A Machine Learning Approach of Lattice Infill Pattern for Increasing Material Efficiency in Additive Manufacturing Processes

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***Abstract*— Additive Manufacturing (AM) has become ubiquitous in manufacturing three-dimensional objects through 3D printing. Traditional analytical models are still widely utilized for low – cost 3D Printing, which is deficient in terms of process, structure, property and performance relationship for AM. This paper focuses on the introduction of a new infill pattern – the lattice infill to increase material efficiency of 3D prints, coupled with Machine Learning (ML) technique to address geometric corrections in modelling the shape deviations of AM. Encompassed by ML algorithms, the neural network (NN) is used to handle the large dataset of the system. The 3D coordinates of the proposed infill pattern are extracted as the input of the NN model. The optimization technique of scaled conjugate gradient (SCG) is the algorithm used to train the feedforward ANN, and sigmoidal function was used as the activation type for output neurons. There is 0.00776625 cross-entropy (CE) performance and 98.8% accuracy during network training. The trained network is implemented to STL file for geometric corrections of the lattice infill pattern then made in a 3D printer slicing software. Conventional designs such as the cubic and grid infill pattern were also made for comparison. Engineering simulation software were used to simulate all three infill patterns, to measure approximate product weight, stress performance and displacement, given that there is an external force applied. Comparisons showed that the new infill pattern is more efficient than conventional infill patterns saving material up to 61.3%. Essentially increasing the amount of prints produced per spool by 2.5 times. The structure of the proposed design can also resist up to 1.6kN of compressive load prior to breaking.**

***Index Terms*— machine learning, additive manufacturing, infill, lattice**

I. INTRODUCTION

The technology of creating physical 3D objects from a virtual computer assisted design through sequential addition of material without the aid of external tooling is called Additive Manufacturing (AM) or commonly known as 3D printing. Opposing the subtractive manufacturing, which creates 3D objects by material removal. This technology is more acceptable in cost, speed, quality and impact. It is customarily used in rapid prototyping and manufacturing, production of spare parts, small volume and very complex work pieces because of its advantages. It allows the rapid creation of sustainable objects and has been utilized to fabricate lightweight parts [1].

For good production, additive manufacturing (AM) has been using infill patterns to reduce the weight of the product and to save up material expend as low as possible but not trading the quality [2]. It is accomplished with the use of cellular materials with a regular and periodic microstructure [3].

The interior microstructure of an object printed is called, "infill". It follows a regular structures and patterns. Usually advanced slicing software is pre-loaded with infill patterns for the user to select along with a specific volume percentage [4]. The infill pattern and volume percentage significantly influence the printing process as well as physical properties of the printed object [5]. Greater the preferred volume percentage the greater the material and the longer the print time that leads to a more resistant print [6].

Even though there are many available types of infill due to AM advancement, there are several types that are commonly used because of their efficiency and comfortability compared to others. The grid or also known as rectangular infill pattern is the traditional and general purpose pattern being used nowadays [7]. At the same time Fused Deposition Modeling (FDM) meanwhile, is considered as one of the most productive technology typically used in low-cost 3D printers. A software will process an STL or CAD (computer-aided design) file, then geometrically slicing and conditioning the model generating GCODEs, and finally running the generated GCODEs through the printer before printing begins [8]. The mechanism approach of the it uses a plastic filament that is pushed through a heated extrusion nozzle melting [9]. This provide distinction to SLA (stereolithography) process, which is characterized by printing layer by layer using photo-polymerizable liquid resin through ultraviolet light [10].

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Acrylonitrile Butadiene Styrene (ABS) and Polylactic Acid (PLA) is the commonly used specific plastics in the filament of FDM printers. The only drawback factor of those is the costly price. This filament material is being inflated in the market by providing a huge markup over the cost of the plastic pellets used in making such filaments [11]. These filaments are available the market in terms of spools, which weighs approximately a kilogram each. Plastic filament consumption is responsible for the over-all cost of producing a printed object. Correspondingly, the type of the infill design influences the filament consumption of the print.

For this reason, a need for developing an algorithm that will require less filament material arises; which in effect will lessen the cost needed for a print and increase the number of prints in a single spool.

In a case study, performed by Zhu, et. Al in 2018, showed machine learning, particularly Bayesian inference and decision trees as a method utilized for prescriptive deviation modelling to estimate geometric deviations patterns by statistical learning from multiple shapes data [12]. Established research about Machine Learning performing complex pattern recognition and regression analysis without a definitive need to build and calculate the fundamental physical models [13].

Researchers from Huazhong University in China conducted a study that utilizes the concept of Topology optimization, specifically the Level Set Method (LSM) [14]. Topology optimization is a design process wherein it determines the optimum balance between weight reduction and structural integrity. The objective of the study was to present a multiscale topology optimization method capable of providing the optimal shell layout and infill pattern by defining the parameters for shell thickness and infill density. The researchers used beams and trusses as their experimental design for the optimization. Simulating the method on the experimental designs, it was concluded that the method was effective for both 2D and 3D models. While this method provides a mathematical model for concurrent optimization of the shell and infill, the approach focused on the microstructure of the infill. This sets the limit for method's application only for compliance minimization [15].

