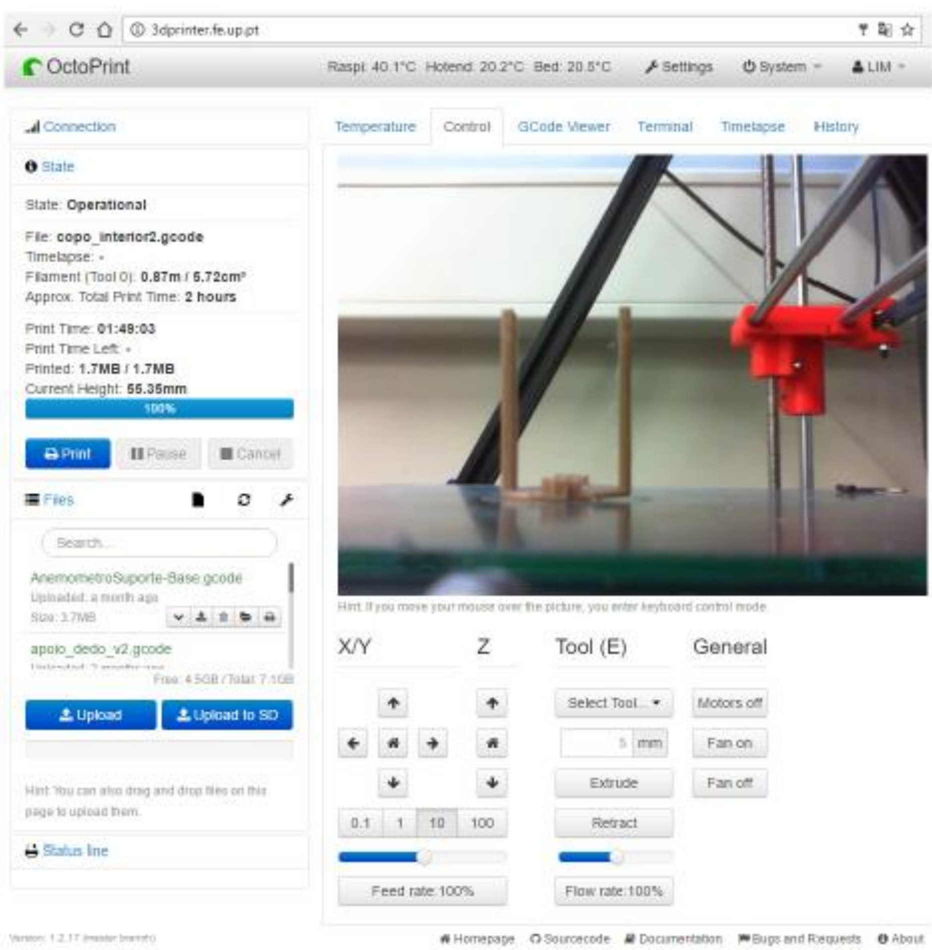

Figure 2.7 Web interface for remotely operating the 3D printer on a computer (Andrade et al. 2017)

Mehrpouya et al. [39] discussed how laminated modeling and Industry 4.0 work together. The author has organized how AM technology can improve the industry. There were many challenges, such as defects and costs. AM had many pioneers in the aerospace and medical fields. While 3D printing has its advantages, it is still a new field, allowing researchers to develop new ideas. Caputo et al. [40] described a framework for innovation in the manufacturing process. The framework was applied to 3D printers for implementation. The results were encouraging, and they applied the Henderson and Clark models. They were applied to help managers gain an advantage. Future researchers will be able to find fascinating comments and fix the shortcomings that exist in the frame. Kumar [41] described the processes and materials used in Industry 4.0 smart manufacturing. The author is an existing strategy and material advancement, as well as the IoT, CPS, and human-robot collaboration augmented reality. The author highlights some of the recent advances in countermeasures, frameworks, and editing of related things and begins a conversation between researchers about possible study camps. Qin et al. [42] discussed an energy-saving framework for layered modeling using the IoT. Raw data was collected, and the information was interpreted by information diagnostic techniques. The data were reformatted to the cloud, after which the energy-saving process in layered modeling was identified. The author also used the EOS P700 case study which is shown in Figure 2.8. Researchers can do the rest of the work in the future.

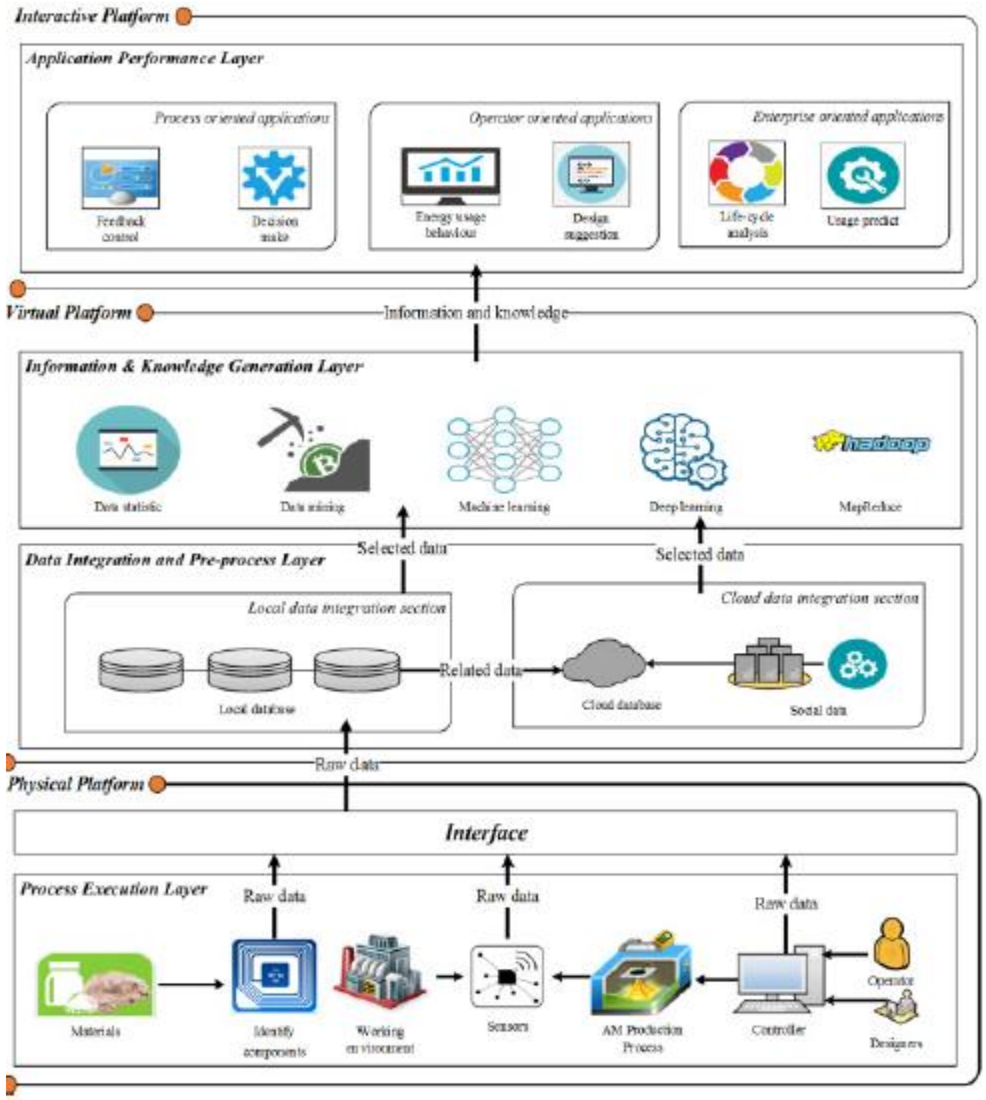

Figure 2.8 Internet of Things framework of energy consumption analysis (Jian et al. 2017)

In this framework, there was an exclusive platform that was the interactive, digital, and bodily platform with exclusive layers which incorporates utility overall performance layer wherein there may be remarks managed and through which choice was made. Associated power productions were made in operator-orientated elements, and the corporation, there was an existence cycle evaluation of the product, and they were a part of an interactive platform. In the digital platform, records and an information era layer were accrued through exclusive strategies, statistics mining, and device learning. In the statistics integration layer, nearby records were accrued to a cloud. In the bodily platform, substances were recognized, sensors were set up, and uncooked statistics were shipped to the digital platform. The operator operates on laptop wherein additive production strategies are being held, and uncooked statistics from this system additionally go to different platforms. Lu et al. [43] mentioned virtual dual clever production. The authors reviewed approximately the cutting-edge scenario of dual technology in manufacturing equipment and virtual dual production primarily based totally on the IoT. They mentioned approximately exclusive strategies. The framework can be seen in Figure 2.9. They mentioned an advocated replica. The researchers should focus on the upcoming phase for extra work in close time.

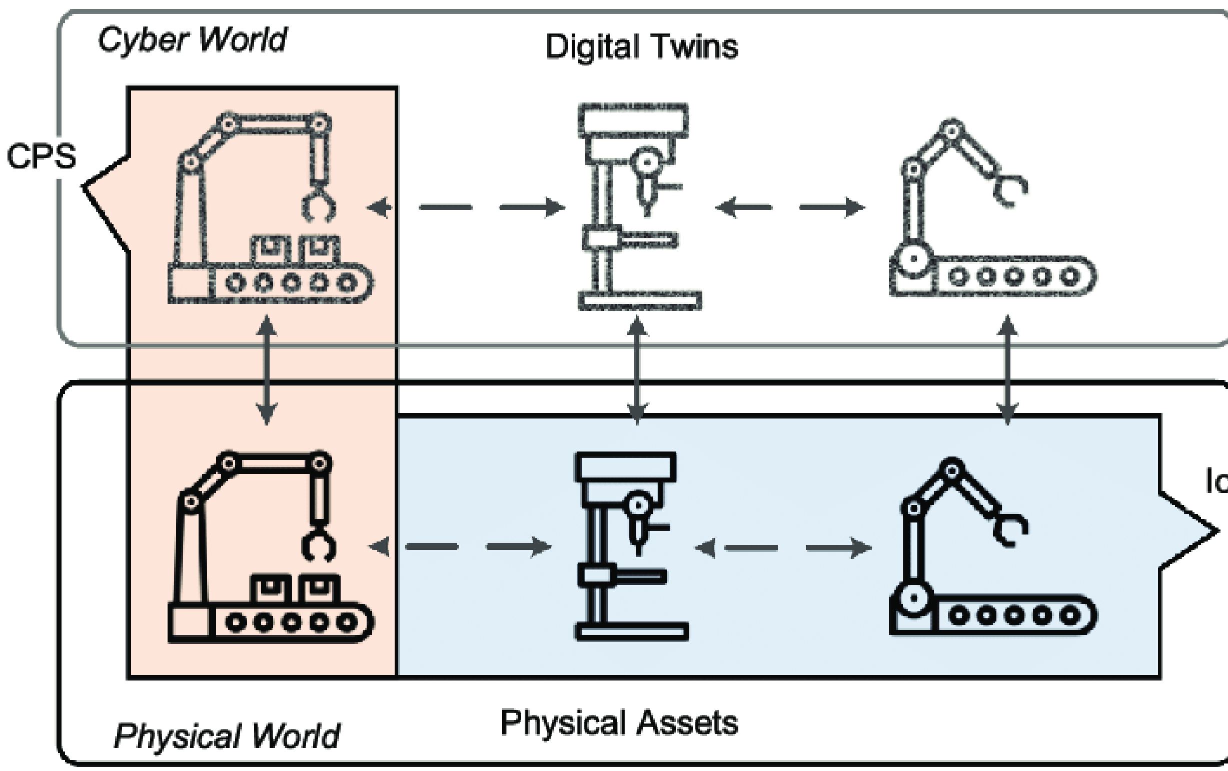

Figure 2.9 The relationship between Digital Twin, CPS and IoT (Lu et al. 2020)

Yee et al. [44] studied Chiga Light Industry's production line monitoring system to see how it may boost IoT-based manufacturing capabilities. This firm manufactured plastic packaging. However, a planning system (ERP) provided production managers and their managers with a mechanism to keep track of and record the length of the plastic film created on your press. The total quantity of item donations was given in kilogrammes. The entire amount of plastic produced, as well as the time required to complete production planning and hose machine analysis, were required. Consequently, a length encoder was employed. The amount of plastic film produced was established, and it was linked to a counter that displayed the market price of generated plastic as well as the predetermined price of plastic rolls. It also used an Arduino board to get information from the metre. The ESP8266-01 Wi-Fi module was used to transmit and save data to the ThingSpeak$_{TM}$ cloud.

