Evaluating the performance of active learning models on selective laser melting data sampling

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Abstract. Data acquisition in additive manufacturing, specifically selective laser melting, is always expensive and worsens when the material under study is also costly. To address this challenge, researchers use available design of experiment (DoE) tools. This marks a shift away from trial-and-error and one-factor-at-a-time approaches, which are ineffective and cause the number of required experiments to grow exponentially as the number of parameters increases. However, the traditional design of experiments struggles in analysing complex, multi-parameter, and noisy systems, inherent characteristics of selective laser melting data. Active machine learning can excel in this limited data and sophisticated field. This study evaluates the performance of active machine learning models based on neural networks and Gaussian process regression (GPR) with a D-optimal design for predicting Ti-5-5-5-3 and Beta 21S samples. This study demonstrates the ability of both active learning methods to reduce data required with improved predictability, with GPR outperforming the others. These results demonstrate the potential of GPR for effective SLM experimentation and emphasize the necessity of improving active learning based on neural networks to increase experimental accuracy with less data.

1 Introduction

Selective Laser Melting (SLM) is a metal additive manufacturing technique that fabricates components by layering them layer by layer using high-powered lasers [1]. This manufacturing method holds significant potential to transform the manufacturing sector due to its ability to produce intricate geometries, support extensive customization, accommodate diverse metal and metal composite materials, and align with lean manufacturing principles by minimizing waste and enhancing material reusability [2]. Notwithstanding these benefits, SLM use is still restricted to the experimental and prototype phases in many nations, particularly in Africa [3]. This slow adoption may have been attributed to the high cost of data acquisition, unpredictable magnitude of noise in collected data, lack of repeatability in data, and numerous experimental parameters with complex correlations affecting product quality [4, 5].

Scientists have made efforts through experimentation to understand the underlying patterns between investigated parameters and the measured outputs. One factor at a time (OFAT) [6] and the use of trial and error were used in past experiments but proved to be

inefficient, and costly when handling many factors, and researchers may barely get a clear understanding, especially in interactions between variables, among other limitations [7]. Several designs of experiments (DOEs) tools have been developed to mitigate the limitations of the trial and error and OFAT techniques. Among these techniques, the surface response method [8] and Taguchi [9] have largely been explored in SLM experiments due to their ability to design experiments with a smaller number of samples. However, these traditional (DOEs) techniques, while they are capable of minimizing experimental runs, struggle in their performance with high-dimensional problems, while assuming normal mathematical relationships that do not accurately represent the highly nonlinear nature of SLM datasets [10]. These limitations call for more flexible and adaptive DOE approaches.

Active learning is a subset of machine learning that aims to improve model/ experimental outcomes while reducing the amount of labelled data required by intelligently selecting the most informative data point for sampling [9],[10]. Its basic tenet is the fact that not all data points contribute equally to learning; hence devising a way to only focus on the most uncertain point in the data, models can learn more efficiently [12]. Active learning is particularly valuable where labelling data is expensive, time-consuming, or requires expert knowledge, as for the case with selective laser melting datasets [4].

In finding the most informative points for sampling, several common query strategies used in active learning include uncertainty sampling [13], where the model chooses the least confident point, query by committee (QBC) [14], [15] where multiple models select the point where they disagree most, and the expected model change [16] where the model queries a point that causes the most change in model parameters. These strategies can be implemented using various model types, including neural networks, support vector machines, or Gaussian process regressors [11]. When applied to SLM fields, active learning has the potential to drastically reduce the amount of data needed while achieving accurate pattern recognition, optimization of SLM processes, and maintaining predictive accuracy compared to the existing DOEs [5], [24]. However, its adoption in SLM remains underexplored due to high computational time and the need for expert knowledge in algorithm implementation.

