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3D Printing Monitoring System Based on Supervised Machine Learning

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Abstract: One of the additive manufacturing processes that is quickly evolving is metal 3D printing. Selective laser melting (SLM) is one of the popular methods for metal 3D printing. Although it has many advantages and capabilities, there are still unsolved problems like process monitoring and printing reliability. Printing high-quality robust products require appropriate parameter settings and real-time monitoring. In order to satisfy the requirement, we propose a new monitoring system based on multiple sensors that can measure the index of different quality affecting parameters of SLM 3D printing. The system serves to improve printing quality; it involves supervised machine learning to predict the expected tensile strength of the printed product. We trained the machine learning model on our new "tensile strength" dataset which includes multiple sensing data and indexes of tensile strength. While collecting data we printed products that have a tensile strength between 449 and 506 MPa. A number of SLM 3D printing tests are carried out to show the viability of the proposed approach. After testing the tensile strength of the printed product, test results were compared to the results of the tensile strength predicting model. According to experiments, the monitoring system showed satisfactory results predicting expected tensile strength. The highest accuracy has been achieved with Multiple Linear Regression, recording 97%. The monitoring system helps not only to predict the tensile strength of the printing product but also to find optimal parameter settings of the SLM printer.

Keywords: Tensile Strength, Overlap Rate, Scan Speed, Laser Power

1. Introduction

Additive Manufacturing (AM) is a method of producing 3D objects in which computer control is used to construct layers of different materials[1]. It has become a viable option for the production of complicated design models. AM runs on top of advanced design software, giving more options for manufacturing and allowing to create of complex geometric models. Additionally, AM includes inventory reduction and distributed manufacturing through rapid prototyping. Compared to traditional manufacturing techniques, 3D printing or additive manufacturing techniques are economically superior as they do not require part-specific tools. Additive manufacturing techniques have recently been employed to mass-produce components, and the new design modes enabled by additive processes have

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evolved to be a key value proposition. As mentioned earlier, additive manufacturing is used to manufacture complex geometric components because it can print any kind of design created in design software which is not possible with traditional manufacturing methods.

Despite the fact that additive manufacturing has been widely industrialized, it still faces several challenges, such as process monitoring and inspection problems. Furthermore, surface quality and robustness of the printed products are stable. It is required to make real-time monitoring during the printing process to achieve high-quality and robustness. But it takes much time and manpower to make individual monitoring of each product. Moreover, it is impossible to predict robustness of the printing product during the printing process. This factor leads to waste of time, energy and raw material. These difficulties provide roadblocks to the industry's extensive adoption of AM and the academic community's in-depth study of AM. Machine learning (ML) technologies are developing to play a critical role in tackling the challenges as they provide effective means for quality control, real-time monitoring, defect detection, and predicting errors that could happen[2].

In this work, a metal 3D printing process monitoring model was proposed using new multiple sensors based approach to monitoring a printing process layer by layer and all analyses take place from the database. The data, which were collected from multiple sensors build a reliable dataset, for training machine learning models to accomplish monitoring automatically.

This paper proposes multiple sensor-based monitoring systems that can predict tensile strength models using a new tensile strength prediction approach to monitor a printing process layer by layer. We conducted several experiments for generating datasets and determining tensile strength. We collected sensing data from the printing process of the same product five times in different environments and settings. The indexes of tensile strength we measured are between 459 and 506 MPa. The generated dataset consists of 12 features since standard deviation and mean-average precision were calculated for each data point. We trained the dataset with state of art machine learning algorithms and selected the most well-performed model. According to the comparison result, the “Multiple Linear Regression” algorithm recorded the best result showing minimum error rate: MSE=0.41, MAE=0.43, R-squared = 0.97. Finally, we achieved a satisfactory monitoring system that can contribute to improving product quality and predicting expected tensile strength.

The following sections contains this paper. Section 2 includes a brief introduction of the SLM metal 3D printing method and monitoring while section 3 introduces dataset generation process. The section 4 is about process parameters and proposed method and experimental results are provided in section 5. The conclusion and future works are provided in the last section.

