

MACHINE LEARNING FOR CONTINUOUS LIQUID INTERFACE PRODUCTION: PRINTING SPEED MODELLING

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Abstract

Continuous Liquid Interface Production (CLIP), a variant of vat photopolymerization additive manufacturing, can achieve build speeds an order of magnitude faster than conventional layer-by-layer stereolithography process. However, identification of the proper continuous printing speed remains a grand challenge in the process planning. To successfully print a part continuously, the printing speed needs to be carefully adjusted and calibrated for the given geometry. In this paper, we investigate machine learning techniques for modeling and predicting the proper printing speed in the CLIP process. The synthetic dataset is generated by physics-based simulations. An experimental dataset is constructed for training the machine learning models to find the appropriate speed range and the optimum speed. Conventional machine learning techniques including Decision Tree, Naïve Bayes, K Nearest Neighbors, and Support Vector Machine (SVM), ensemble methods including Random Forest, Gradient Boosting, and Adaboosting, and the deep learning approach Siamese Network are tested and compared. Experimental results validate the effectiveness of these machine learning models and show that the Siamese Network model gives the highest accuracy.

KEYWORDS

Video Projection Stereolithography; CLIP; Machine Learning; Deep Neural Network; Siamese Network; Continuous Printing Speed

1 Introduction

CLIP is a vat photopolymerization based additive manufacturing technology that does not involve discrete layers because the curing part is drawn out of the resin without interruption [1, 2], as illustrated in Fig. 1. It is also known as video projection stereolithography and orders of

magnitude faster than the layer-by-layer photopolymerization, which has been demonstrated in Tumbleston *et al.* work [1] and Chen *et al.* work [2]. A key factor to the success of continuous printing is a proper continuous elevation speed V as shown in Fig.1, which is, however, challenging to identify. An over fast speed will result in the failure of bonding newly cured material to the part. On the other hand, an over slow speed tends to lead to the adhesion between the part and the oxygen permeable window. Current approaches to searching for the proper continuous elevation speed mainly rely on empirical knowledge gained from trial and error experiments. Since the working continuous elevation speed varies with the printing geometry, there is an urgent need to develop a systematic and fundamental approach to replace the current trial-error method for identifying the proper speed. To address this challenge, this work focuses on investigating machine learning techniques for the continuous printing speed modeling, selection, and optimization.

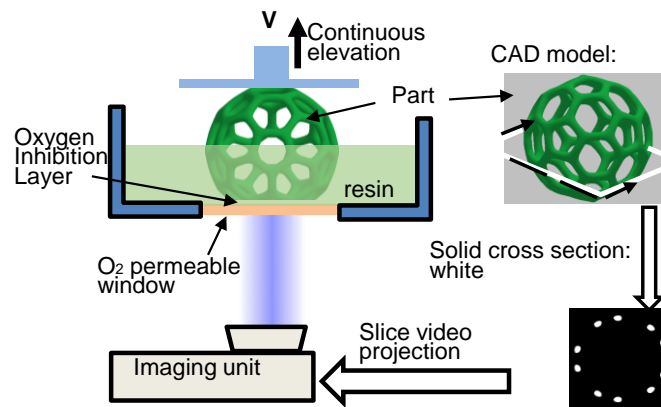


Fig. 1 Illustration of continuous printing with oxygen permeable window

Machine learning has been proved effective in various manufacturing systems. In [3], advances and trends in cyber-physical manufacturing systems have been discussed. It reviews applications of big data analytics in manufacturing systems. An overview of additive manufacturing informatics has been provided in [4], which emphasizes the importance of integrating data mining and additive manufacturing systems. The advantages, applications, and technology progress of AM, AM data and big data analytics for AM are presented in [5]. The study of data mining in selective laser melting (SLM) sensor data is conducted in [6]. Data-driven surrogate models are proposed in [7] to identify important variables and find appropriate process parameters in SLM. In [8], a data-enabled interferometric curing monitoring and measuring model is proposed to estimate the height profile of cured parts and realize the desired real-time measurement for polymer additive manufacturing processes. A random forests (RFs)-based prognostic method for tool wear prediction was proposed in [9] for manufacturing systems. In [10], machine learning was used to classify additive manufactured (AM) parts contingent on the severity of their dimensional variation from laser-scanned coordinate measurements. In [11], two predictive models were developed to predict droplet velocity and volume using ensemble learning. In powder-bed AM process in [12], machine learning was employed to determine the spreader parameters. Despite those advances of machine learning in manufacturing, its application in CLIP has not been investigated yet. In this paper, we aim to investigate various machine learning techniques for printing speed selection and optimization in CLIP. The contributions of this paper include: 1. This paper represents the first study of applying machine learning in projection