This study evaluates the performance of two active learning models based on Neural Networks and Gaussian Process Regression (GPR) for data sampling in SLM with uncertainty sampling as an active learning strategy. Their effectiveness is compared to part of Rudolph's master's research [17] the D-optimal design of the response surface method for optimizing the density of Ti-5Al-5V-5Mo-3Cr (Ti-5-5-5-3) and Ti-15Mo-3Nb-3Al-0.2Si (Beta 21S) alloys. Results indicate that both active learning strategies significantly reduce data requirements, with GPR outperforming the neural network model. Based on these findings, we advocate for the adoption of GPR in SLM, further refinement of neural network models, and the development of user-friendly active learning interfaces like traditional DOE frameworks. By integrating active learning in SLM, optimal analysis of data and predictability can be achieved with limited data, as models are dynamic and self-improving, breaking research barriers existing in this field.

1.1 Data size in selective laser melting

To grasp the nature of datasets in this promising field of metal additive manufacturing, in this case SLM, this paper extensively researched recently published work done using SLM data sets to quantify the size of data used in their work, while excluding in situ data collection research work. The research confirmed the availability of small-sized data for each published material, as other researchers opt to combine data from several literature [18] and simulations to enlarge the size of the dataset. Table 1 shows some of the work published on SLM since 2024 with their data size, method of DOEs, objective, material, and parameters investigated.

Table 1. Works research on SLM and the number of samples used.

Authors	Method	Objective	Material	parameters	Data size
Yang et al. [19]	GPR-Boosted	Density prediction (PP)	CuCrZr	• Laser power • Scanning speed	36
Igwe et al. [20]	Taguchi	Surface roughness	AlSi10Mg Aluminium alloy	• Building orientation • Laser power • Scan speed • Hatch spacing	9
Bakhtiarian et al. [21]	Taguchi	Density hardness	SS316L	• Scanning speed • Laser power • Layer thickness	16
Chung et al. [18]	Random forest algorithm Surface response method	Density optimization prediction	Mar-M247LC	• Laser power • Scanning speed • Hatch spacing • Layer thickness	223
Rudolph [17] Previous study	Surface response D-optimal	Density prediction	• Ti-5-5-5-3 • Beta 21S	• Laser power • Scanning speed • Hatch spacing	50
This study	• GPR • Neural Networks	Density prediction	• Ti-5-5-5-3 • Beta 21S	• Laser power • Scanning speed • Hatch spacing	45

2 Methods

Active machine learning is implemented by first training the model on an initially small, labelled dataset. The model is then made to predict the next informative point from the unlabelled dataset to learn from using one or a combination of the earlier-mentioned strategies. The sampled data point is added to the labelled dataset, and the process is repeated until the designated end is reached, mostly in terms of model performance. To effectively evaluate the model, a small validation dataset is used to evaluate the model's accuracy in prediction given input parameters. The active learning cycle can be best demonstrated in Fig.1, as shown.