2. Background

2.1 SLM 3D Printing

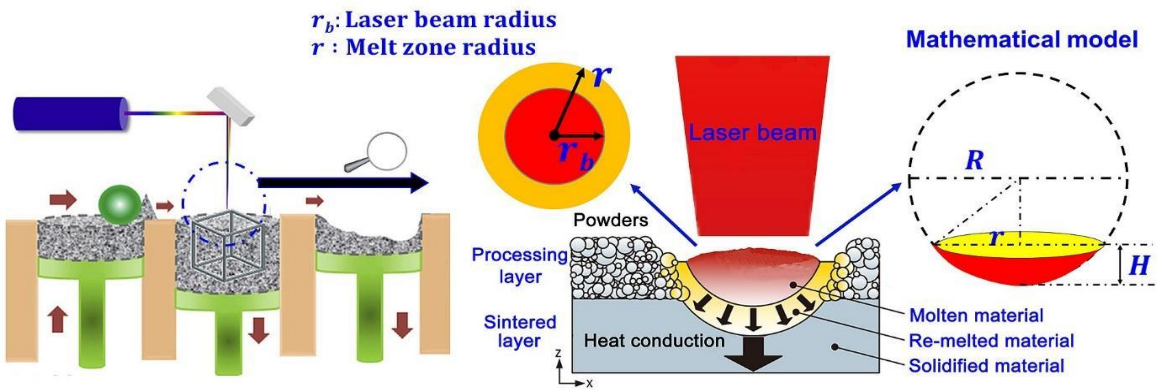
SLM 3D printing technology [Fig. 1] is one of the most widely used metal 3D printing techniques. The technology is based on using a UV laser. In this technology 3D parts are printed by using a high-powered laser beam, melting and fusing different metallic powders together. When the laser beam strikes a tiny layer of material, it welds or unites metallic particles. Following a full print cycle, the printer adds a new layer of powdered material to the previous one. The item is then accurately lowered by the thickness of one layer. When the print process is completed, the unused powder will be manually removed from the object[3]. Similar to the vast majority of 3D printing processes, selective laser melting gives a ton of geometric flexibility. Tools are not necessary for projects requiring bionic lightweight construction and incredibly intricate geometry. Assembly consolidation is another advantage of SLM and other 3D printing technologies. It is required to combine many components and print them all at once to save money on materials, labor, and assembly. However, because of the technology's geometric flexibility, new parts also be made[4]. The component's intrinsic properties also be improved using the SLM approach. The components, for example, have extremely thick, pore-free surfaces. Selective laser melting is a method for additive manufacturing that is useful in many sectors. These include engineering in the fields of aerospace, automotive, dentistry, medical, and mechanical. However, small series now be manufactured affordably utilizing SLM metal 3D printing. The method is mostly utilized for quick prototyping[5].

2.2 SLM 3D Printing Monitoring

As all industrial systems do, 3D printing uses process monitoring widely. The purpose of process monitoring system implementation is to ensure print quality. Process monitoring is being used by numerous businesses for a variety of objectives, including regular inspection of the manufacturing process[6]. Process monitoring has become increasingly practical as a result of the development of high-precision devices that can measure the index of various parameters that can affect manufacturing product quality. Usually, SLM 3D printing monitoring system is divided into two parts: power monitoring and melting pool monitoring.

Laser power monitoring. The laser beam is directed from the laser unit to the focusing unit via a fiber optic cable. A part of the laser beam is redirected by the coating of a beam splitter into a photodiode. There, the intensity of the reflected beam is measured. The measured power is compared to the expected power level. This allows for reliable laser power monitoring. Measured data can be archived and displayed later in graphical form[7].

Melting pool monitoring. Most of the laser beam passes straight through the beam and enters the build chamber. The heated material emits heat waves some of them directly into the scanning head. The beam is then directed completely upwards. The photodiode measures the beam intensity. The capture scanner coordinates are visualized as thermal emissions. Even the exposure information of individual scan vectors is graphed in detail. Each layer can be visualized and archived[8].