2.3 Big Data

Big data is everyday life. Alabi [45] discussed the importance of big data. The researcher covered many industrial uses for laminated molding using various varieties. Future considerations might include several uses. (See Table 2-1). ML is used to collect large amounts of data. Liu et al. [46] utilized ML in 3D printing. The author looked at the information mining-supported ML information structure. The Bayesian model was a backup plan far more practical, beyond modeling interaction attribute connections, and superior to SVMs. Data collection was done with previous information, and it may be processed using a violin-shaped histogram and the feature's property number. For dimensional accuracy, they employed ANOVA, and for data-driven models, they used neural networks. They assessed the model using receiver operating characteristics. Second, process optimization and property prediction were successful when using models. To obtain reliable results, they used an experimental design. Future work may be done to improve layered modeling using ML. Much work has gone into integrating AM with the IoT and the Internet of Big Data. A framework has been used to bring big data into practice. Figure 2.10 shows the framework.

Ser	The Nine Digital Technologies of Industry 4.0	Emerging Application Areas of Industry 4.0
1	Advanced Robotics	• Collaborative, self-driving industrial robots • A plethora of standardised interfaces and integrated sensors
2	Additive Manufacturing/3D Printing Technologies	• 3D printing is very useful for replacement components and prototypes. • Decentralized 3D facilities to reduce inventory and transit time
3	Augmented Reality	• The application of augmented reality in maintenance, logistics, and a variety of SOPs (SOP) • For example, use glasses to display information that support your point.
4	Simulation	• Value networks can be deployed for simulation in Industry 4.0. • Smart devices' real-time data is employed in optimization.
5	System Integration	• Data integration among businesses based on data transport standards. • The necessity for a fully automated value chain (from supplier to customer, from management to shop floor)
6	Cyber-Security	• Network and open system applications • Significant networking of commodities, systems, and intelligent machines
7	Internet of Things (IoT)	• IoT enables the networking of devices and products. • Interaction between networked things in both directions
8	Cloud Computing	• Controlling massive volumes of data in open systems. • Real-time connectivity is necessary for production systems under Industry 4.0.
9	Big Data and Analytics	• Complete data assessment (e.g., from ERP, SCM, MES, CRM, and machine data) • Industry 4.0 offers optimization and real-time decision-making help

Table 2-1 Identification of the nine industry 4.0 digital technology and application areas (modified from Alabi 2018)

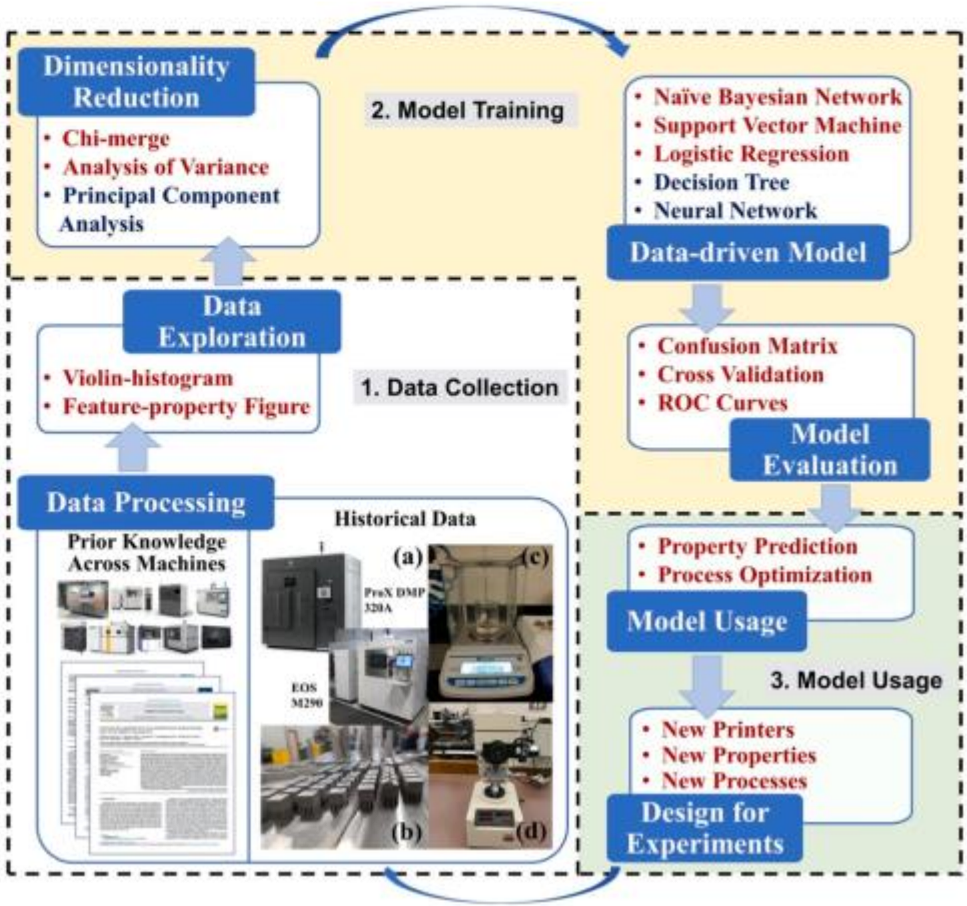

Figure 2.10 The learning framework for AM knowledge extraction and AM development. The blue boxes indicate general steps while white boxes describe the methods that can be used within this step. Methods used as part of this work are highlighted in red. Sub-graphs experiments shows (a) samples were manufactured by ProX DMP320A (3D systems, CO) and EOS M290 (Elementum 3D, CO), (b) printed samples, (c) relative density and (d) microhardness measurement. (Liu et al. 2021)

Majeed et al. [47] developed a framework that uses several sensors to monitor various factors and optimize for better outcomes which is shown in Figure 2.11 . RFID tags were also used to identify things, and smart sensors like temperature sensors were used to keep track of the temperature of processing beds and additive manufacturers' electrical energy usage. Additionally, a case study was undertaken. A pressure sensor measures data on pressure from a particular laser measuring device. Calipers were used to assess the dimensional correctness of the product. The product's surface quality was assessed using a surface roughness tester. The product's construction was evaluated using scanning electron microscopy. A LECO hardness tester was used to determine the product's hardness. The author utilised a tensile tester, and they used selective laser measurement to determine the mechanical properties of the product. The author has imposed a limitation that only applies at the start of the life cycle for accessible assets and only for printing systems.

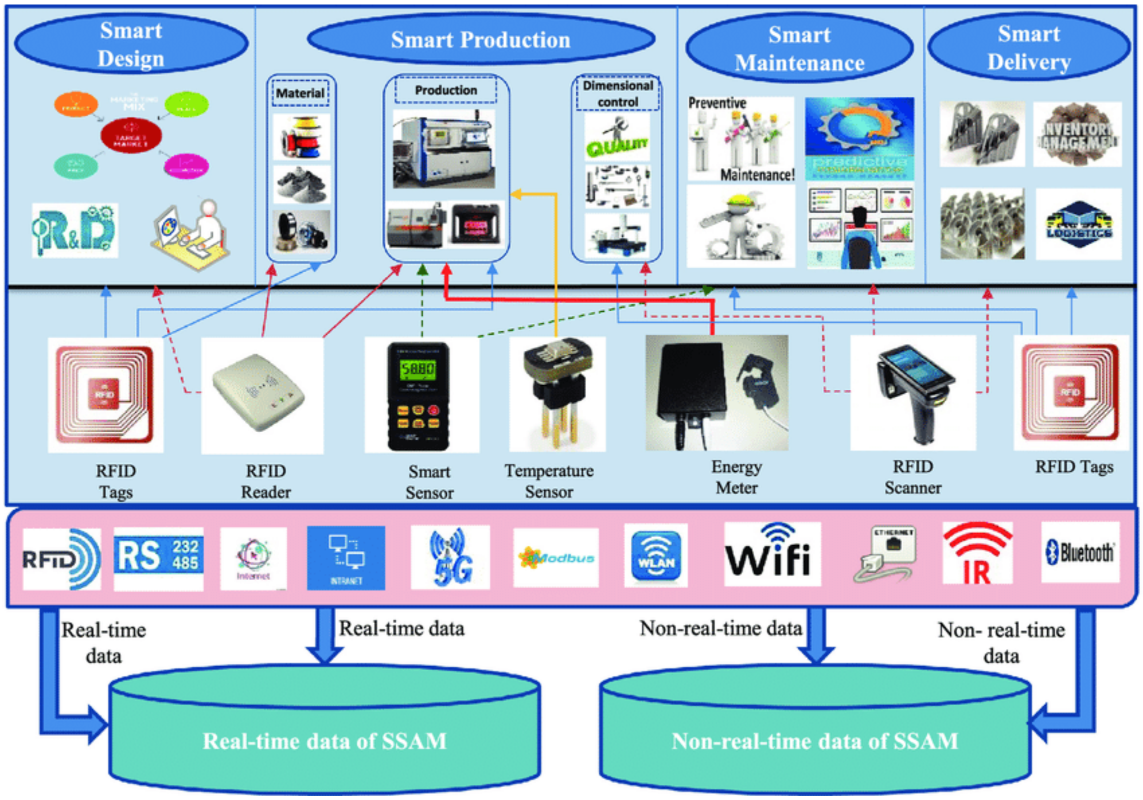

Figure 2.11 Big data perception and acquisition framework of product manufacturing cycle for SSAM. (Majeed et al., 2021)

Delli et al. [48] significantly used gadget training to automate 3-D printing approach tracking. The authors present a method for investigating the nature of three-dimensional published leaves after coordinating the camera, photo editing, and controlled AI. The various levels are as follows: Differentiate between legitimate precise locations for 3-D printing components as suggested by its math, take pictures of the partially completed component at each specific location, carried out photo handling and analysis. The outcome guided them for a forthcoming test that required them to weld cameras on both printer's edges and comprehended abandons on both the even and upright levels. The ability enhancement can be done by setting up cameras on a website or through print heads.

Future assignments will also concentrate on the investigation of influencing selection criteria for reliable exact locations. The experimental setup can be seen in Figure 2.12.

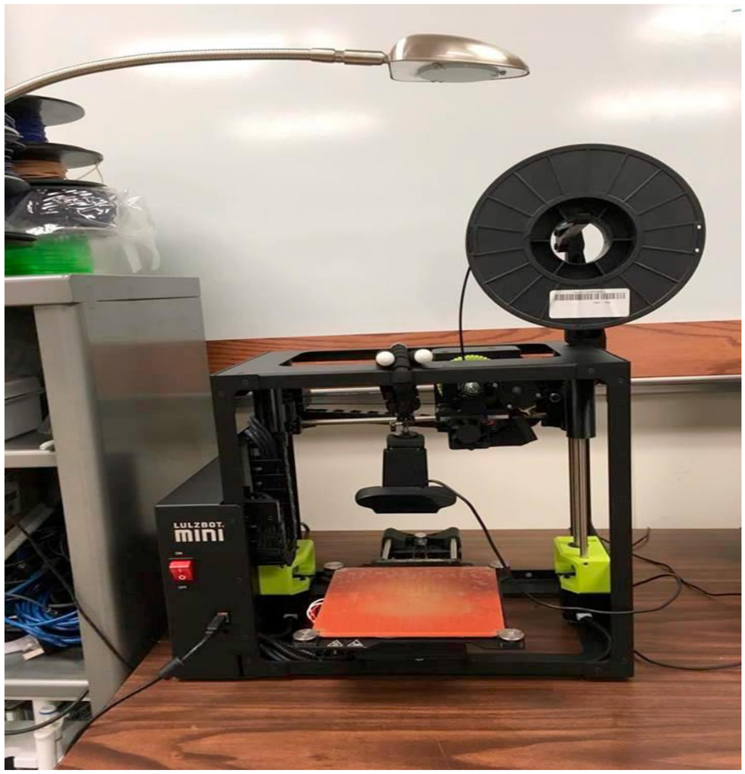

Figure 2.12 Experimental setup (Delli et al, 2018)

As a foundation for resolving the difficulties faced in big data linking with AM , Perišić et al. [49] presented an AM framework. AM data are automatically streamed, verified, and placed in the framework for real-time analysis and batch processing, increasing the efficiency of storing and accessing that data. The design also provides a description of the AM metadata, which connects the many data kinds and makes data browsing, discovery, and analysis easier. As illustrated in Figure 2.13, the framework may be used to set criteria for data-sharing standards.