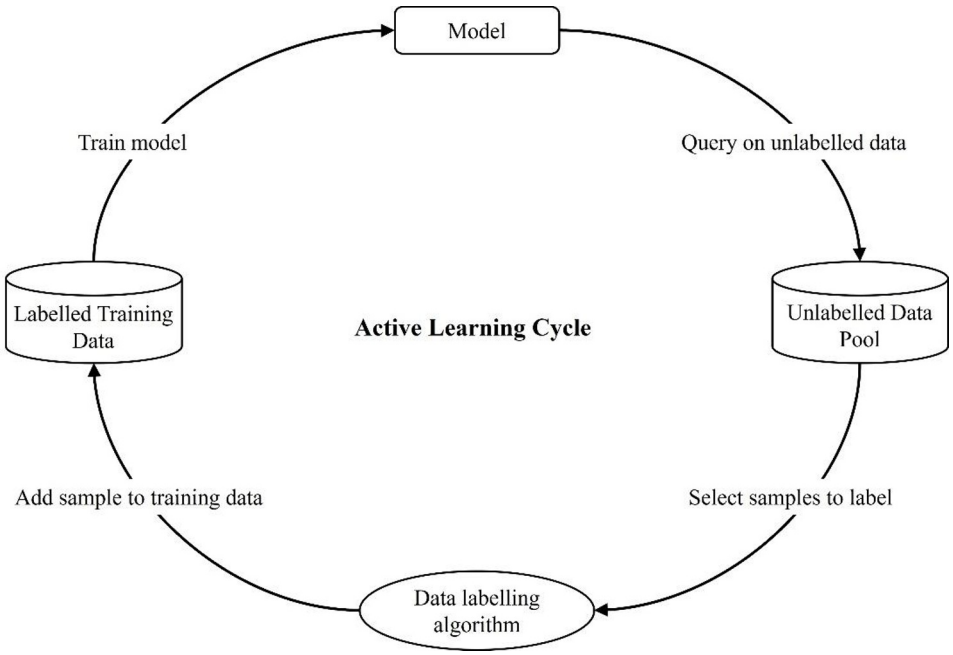

Fig. 1. Active learning loop.

Following Rudolph's experimental design and dataset for the D-optimal method, this work excluded the five failed samples from the datasets and worked with the remaining 45 samples. The study went ahead to use 10 random data points from the dataset as initial training data, for both GPR and neural network models, just as in Rudolph's work. However, with active learning, even one data point could be sufficient to be an initial training data. The models were then allowed to intelligently sample the most informative data point from the remaining data and add to the training data using uncertainty sampling, retrain, and evaluate their performance against five validation data points randomly picked from the dataset. The process was then repeated until the models' predictions were close to the actual output with the given inputs of the five validation data points. This is likened to an additional 40 data points in the counterpart D-optimal method. The models also traced the absolute error for the first point and the absolute mean error for the five validation points for their performance evaluations. The inputs to the models were laser power, scanning speed, and hatch spacing, while the measured output was sample porosity. The two models were both trained on two separate datasets (Ti-5-5-5-3 and Beta 21S) for better comparison and understanding of their performance. For this study, all active models were coded using Python on Google Colab.

3 Results

3.1 Active Gaussian process regression

Evaluating active GPR on the two SLM datasets, with both datasets having 3 input and 1 output, the model output (porosity) prediction of the actual percentage of scaled porosity (Rudolph datasets were scaled by zeroing the smallest porosity and the rest of samples' porosity were a measure of deviation from the datum) for the five validation samples, as provided by Rudolph, was plotted as the number of samples was added/in steps of iterations. This paper presents the active GPR model performance at the 1st, 10th, 20th, and 30th iterations as shown in Fig.2 and Fig.4. Consequently, the respective model errors for the first point and

mean absolute error for five points were plotted for both materials as shown in Fig. 3 and Fig. 5.