stereolithography and continuous printing for process modeling. 2. This study established a new modeling method for identifying the proper working speed range and the optimum speed in continuous printing, by combining physical modeling and machine learning approaches. 3. This work investigated the effectiveness of Siamese network on small dataset, which is common in manufacturing systems and challenging for machine learning. The Siamese network can also be extended to other scenarios in manufacturing systems. Due to the large design space of parameters for continuous printing, it is critical to first identify a reasonable speed range and then identify the optimum speed. Previous studies [13-15] have shown that the separation force incurred in the process is closely related to the manufacturing speed. In addition, the separation force is a strong indicator and a readily measurable signal of whether the printing is successful. Therefore, the magnitude of separation force in a certain printing process can be used to evaluate the current condition or predict the outcome of the process. To take advantage of this relationship between separation force and the printing process, a theoretical model of separation force has been utilized as a heuristic for determining the initial proper speed range. A synthetic dataset is generated by enumerating the combinations of various levels for each factor in the theoretical model. Experiment data is collected from our established continuous printing setup. The idea and workflow of this paper is illustrated in Fig. 2.

As illustrated in Fig. 2, when there is no experimental dataset available, a synthetic dataset is first generated by using a small subset of the original design of experimental (DOE) table S. Machine learning models are trained and tested on the synthetic dataset. The most effective model is selected and implemented for predicting the outcome (success or failure) of all the designed experiments in S. According to the predicted results, the designs in the original DOE will be screened. For instance, priority will be given to the DOEs which are predicted as success cases. This procedure reduces the effort of trial and error when initiating experiments without prior knowledge of experimental data. A dynamically growing two-class (success or failure) experimental dataset is generated as new experiments are performed. As new experimental results are added to the dataset, machine learning models will be trained on experimental dataset instead of the synthetic dataset. This is because experimental data will better capture the pattern of continuous printing. The most effective machine learning model will be used to predict whether a speed range is working by discretizing the range and predicting the outcome at each specific speed point. Given the dataset which contains experimental results from proper working speed ranges, surface quality will be further studied. The successfully printed parts will be graded by four levels, level 0, 1, 2 and 3, based on the surface quality. The experimental dataset will be then upgraded to a multiclass dataset. Machine learning models will be trained and tested on this newly created dataset. The most effective model will be used to predict the surface quality of the printed parts for future experiments. In this way, future experiments can be carried out selectively and the optimum printing speed can be identified efficiently based on the predictions. The experimental results will be added to the dynamically growing dataset.

The proposed workflow concerns the situations of with and without experimental dataset. The proposed machine learning models aim to avoiding trial and error efforts and improving the efficiency of identifying proper working speed ranges and the optimum speed for continuous printing.

The organization of this paper is as follows: section 2 presents how the synthetic and experimental datasets are constructed and introduces the machine learning models tested in this

study. Section 3 demonstrates the constructed machine learning models and discusses the corresponding modeling results. Conclusions are given in section 4.