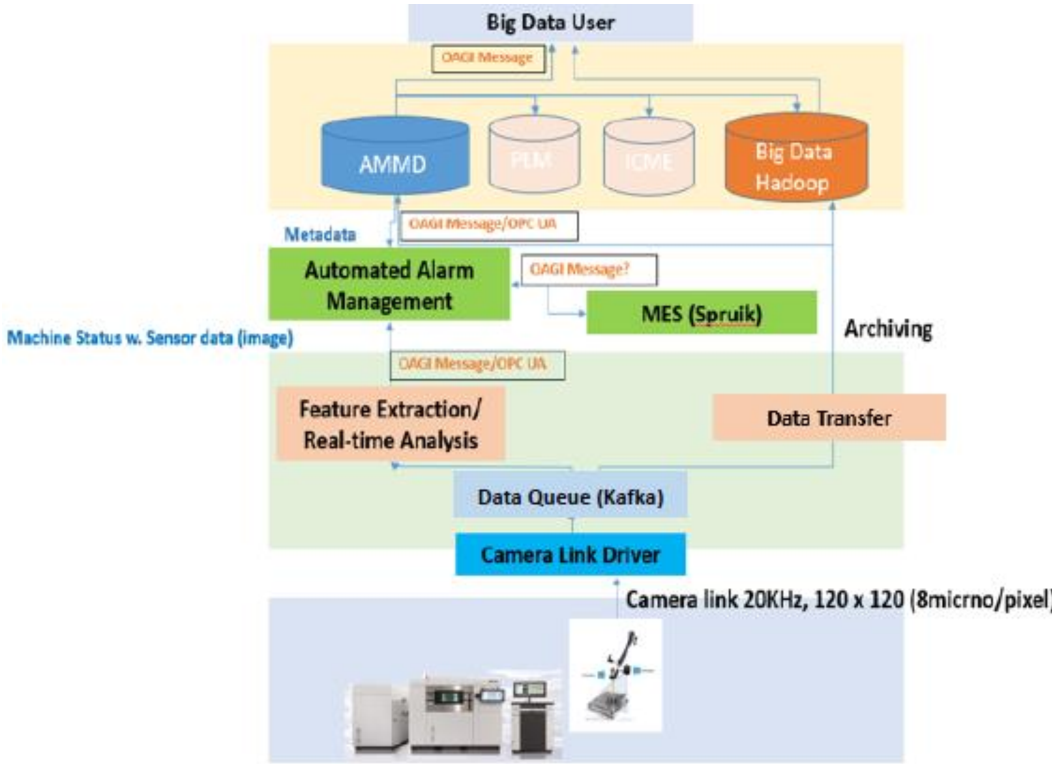

Figure 2.13 AM in-process Data Integration Architecture (Perišić et al. 2021)

2.4 Microsoft Azure Machine Learning

Information acquired for a polymer powder bed melting method. Baturynska et al. [50] meant to determine the scaling factor for each part separately, depending on the item's position, orientation, and CAD properties. Using cutting-edge ML techniques, this has been proven to be a data analysis tool for AM. CNN and MLPs, two examples of conventional ANNs, are methods with much potential. It outperformed CNN in prediction accuracy and mean squared error, or prediction scaling ratio, which may be used to scale the part before manufacturing. Meng et al. [51] discussed and investigated the most recent ML applications in the AM field . Regression, classification, and clustering were some of these applications, along with anomaly detection and parameter optimization. The effectiveness of different ML algorithms was compared and assessed on these kinds of AM tasks. They concluded by offering some suggestions for further investigation. Jo et al. [52] provided a system with sensor modules, communication guidelines, and a base station running Azure ML Studio had been suggested. Eight distinct limit-based Arduino-based sensor modules were presented in the remote area of the UCM. The suggested methodology evaluated mine air quality concerning the conditions of the mine today using the data gathered. The four gases, CH4, CO, SO2, and H2S, had been found to have the most significant overall effects on mine air quality in overhead investigations. ANN model was utilized in Azure ML studio to account for a continuation of PCA and forecast the MEI. The researcher's PCA-based ANN for MEI prediction performed well, as seen by the data, which indicated that coefficient of determination and Root Mean Squared Error rose by 0.6654 and 0.2104, each. Thus, by quickly evaluating and forecasting air quality inside mines, the suggested Arduino and Azure ML-based architecture enhanced the natural well-being of mines. Milad et al. [53] suggested a framework for Azure ML to handle customized contracts and inquiries for Asphalt support. It was essential to restrict the findings by employing four factors as data sources for predicted values: severity, thickness, road tolerance, and average daily traffic volume. In this paper, researchers investigated degree calculus, including multiclass decision forests, multiclass neural networks, and two-class SVM. Using Azure ML characteristics on asphalt systems, examine how each classifier uses the data present in the dataset with an emphasis on anticipated outcomes. The researchers carried out a materiality check. Paolanti et al. [54] proposed a random forest-based ML architecture for preventative maintenance. The system was evaluated in real-world instances by creating data collecting and data system analysis, using ML techniques, and contrasting with the analysis of simulation tools. Data was collected using numerous sensors, machine PLCs, and communication protocols, which were then made available to data analysis tools in the Azure cloud architecture, as illustrated in Figure 2.13. According to preliminary findings, this method is effective at accurately anticipating different machine states.

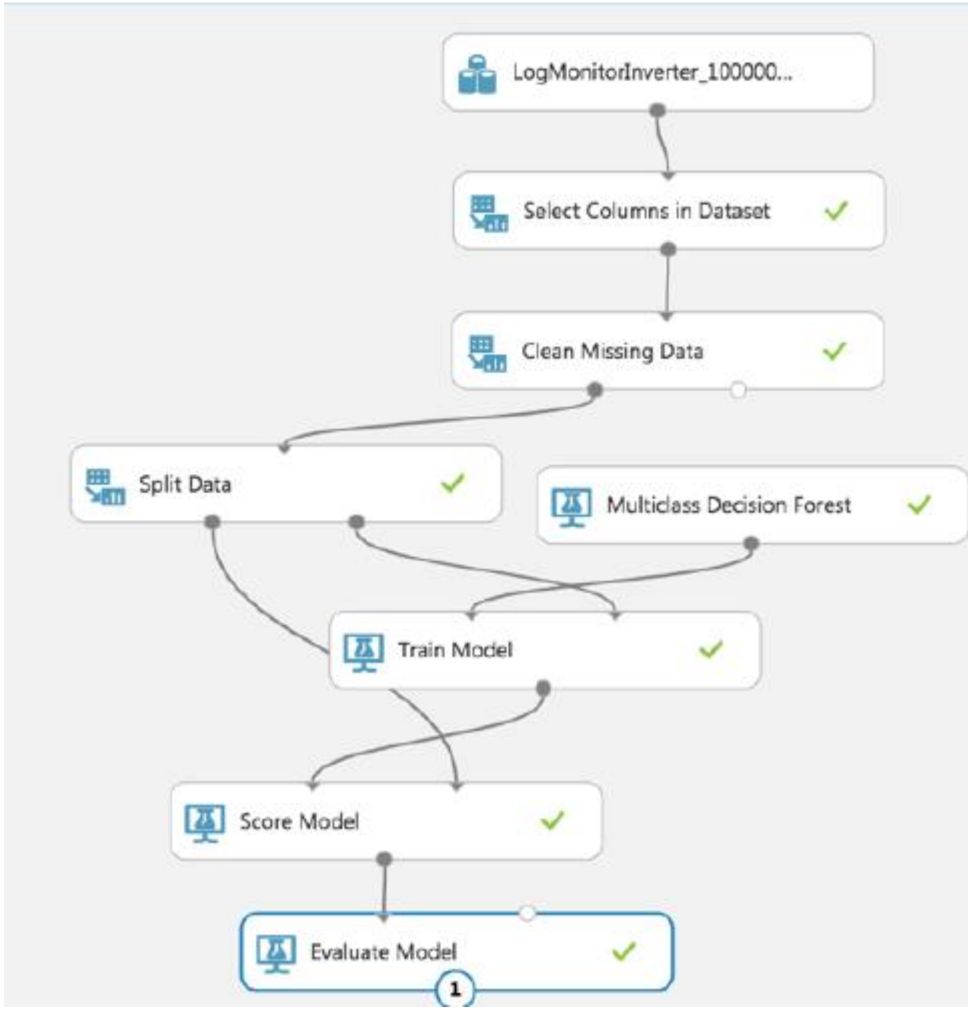

Figure 2.14 General schema of Classification Process on Azure Machine Learning Studio (Paolanti et al. 2018)

Azure Sentiment Analysis, a cloud-based tool, was developed using two algorithms. Harfoushi et al. [55] compared the two algorithms in an attempt. In Azure ML, they used Microsoft Logistic Regression and SVM. Three TD were used in studies to show this. As a result, the information was obtained from the microblogging website Twitter. The following types of data were gathered: individual viewpoints, images, and Twitter views and adjustments. Another researcher's thorough examination of a master's thesis improved this study. Therefore, it was established that the Microsoft Azure ML platform could be used to produce a legitimate Sentiment Analysis. Klochko et al. [56] presented the possibility of applying regression analysis approaches to ML systems and introduced data mining based on mathematical statistics and ML techniques. Bayesian linear ANN, decision trees, decision forests, and regression analysis modules based on linear regression were examples of developed ML models. The relevant regression model was developed using the above technique to apply this ML model. Their comparison was then made, and the outcomes were examined. The results illustrated the viability of applying data mining in medical research using ML algorithms. Yang et al. [57] studied the DSS. An application framework that uses ML and carefully chosen candidate criteria to automatically identify appropriate components or assemblies. These criteria were further translated into crucial characteristics that may be taken from the digital model or resource planning database to facilitate effective candidate screening even in the early conceptual phases. The benefit of the proposed DSS framework was that it was built as a web application that combined cloud-based databases with ML services, making it easier to maintain, update, and retrain ML models. More than 200 actual instances from the business were personally gathered and designated as training data. On the other side, several regression techniques were explored for each AM possibility to improve prediction accuracy as shown in Figure 2.15

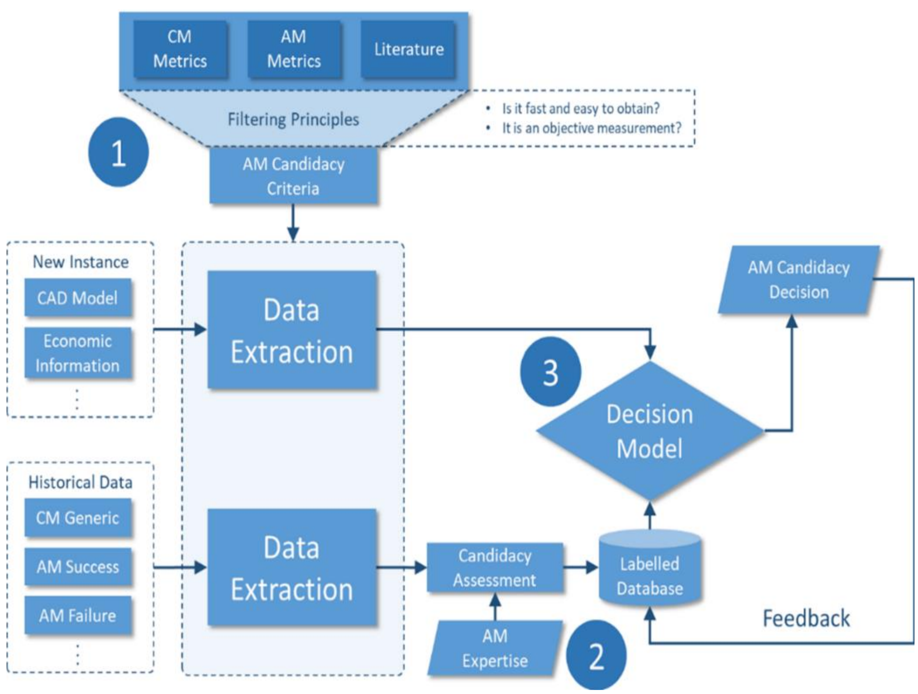

Figure 2.15 The proposed framework of the decision support system for AM part candidacy identification. (Yang et al. 2020)

2.5 Gap Analysis

After going through the literature review, some gaps were identified that were in the paper:

a) How can Azure ML be used for process parameter optimization?
b) The IoT in Python can be used for prediction.

CHAPTER 3 : METHODOLOGY

The purpose of this thesis is to improve process parameters to maximize tensile strength. The printer is suitable for this job. SLA and FDM printers rank among the best. SLA printers use photopolymers, and FDM printers create layers by capturing molten polymers. The execution time of SLA printers will be larger than that of FDM printers due to the small area. The accuracy and resolution of SLA printers were better than FDM, but because of the expensive plastic, FDM printers were used. For the FDM printer, the material was studied. The primary materials used are PLA, PETG, and TPU. The properties were studied, and an ANSYS model was created to see the tensile strength.

The parameters were considered, giving mixed results. Infill density has been widely used, directly related to tensile strength. The second parameter is layer height. A layer height of 0.28 mm is considered the best. Another parameter used is the infill pattern. Different infill patterns give different strength values. The infill patterns mainly affect the tensile strength of the material. The last parameter is the number of perimeter walls. It has a direct relationship with tensile strength. To incorporate these parameters, the Taguchi design of the experiment was created. Three levels have been created and some values have been added concerning the printer. The part is made, and its tensile strength is measured with a multi-purpose testing machine. In the universal test system tensile test, we join pieces of the same object and stretch it until it breaks. This measures the tensile strength of the object. After collecting the data, it is delivered to the Azure ML database. Then apply a linear regression model and then deploy a web service that predicts strength at different values. API keys can be used to predict values in a variety of programming languages.