[Fig. 1] An Example of a Typical SLM [9]

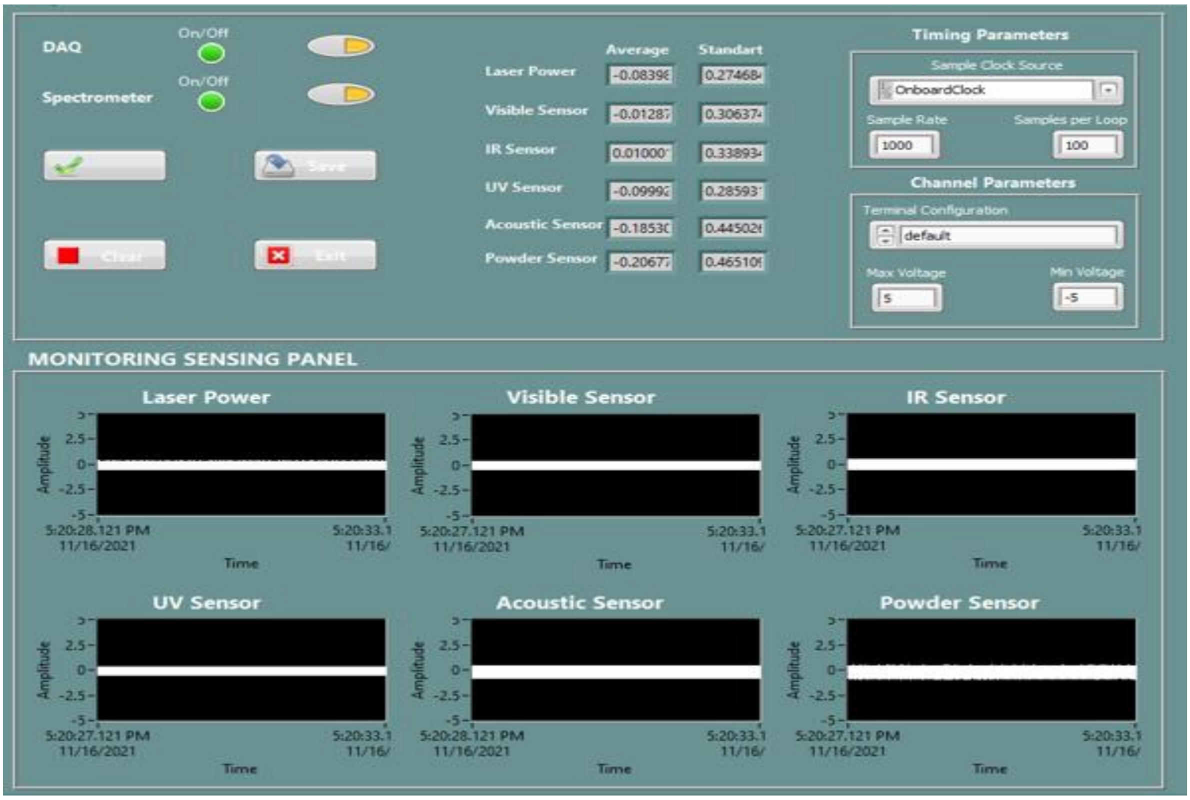
3. Dataset Generation

Generation of the dataset is divided into two sections, data collection and data analysis. Following, more details of data collection and

3.1 Data Collection

In the first step, we have made a data acquisition system based on six different sensors [Fig. 2]: Visible sensor, UV Sensor, Temperature Sensor, Acoustic Sensor, Photodiode Sensor, Powder Sensor.

All DAQ sensors are connected to the machine by using “The National Instruments USB 6001” device, the USB-6001 is a basic multifunction data acquisition device. It provides analog, digital inputs and outputs. It has 32-bit counters. The USB-6001 has fundamental functionality for use in data logging applications. Furthermore, it is used for experiments and portable measurements. The device includes a lightweight enclosure and is bus powered, making it highly portable. Sensors and signals can be conveniently connected to the main board via a screw terminal connection. The built-in drivers and configuration utility make configuration and measurement more simple.

