INTERNATIONAL DESIGN CONFERENCE – DESIGN 2024
https://doi.org/10.1017/pds.2024.183

A Bayesian expert system for additive manufacturing design assessment

Benedict Alexander Rogers ✉, Neill Campbell, Mandeep Dhanda,
Alexander James George Lunt, Elise Catherine Pegg and Vimal Dhokia

University of Bath, United Kingdom

✉ bar34@bath.ac.uk

Abstract

Tools for analysing additive manufacturability often employ complex models that lack transparency; this impedes user understanding and has detrimental effects on the implementation of results. An expert system tool that transparently learns features for successful printing has been created. The tool uses accessible data from STL models and printer configurations to create explainable parameters and identify risks. Testing has shown good agreement to print behaviour and easy adaptability. The tool reduces the learning curves designers face in understanding design for additive manufacturing.

Keywords: *additive manufacturing, expert systems, bayesian, design for additive manufacturing, machine learning*

1. Introduction

It is not uncommon for print preparation software to feature basic predictor tools for print success, going so far as identifying overhangs and other parametrically identified risk factors (Claudius Ellsel, 2021a; Wiberg *et al.*, 2019a). Despite such tools, prediction of the suitability of a geometry for Additive Manufacturing (AM) is often the remit of those with accrued expertise. Existing methods can prove opaque to users (Jiang *et al.*, 2022; Wang *et al.*, 2020), hindering users from understanding the limits of their printers. Developing more refined predictions in this context then relies on the skills of the designers, which can prove a limit to novice users (Haug *et al.*, 2023; Wang *et al.*, 2018). The resulting inefficiency in the AM process limits the material efficiency of AM technologies (Schmitt *et al.*, 2021).
In this study, the challenge of increasing the reliability of AM towards right first time printing is approached by creating an explainable expert system. The tool will indicate the important geometrical factors for its prediction which will uniquely allow designers to fully and transparently probe their models for print suitability specific to a given AM method against prior build data. The tool uses human-understandable print parameters based on Standard Tessellation/Triangle Language (STL) data to predict print success and highlight likely geometric problem areas. A Bayesian ontology is proposed which can learn from a growing base of training data, resulting in a tool which is able to make blunt predictions from the geometry but refine these by identifying and focusing on data from similar prints.
This paper will begin with outlining the niche for transparent build outcome prediction tools that is intended to be filled in section 2. From this, the statistical approach will be defined and the tool methodology explained in section 3. The paper will then document trials carried out on the tool predicting print quality of controlled test parts in section 4, then discuss the outcomes of the study alongside strengths and weaknesses of the methodology in section 5.

2. Background

2.1. Risk factors for AM designs

Fused Filament Fabrication (FFF) is one of the most popular AM processes (Bhuvanesh Kumar and Sathiya, 2021), and prints by extruding plastic filaments heated slightly beyond their melting points and depositing them to build up a solid (Lluch-Cerezo *et al.*, 2019). FFF builds that failed due to geometry will usually fit into a common set of fault causes (see Figure 1). One of the easiest to detect is the overhang (Claudius Ellsel, 2021; Rogers et al., 2022; Wiberg et al., 2019). Thin parts also prove a risk, with the parts not having sufficient strength to survive the print process (Bhuvanesh Kumar and Sathiya, 2021). Similarly, features near to or smaller than the size of the filament are likely to cause further issues for the manufacturing process (Medellin-Castillo and Zaragoza-Siqueiros, 2019).

2.2. The problem of transferable knowledge in AM

Historically, AM has relied heavily on experience derived knowledge (Haug *et al.*, 2023). These skills are by nature localised to a small number of machines and general geometry motifs (Haug *et al.*, 2023). they have limited transferability, and are redundantly acquired by separate users. The issue is particularly acute for individual hobbyists and novice users, who are likely to loose a large fraction of print attempts and so incur frustration and inefficiency (Haug *et al.*, 2023; Schmitt *et al.*, 2021).
To address these challenges, the works of Ngaim and Khor (Ngaim, Kee Yuan; Khor, 2019) and Hemmer, Schemmer and Kühl (Hemmer *et al.*, 2021) provide strong examples of the numerous studies that emphasise the importance of user understanding. In this, they conclude that an algorithmic tool should be designed to encourage the use of the designers cognition first, which allows full leverage of human insight. The tool can then act as a check to the designer cognition and create a healthy discord between machine and designer. For this reason algorithmic transparency is paramount. Providing transparency allows human and algorithm strengths to mutually complement each other.