Python was used in this paper to forecast the value of tensile strength. Figure 3.1 shows the proposed methodology.

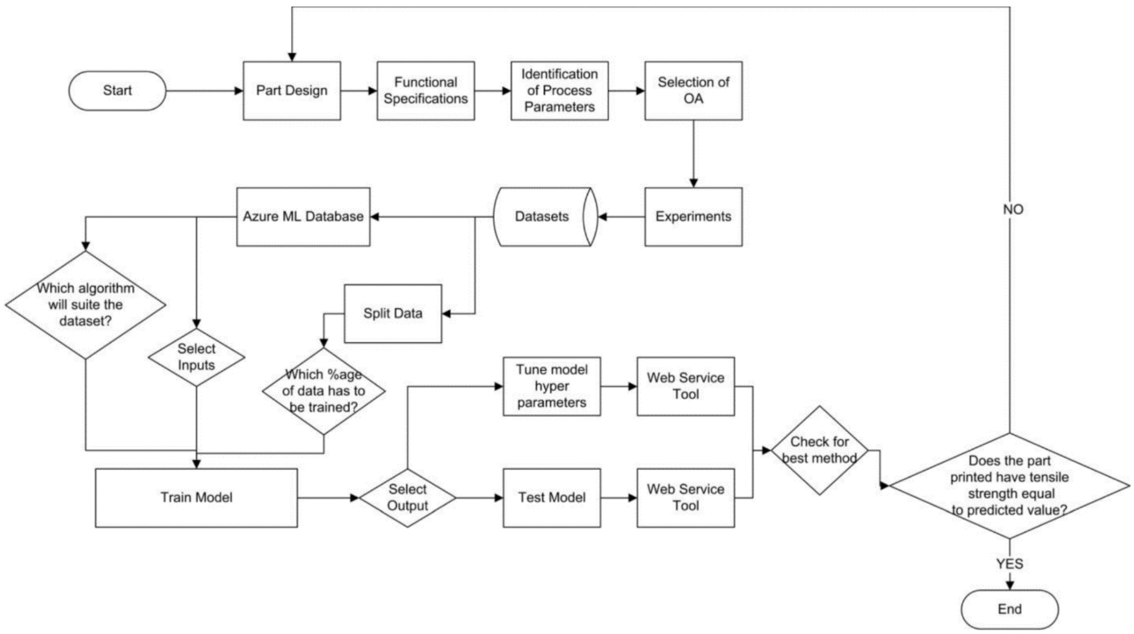

Figure 3.1 Methodology of the proposed system

3.1 Printer's Selection and Process Parameters selection

The trials were carried out with the assistance of an ENDER 3 V2 PRINTER as seen in Figure 3.2. You may construct this open-frame 3D FDM printer from a kit. It usually creates prints that are above average; however, leveling the print bed can be challenging. The printer's resolution was up to 0.1 mm, and the accuracy was up to 100 microns. PLA material was used. The connection between the printer and the computer is established via a USB cable. Creality Prussa software was used to change the settings. Printer ENDER 3 V2 is an FDM printer. It uses different settings, so researched how different settings affect tensile strength. Therefore, a decision must be made on the variables most likely influencing the component's tensile strength quality. Four criteria were used in this research: layer thickness, infill pattern, infill density, and perimeter wall count. The chosen variables and their related explanations are listed below:

a) Layer thickness: It is each layer's thickness that has been deposited. It directly affects the tensile strength from 0.16-0.28 mm and then inversely affects the tensile strength after 0.3 mm.[58]

b) Infill density: It is the density of the infill of mid-layers. It has a direct relationship with tensile strength.

c) Infill Pattern: Different infill patterns will give different results.

d) Perimeter Walls count: It directly correlates with tensile strength.

Figure 3.2 ENDER 3 V2 FDM PRINTER

3.2 Parts Design and Testing

T-shape Shape geometric drill mesh created with Solidworks software. A geometric T-shaped drilling grid is proposed in this paper with citation derived from Zaman et al. [59] as demonstrated in Figure 3.3. The section with dimensions (50 × 20 × 5) mm was selected. A clamping element measuring (15 x 15 x 6.5) mm is made to clamp it in the general-purpose testing machine. The part is created, then assembled, and clamping is performed on it on the advice of the laboratory assistant where the testing machine is located.

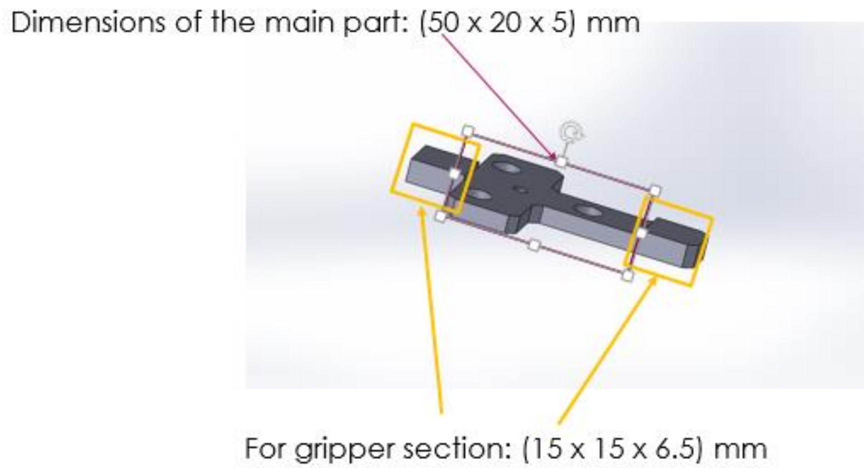

Figure 3.3 Drilling Grid (adapted from Zaman et al. 2018)

Materials' hardness and compressive strength are tested using a UTM as can be seen in Figure 3.4 , often referred to as an extensive testing machine, a material testing machine, or a material testing plane. The word "universal" in the name alludes to the fact that it is adaptable in general and can carry out a variety of standard flexural and pressure tests on materials, components, and designs. A towable was once known as a tension tester.

Figure 3.4 Shimadzu Universal Testing Machine

A part is created, various parameters are studied, parts are printed, and testing is performed using a multi-function tester. In the UTM, a component is clamped between two clamps, and a force sensor is used to calibrate the weight. When the sound of breaking is heard, the part has reached its maximum tensile strength. A computing device is also present to initiate the test, which is then used to analyze and print the results. 27 repetitions were performed. Figure 3.5 can be seen to test the parts.

a b

Figure 3.5 Sample part before test (a) Sample part after test (b)

The results shown were a graph in which the maximum tensile strength and breaking part was shown in Figure 3.6

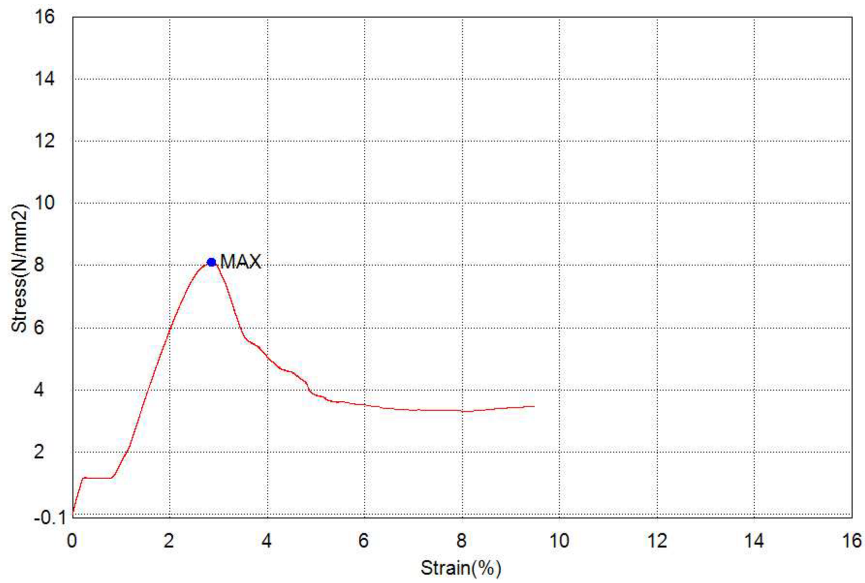

Figure 3.6 Graph between tensile strength and strain

3.3 Microsoft Azure Machine Learning

Taguchi Design was designed. Choosing the controllable components for the tests is a key step in laying the groundwork for the exploratory arrangement. As three-level changeable elements, layer height, infill density, infill pattern, and perimeter wall count were chosen. (See Table 3-1).

Ser	Layer Height (mm)	Infill Density (%)	Infill Pattern	Number of Perimeter Walls	Tensile Strength (MPa)
1	0.16	10	Grid	1	5.65
2	0.16	10	Grid	1	5.92
3	0.16	10	Grid	1	7.3
4	0.16	30	Honeycomb	2	14.09
5	0.16	30	Honeycomb	2	13.61
6	0.16	30	Honeycomb	2	14.85
7	0.16	70	Triangle	4	16.98
8	0.16	70	Triangle	4	18.15
9	0.16	70	Triangle	4	18.45
10	0.2	10	Honeycomb	4	13.06
11	0.2	10	Honeycomb	4	13.23
12	0.2	10	Honeycomb	4	13.91
13	0.2	30	Triangle	1	10.97
14	0.2	30	Triangle	1	10.52
15	0.2	30	Triangle	1	8.78
16	0.2	70	Grid	2	17.48
17	0.2	70	Grid	2	15.31
18	0.2	70	Grid	2	15.48
19	0.28	10	Triangle	2	11.61
20	0.28	10	Triangle	2	11.73
21	0.28	10	Triangle	2	12.19
22	0.28	30	Grid	4	18.29
23	0.28	30	Grid	4	17.69
24	0.28	30	Grid	4	16.69
25	0.28	70	Honeycomb	1	13.09
26	0.28	70	Honeycomb	1	12.41
27	0.28	70	Honeycomb	1	12.13

Table 3-1 Manufacturing factors and its values

3.3.1 Inputs Relationship with Tensile Strength

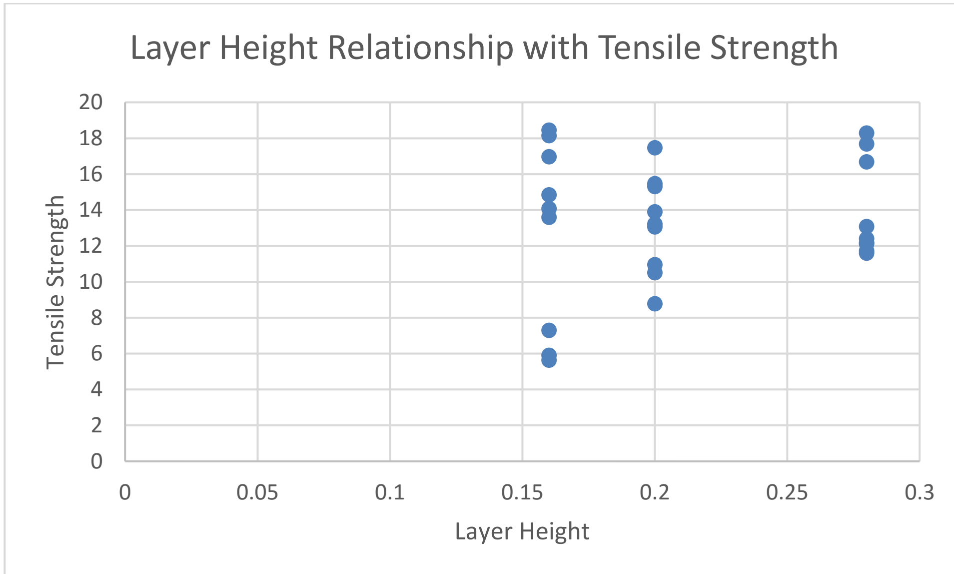

Figure 3.7 Layer Height Relationship with Tensile Strength

As you can see in Figure 3.7, Tensile Strength increases when layer height increases but not so dramatically.

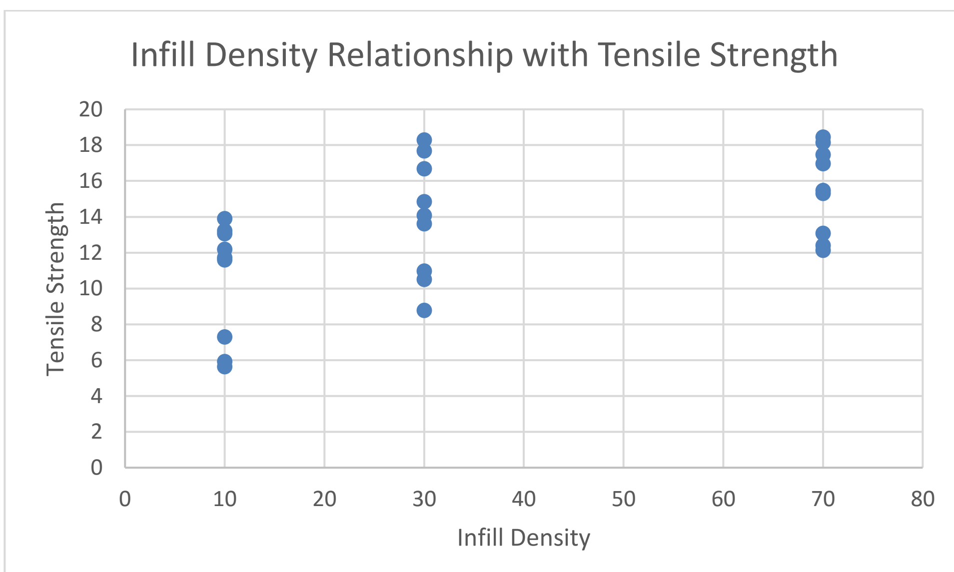

Figure 3.8 Infill Density Relationship with Tensile Strength

In Figure 3.8, Tensile Strength increases when density increases from 10 to 70%.