A new approach in combining structural and optimization techniques is presented in the study of Wu, et.al in 2018 [6] wherein the infill pattern used is based from the structure of the bone. The basis of this study is the Wolff's law [16] which states that that bone grows and remodels in response to the forces that are placed upon it. As a result of this natural adaptation, micro-structures of trabecular bone are aligned along the principal stress directions. The resulting composition is lightweight, resistant, robust with respect to force variations, and damage-tolerant [17], [18]. This makes the optimized interior structures an ideal candidate for application-specific infill in additive manufacturing.

While this approach is effective in lessening the object weight, the resulting infill lacks uniformity of pattern around its shell. This is because as the volume limit is being decreased, porosity in the infill region surrounding the shell is increased. While it is applicable to slender shapes like bones, challenge of sturdiness can be ascertained once used on shorter or equidistant shapes.

This paper presents a new and innovative infill pattern design coupled with Machine Learning (ML) technique to address geometric corrections in modelling the shape deviations that will increase material efficiency of additive manufacturing using FDM technology and offers permissible rigidity like that of a typical print. Validations are utilized to measure its effectivity while simulations are employed to determine the strength of the proposed design.

II. Infill Design Development Concept

The term ''lattice" in mathematics usually refers to a group of points whose positions follow a predefined pattern. Based on the pattern, a network that represents the connections of points can be obtained [19].

In the past decade, with the advances in innovative constructional technologies and high-strength materials, the steel tre structure has been increasingly incorporated in the construction practice of high-rise and spatial steel structures such as power transmission towers and long-span. In a separate research [20], the lattice girder was introduced to overcome the weakness of H-shaped steel ribs, and its geometric characteristics significantly reduce the possibility of an internal gap. The flexural stiffness and strength of lattice girders have been studied via analytical and experimental methods, and its structural benefits were widely recognized.

A new design for infill pattern is proposed in this paper called the lattice pattern which aims to save material consumption in 3D printing. The design is called lattice since the structure mainly focuses on the edges of a cube forming a lattice-like pattern inside the model (Fig. 1). This concept was engendered by the design concept of steel structures, whereas a typical steel structure design would consist of a combination of columns, beams, and girders subjected to compressive loads in hundreds of metric tons while it can be considerably hollow inside. Likewise, since steel structures serve as the skeletal system of a structure, the lattice pattern will similarly serve as the skeletal framework of the model.

Printer slicer softwares like Cura® introduce a number of pre-loaded infill patterns where designers choose. Some of which are: Grid, which is a grid shaped infill with lines in both diagonal directions on each layer; Lines, which creates grid shaped infill but printing in one diagonal direction per layer; Triangles which creates a triangular shaped infill pattern; Cubic, which is a 3D infill of tilted cubes; Tetrahedral, which comprises of 3D infill pyramid shapes; Zig Zag which is also a grid shaped infill but printing continuously in one diagonal direction; and many others [21].

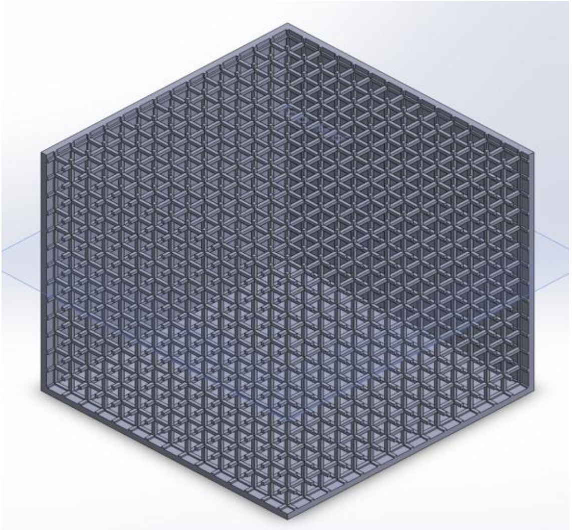


Figure 1. Zoom-out view of the lattice pattern

But all of these built-in pattern designs are printed horizontally by layers on top of each other thus creating vertical faces, which in effect consumes a lot of plastic material to construct. Meanwhile, the studied lattice pattern being used in construction industry for their steel structures do not require vertical faces, while still maintaining the pattern's rigidity.

Fig. 2 (Lattice Infill Pattern) details the steel structure used in the construction industry which is used as an inspiration for the proposed lattice infill structure. It is noticeable that the adopted design was slightly altered by making the beams consisted in profile, with even spaces and supporting beams removed as a requirement for an easy layer slicing. This structural-like pattern was used to function as the infill pattern for 3D printing.

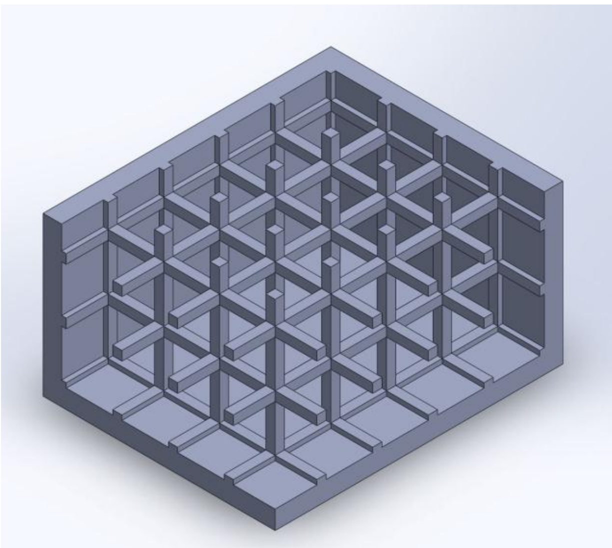


Figure 2. Lattice Infill Pattern

III. Methodology

The flowchart in Fig. 3 detailed the methodology used in conducting this research. It focused on three parts: Development of Artificial Neural Network algorithm, two design phases, two simulation phases and one evaluation phase.