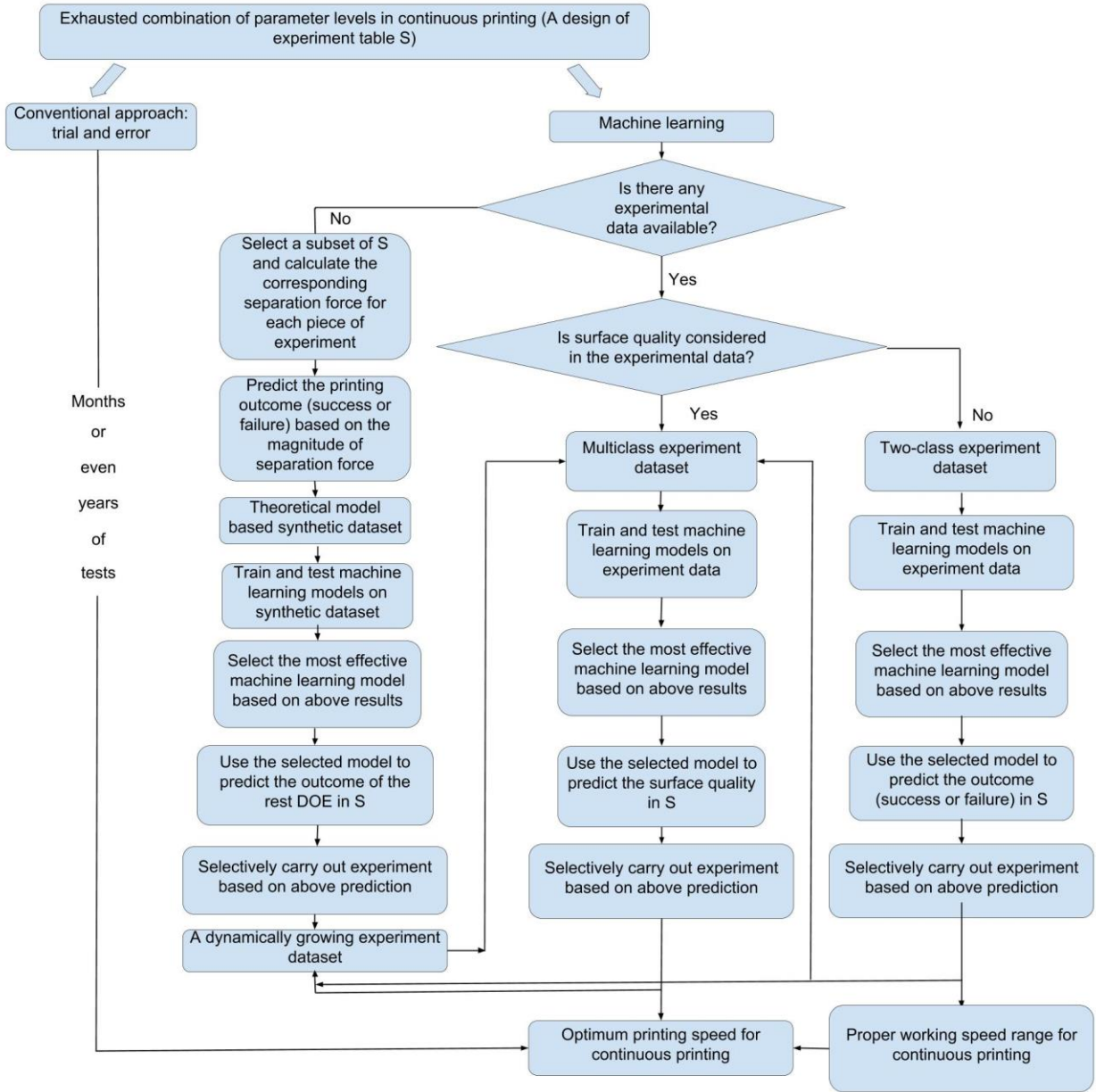


Fig. 2 Workflow of the proposed approaches

2 Theoretical Modelling, Data Collection and Model Introduction

2.1 Theoretical Modelling of the Separation Process

The separation of the newly cured layer from the constrained surface together with the liquid filling induced by this separation process is a significant procedure of the constrained surface projection SL technique. The force incurred in this separation process is a strong indicator

for the success of the printing, as illustrated in equation (1), where $F_{separation}$ denotes the maximum separation force for printing a certain layer, F_0 and F_1 are the lower bound and upper bound of the reasonable separation force range for printing that layer, respectively. An over large separation force usually implies the adhesion between the printed part and the constrained surface. While an over small separation force commonly relates to the failure of bonding newly cured material to the printed part.