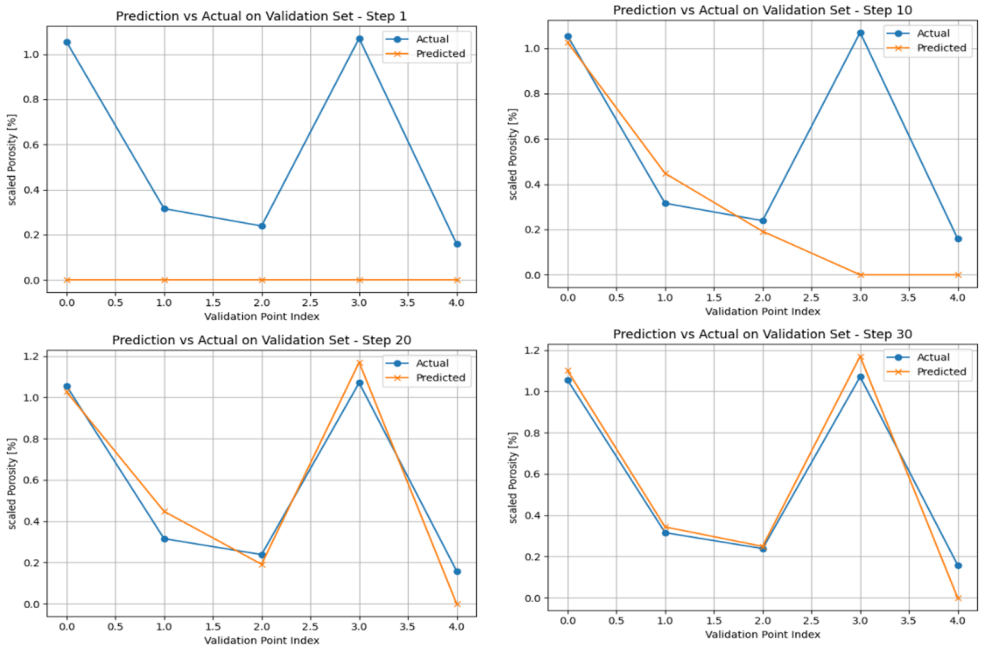

Fig. 2. Active GPR performance on the Ti-5-5-5-3 dataset: Stepwise performance.

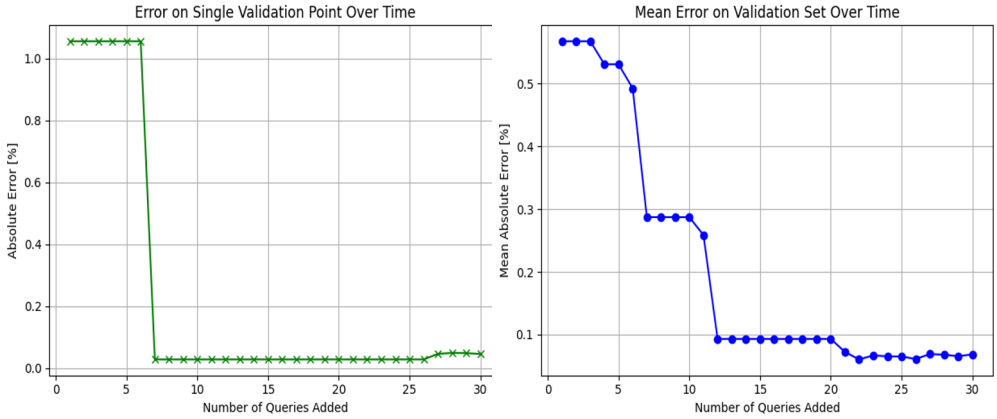

Fig. 3. Active GPR performance on Ti-5-5-5-3 dataset: Mean errors for single and five points.