A. Design Phase

The design phase consisted of two components: defining of benchmark infill pattern parameters and designing of proposed infill pattern. For consistency and due to its simplicity, all patterns are designed to make a 100mm x 100mm x 100mm cube print. ABS filament is used as material for 3D printing as it is one of the most commonly used filaments by users. The study is initiated by defining benchmark parameters allowing the researchers to compare and analyze the obtained data and performance of the proposed design with respect to the reference data sheet. The researchers decided to use the grid infill pattern to serve as the benchmark infill pattern, since this is commonly used by 3D Printer users. The cubic infill pattern is also utilized in this study for additional validation. Parameters are set to 5 mm infill line distance with 250 microns of layer thickness for the infill, and a shell thickness of 2mm for the cube surfaces. Testing and simulation of both benchmark and proposed using Lulzbot Cura® printer slicing software.

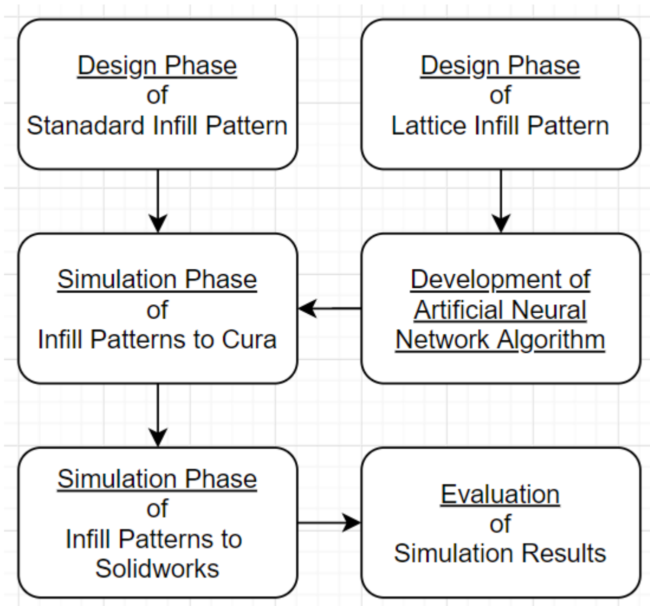
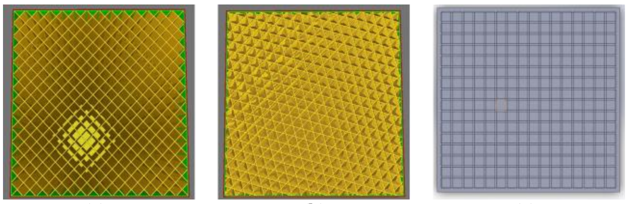


Figure 3. Flowchart of the Research Methodology

Fig. 4 presented the zoom-in view of both the grid (a) and cubic (b) infill patterns. Differences of the two is difficult to ascertain at a glance, but noticeable on the edges. Uneven triangles are seen on the edges of cubic pattern model, while equilateral ones are surrounding the grid pattern model. This is due to the design of the cubic pattern, wherein it utilizes tilted cubes.



(a) (b) (c)

Figure 4. Top view of grid (a) and cubic (b) patterns as benchmark infill models to the proposed lattice infill design (c).

Meanwhile the design of proposed lattice infill pattern is constructed using Solidworks® 3D design software. The researchers used an infill layer thickness of 1 mm and the same infill line distance parameters that of benchmark designs. The lattice infill assumed a layer thickness of 1mm due to slicer limitations of it being unable to print solid parts less than 0.75mm. After designing, the proposed design is then exported as an STL file extension for compatibility with Cura® software. Fig. 4c illustrated the top view of lattice infill design. As compared to the other models, the proposed design is composed of squares drawn perpendicular to the edges, unlike the other two, which were drawn diagonally to their respective edges.

B. Development of Artificial Neural Network

Additive Manufacturing (AM) involves building a computer aided design (CAD) model before the physical printing. Nevertheless, there are always geometric errors in modelling the shape deviations between CAD models and the printed parts, because of residual stress introduced by distortion [22]. Machine learning algorithm will make the required geometric corrections so that manufacturing the object using the modified geometry results in dimensional-accurate finished product.

Among Machine Learning algorithms, the Artificial Neural Network (ANN) is preferential because of the large dataset offered by the system. ANN has a substantial computational power and wordly-wise algorithm architecture that can handle large datasets [23]. There are some studies showing ANN excels at training the system in avoidance of deviation and inaccuracy and also target location, which is adequately needed in Additive Manufacturing to prevent geometric errors produced by the proposed infill pattern [24].

After the analysis and evaluation of the predefined CAD model of the proposed lattice infill pattern, its surface 3D coordinates are extracted as input of the ANN model. While the symmetrical deviation surface coordinates are extracted as the output of the ANN model.

The whole model is divided into three blocks of processes: design of neural network, training of neural network, and testing of neural network. After gathering and analysis of coordinate parameters that will serve as the training set of the model, initialization of number of artificial neurons, network hidden layers, weights and biases were done using MATLAB.