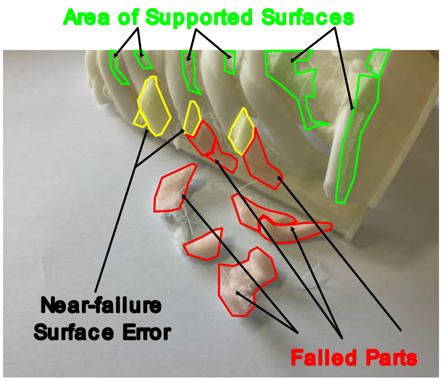

Figure 1. Classifications of build outcomes

3. Methodology

3.1. Process overview

To build a positive user interaction, the intended architecture has been created from the ground up to promote transparency (Hemmer *et al.*, 2021; Yang *et al.*, 2020). The statistical approach seeks in turn to curate the data set and establish relevance, to identify which transparent parameters are relevant, then to fit a model to make predictions, all using geometrical properties that are easily understandable.
Each class of build outcome is best represented by a different set of metrics, and this is to be reflected in the tool primarily through the feature selection approach, which is dynamic for the different built forms. The two forms of fault, failure to print and noticeable surface deviation, were chosen as separate categories to be predicted by the tool. Examples of each can be seen in Figure 1. Further, Figure 2 shows the data process of the tool, both for identifying the input of query build settings, and for the process by

https://doi.org/10.1017/pds.2024.183 Published online by Cambridge University Press

which prior training data (including STL layouts, prior classifications, printer settings, printer and material types) are implemented into the statistical model.

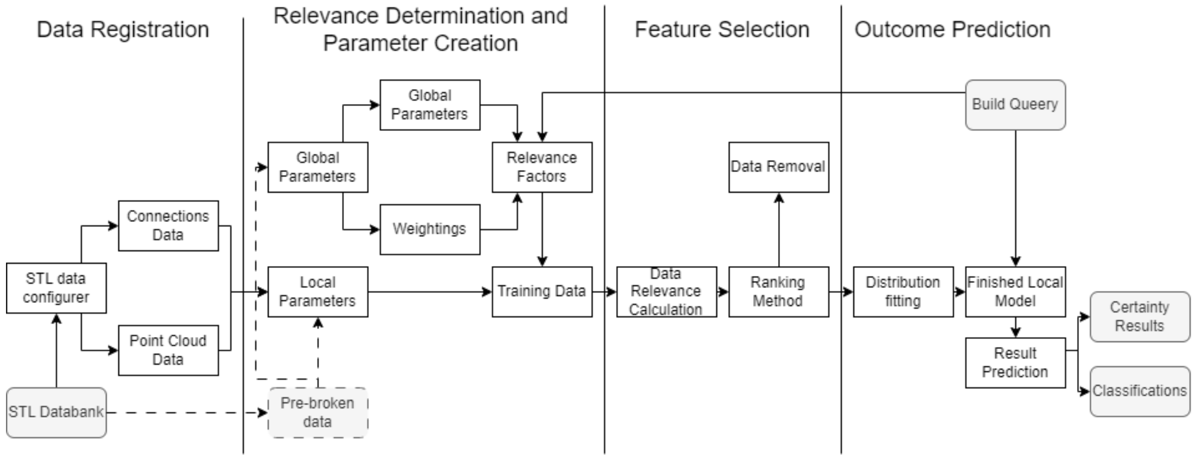

Figure 2. The data handling process

3.2. Explainable indicative parameters

There is no shortage of computational tools which can be used to predict manufacturability (Claudius Ellsel, 2021; Wiberg et al., 2019), however, the tools can prove opaque (Jiang *et al.*, 2022; Wang *et al.*, 2020) which reduces the useful knowledge transfer. The research has led to a new tool, which has been built purely around explainable metrics to improve human interpretability. In combination with the transparent and explainable approach to Machine Learning (ML), this will give every opportunity for a designer to understand and justify the results that the tool returns, and so incorporate the generated insights into their work.

The machine and material used were categorical data which are difficult to enumerate. The approach taken for these was to assign a similarity weighting for each of 1 if they match the build under analysis, and 0.2 if not, in a blunt binary system to account for the difference and in lieu of more detailed data. These two categorical scores offer scope for further development and their values can be treated as a hyperparameter for the fit, which further investigations could refine.

Another hyperparameter for the statistical model is the number of factors that the model trains for. Feature selection trials included variations in which features had their level of relevance to the outcome assessed by the Ordinary Least Squares (Sebenius *et al.*, 2022) and ARD Automatic Relevance Determination (Wipf and Nagarajan, 2007) methods.