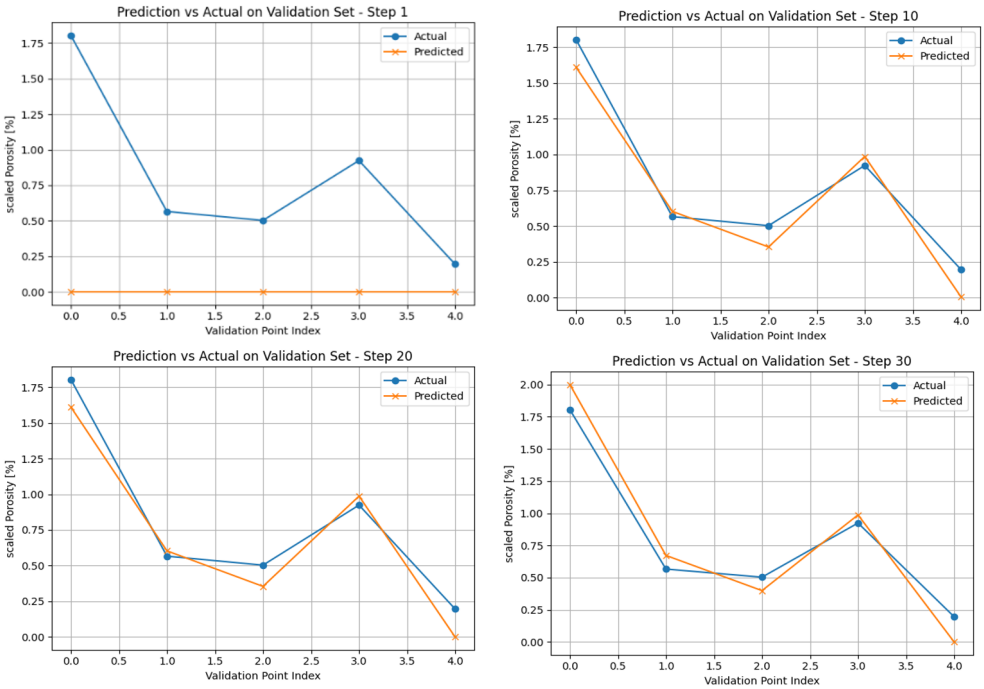

Fig. 4. Active GPR performance on the Beta 21S dataset: stepwise performance.

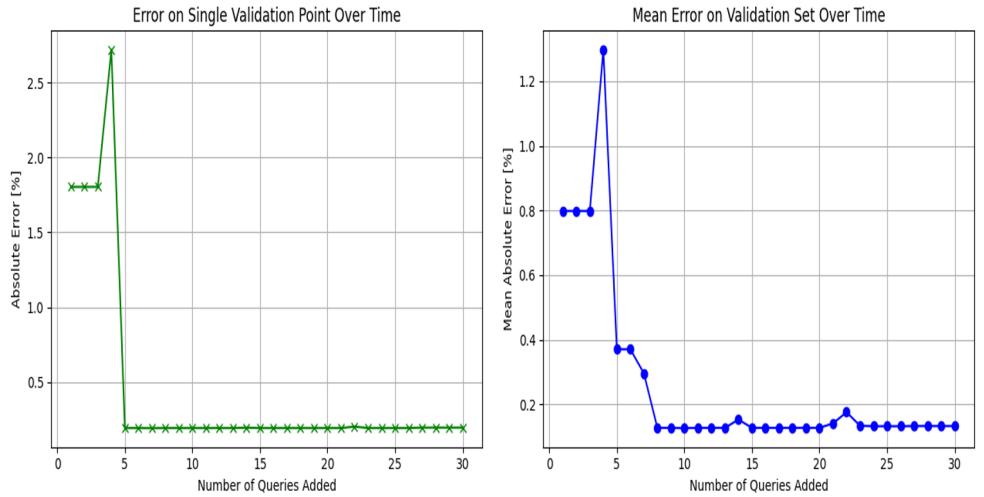

Fig. 5. Active GPR performance on Beta 21S dataset: Mean errors for single and five points.

3.2 Active neural networks

Unlike GPR models, Neural network models have no inbuilt uncertainty estimation. To maintain the same sampling strategy (uncertainty sampling) as GPR, this study deploys a

dropout rate of 0.2 into the neural network to achieve active learning. The neural network model was also trained and evaluated just as the Active GPR. Its performance for the two datasets is shown in Fig.6, Fig.7, Fig. 8, and Fig. 9.