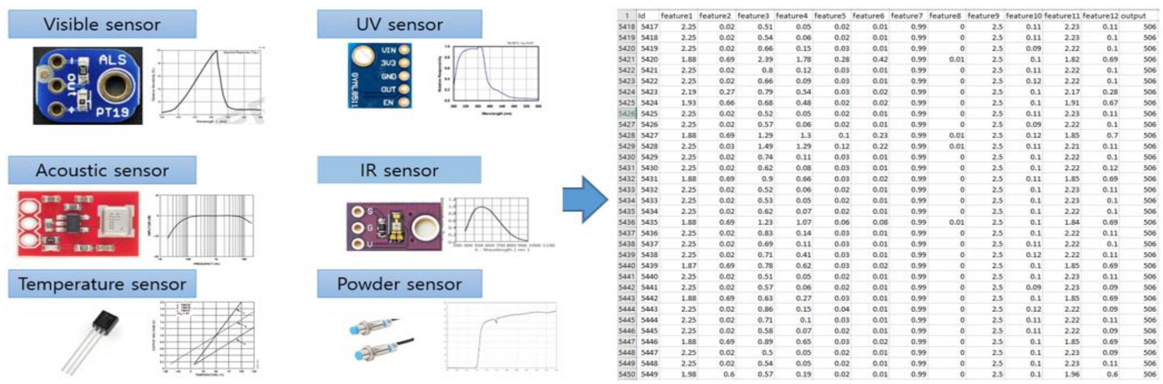


[Fig. 2] User Interface of Monitoring System

As shown in [Fig. 2], the application displays the current data stream on graphs and standard deviation and mean-average precision values in real-time. Values from data stream input to the data analysis process and it calculates mean average precision and standard deviation values. The data stream can be logged in csv file automatically by pushing save button. Data acquisition devices are connected to the main server and utilized by the Metal 3DP monitoring application. The main software was developed with LabVIEW 2021, main function of the application is data acquisition, transferring real-time logging data to the main server, and setting main parameters of monitoring. As shown in [Fig. 3] there are 12 features including standard deviation and mean average precision values for each sensor.

The data acquisition process makes a way to generate a monitoring dataset. We have generated a new “tensile strength” dataset to train our tensile strength prediction system. The dataset consists of six types of sensor data values and five types of output data (tensile strength).

Tensile strength is the index of the robustness of the material, it indicates withstanding of the material to pulling force. It is assessed by the amount of stress that a material can withstand before stretching and breaking. As the name implies, it relates to a material's resistance to tension caused by mechanical forces. One of the most important and frequently researched properties of materials used for structural reasons is their ability to withstand tensile stress.



[Fig. 3] Dataset Generation with Sensing Devices

3.2 Data Set

We calculated the tensile strength of the printed product [Table 1] through many experiments, and that value was saved as the dataset's target variable. The dataset consists of 52440 data samples for each feature since we have 12 features (input variables) as 2 features from every sensor, totally our dataset includes 629280 data samples.

3.3 Data Analysis

The dataset consists of 52440 rows of data and 12 input variables and single numeric target variables (13 in total). The dataset was divided into train and test sections, with 67 percent of the dataset being used to train the model and 33 percent being used to test it. Use the fit model to create predictions, and utilize the mean absolute error (MAE) performance measure to assess the accuracy of the predictions.