The OLS model in early tests proved better able to capture features such as overhangs as sources of concern (see Figure 9). Relevance scores from this approach were generated for each factor in each model, weighted according to the relevance scores and the highest resulting features taken forwards. This was done to preserve explainability for each decision but does mean that each query can be fit to a different set of parameters dependent on global variables.

3.3. Local parameter explanations

Local parameters were generated from the STL data. All parameters are calculated for each STL to allow appropriate combinations of features. These are explained below:

- Bed normal angles – This is the inclination of each triangles outer surface from the base
- Spike volumes – The STL processing will translate any STL to the position with the lowest z position at z = 0, and the centroid directly above at x=0, y=0. Relative to this point, the volume of the tetrahedron formed by the surface element is calculated
- Areas – The area of each triangle on the surface.
- Height above base – The centre of each element was calculated as the linear average of the corners, and the z coordinate (Height above the base) used.
- Eccentricity – A measure of the distortion, the sum of all side lengths over the root of area.

https://doi.org/10.1017/pds.2024.183 Published online by Cambridge University Press

- Triangular skew – A measure of the regularity of a triangle based off assessing the maximum ratio of a bisecting line through a corner with the length of the base it crosses.
- Local curvature – This was calculated by the average change in normal angles for the three bordering elements, with a larger average change taken to represent higher local curvature.
- Through model thickness – Taking the normal of each triangle, this was represented by finding the straight line distance to the nearest opposing face.
- Base distance metric - Calculating the minimal surface distance to a supported surface is a computationally heavy and complex process (Maekawa, 1996). While not exact, a metric was developed that approximates this value in an STL. Supported triangles were marked, and the triangles that border them identified. For each, the shortest distance from the centroid of the base to the new triangle was established as a separation metric. Those triangles that connect to these were considered next, and if with multiple competing connections only the shortest considered. The process was iterated until the entire surface has been considered. While factors such as triangle skew add noise to this, it will grow with the true distance and is a computationally efficient approach to this type of metric.
- Base member register (Boolean) – If all three points of a triangle are on the base (z = 0) or input data labels a triangle as supported, then the triangle is given a Boolean value of 1 in this vector.
- Class of surface (labels, used to train) – Each triangle is given a class: 0 – surface element prints successfully, 1 – support face, 2 – fails to print 3 – significant surface error.

Global parameters were employed to assign weight to the influence of each build's triangle sets on the statistical model. They are both calculated from a requested STL and given by the end user. This will create a vector associated with each build and a similar vector $\underline{S}$ for the user request, which is used to weight prior data:

$$\underline{S} = \underline{M}_{material} \cdot \underline{M}_{Printer} \cdot e^{\sum_{Glob\,Vars} \ln\left(\left|\frac{\underline{V}}{\underline{V}_{req}}\right|\right)} \cdot e^{\sum_{Glob\,Vars} \ln\left(\left|\frac{\underline{P}}{\underline{P}_{req}}\right|\right)} \Big/ |\underline{S}| \tag{1}$$

Where $\underline{M}$ are the classification vectors for if the material or printer matches, $\underline{V}$ is a vector of global scores for all geometric aspects, $\underline{P}$ is the same for global registered parameters, the subscript req indicates the states provided by the user request and all are vectorised, indexed by build.
The following global parameters were considered based on the geometry:

- **Surface area**
- **Foot area**
- **Total volume**
- **Overhang area**
- **Head temperature**
- **Bed temperature**
- **Support infill**
- **Layer height**
- **Filament gauge**
- **Registered material**
- **Registered printer type**

Comparative parameters are given as strings, which if different will multiply the weightings of a given build by 0.2. This total weighting is used when averaging data in the model fitting and parameter selection, to establish the relevance of the available data sets.

3.4. Data combination

Each model calls a bespoke combination, based on the provided print data and its comparison with the database. This allows the relevance weightings (as defined in Vector $\underline{S}$, in Equation 1) to be applied to each gaussian prior distribution from the prior data, and then weighted results be combined for each class prediction.
The data sets are fitted into a Gaussian Naïve Bayes (GNB) model, a supervised model which classifies based on the likelihood of a data point originating from one of a set of Gaussian distributions. The approach allows the use of a Bayesian information criteria to assess certainty of fits to each class. The highest likelihood class for each triangle is then used to classify the surfaces into the expected print outcome. The prediction method uses a Gaussian Mixture Model (GMM) fitting with GNB distributions to a space featuring each recommended parameter. The reduced dimensionality that the feature selection created aids to reduce the dimensionality and avoid associated problems (Carbon-Mangels and Hutter, 2011).