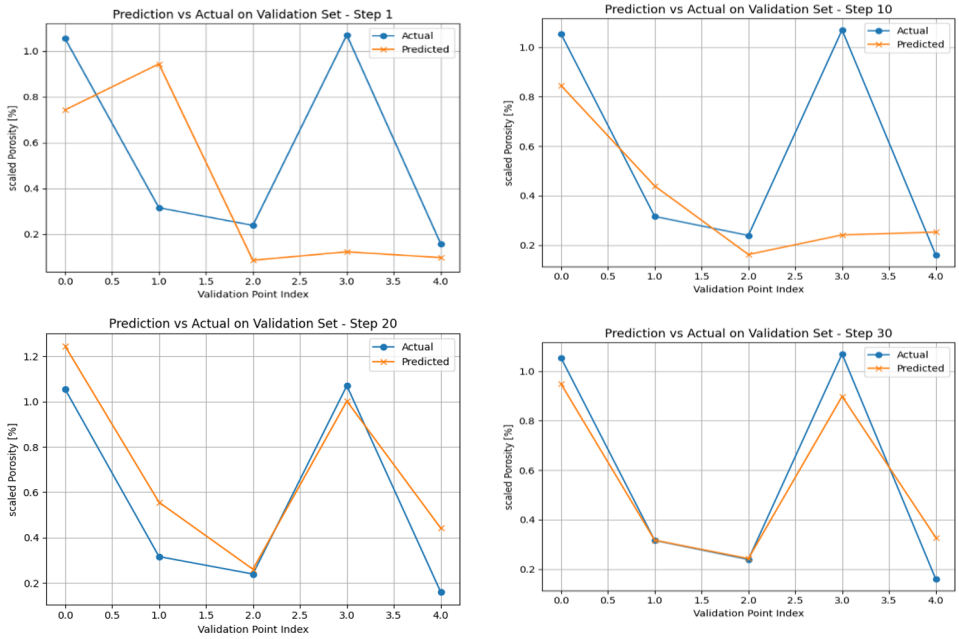

Fig. 6. Active neural network performance on the Ti-5-5-5-3 dataset: Stepwise performance.

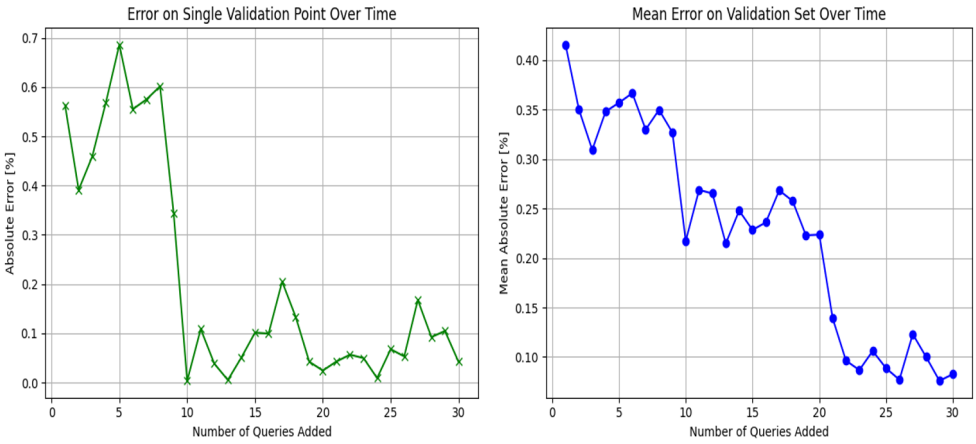

Fig. 7. Active neural network model performance on Ti-5-5-5-3 dataset: Mean errors for single and five points.