[Table 1] Tensile Stress and Tensile Strength

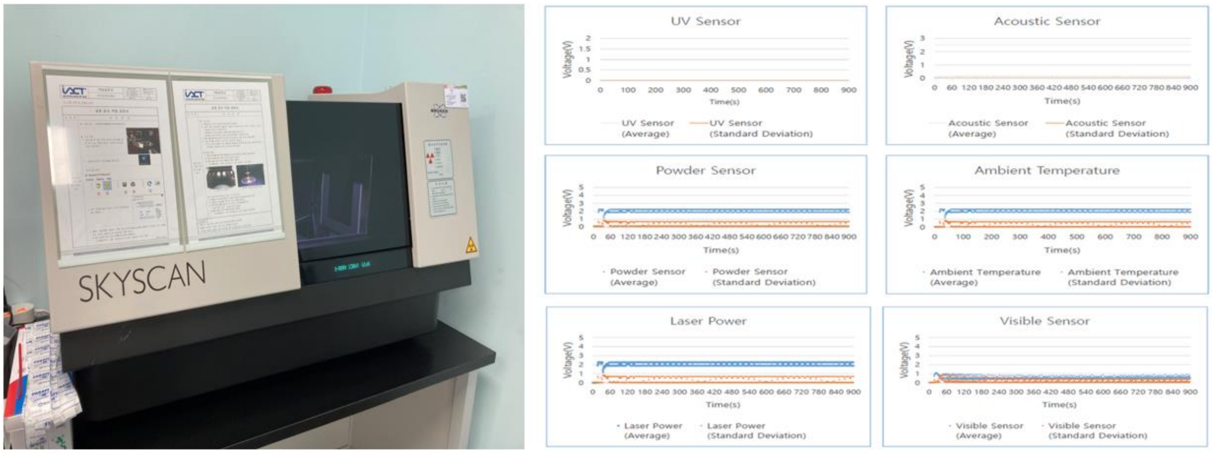
Tensile stress	Tensile strength
Its definition is the force per unit area that induces stretching, and it is symbolized by the σ.	The highest amount of tensile stress that a material can withstand before failing is denoted by the letter s.
$\sigma = \frac{F}{A}$ when, σ is tensile stress F is the active force. A is cross-sectional area	$s = \frac{P}{a}$ when, s is tensile strength P is the amount of force needed to shatter an a cross.

4. Process Parameters and Proposed Method

The quality of SLM 3D printing is based on material properties and process techniques. One of the most widely used materials AlSi10Mg is selected as a target material in this research. In the field of metal 3D printing, aluminum alloys are frequently employed due to their good mechanical qualities. AlSi10Mg is a commonly used aluminum alloy that has a decreased thermal expansion coefficient and can prevent the manufactured product from solidifying and cracking. Due to that aspects, in this research, we experimented with AlSi10Mg as the material[10].

SLM printing is a sophisticated manufacturing process with multiple parameters. In order to achieve better accuracy, it is necessary to separate parameters that are the most closely related quality of the printed product. Thus, the optimization research should solely take into account the primary SLM parameters.

In this research, laser power, scan speed, and overlap rate were selected as the main parameters of SLM 3D printing. The fundamental parameter, particularly for the strength of the printed portion, is the overlap rate. Due to that, the overlap rate has to be determined at the first beginning of the SLM printing process. Moreover, it can affect mechanical characteristics, surface roughness, and porosity. SLM printing shows better surface roughness with a higher overlap rate, lower porosity, and better mechanical properties. Thus, the variables chosen for the method were the laser strength, scan speed, and overlap rate. During the data collection by sensors, the indexes of the main parameters were set as follows: indexes of laser power were 320, 360, and 400 W, since scan speed was fixed at 600, 800 mm/s and overlap rate indexes were equal to 0.25, 0.30, and 0.35. Previous indexes were tested in various combinations. The system evaluation experiments were conducted with the same parameters and indexes of parameters [Fig. 4]. The collected data was trained by state of art AI models.



a) b)

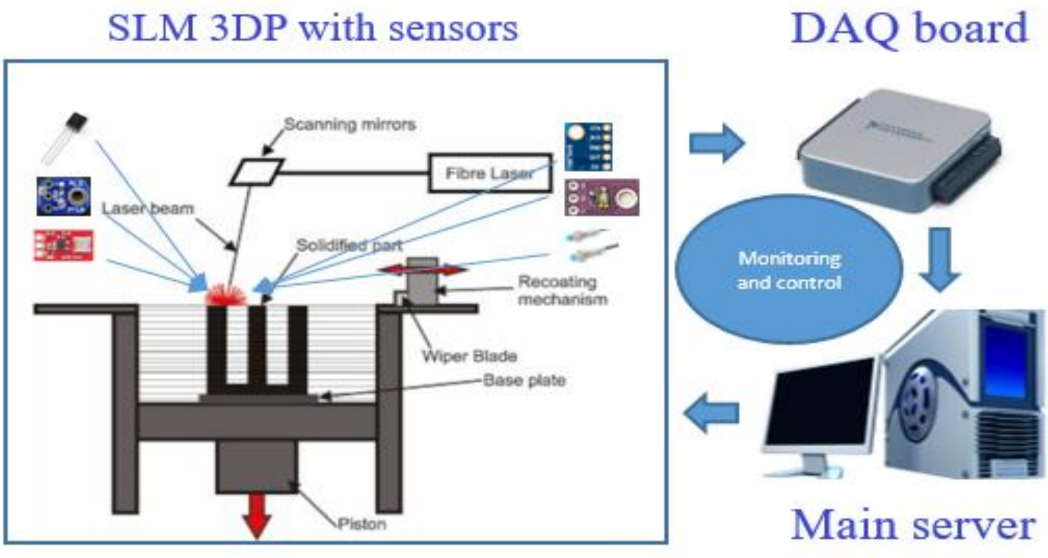
[Fig. 4] a) Micro CT Analysis Monitoring Applied Printing Material Analysis of Tensile Properties, b) application of monitoring function of developed SLM printer and analysis of defect occurrence trend according to performance