https://doi.org/10.1017/pds.2024.183 Published online by Cambridge University Press

4. Model validation

4.1. Training of the tool for validation

One of the biggest challenges to any ML related study is to amass a sufficient data set to derive causal relationships. Models are only as good as the data they are provided with, and this is particularly true with an expert system such as in this study. While developing the tool, evaluation prints were carried out on data from two printer types: Two Prusa I3 Mk3 and two Stratasys F370. All tests were limited to PolyLactic Acid (PLA) as a trial material. To build a data set, a total of 118 test prints were undertaken and their results categorised (see Table 1). The work made use of a test model low poly Samoyed (The mounting part was neglected, obtained under a Creative Commons Attribution Licence from BrunoPizza on Thingiverse (see Acknowledgements).

Table 1. The log of test prints and outcomes used to train the tool

Printer	Total Tests	Failed Prints	Surface Deviation
Prusa I3 mk3	22	1	6
Stratasys F370	96	3	5

4.2. Variation in prediction from changes in number of parameters

The key hyperparameter for the tool was the number of parameters to be used to fit the GNB model. If an excess number of parameters are used the model will be more computationally expensive and more prone to latching onto noise (Andrews, 2018). Conversely, a single parameter model in effect becomes a linear clustering exercise, with classifications drawn by points in a single metric.

Varying the number of parameters that were considered in the model resulted in a model that converged to a consistent certainty. Tests showed that the flagged areas were not significantly changed, nor were the average uncertainty levels when changing the included data beyond the third dataset. The results of this investigation subsequently lead to the decision to carry out tests of the model with three parameters.

Num. of Paras	1	2	3	4	5	6	7	8	9
Certainty	0.8064	0.8667	0.8390	0.8420	0.8420	0.8422	0.8422	0.8422	0.8422

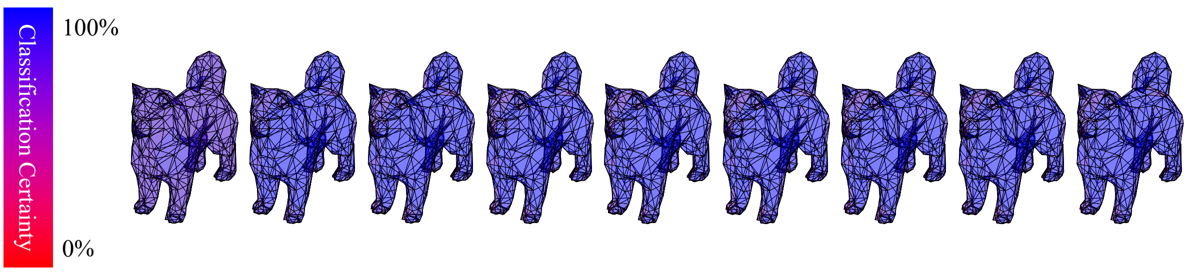

Figure 3. Samy models with the varying parameter count showing the certainty

4.3. The impact of scale on predictions

The Prusa I3 Mk3 was similarly used to trial the test part in the standard (feet on base) orientation, with the length (nose to tail distance along the bed and line of symmetry) set to 30 mm, 40 mm, 50 mm, 75 mm, 100 mm, 125 mm and 150 mm as shown in Figure 4. Surface deviation was apparent in the 30 mm and 40 mm builds around fine features like the ears and tail of the dog. The approach confirmed the suitability of the 75 mm model as the standard test scale.

Test parts in general did display some error around the fine tips of the ears, which as the primary thin section indicated the risk of through part thickness. The algorithm failed to detect this issue, likely because the low triangle count in the ear region meant the tip end thickness was neglected. The model flagged three parameters; the curvature radius metric, spike volume (related closely to area) and

https://doi.org/10.1017/pds.2024.183 Published online by Cambridge University Press

Jacobians, related to surface element regularity, as the metrics with sufficient influence. That they proved insufficient to detect this aspect of the model demonstrates a limitation of the simplistic model.