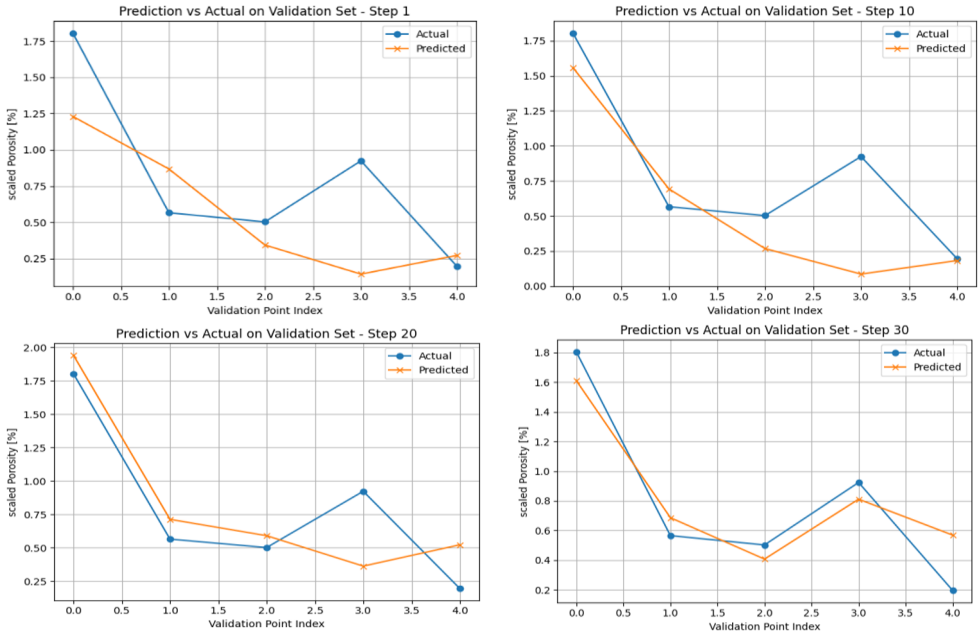

Fig. 8. Active neural network model performance on the Beta 21S dataset: stepwise performance.

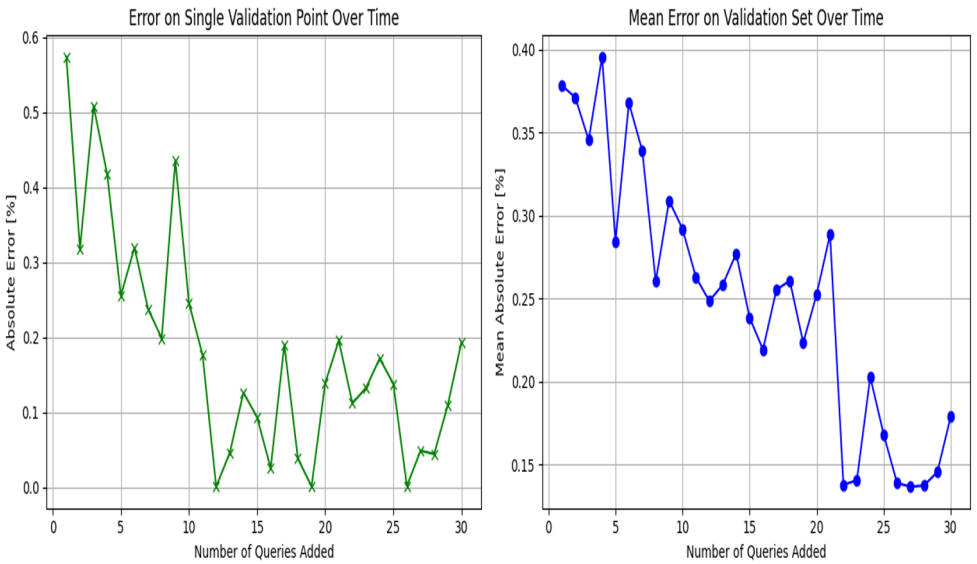

Fig. 9. Active neural network model performance on Beta 21S dataset: mean errors for single and five points.

4 Discussion

The two active learning models using the uncertainty sampling strategy demonstrate the capability of learning underneath patterns between the input parameters and the output measurements. This is shown by the constant improvements in their predictions for both single-point and collective five-point predictions. Their absolute mean errors drop as the models intelligently learn from an unlabelled dataset. As the two models sample the noise data, their predictions also improve as illustrated in Fig. 2, Fig.4, Fig.6, and Fig. 8.

From the graphs this study provided, the two models confirm their ability to perform sufficiently with fewer data compared to the 50 provided in Rodolph's D-optimal experimentation. Active GPR, for example, proves that it needs only an additional 20 and 10 data points, respectively, for the two materials for the model to predict five validation points with the highest accuracy. On the other hand, although the active neural network model struggled to reach a plateau in higher prediction accuracy, it's evident that some of the points in the validation dataset could be predicted with sufficient accuracy before the model learned all the data.