As mentioned in earlier sections, this paper proposes multiple sensor-based monitoring of SLM 3D printing [Fig. 5]. We know that there are several aspects that could affect the performance of 3D printing. Thus, we implanted a multiple-sensor approach. The sensors that are used are a visible sensor, UV sensor, photodiode, powder sensor, temperature sensor, and an acoustic sensor. The models of sensors we used are presented in [Table 2].

[Table 2] List of Used Sensors

Sensor	Model
Visible Sensor	ALS-PT19-315C
UV Sensor	GYML 8511
Temperature sensor	LM35
Acoustic Sensor	ICS-40180
Photodiode sensor	Keyes photodiode
Powder sensor	M12

We focused on the placement of sensors since it is an important factor in sensing-based monitoring. Thus, the visible sensor, UV sensor, photodiode sensor, and temperature sensor were oriented to the laser beam while the acoustic sensor was attached closely to the motors. The powder sensor was directly oriented to metal powder. These sensors were connected to a data acquisition board that collects all sensing data. The monitoring system analyses the data stream that comes from sensors and predicts expected tensile strength [Fig. 5].



[Fig. 5] Monitoring System Overview

The main operation of the monitoring system is performed by an AI model that can predict expected tensile strength and propose optimal process parameters. The generated dataset was trained with state of art regression algorithms to achieve the most efficient results. We have trained data with the six most used regression algorithms: Multiple Linear Regression, Polynomial Regression, Robust Regression, Decision Tree, Gaussian Process Regression, and Support Vector Regression.

The performance of regression models on our new dataset was evaluated using “Mean Absolute Error”, “Mean Square Error” and “R-squared”. According to the results of the training model evaluation (MSE=0.41, MAE=0.43, R squared=0.97), the highest accuracy was indicated by the Multiple Linear Regression algorithm. By utilizing a trained model, the monitoring system is able to predict expected tensile strength in advance while the printing process. This method allows for the enhanced quality of 3D printing.

As shown in Fig. 5, the main server analyses data and provides prediction results. According to prediction results human beings control 3DP with existing PC-based Metal 3DP controlling systems.

5. Experimental Results

As mentioned in the previous section, we have trained our dataset with the most popular regression algorithms and evaluated the performance of the algorithms by using regression evaluation techniques such as MSE, MAE, and R-squared.

When the data are completely matched by the regression model, the rates MAE and MSE have a value of 0, and they have a positive value when the fit is imperfect[11].

When regression is carried out incorrectly, R-squared gets negative results. When the regression model does not show any variability in the response data around its mean, R-squared has a value of 0[12]. If the coefficient of determination has values between 0 and 1, then 1 represents a perfect prediction.

In [Table 3], the mathematical background of the techniques is provided.