The neural network used in the study, works on supervised learning using backpropagation algorithm [25]. The activation function of the artificial neural neurons implementing backpropagation algorithm is a ‘weighted sum’ of the sum of inputs xi multiplied by their respective weights w1.

$$I = \sum w_1 x_i \tag{1}$$

Output function used in the model is the sigmoidal function that resembles a very close to one for large positive numbers, 0.5 to zero, and very close to zero for large negative numbers. It denotes leverage to others specially in classification models because it shows an ease polished transition between low and high output of neurons.

$$\phi(v) = \frac{1}{1+e} \tag{2}$$

The developed three-layer feedforward ANN with backpropagation algorithm has three input neurons at the input layer, 90 neurons at the hidden layer and three neurons at the output layer. The output is calculated by summing the three inputs range. The 70% of the total input data was used for training, 15% for validation and 15% for testing. Training data are conferred to the network during training, and the network is conformed and adjusted according to its error. Validation data are used to measure network generalization. Testing data provides an independent measure of network performance during and after training.

The use of machine learning and the artificial neural network has been studied to be the most economical and easiest way to address geometric corrections in modelling the shape deviations of AM [13]. To generate the best performance, the developed ANN model was analyzed and varied based in the number of hidden artificial neurons and hidden layers attained. The principal parameters to determining the best neural network are the processing time or learning time, cross-etropy (CE) value and the confusion accuracy.

By remarking to Fig. 5 and Fig. 6, it is apparent that the lowest cross-entropy and learning time are obtained from hidden node size between 0 and 100.

Fig. 7 shows the highest regression coefficient was obtained at hidden node size between 300 and 400. As illustrated, an increase happens from hidden node size 0 to 100 in a variable case then starts to decrease between hidden node size 300 to 400. The Cross-Entropy performance error proves the divergence and disparity of predicted from actual values.

Fig. 6 shows three scenarios of increase; hidden node size 0 to 100 gives a little increase, hidden node size 100 to 200 is in stable escalation, and a great increase in hidden node size 300 to 400. Fig. 7 shows a consistent approach, a considerable increase, and decrease throughout the testing. It shows no particular pattern in confusion accuracy in increasing the magnitude of hidden artificial nodes.

Fig. 8 emphasize in graphical form the training, validation and test performances of the trained ANN. Its best cross-entropy performance is 0.00776625 which testifies good performance of the network, wherein 0 being the ideal value that every predicted value corresponds to actual value. Cross-entropy provides good classification of the system 11 epochs were used by the network to achieve best validation. The gradient mechanism of the model is utilized in updating the weights and biases during iterations of testing.

Fig. 9 shows the variation in gradient value as to changes of validation checks. After the sixth validation check, the cross-entropy value and mean square error fails to decrease.

Fig. 10 outlined the overall confusion matrix of the developed neural network. This matrix is known to illustrate and show how accurate the system classifies each entry data sets. The training, validation, and test accuracy are 97.1%, 100%, and 100 % respectively. Out of 720 attempts to classify target output, 1.2% is wrong. Hence, overall system accuracy is 98.8%. The neural network was tested using 720 samples and resulted in the cross-entropy error measure of 7.4015E-17, and the percentage of misclassified samples is 1.2%. With the tested samples, the mean relative error is 0.00020734.

After analysis and validation of results. It is concluded that the developed ANN model can be a valid way to train a complex pattern recognition and regression analysis without an explicit need to construct and manually solve the underlying printed objects. It is also an effective approach to solve the geometric deviations between the model and actual print.

The 3D coordinates of the proposed infill pattern are extracted as the input of the NN model. The optimization technique of scaled conjugate gradient (SCG) is the algorithm used to train the feedforward ANN, and sigmoidal function was used as the activation type for output neurons.

The trained ANN network is implemented to STL file for geometric corrections of the lattice infill pattern then made in a 3D printer slicing software.