To measure the models' ability to predict with accuracy, this study plots the mean absolute error when five data points are under study and compares the results when only one point is under study. Further, to cement the models' capabilities, these two models were tested on two different datasets made of different materials under study without changing model hyperparameters as shown in Fig.3, Fig.5, Fig.7, and Fig. 9. The plots discourage the use of single data point prediction but rather advocates the use of several data points validation to measure prediction ability of the model. All the models' performance for one-point prediction was extremely high using fewer data, which could give a false impression of the models' superiority and be disappointing when the study focuses on prediction for other points.

The models' performance on the two datasets was summarized in Table 2, with the bolded value being the most preferred. Comparing the performance of the two active learning models, the active GPR model outperforms active learning based on neural networks in terms of data points required for correct pattern recognition and prediction of the five validation points. The active neural network model barely comes to the point of confident prediction of the five data points, but however the same to active GPR, the model prediction error reduces as the number of samples added increases. This active neural network model behaviour compared to GPR could be attributed to the hyperparameter sensitivity of neural networks compared to GPR models [22, 25].

Although Traditional DOEs work to reduce the number of experiments compared to one factor at a time (OFAT) experimental design and trial and error method, these methods rely on known mathematical correlations between the inputs and outputs, as demonstrated by Rudolph's work [17]. This is not always the case with real SLM data, whose pattern can only be picked up by machine learning algorithms such as GPR and Neural networks. These models also scale well when more parameters, i.e., more than 5, are being investigated when compared to traditional DOEs.

Table 2. Performance comparison of models under study.

DOE under study. (Lower is better)	D-optimal	Active GPR	Active Neural Network
Data set size used	50	**45**	45
Extra data points for confident prediction of Ti-5-5-5-3 five samples' porosity	40	**22**	27
Extra data points for confident prediction of Ti-5-5-5-3 one sample' porosity	40	**7**	15
Extra data points for confident prediction of Beta 21S five samples' porosity	40	**10**	26
Extra data points for confident prediction of Beta 21S one sample' porosity one sample porosity	40	**8**	26
The approximate mean error for confident prediction of Ti-5-5-5-3, five samples'	NA	**0.05**	0.1
The approximate mean error for confident prediction of Ti-5-5-5-3 one sample' porosity	NA	**0.01**	0.08
Approximate mean error for the confident prediction of Beta 21S' five samples' porosity	NA	**0.1**	0.15
Approximate mean error for confident prediction of Beta 21S one sample' porosity	NA	0.1	0.1

5 Conclusion and future work

The GPR model outperformed both the D-optimal surface method and the active neural network model, making it a suitable model for limited data fields with complex data, such as SLM, based on the analysis of the two datasets. The few non-in-situ data used in available published research based on SLM is a clear indication that costly and time-consuming data acquisition is required in this field. The whole experimentation becomes even more expensive when materials under study are also expensive and not readily available, such as titanium and its alloys. This high experimental cost has largely hindered in-depth research and understanding in this manufacturing field. These experimental costs may translate into the final product cutting into the affordability brackets for customers. Adoption of active learning in the fields that utilize SLM in designing and manufacturing products would not only reduce the number of experimental data needed but also improve the outcome of the experiments due to the ability of the model to pick complex parameter correlations.

While this work serves as an introduction to the field, future research should explore batch active learning, a technique in which multiple data points are selected at once based on their potential to improve the model. This approach can better align with the practical constraints of real-world SLM, where batch printing is a preferred cost-efficient method,

especially when using non-in-situ data. Additionally, investigating more advanced sampling algorithms tailored for active machine learning could further enhance experimental efficiency, along with the design and manufacturing of products. Moreover, future studies should focus on developing active learning model infrastructures with a user-friendly interface to enable utilization by end users with little or no knowledge of coding.

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