[Table 3] Mathematical Background of Evaluation Techniques

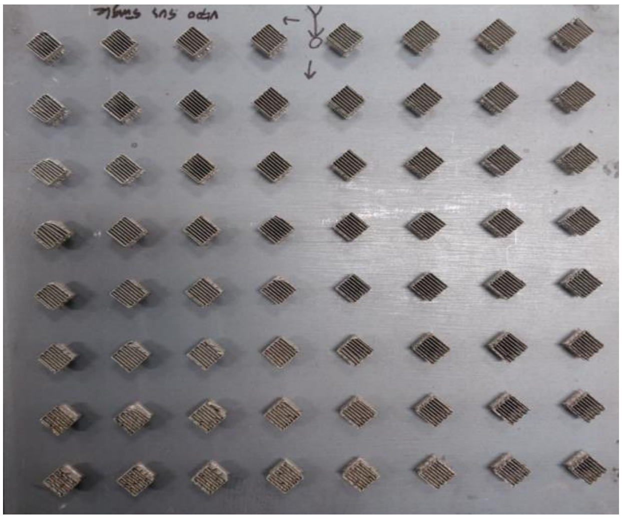
MSE	MAE	R-squared
$\text{MSE} = \frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2$	$\text{MAE} = \frac{1}{m}\sum_{i=1}^{m}\lvert X_i - Y_i\rvert$	$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(\bar{Y}_i - Y_i)^2}$
Where, X_i represents predicted i^{th} value and Y_i represents the actual i^{th} value.		

We have achieved 97% of predicting accuracy with Multiple Linear Regression algorithm. Following, the results of the experiments are provided in [Table 4]:

[Table 4] Evaluation of Regression Models on Our “Tensile Strength” Dataset

Regression algorithm	**MSE**	**MAE**	$\boldsymbol{R^2}$
Decision tree	0.88	0.85	0.57
Robust Regression	0.91	0.86	0.53
Gaussian Process Regression	0.75	0.73	0.63
Polynomial Regression	0.55	0.57	0.79
Support vector regression	0.53	0.51	0.87
Multiple Linear Regression	**0.41**	**0.43**	**0.97**

Furthermore, using varying laser power, scan speed, and overlap rate process parameters, we performed experiments to forecast tensile strength. The experiment was conducted on 64 multiple-layer samples as shown in [Fig. 6].



[Fig. 6] Multiple Layer Samples Manufactured by the SLM Process

Tensile strength index measurements were made on the samples. The tensile strength is equal to 449.6 MPa when the laser power, scan speed, and overlap rate are 360 W, 800 mm/s, and 0.35, respectively. However, our system predicted 448.4 MPa.

Following we provide a number of experimental results of tensile strength prediction.

[Table 5] Outcomes of Tests on Predicting Tensile Strength

Laser Power (W)	Scan Speed (mm/s)	Overlap Rate	Predicted (MPa)	Measured (MPa)	Accuracy (%)
320	600	0.30	447.3	442.1	97.3
320	800	0.35	437.8	439.3	99.4
360	600	0.25	433.7	436.5	98.8
360	800	0.35	448.4	449.6	99.6
400	600	0.30	445.9	442.7	98.2
400	800	0.35	436.4	433.9	99.3

As shown in [Table 5] the predicting model recoded high accuracy in various combinations of indexes of SLM printing process. Thus, the high index tensile strength was reached using a 360 W laser, an 800 mm/s scan speed, and an overlap rate of 0.35.

6. Conclusion and Future Work

In this paper, we proposed a monitoring system for metal 3D printing namely SLM technologies to improve the quality of printing products. We collected the dataset based on sensing data from multiple sensors and the tensile strength of printed products. Our system is based on supervised machine learning techniques to predict expected tensile strength. The system predicts expected tensile strength and helps to find appropriate parameter settings for high-quality product printing. The proposed monitoring system prevents wasting time, energy and raw materials as it works in real time and monitors each layer of the printing process.

We can draw the following conclusions about process parameters based on theoretical and experimental research: The best index for laser power is between 320 W and 400 W, while the optimal index for scan speed is between 600mm/s and 800mm/s, and the optimal index for overlap rate is between 0.25 and 0.35. Furthermore, for predicting tensile strength Multiple Linear Regression achieved 97% accuracy.

As a future work, we will improve monitoring system adding more options like defect detection, automatic control of 3D printing based on artificial intelligence and based control of 3D printing and computer vision based error detection.

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