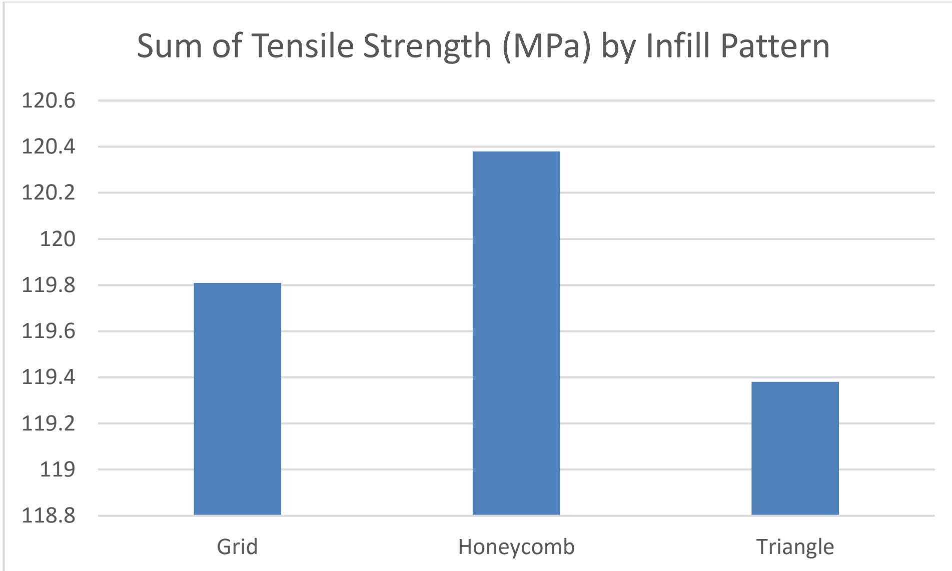

Figure 3.9 Infill Pattern Relationship with Tensile Strength

In Figure 3.9, it can be observed that Honeycomb pattern gives the most results of Tensile Strength.

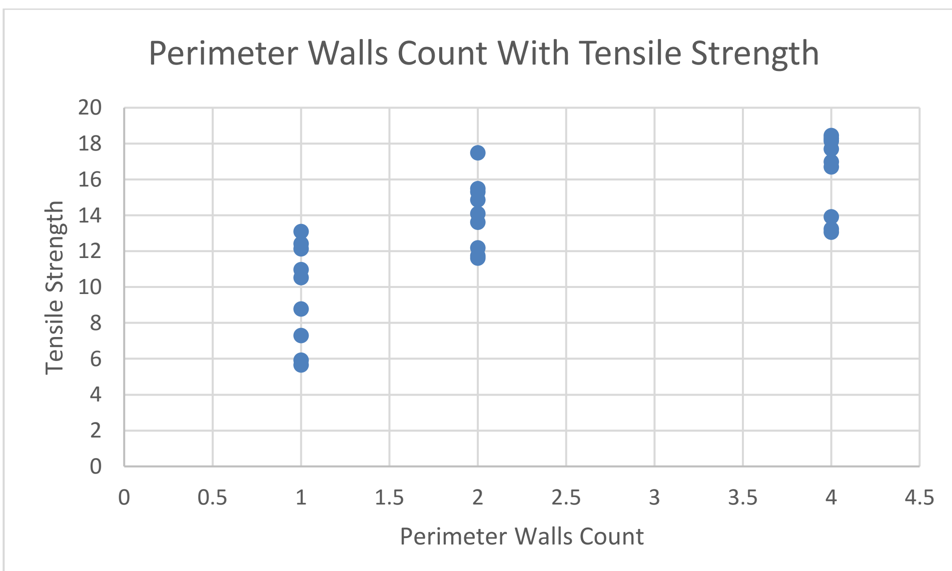

Figure 3.10 Perimeter walls relationship with Tensile Strength

Figure 3.10 observed that perimeter walls significantly affect tensile strength, but its effect decreases when the value reaches 4.

The database was constructed and uploaded to Microsoft Azure. A ML portal was utilized which can be seen in Figure 3.11 and the database was stepped through different methods of the Azure database.

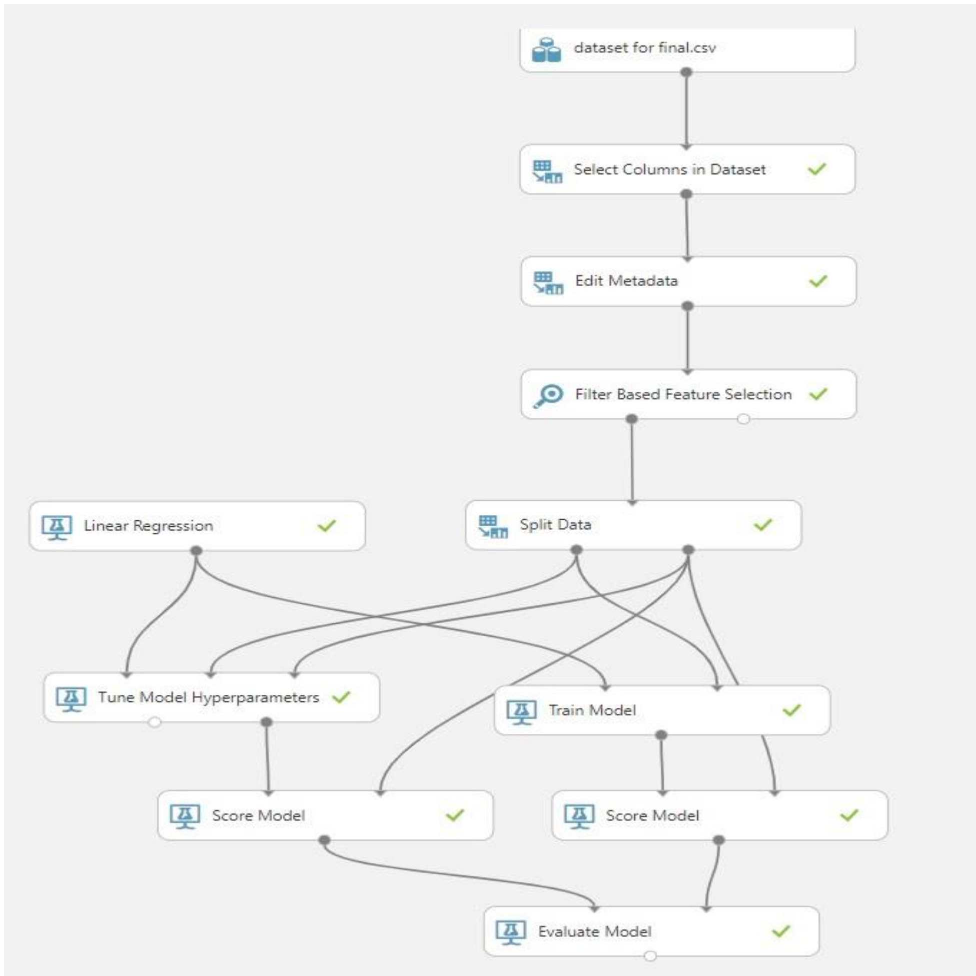

Figure 3.11 Microsoft Azure Learning Database

3.3.2 Choose a column from dataset

Columns of considerable importance were chosen for this section.

3.3.3 Edit Metadata

Using the Edit Metadata component, one may change the metadata associated with a dataset's columns. The dataset's value and data type will be updated after using the Edit

Metadata component. The usage of text, Boolean, and numeric values as categorical estimates is a common metadata update. The infill pattern was a string value in this situation, categorical value was produced.

3.3.4 Filter based Feature Selection

Based on the one statistical measure you choose that best matches the data, each feature column is given a score by the component. Using the selected metric, it is easier to identify unimportant traits. Then, using a filter, you delete pointless columns from your model as shown in Table 3-2.

Ser	Layer height (mm)	Infill Density (%)	Infill Pattern	Number of Perimeter walls	Tensile Strength (MPa)
1	0.140533	0.539466	0.012817	0.661683	1

Table 3-2 Filter Based Feature Selection

3.3.5 Data Segmentation

The data in this area was split based on the needs. After training on 80% of the data, the model was evaluated on the remaining 20%. Table 3-3 shows the split data and Table 3-4 shows the statistics.

Ser	Layer height (mm)	Infill Density (%)	Infill Pattern	Number of Perimeter walls	Tensile Strength (MPa)
1	0.2	10	Honeycomb	4	13.91
2	0.16	30	Honeycomb	2	14.09
3	0.2	70	Grid	2	17.48
4	0.16	10	Grid	1	5.92
5	0.2	70	Grid	2	15.31

Table 3-3 Split Data (20% data will go to test while remaining 80% data will be used for training the model)

Statistics	Value
Mean	13.342
Median	14.09
Min	5.92
Max	17.48
Standard Deviation	4.3865
Unique Values	5
Missing Values	0
Feature Value	Numeric

Table 3-4 Split Data Statistics

3.3.6 Algorithm for Regression

The regression algorithm was used because it was used to predict the output values from input values. Because there was only one output, linear regression was used. Table 3-5 shows different values of settings used for gradient online regressor.

Setting	Value
Normalize Features	True
Averaged	True
Learning Rate	0.27507
Num Iterations	1
Decrease Learning Rate	True
L2 Regularizer Weight	0
Allow Unknown Levels	False
Random Number Seed	0

Table 3-5 Online Gradient Linear Regressor

Both online gradient descent and a linear regression were employed. So that the regression does not have to cross the plot's origin, the bias is kept. There is no bias in the model coefficients or the forecasts. The L2 regularization weight, which modifies the loss function by introducing the fined label which prohibits excessive coefficient volatility, reduces the potential of overfitting. Regularization aims to lessen the assessor's difference by making the estimator more straightforward and raising the bias to decrease the prediction error. Therefore, using the hit-and-trial method, the weight of L2 regularization is kept between 0 and 0.23. Using first-order iterative optimization, the local minimum of a differentiable function is found.

Because of the large number of inputs, a parameter range was specified. Various learning rate values were used. The learning rate influences the magnitude of criterion upgrades during gradient descent. The estimate set for this limitation may affect the process's learning rate as well as whether the cost function has been reduced. Because the optimal learning rate should be between 0.275 and 0.5. The number of iterations indicates how frequently the parameters of the algorithm are modified. The internal model parameters were permitted to vary for each sample in the training dataset. An era consists of one or more batches. In this case, a scale of 1 to 100 was used. The purpose of normalizing is to reduce the size of characteristics to a comparable level. Therefore, the utility and training stability of the model improve. Averaging is a technique for reducing the influence of noise.

3.3.7 Train Module

In this section, the model is trained according to the abovementioned conditions. This model was designated feature weights so that it may be modelled using linear regression, which will produce the results in the scored model which is shown in Table 3-6.

Feature	Weight
Layer Height(mm)	-0.621489
Bias	6.43571
Perimeter Walls	5.50991
Infill Pattern_Honeycomb_1	0.545529
Infill Pattern_Grid_0	2.62925
Infill Pattern_Triangle_2	3.26093
Infill Density (%)	4.5205

Table 3-6 Feature Weights without Tune Model Hyper parameter

3.3.8 Score Module

In this section, according to the linear regression, the model predicted values. (See Table 3-7). Table 3-8 shows the statistics.

Ser	Layer height (mm)	Infill Density (%)	Infill Pattern	Number of Perimeter walls	Tensile Strength (MPa)	Scored Labels
1	0.2	10	Honeycomb	4	13.91	12.283989
2	0.16	30	Honeycomb	2	14.09	11.243031
3	0.2	70	Grid	2	17.48	16.133255
4	0.16	10	Grid	1	5.92	10.442442
5	0.2	70	Grid	2	15.31	16.133255

Table 3-7 Scored data without tune hyper parameter (20% data results after linear regression

Statistics	Value
Mean	13.2472
Median	12.284
Min	10.4424
Max	16.1333
Standard Deviation	2.7143
Unique Values	4
Missing Values	0
Feature Type	Numeric Score

Table 3-8 Scored Data Statistics without Tune Model Hyper parameter

3.3.9 Evaluate Model

The various error results and coefficients of determination were discovered in this section. Table 3-9 showed the statistics.