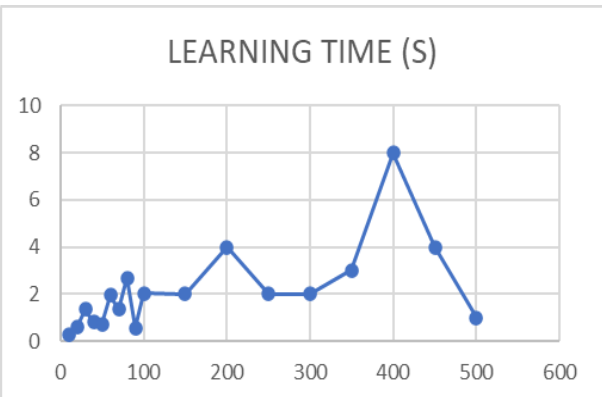


Figure 5. No. of hidden nodes vs Learning time in seconds

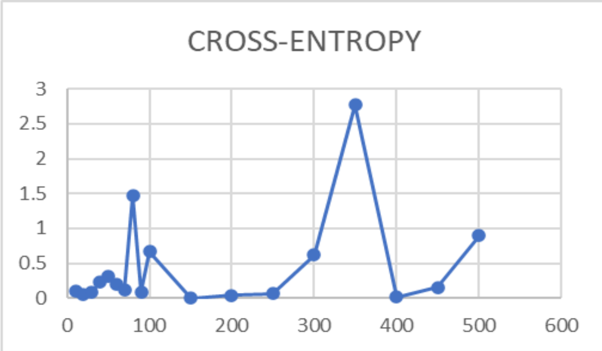


Figure 6. No. of hidden nodes vs. Cross-Entropy

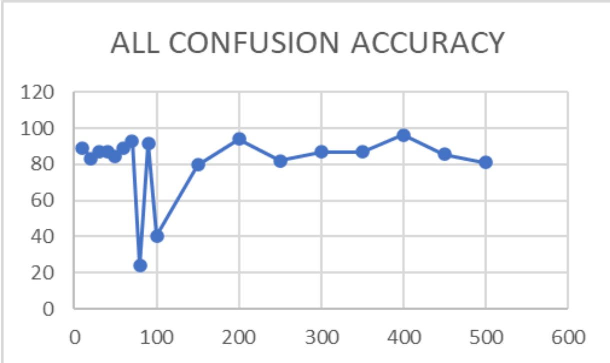


Figure 7. No. of hidden nodes vs. All confusion accuracy

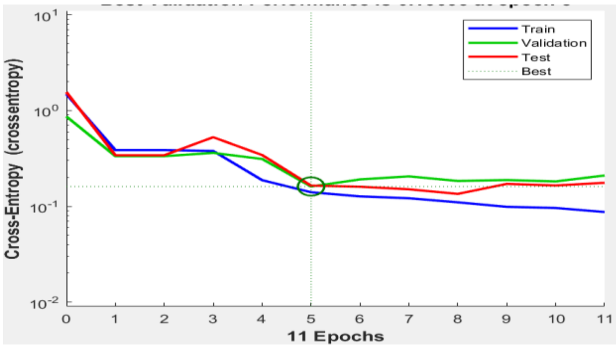


Figure 8. Performance Plot of the Trained Neural Network

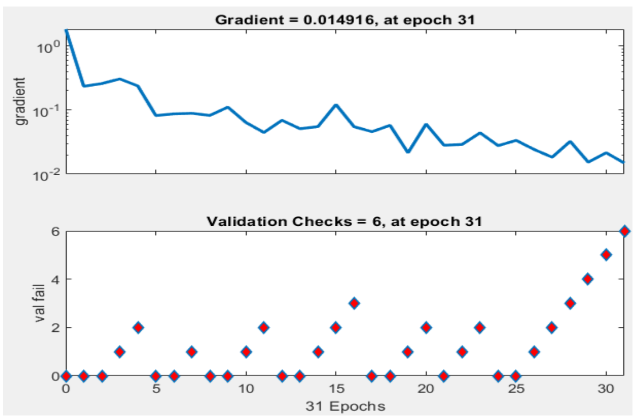


Figure 9. Training State Plot

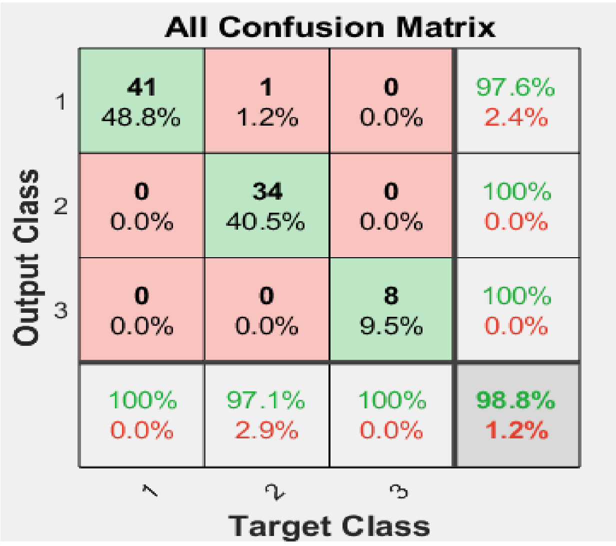


Figure 10. Confusion matrix of the developed ANN

After analysis and validation of results. It is concluded that the developed ANN model can be a valid way to train a complex pattern recognition and regression analysis without an explicit need to construct and manually solve the underlying printed objects. It is also an effective approach to solve the geometric deviations between the model and actual print. The trained ANN network is implemented to STL file for geometric corrections of the lattice infill pattern then made in a 3D printer slicing software.

C. Simulation Phase

The simulation phase is composed of two components: the printing simulation and the impact force simulation. Printing simulation is done using Lulzbot Cura® printer slicing software. Since the two benchmark patterns were originally created using the same software, no further configuration was needed. Meanwhile, since the proposed lattice infill design was created and exported from another software, a 0% infill configuration to Cura® Slicer software was needed. This is done to remove any infill influences since the design accounts for the other parameters to avoiding hollow portions. Moreover, impact force simulation was done using Solidworks® Engineering Simulation & 3D Design Software. This is to determine the contribution of the infill to the durability of the model. As per the technical data sheet, ABS can withstand up to 139N of impact force. Hence, the simulation began by subjecting the model to 139N compressive load. The load was applied on one side, while the opposite side served as a fixed point. Since the design model is uniform in shape, it is assumed that the exhibited behavior of compressive load tests is the same all throughout.

Additional simulations are done with relevant increments of compressive loads until the model is near breaking point. This simulation is done only on the proposed lattice design so as to determine if the model can exhibit the same performance as determined by the technical data sheet and by how much it can resist up to near breaking point.