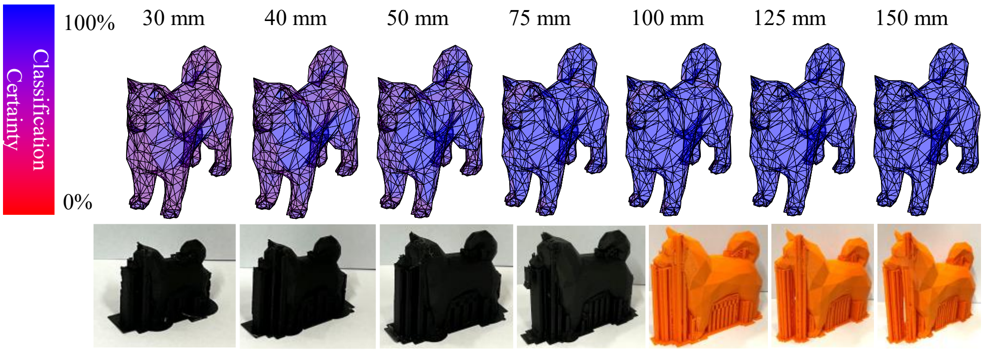

Figure 4. The core tests of the impact of scale on the test parts

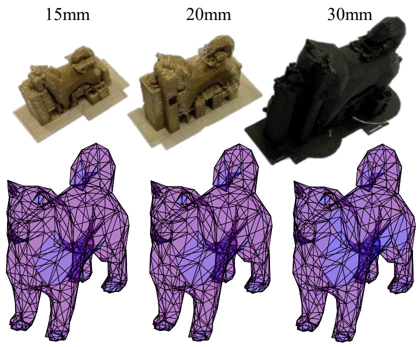

Figure 5. The small scale test prints and the associated reduced surface quality

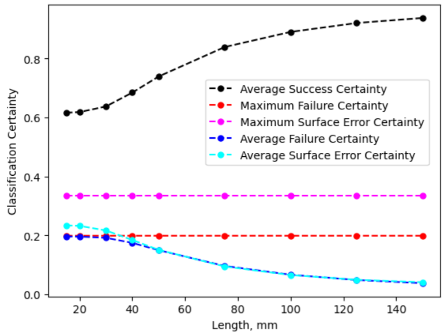

Figure 6. The certainty scores varying with scale

The tool predicted all parts would succeed in printing, and other than very local surface error at the ear tips, below the triangle size, was accurate in this regard. This reflects that the specific parameter selection did not use features relating to the thickness directly, although the influence may have been passed in the spike volume and curvature radius. Positively, as the scale reduced the certainty dropped. The certainty of success of fine features reduced to at or below 50% on the 30mm build, indicating the part would likely fail in printing at scales significantly below this, which with fine features was assessed to be likely true. Indeed, running this statistical model, the 30mm Samy predicted a 33.5% certainty of local surface deviation (the highest on any triangle) and 19.8% for failure of some areas.

These certainties remained very consistent with scale and are likely the results of local features such as small details more than global changes, the peaks remaining nearly perfectly static as the scale varied. The bulk of the certainties and their average changed significantly. The variation of these parameters can be seen in Figure 6. To explore this, a 15 mm and 20 mm model of Samy were printed (see Figure 5). While these prints did complete successfully, the smaller surface elements were influenced by the filament gauge, which was reflected in the spike volumes and lead to the increased prediction.

4.4. The impact of orientation on the predictions

Support for printed geometries will vary between print orientations, as different sections of the geometry become unsupported. No rotation was trailed in X (yaw) because as a simplifying assumption the statistical model treats the print process as having planar isotropy about X, so will not change predictions based on flat rotation of a part. Varying orientation, predictions of the success when factoring in the varying support surfaces showed low chances of build failures. The success of all prints (see Figures 7 and 8) demonstrated that the tool factored in the support assignment correctly, but the lack of predicted failures does limit the insight that can be derived from these tests. The thin sections at the ears were a

https://doi.org/10.1017/pds.2024.183 Published online by Cambridge University Press

noted area of concern, and in some orientations the local print saw failures despite the support. Despite this, the tool was able to account for the varying support locations correctly and make rational predictions about risk factors such as remaining overhangs (Ahn et al., 2002; Lluch-Cerezo et al., 2019).

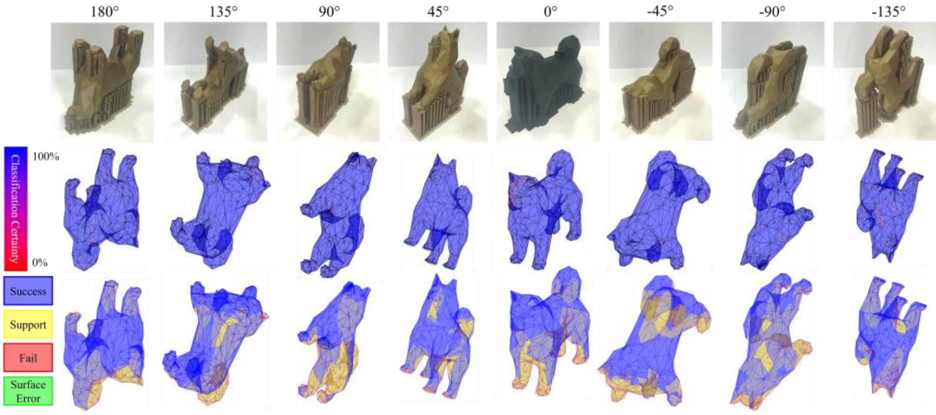

Figure 7. Surface classifications, images and certainties of the Samy test part changing orientation in pitch