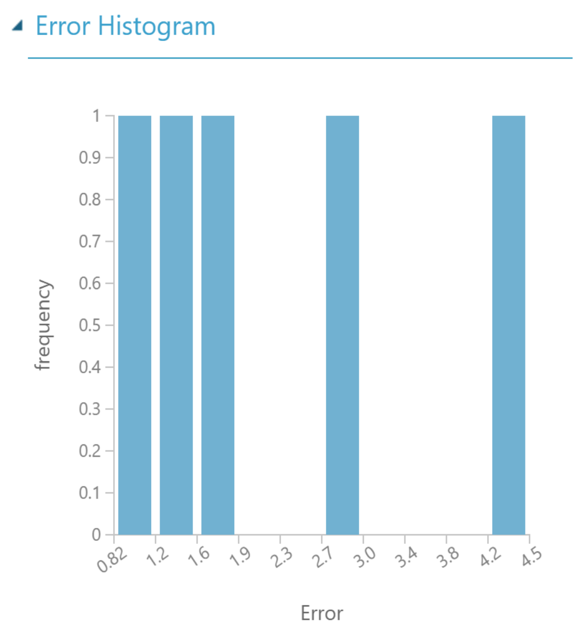

Figure 3.12 Error Histogram without tune model hyper parameter

Regarding prediction mistakes, the residual plot is a histogram of the residuals generated by regression and prediction research. To demonstrate the model's bias, the residuals are created for each sample as y predicted-y true and displayed as a histogram. In Figure 3.12, we can see that the error histogram is not organized, and it is in a straight line.

Metrics	Value
Mean Absolute Error	2.233084
Root Mean Absolute Error	2.595885
Relative Absolute Error	0.752184
Relative Squared Error	0.437776
Coefficient of Determination	0.562224

Table 3-9 Evaluate data statistics without the aid of hyperparameters settings

Mean absolute error is active against the effects of exceptions. The smaller the value, the better. The distance between the residuals and the total vacant space determines the root mean square error. Disables the square root effect of MSE squared and reported the result in a unique unit of information. The smaller the value, the better. Relative absolute error is a method of estimating the existence of a predictive model. A typical squared model is obtained by dividing the MSE of the model by the MSE of the model that contains the mean as the expected value. Values close to 0 are considered significant. The coefficient of determination recommends a degree of Y diversity that is meaningful for autonomous factors. Values from 0.8 are considered significant. Table 3-8 is less accurate since its error values are higher. It is not ideal that the coefficient of determination is 0.56224.

3.3.10 Optimal Conditions

A network connection was required, and various variables were checked via an online interface. Installed the web service and then copied the API key for the Python code available through the web service, as shown in Figure 3.13, to get the most significant value. The maximum value of 18.65 MPA was obtained by using the settings listed ahead: 0.28 mm layer height, 100% infill density, honeycomb pattern, and 4 perimeter walls.

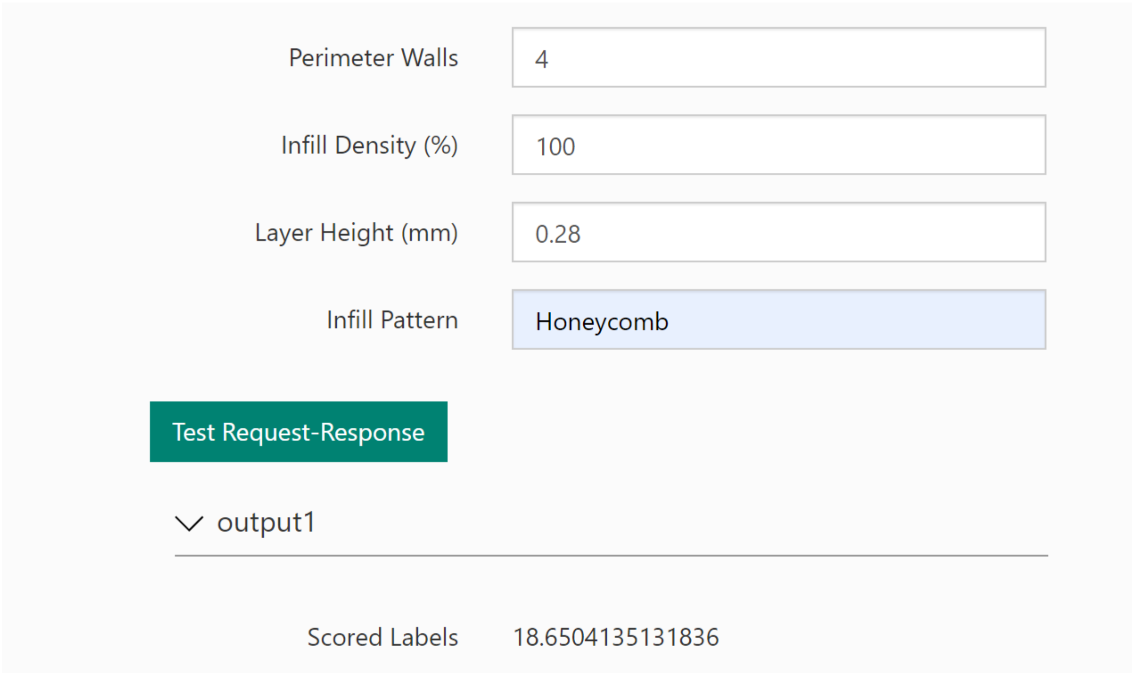

Figure 3.13 Optimum Values without tune model hyperparameters

3.3.11 Inputs Relationship with Output without Tune Model Hyperparameters

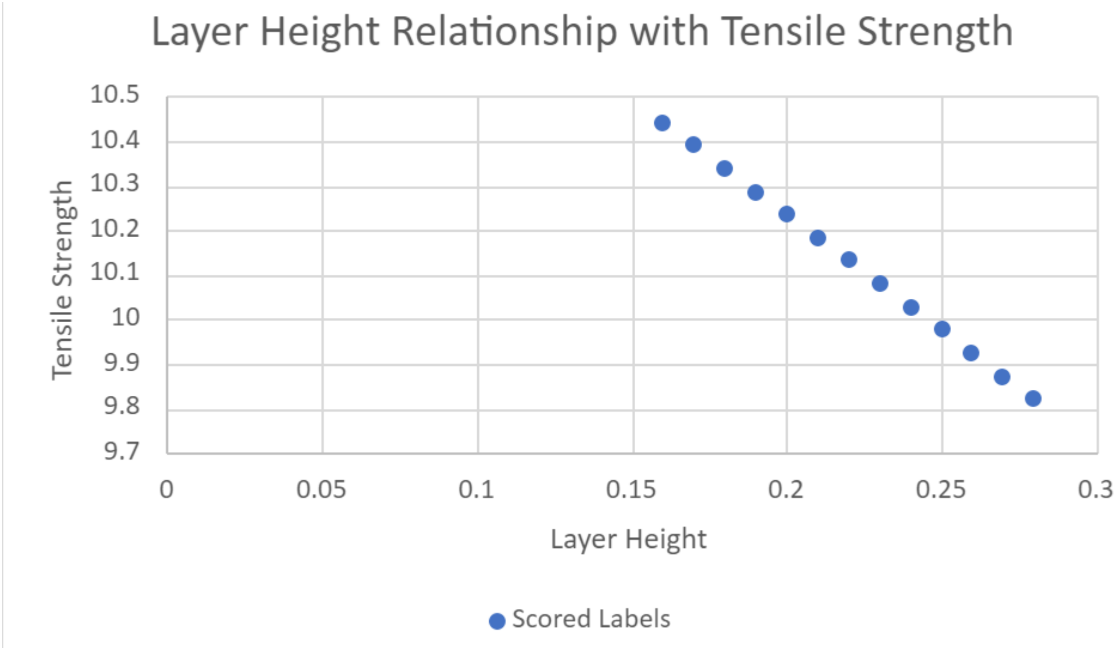

Figure 3.14 Layer Height Relationship with Predicted Values

As can be observed in Figure 3.14 that tensile strength will decrease with an increase in layer height which is the opposite in the case of input vs. experimental values.

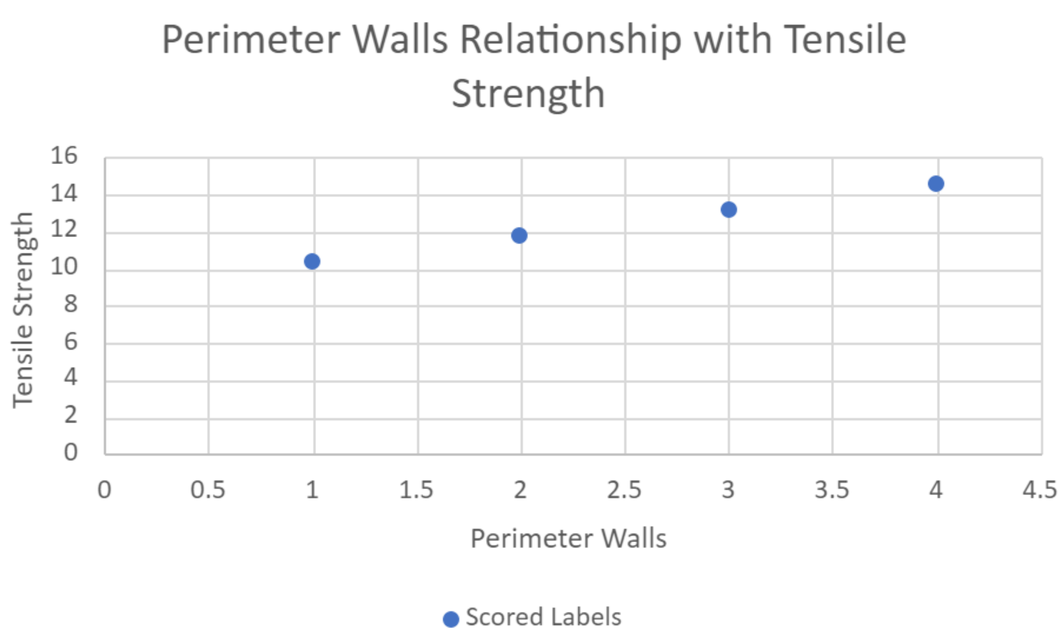

Figure 3.15 Perimeter Walls Count Relationship with Predicted Values

As can be observed in Figure 3.15, Tensile Strength will increase with the increase in perimeter walls count, but its maximum value drops from over 18 to almost 15 MPa.

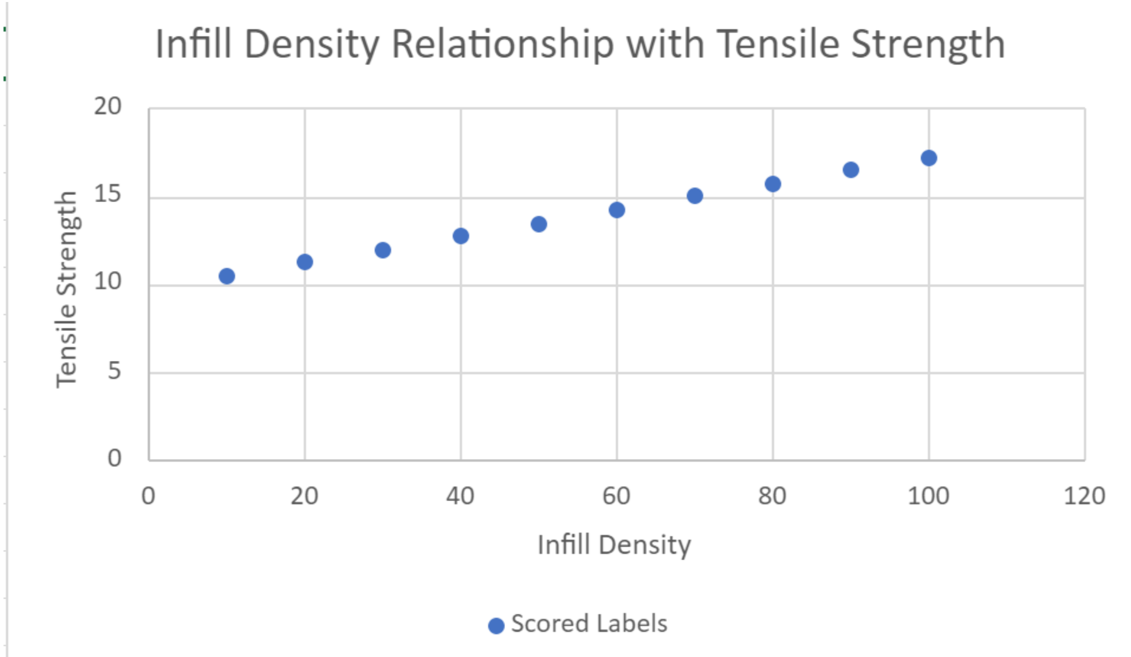

Figure 3.16 Infill Density Relationship with Predicted Values

It can be observed that tensile strength increases with an increase in Infill Density, but the graph looks uneven, meaning there is no regular pattern.