Evaluation commenced after simulations. The formula below was used to determine the number of prints per spool each models can considering their respective weight.

$$N_{prints} = \frac{W_{spool}}{W_{model}} \tag{3}$$

where N_{prints} denotes the estimated number of prints per spool each design model can produce, W_{spool} pertains to the weight of a spool of filament, which is approximately 1 kilogram, and W_{model} is the weight of the product of each models acquired from the slicer software. The measurement is used to determine if increasing material efficiency is enough to yield additional prints.

Meanwhile, the gathered data for weight of each design is also used to compute efficiency in terms of the percentage of materials saved with respect to the benchmark model using the formula below,

$$\%materials\,saved = \left(1 - \frac{W_{proposed}}{W_{benchmark}}\right) x100 \tag{4}$$

where $W_{proposed}$ is the weight of the lattice infill pattern design and $W_{benchmark}$ is the weight of the benchmark infill pattern design.

Results from compressive force simulation were evaluated in terms of the ratio between the experienced maximum pressure on a simulated compressive load over ABS standard stress capacity from Makerbot of 1100psi (or 7584 KPa). The standard (STD) stress capacity data [26] is used in this study since the STD stress capacity is defined in as the printed output possessing a standard resolution with infill influences, which is this study is all about. This to determine about how much percentage the model is near breaking point. The proponents utilized this data from Makerbot's Technical Datasheet [26] as the baseline data since the company is a well-known manufacturer of quality filaments used in FDM printing.

IV. RESULTS

A. Grid Infill Performance

The data from printing simulation of grid infill pattern served as the benchmark of the study. The grid infill pattern, as shown in the Fig. 11, marked yellow, would consume around 298g of material as mentioned in the slicer software outlined in red. The standard weight of one spool of filament is 1kg, though there are variations as made by manufacturer. For the sake of comparison, the researchers use the 1kg as the baseline. With this information, around 3 cubes can be printed with the given specification.

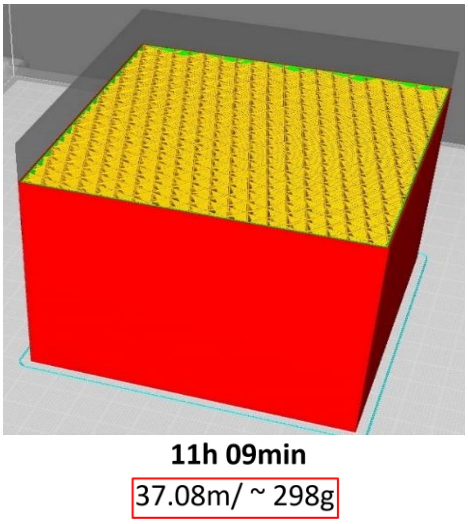


Figure 11. Grid Infill pattern results

B. Cubic Infill Performance

The cubic infill pattern is used in this design as additional benchmark model since this pattern is also starting to gain popularity for novelty purposes. It is used for 3D prints which requires high strength in multiple directions. Nevertheless, it can engage with the conventional infill patterns available in the market. This infill pattern would therefore be a good choice for a part that will be stressed in multiple ways.

The cubic infill pattern as show in Fig. 12, marked yellow, consumed around 416g of material; which leads to a maximum of 2 prints of cube per 1kg of spool. This infill pattern shows that it needs 39.5% more material than the grid pattern. Note that the Cubic Infill Pattern can be made efficient by manipulating infill line distance, so that it can obtain the same efficiency as compared to the grid pattern. The same can be concluded with the proposed design to achieve better efficiency. For consistency, the researchers defined the infill line distance of 5mm for all patterns for comparison.

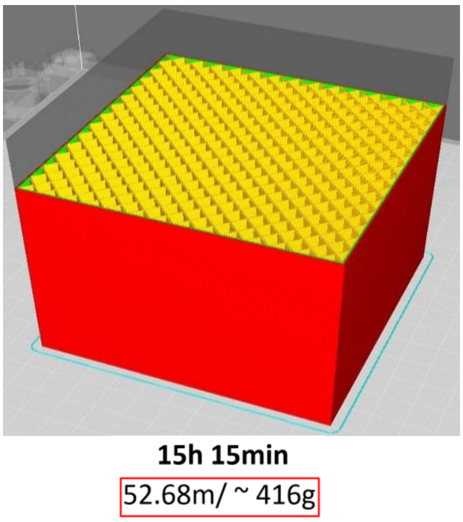


Figure 12. Cubic Infill pattern results

C. Proposed Lattice Infill Coupled with ANN Algorithm Performance

The lattice infill pattern as show in Fig. 13 is the proposed design of this paper. The lattice pattern would consume 198g of material to print a cube. In effect, this result allows 5 cubes to be printed with 1 kg spool. This pattern saves up to 33.5% of material consumption compared to the grid pattern and 52.4% material consumption compared to the cubic pattern.