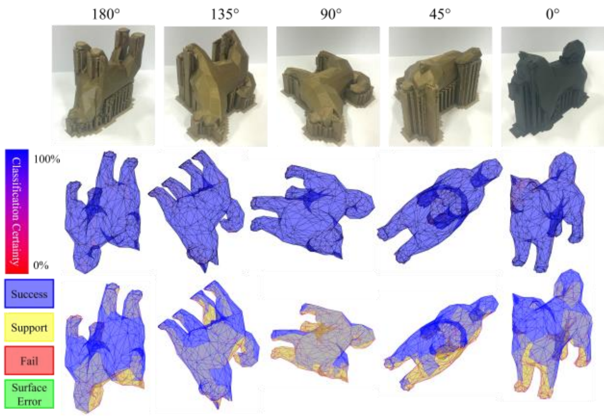

Figure 8. Surface classifications, images and certainties of the Samy test part changing orientation in roll

5. Discussion

Although the tool was not always able to identify the areas that cause failure of the builds with the provided data set, it was taken as a very positive result that common known failure causes were able to be flagged as concerns (see Figure 9) and risk factors were seen throughout tests to reduce the certainty of the pass status (See Figures 3, 4 and 7). Remarkably, this was achieved despite the very limited data set of 118 builds available for testing.

The tool has been designed to allow easy inclusion of further data, and it is the intent of the authors to continue adding data to train the statistical model further as it becomes available. The choice of transparent parameters would often select features which do not have as much apparent physical logic but made sensible predictions. For instance, in trial screw-thread models, the parameter selection was seen to prioritise eccentricity, thus picking a metric that would isolate the screw thread areas in order to flag these as risk areas for surface deviation. While a positive result, the finding does leave considerable scope for further parameters to be added with the scope for each parameter to identify features not envisaged by the designers of the software and a larger bank being desired. As such, including more explainable parameters, and exploring with deeper ML methods for potential further parameters are both achievable and beneficial areas for further exploration. It is potentially possible to work into the tool additional factors such as specific lattice structures for infill, which can significantly impact AM outcomes (Amaechi *et al.*, 2022). While beneficial for bulk accuracy, this is not an intended extension.

https://doi.org/10.1017/pds.2024.183 Published online by Cambridge University Press

This is because including additional ML complexity would reduce transparency and make user interaction more cumbersome. The tool is designed to work as an expert system that is practical to use for a designer who needs useful technical insight but would not have time to do in-depth part classification or analysis to feed into the tool. Extending the tool to additional file formats would be a rational extension, and a notable exception to this approach is the potential to expand the tool to concerns regarding the specific support structures (Jiang *et al.*, 2022). The model could be further applied to predict support mass, print times and with minor adaption used to calculate optimal print orientations to maximise success chances. The current statistical model is also somewhat limited by a lack of insight into the amount of data needed to increase the certainty of the predictions. While more data would doubtless improve the tool, it would be worth conducting a more strenuous test series with more diverse data available to test how the available data impacts certainties and predictions.

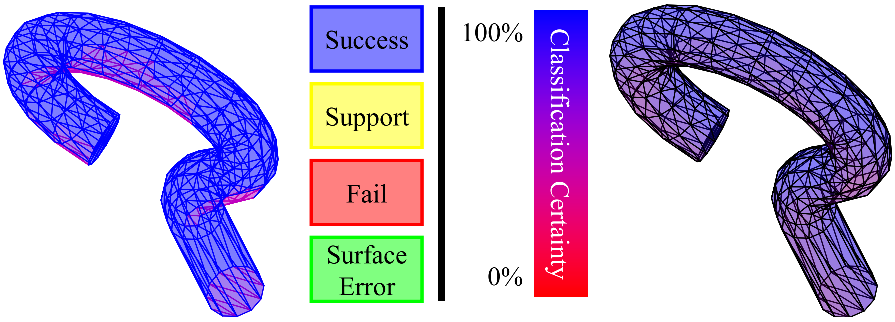

Figure 9. A hook model showing predicted surface error (left) and certainties (right) on unsupported faces

A noted benefit, as reflected in the analysis was that the explainable parameters and transparency focused statistical model allowed for the causes of certain results to be easily directly interrogated. This angle of allowing designers both a simple use case for the tool, and also to dig into the results is hoped to be a noted positive and offset the reduced accuracy that is likely over deeper ML methods by encouraging positive user interactions (Hemmer *et al.*, 2021; Ngaim, Kee Yuan; Khor, 2019).