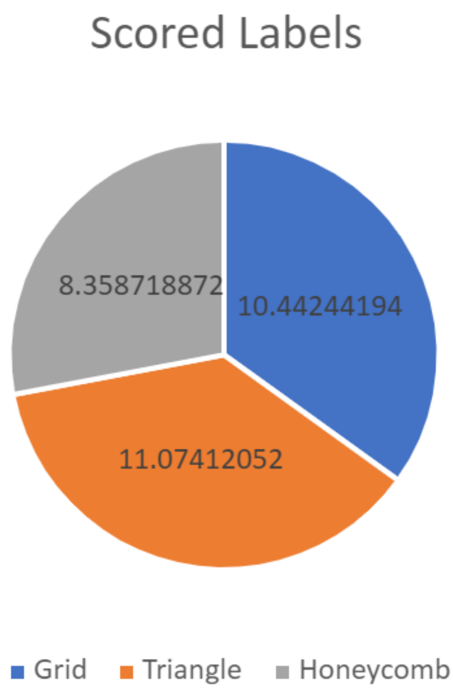

Figure 3.17 Infill Pattern Relationship with Tensile Strength

In Figure 3.17, the triangle pattern has the highest chance of getting the highest Tensile Strength, which is not valid in the experimental values.

3.4 Tune Model Hyperparameters

Adjusting a learning algorithm's hyperparameters includes selecting the best hyperparameter values and then using the customized algorithm on every given piece of data. Such hyperparameters improve model accomplishment by reducing the defined loss function, resulting in preferable outcomes with little mistakes. The tuned model hyperparameters are utilized as inputs for the regression model and split data in this phase, which sets the perfect learning rate, quantity of repetitions, and error values preserved in the sweep results. Table 3-10 showed the results.

Ser No	Learning Rate	Number of Iterations	L2 Regularizer Weight	Mean Absolute Error	Root Mean Absolute Error	Relative Absolute Error	Relative Squared Error	Coefficient of Determination
1	0.425057	34	0	1.451801	1.716379	0.48902	0.191385	0.808615

Table 3-10 Sweep Results for Model Hyperparameter Tuning (Ideal Values)

3.4.1 Train Model

This section trains the model according to the conditions given by tuning the hyperparameters. In this model, feature weights were assigned to be modelled using linear regression, which will yield results in the scored model as shown in Table 3-11.

Feature	Weight
Layer Height(mm)	1.45757
Bias	4.79949
Perimeter Walls	7.3376
Infill Pattern_Honeycomb_1	1.85053
Infill Pattern_Grid_0	1.39499
Infill Pattern_Triangle_2	1.55398
Infill Density (%)	4.83268

Table 3-11 Feature Weights of tune model hyper parameters

3.4.2 Score Model

In this section, the model is scored according to the hyper parameter tuning and shown in Table 3-12 and statistics shown in Table 3-13.

Ser	Layer height (mm)	Infill Density (%)	Infill Pattern	Number of Perimeter walls	Tensile Strength (MPa)	Scored Labels
1	0.2	10	Honeycomb	4	13.91	14.473476
2	0.16	30	Honeycomb	2	14.09	11.929712
3	0.2	70	Grid	2	17.48	15.181818
4	0.16	10	Grid	1	5.92	8.028878
5	0.2	70	Grid	2	15.31	15.181818

Table 3-12 Scored data of tune model hyperparameters (20% data results after linear regression)

Statistics	Value
Mean	12.9591
Median	14.4735
Min	8.0289
Max	15.181818
Standard Deviation	3.0635
Unique Values	4
Missing Values	0
Feature Type	Numeric Score

Table 3-13 Scored Data Statistics after Tune Model Hyperparameters

3.4.3 Evaluate Model

In this section, different errors are investigated. In the Figure 3.18, the error histogram is looking like more normally distributed. In this model, the error's value is less than the previous one, which is good. The coefficient of Determination is 0.808615, which is better than the previous model as shown in Table 3-14.

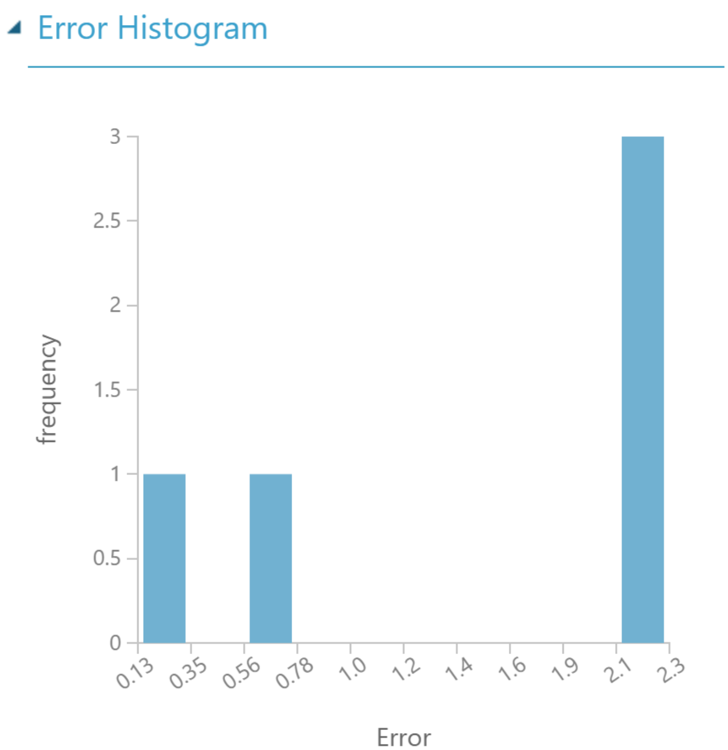

Figure 3.18 Error Histogram with Tune Model Hyperparameters

Metrics	Value
Mean Absolute Error	1.451801
Root Mean Absolute Error	1.716379
Relative Absolute Error	0.48902
Relative Squared Error	0.191385
Coefficient of Determination	0.808615

Table 3-14 Gauge Data statistics after tuning Hyperparameter Settings

3.4.4 Optimal Values

In this module, the optimal value was found as shown in Figure 3.19, which was 22.69 MPa, better than the previous model due to a better coefficient of determination and other values.

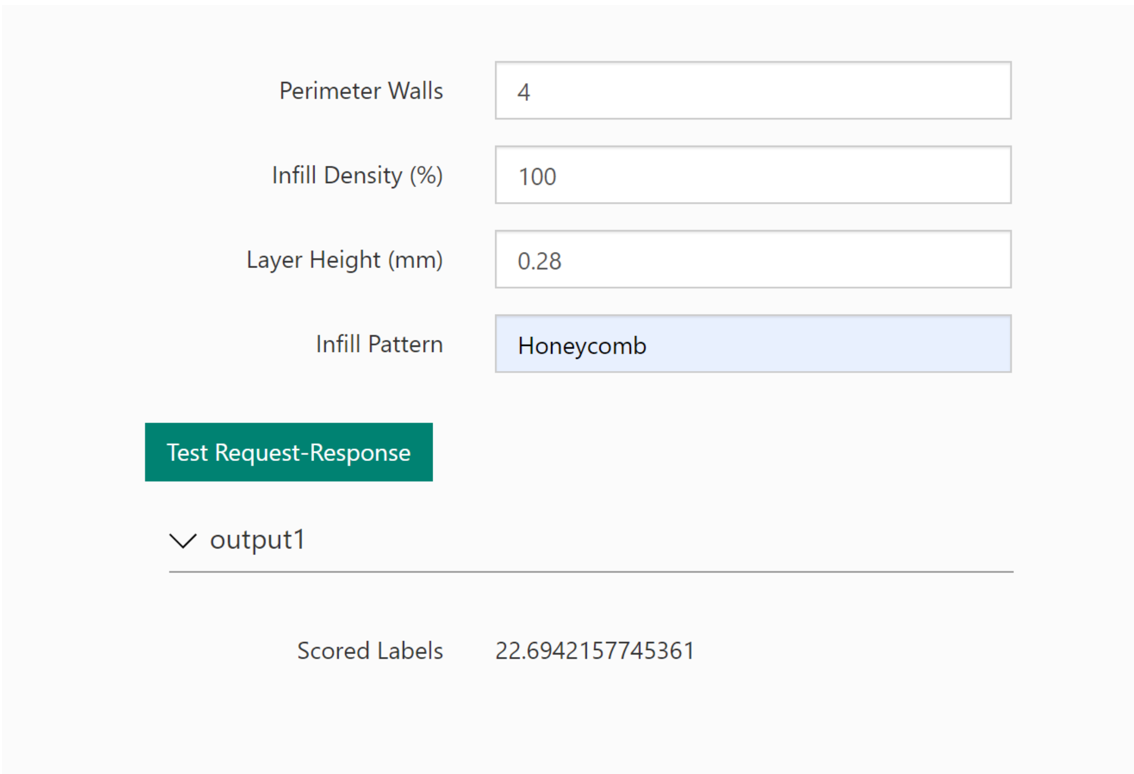

Figure 3.19 Optimum Values with Tune Model Hyper parameters

3.4.5 Web Service

Once a regression has been completed in the Azure ML database, pick the option to set up a web service before selecting the prediction experiment option, which will lead us to a different page. We deselect the output columns in select columns to anticipate the tensile strength. Then, in the second, we chose the scoring labels that would aid in calculating tensile strength at any value. The web service is shown in Figure 3.20.

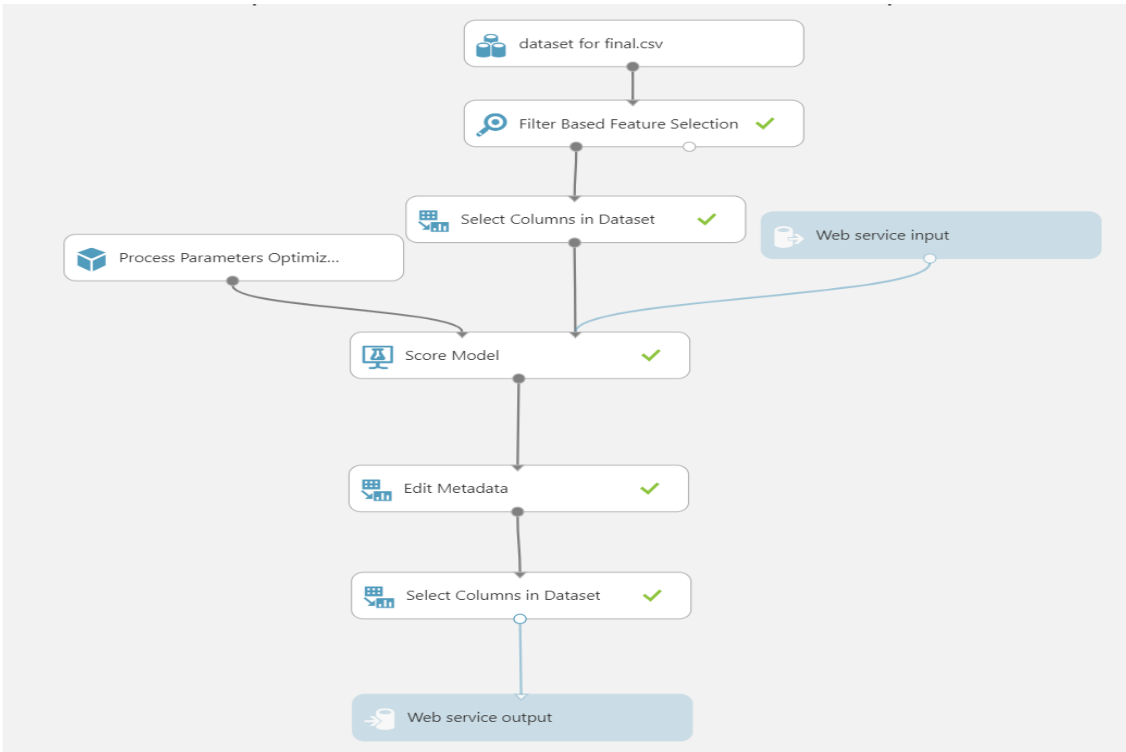

Figure 3.20 Online Interface

It was feasible to discover the link between the string value's layer height, infill density, and the number of perimeter walls using a scatter plot and an excel sheet prepared and kept locally or online, and to determine the infill pattern using a pie chart. Change only the layer height at first, leaving the other parameters alone, and then repeat for the other three.