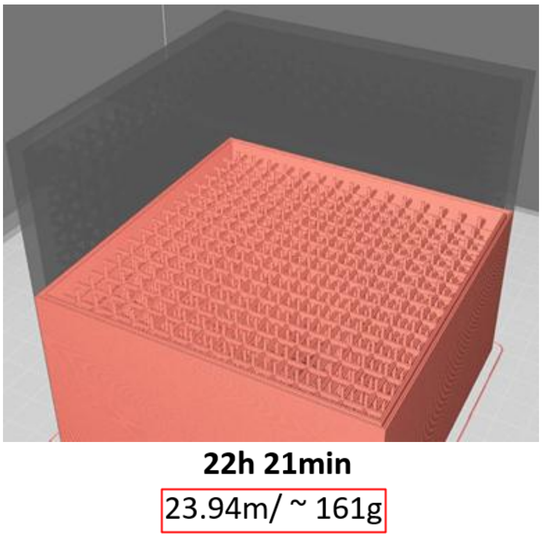


Figure 13. Proposed Infill pattern results

D. Stress Simulation Analysis

Table I shows the complete results gained from this simulation. At 139N, the model is subjected to a pressure of 559 kPa which is 7% of the allowable pressure of the material specification with a displacement 0.018mm. Load Stress and Displacement Analysis at 139N are illustrated in Fig. 14, Fig. 15 Fig. 16 Fig. 17, respectively. The colors indicate the amount of pressure or displacement is experienced in the area, Fig. 14 shows a color of blue around the cube, suggesting that the blue sections are experiencing an average of 47 kPa. Meanwhile, Fig. 17 shows a variety of colors suggesting that a particular section is experiencing varying displacements. The blue section around the edges of the top surface is experiencing a displacement between 1.508 µm to 3.015 µm, the green area is experiencing an average displacement of 9.045 µm, and in the center marked as red is experiencing an average displacement of 0.018 mm. The simulation also determined that a maximum pressure of 7572 kPa is experienced by the model, which is significantly close to the standard stress capacity dictated by Marketbot, upon an application of a compressive load of 1.6kN. This suggests that the lattice infill design is capable of holding up to 1.6 kN or a mass up to 163 kg prior to breaking. The Load Stress and Displacement Analysis for 1.620kN load are illustrated in Fig. 15 and Fig. 16 respectively. Fig. 16 suggests that the cube is experiencing a maximum displacement of 0.212 mm at the red area.

TABLE I. STRESS PERFROMANCE ANALYSIS

Compressive Force Load (N)	Max Pressure Experienced in Model (kPa)	Makerbot STD Stress Capacity (kPa)	Percentage Experience Pressure over Max Pressure	Displace-ment (mm)
139	559	7584	7%	0.018
150	604	7584	8%	0.0194
200	805	7584	11%	0.0259
500	2320	7584	31%	0.065
1000	4640	7584	61%	0.13
1632	7572	7584	100%	0.212

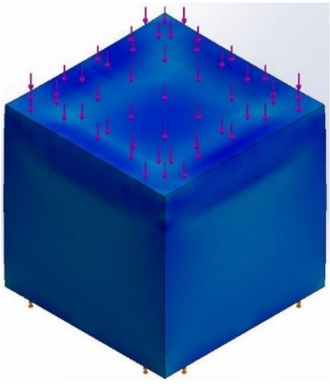


Figure 14. 139 N Load Stress Analysis

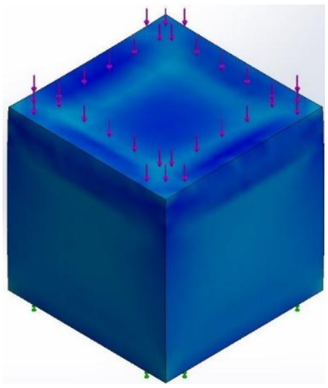


Figure 15. 1.620 kN Load Stress Analysis

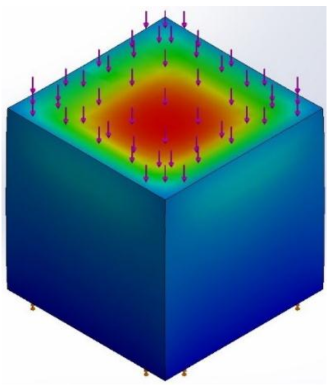


Figure 16. 1.620 kN Load Displacement Analysis

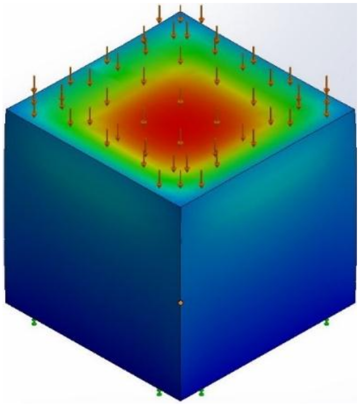


Figure 17. 139 N Load Displacement Analysis

E. Printing Simulation Results

One of the features of Lulzbot Cura® is the estimation of the material consumption and printing time displayed in the software's graphic user interface (GUI) after the simulation. These data were acquired, tabulated. Moreover, the data for number of prints was computed using Equation (1) detailed in the methodology. Table II summarizes the results of printing simulation. The data is further evaluated in the succeeding subsection.

TABLE II. SUMMARY OF PRINTING SIMULATION

Infill Pattern	*Material Consumed*	*Estimated Printing Time*	*Number of Printable cubes based on 1kg spool*
Grid	298g	11h 09min	3
Cubic	416g	15h 15min	2
Lattice	161g	22h 21min	6

F. Evaluation

Table I shows the data on various applied compressive force loads and the respective maximum experienced pressure of the model which were obtained from the simulation. This was done to determine how much force and mass can the model withstand with respect to the pressure it develops in the model. The obtained pressure values which were compared to the STD stress capacity showed that the model can withstand 1.6 kN. This can be interpreted that the model can withstand a mass up to 163 kg or 359 lb_{mass} prior to breaking.