6. Conclusion

Even using the data set of 118 prints, the novel methods developed and embodied in this new tool demonstrated a good capture of key AM design techniques. The tool generally made sensible predictions about manufacturability, which line up well with known results and expert perspectives. The tool followed provided data in rarely predicting failure or surface deformation, but with factors such as scale and overhangs, the certainty was clearly reduced. This was often traceable to single parameters and in that way provides unique insights to the designer not possible in more opaque tools (Claudius Ellsel, 2021; Wiberg et al., 2019). The ability to trace numerical reasoning through the model and understandable parameters will give unparalleled scope to query the results and reasonings for a prediction made by the tool. There is significant scope for future development of the method, and it is intended that more parameters and model formats (particularly the .3mf file format) will be added into the tool alongside further data and refinement of the user experience. It would be further possible to expand the study to provide material and time usage predictions, and combine with an optimisation loop to indicate beneficial print orientations for part success.

Acknowledgements

The PhD funding of the lead author was provided by the ART_AI CDT at the University of Bath, to whom gratitude is extended (https://cdt-art-ai.ac.uk/). We would like to thank Gary Barter and Joshua Barnes for their printing and data gathering used throughout this project, particularly in the training of the model. We would also like to thank Nguyên Võ-Bùi for his help with coding the input of STL files. The test model 'Samy' was used under the CC-NY licence and was created by BrunoPizza, and made available on Thingiverse. It can be obtained from https://www.thingiverse.com/thing:4725102

References

Amaechi, C.V., Adefuye, E.F., Kgosiemang, I.M., Huang, B. and Amaechi, E.C. (2022), "Scientometric Review for Research Patterns on Additive Manufacturing of Lattice Structures", Materials, Multidisciplinary Digital Publishing Institute (MDPI), Vol. 15 No. 15, https://dx.doi.org/10.3390/MA15155323.

Andrews, J.L. (2018), "Addressing overfitting and underfitting in Gaussian model-based clustering", Computational Statistics & Data Analysis, North-Holland, Vol. 127, pp. 160–171, https://dx.doi.org/10.1016/j.csda.2018.05.015.

Bhuvanesh Kumar, M. and Sathiya, P. (2021), "Methods and materials for additive manufacturing: A critical review on advancements and challenges", Thin-Walled Structures, Elsevier, Vol. 159, p. 107228, https://dx.doi.org/10.1016/j.tws.2020.107228.

BrunoPizza. (2021), "Low Poly Samoyed Dog", Ultimaker, available at: https://www.thingiverse.com/thing:4725102.

Carbon-Mangels, M. and Hutter, M.C. (2011), "Selecting Relevant Descriptors for Classification by Bayesian Estimates: A Comparison with Decision Trees and Support Vector Machines Approaches for Disparate Data Sets", Molecular Informatics, John Wiley & Sons, Ltd, Vol. 30 No. 10, pp. 885–895, https://dx.doi.org/10.1002/MINF.201100069.

Claudius Ellsel, S.W. (2021a), "Evaluation of design support tools for additive manufacturing and conceptualisation of an integrated knowledge management framework", DS 111: Proceedings of the 32nd Symposium Design for X, The Design Society, https://dx.doi.org/10.35199/dfx2021.17.

Claudius Ellsel, S.W. (2021b), "Evaluation of design support tools for additive manufacturing and conceptualisation of an integrated knowledge management framework", DS 111: Proceedings of the 32nd Symposium Design for X, The Design Society, https://dx.doi.org/10.35199/dfx2021.17.

Haug, A., Wickstrøm, K.A., Stentoft, J. and Philipsen, K. (2023), "Adoption of additive manufacturing: A survey of the role of knowledge networks and maturity in small and medium-sized Danish production firms", International Journal of Production Economics, Elsevier, Vol. 255, p. 108714, https://dx.doi.org/10.1016/j.ijpe.2022.108714.

Hemmer, P., Schemmer, M. and Kühl, N. (2021), "Human-AI Complementarity in Hybrid Intelligence Systems: A Structured Literature Review Needmining View project Development of a Point Cloud Labeling Tool to Generate Training Data for 3D Object Detection and 6D Pose Estimation View project", Twenty-Fifth Pacific Asia Conference on Information Systems, Dubai, UAE, pp. 1–14.