3.4.6 Inputs Relationship with Output with Tune Model Hyperparameters

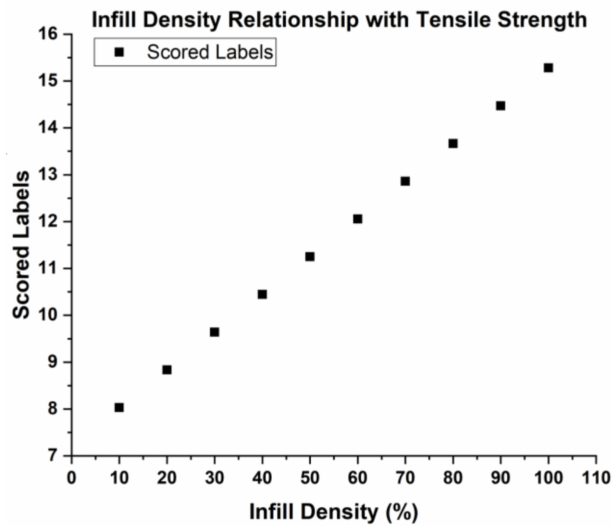

Figure 3.21 Infill Density Relationship with Tensile Strength

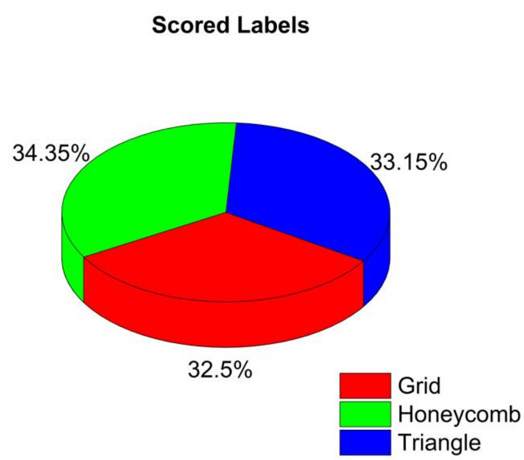

Figure 3.22 Infill Pattern relationship with Tensile Strength

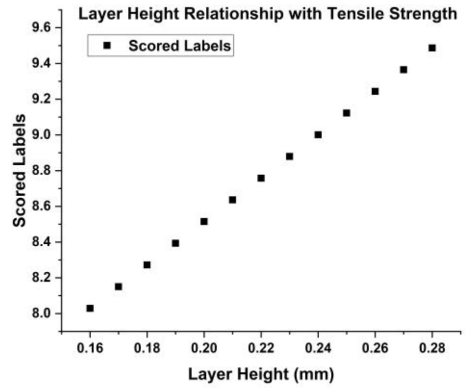

Figure 3.23 Layer Height Relationship with Tensile Strength

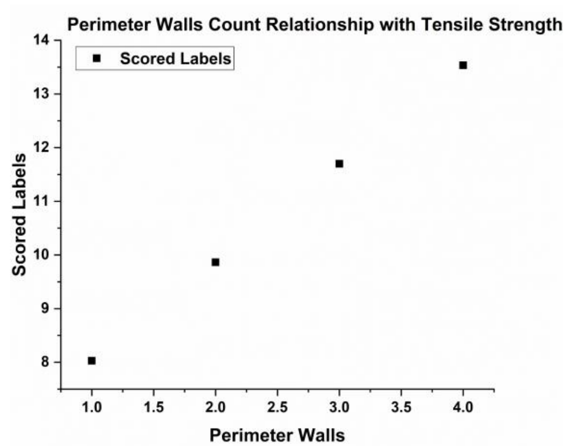

Figure 3.24 Perimeter Walls Relationship with Tensile Strength

From Figure 3.21 to 3.24, it can be seen that tensile strength is related to layer height, infill density, and the number of perimeter walls. Tensile strength increases dramatically as perimeter wall numbers are increased and are closest to the experimental values, followed by infill density. The infill density had a pattern that was missing in predicted values. The impact of layer height on tensile strength is smaller than that of both. The honeycomb pattern has the highest tensile strength, then the triangle and grid patterns.

3.5 Tensile Strength Comparison (Experimental, Hyper and Predicted Values)

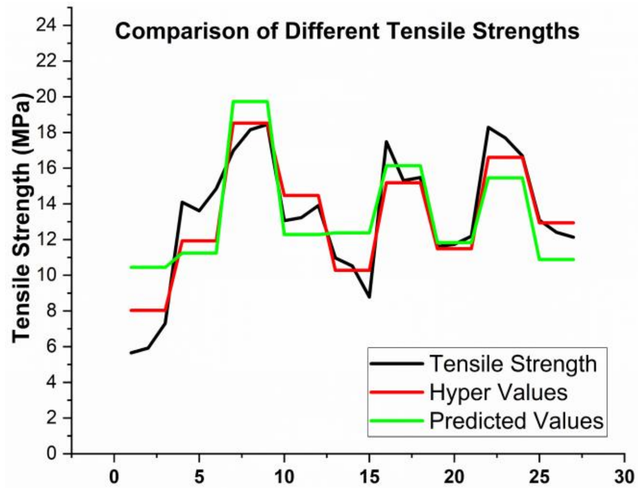

Figure 3.25 Tensile Strength Comparison

Results from Figure 3.25 infer the predicted values. However, they followed a straight line but were far from the experimental values, and the Hyperparameter values were closest, so this method was very efficient in getting the optimized values.

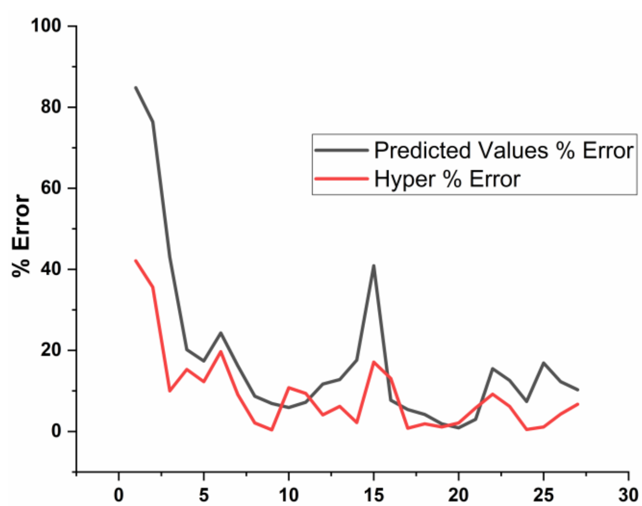

Figure 3.26 Error Comparison in Predicted and Hyper Scored Models

In the graph shown in Figure 3.26, the errors from predicted values were substantial, indicating that this method was not advisable. However, the error was less in the hyper-scored model, which made the optimization easy. The maximum % age error of experimental results with predicted outcomes is around 18.22%, while the % age error in hyper-scored labels is only 9.22 %.

CHAPTER 4 : CONCLUSION

In this thesis, the printer was selected for its process parameters. Process parameters and their relationship to tensile strength were also studied. According to the relationship, layer height, infill density and perimeter walls count were directly proportional to tensile strength. According to expert recommendations, controllable elements (layer height, filling density, filling pattern, and some surrounding walls) were selected along with their levels. L_{27} Orthogonal array was used. On the Ender 3 V2 FDM printer, 27 parts were printed with different settings. The tensile strength of parts made with FDM printers was tested on a UTM. We used Microsoft Azure database for ML. The dataset was subjected to linear regression, and the model was trained. The web service has been launched, and an API key has been generated to aid the Python code. Linear regression model was used because of the lone output. We provided a confidence interval of 95 percent to help the results. First, the model was trained without the hyper parameter tuning. In the relationship, the relations were not the same as the experimental graphs. The result was tensile strength of 18.65 Mpa at the settings of 0.28 mm layer height, 100% infill density, honeycomb pattern, and a perimeter wall count of 4. After tuning the model hyperparameters, the relationship between tensile strength and input factors was according to the experimental conditions. Tensile Strength came out to be: 22.69 Mpa, at 0.28 mm layer height, 100% infill density, honeycomb pattern, and a perimeter wall count of 4. It was concluded that hyperparameter tuning was best because it was closest to the predicted values and error was also less than the predicted values. The coefficient of determination came out to be 0.808615 which is better than when the model was not hyper tuned which had a value of 0.562224.

4.1 FUTURE WORK

In the future, Azure ML can be used on different printers to find tensile strength, such as SLA, SLS, DIW and DMLS. Many more modules can be found to give accurate results such as described in [60,61]. All regression modules have different benefits over other and it can work on various datasets. When the researchers provide a dataset with the Azure ML database with any of the module used, researchers can predict the output without any time taken and it will help them to predict the output beforehand performing an experiment which will also help to minimize the cost of the output since researcher will know which input parameters will be beneficial for output. Figure 4.1 shows the future work in the current domain.

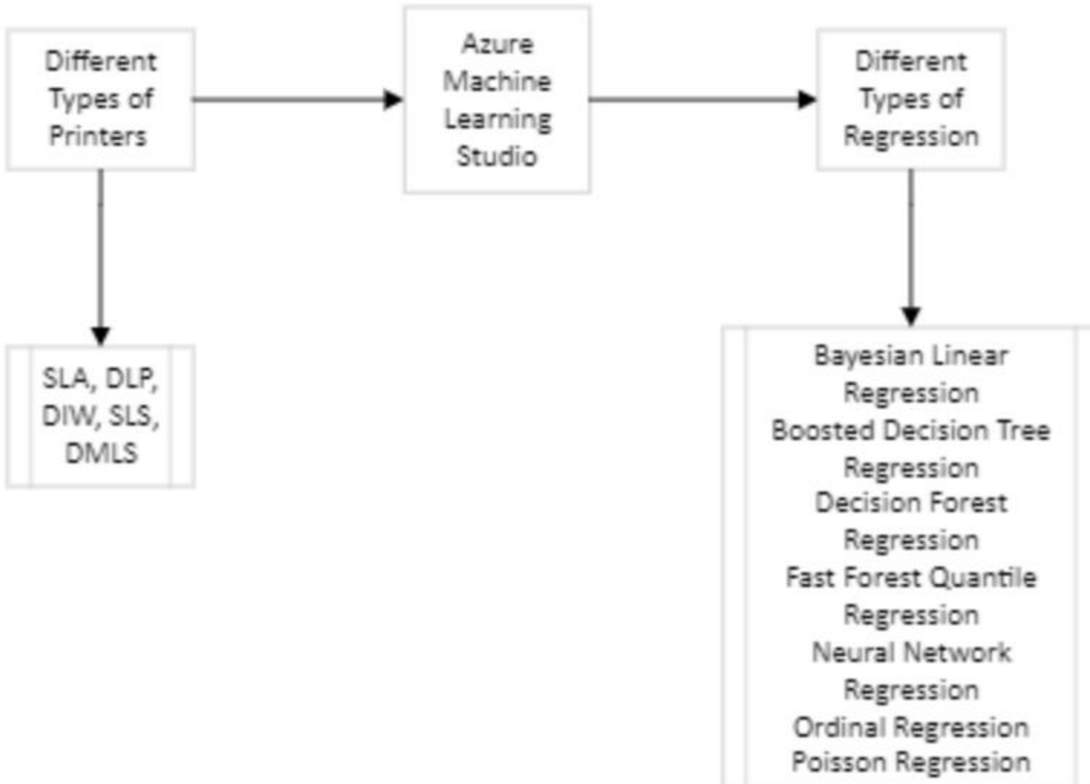

Figure 4.1 Future Directions of this research

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Appendix A

Code

```
import urllib.request
import json
data = {
        "Inputs": {
                "input1":
                [
                    {
                            'Layer Height (mm)': "0.16",
                            'Infill Density (%)': "0",
                            'Infill Pattern': "Triangle",
                            'Perimeter Walls': "0",
                    }




                ],
        },
    "GlobalParameters":  {

    }
}

body = str.encode(json.dumps(data))
url =
'https://ussouthcentral.services.azureml.net/workspaces/5a90fa2b790a4d8b91497639ee3
c78ea/services/823f5a2753af49048ec8d708e2ded688/execute?api-
version=2.0&format=swagger'
```

```
api_key = 'Dw1FWMavGT6b1Cog6C9rS9C47ECiyChA7880ioLET3mkJNYnxuof+rYsHv3VMRpo0gjFkpxcMsdADL8MoJ57dg==' # Replace this with the API key for the web service
headers = {'Content-Type':'application/json', 'Authorization':('Bearer '+ api_key)}
req = urllib.request.Request(url, body, headers)
try:
    response = urllib.request.urlopen(req)
    result = response.read()
    print(result)
except urllib.error.HTTPError as error:
    print("The request failed with status code: " + str(error.code))
    # Print the headers - they include the requert ID and the timestamp, which are useful for debugging the failure
    print(error.info())
    print(json.loads(error.read().decode("utf8", 'ignore')))
```

In this code An API key is generated from azure machine learning, and it is entered and an internet connection is required. If we change the parameters, it will give results of tensile strength.

Completion Certificate

It is certified that the thesis titled **“Process Parameter Optimization of Additively Manufactured Parts Using Intelligent Manufacturing”** submitted by CMS ID. 00000320396, NS Rizwan Ur Rehman of MS-2019 Mechatronics Engineering is completed in all respects as per the requirements of Main Office, NUST (Exam branch).

Supervisor:
____

Dr. Uzair Khaleeq uz Zaman
Date: _______________