Table II detailed the comparison of two benchmark infill pattern designs and the proposed design in terms of material consumption and duration of print. The grid and cubic infill patterns weighs heavier than that of the proposed design. In effect, the proposed design can produce more prints than the two benchmark designs as detailed in Table II.

Using Equation) of the methodology, it is computed that the Lattice infill pattern can save up to 45.97% of material as compared to the grid, and 61.3% of material as compared to the cubic. Both data exceed the research objective of 25% reduction of material consumption.

While the data proves that there is practicality in the proposed infill design, it is also noticeable that the lattice infill has longer printing time than the other two. The lattice infill needs at least extra seven hours of printing as compared to that of the benchmark infill patterns. The lengthy printing time of the proposed design is mainly due to the need for multiple passes in achieving the required thickness of the infill. The nozzle diameter is one main factor for printing the infill. The process of printing the infill of a model is through a single pass per layer from point A to point B. With those considerations, the printing time of the infill is faster than the outer shell of the model since the outer shell would require multiple passes before shifting to the next layer. The layer width of the infill will always follow the specified layer thickness up to a maximum of the nozzle diameter, and the standard nozzle diameter is between 0.4 mm to 0.5 mm. The lattice infill assumed a layer thickness of 1mm due to slicer limitations of it being unable to print solid parts less than 0.75mm. The slicer treated the 1mm infill layer thickness specified in the design as a solid part, requiring it to have multiple passes to fulfill the required thickness before shifting to another layer resulting to a longer printing time as compared to a regular infill pattern. Fig. 18, sums up the comparison of the standard infill patterns (grid, cubic and lattice) and the proposed lattice infill pattern with the aid of machine learning into a illustrative approach, showing that the proposed infill pattern is the best for material consumption. Substantiating, Fig. 19 shows the comparison into a ratio of 1kg spool, which is the existent approximate of the experiment.

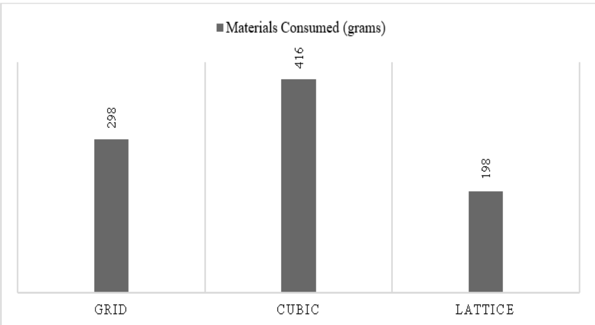


Figure 18. Materials consumed (in grams)

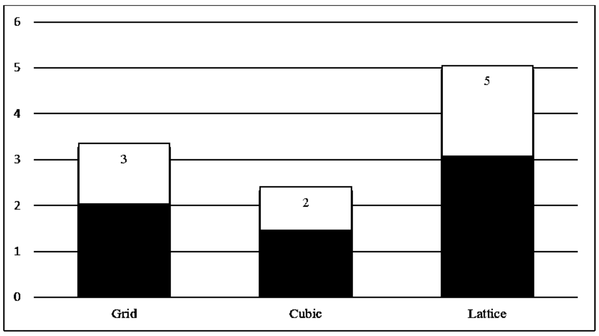


Figure 19. Number of printable cubes based on 1kg Spool

V. Conclusion

This paper proposed a new designed lattice infill pattern coupled with Artificial Neural Network (ANN) technique that effectively increased the material efficiency of additive manufacturing. The proposed lattice infill pattern's surface 3D coordinates are extracted as input of the ANN model. While the symmetrical deviation surface coordinates are extracted as the output of the ANN model. The trained ANN network is implemented to STL file for geometric corrections of the lattice infill pattern then made using Solidworks® and rendered using STL file extension and is reconstructed together with the pattern's shell using Cura®. Cubic and Grid infill designs which are designated as benchmark where the proposed design is compared to, is created using Cura®.

The combination of ANN and lattice infill pattern has demonstrated great potential for realizing the attractive concept of ‘‘agile manufacturing” in manufacturing.

The proposed design saves from 45.9-61.3% of the material consumption compared to benchmark infill patterns. Weight is used as reference of consumption comparison deduced in the simulation of designs to Cura®. It is subjected to benchmark parameters that can withstand up to 1.6 kN of compressive load or 163 kg prior to breaking when the proposed design infill pattern is applied. The data was acquired and analyzed through simulations of the design to Solidworks® and comparing it to the reference datasheet of ABS material given by Makerbot.

However, the proponents recommend further research on the efficiency of material consumption which also considers the total printing time needed by the proposed infill design because machine learning algorithms rely strongly on data collection, and possible optimization solutions to at least make it on par to the time consumption of the benchmark infill patterns utilized in the study.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

J. D. Alejandrino conceptualized the idea of the research, extracted and analyzed the data, developed machine learning algorithm models and wrote the paper; A. A. Bandala, R. S. Concepcion II and E. P. Dadios helped in developing the models; L. A. Venancio Jr. simulate and evaluate the given models and designs; S. C. Lauguico and R. R. Tobias performed the data collection and analysis.

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