Jiang, J., Xiong, Y., Zhang, Z. and Rosen, D.W. (2022), "Machine learning integrated design for additive manufacturing", Journal of Intelligent Manufacturing, Springer, Vol. 33 No. 4, pp. 1073–1086, https://dx.doi.org/10.1007/S10845-020-01715-6/TABLES/7.

Lluch-Cerezo, J., Benavente, R., Meseguer, M.D. and Gutiérrez, S.C. (2019), "Study of samples geometry to analyze mechanical properties in Fused Deposition Modeling process (FDM)", Procedia Manufacturing, Elsevier, Vol. 41, pp. 890–897, https://dx.doi.org/10.1016/j.promfg.2019.10.012.

Maekawa, T. (1996), "Computation of Shortest Paths on Free-Form Parametric Surfaces", Journal of Mechanical Design, Vol. 118 No. 4, pp. 499–508.

Medellin-Castillo, H.I. and Zaragoza-Siqueiros, J. (2019), "Design and Manufacturing Strategies for Fused Deposition Modelling in Additive Manufacturing: A Review", Chinese Journal of Mechanical Engineering (English Edition), Chinese Mechanical Engineering Society, Vol. 32 No. 1, pp. 1–16, https://dx.doi.org/10.1186/S10033-019-0368-0/FIGURES/8.

Ngaim, Kee Yuan; Khor, I.W. (2019), "Big data and machine learning algorithms for health-care delivery | Elsevier Enhanced Reader", Digital Oncology 2, Vol. 20 No. 6, pp. 262–273, https://dx.doi.org/10.1016/S1470-2045(19)30149-4.

Rogers, B., Valentine, M., Dhokia, V., Pegg, E. and Lunt, A. (2022), "IAM2022-93965", ASME IAM2022, ASME, Lisbon, pp. 1–8.

Schmitt, P., Zorn, S. and Gericke, K. (2021), "Additive Manufacturing Research Landscape: A Literature Review", Proceedings of the Design Society, Cambridge University Press, Vol. 1, pp. 333–344, https://dx.doi.org/10.1017/pds.2021.34.

Sebenius, I., Paananen, T. and Vehtari, A. (2022), "Feature Collapsing for Gaussian Process Variable Ranking", 25th International Conference on Artifi- Cial Intelligence and Statistics, PMLR, Valencia, pp. 11341–11355.

Wang, Y., Liao, Z., Shi, S., Wang, Z. and Poh, H. (2020), "Data-Driven Structural Design Optimization for Petal-Shaped Auxetics Using Isogeometric Analysis topology optimization View project Study on cyclic deformation of auxetic honeycomb lattices: experiment and constitutive modeling View project Data-Driven St", Computer Modeling in Engineering & Sciences CMES, Vol. 122 No. 2, pp. 433–458, https://dx.doi.org/10.32604/cmes.2020.08680.

Wang, Y., Zhong, R.Y. and Xu, X. (2018), “A decision support system for additive manufacturing process selection using a hybrid multiple criteria decision-making method”, Rapid Prototyping Journal, Emerald Group Holdings Ltd., Vol. 24 No. 9, pp. 1544–1553, https://dx.doi.org/10.1108/RPJ-01-2018-0002/FULL/PDF.
Wiberg, A., Persson, J. and Ölvander, J. (2019a), “Design for additive manufacturing – a review of available design methods and software”, Rapid Prototyping Journal, Emerald Group Holdings Ltd., Vol. 25 No. 6, pp. 1080–1094, https://dx.doi.org/10.1108/RPJ-10-2018-0262/FULL/PDF.
Wiberg, A., Persson, J. and Ölvander, J. (2019b), “Design for additive manufacturing – a review of available design methods and software”, Rapid Prototyping Journal, Emerald Group Holdings Ltd., Vol. 25 No. 6, pp. 1080–1094, https://dx.doi.org/10.1108/RPJ-10-2018-0262/FULL/PDF.
Wipf, D. and Nagarajan, S. (2007), “A New View of Automatic Relevance Determination”, in Platt, J; Koller, D; Singer, Y; Roweis, S. (Ed.), Advances in Neural Information Processing Systems 20, Neural Information Processing Systems, Vancouver, BC.
Yang, Q., Steinfeld, A., Rosé, C. and Zimmerman, J. (2020), “Re-examining Whether, Why, and How Human-AI Interaction Is Uniquely Difficult to Design”, Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, ACM, New York, NY, USA, pp. 1–13, https://dx.doi.org/10.1145/3313831.3376301.