$$\begin{cases} F_{separation} \subset [F_0, F_1], & \text{success} \\ F_{separation} \not\subset [F_0, F_1], & \text{fail} \end{cases} \quad (1)$$

Our previous study has modelled the separation force for smooth constrained surface and pressure drop for textured constrained surface by concerning the separation mechanism and liquid filling effects around the separation interface, as shown in the following equations [13, 16, 17]:

$$F_1 = \frac{3\pi \cdot \mu V}{2 \cdot h^3} \cdot R^4 \quad (2)$$

$$\frac{dp}{dr} = V \cdot \pi r^2 \cdot 2\mu \cdot \frac{\left(4\pi \cdot r + \frac{2nd}{\cos\alpha} - n \cdot w\right)^2}{(2\pi \cdot r \cdot h + 0.5n \cdot w \cdot d)^3} \quad (3)$$

where V is the separation speed, r is a variable ranging from 0 to R , which is the radius of the part cross section, n denotes the number of grooves of the micro texture, μ represents the viscosity of the resin, w and d are the width and depth of the grooves of the micro texture. h denotes the height of the initial gap, which is the oxygen inhibition layer thickness.

Two constrained surfaces, island surface (IS) and textured surface (TS) are investigated for continuous printing. The surface of IS is smooth, so equation (2) is used for calculating the separation force. TS implements a microtextured surface and equation (3) is applied. By adding terms compensating factors such as the plasticity and deformation of constrained surface, platform initial position calibration, and random noises to above equations, the calibrated equation for separation force for IC and TC are modified as follows:

$$\begin{cases} F_{IC} = k_1 \cdot \frac{3\pi \cdot \mu V}{2 \cdot h^3} \cdot R^4 + k_2 \\ F_{TC} = k_3 \cdot \int_0^R \frac{dp}{dr} dr + k_4 \end{cases} \quad (4)$$

where k_1 is calibrated to be 0.027 and k_3 0.03, mainly for compensating the PDMS deformation, k_2 and k_4 are randomly generated noises with an absolute value of less than 0.02N according to empirical experience.

2.2 Synthetic and Experimental Dataset

2.2.1 Synthetic data generation

Based on the theoretical modelling of the separation force, simulation has been performed by considering nine process parameters, including resin viscosity, cross section size of the part, manufacturing velocity, PDMS thickness, constrained surface type, duration of frame, video projection time, micro texture groove width, micro texture groove depth etc. Each of these process

parameters has several levels, which represent some representative parameter values in the real manufacturing processes. An example of the parameters with their corresponding values are given in Table 1.

Table 1 Various levels of different process parameters

Process parameters	Levels									
Resin viscosity (Pa · s)	0.09			0.12			0.14			
Cross section size j_s used for synthetic dataset construction (mm ²)	3.1			12.6			50.3			
Manufacturing velocity (mm/s)	0.025			0.038			0.05			
PDMS thickness (mm)	1			2			4			
Constrained surface type	Smooth			Textured			Island			
Duration of frame(s)	0.5			1			1.5			
Video projection time (min)	15			20			30			
Groove width (μm)	100									
Groove depth (μm)	100									
Cross section size j_b used for separation force boundary construction (mm ²)	3.1	7.1	12.6	19.6	28.3	38.5	50.3	63.6	78.5	

Combinations of different levels for these parameters will result in different sets of experiments. The corresponding separation force is calculated using Equation (4). In total, 6000 instances are generated in the simulated dataset. Threshold F_{0j} and F_{1j} , which are the proper lower bound and upper bound of empirical separation force, are set to generate the corresponding labels for each piece of data. In F_{0j} and F_{1j} , j is the index for distinguishing parts of different sizes. i is the instance index and $y_{j,i}$ is used as the label for each piece of data, with a value of 1 means the part with a size in j level is successfully printed and 0 denotes a failure:

$$y_{j,i} = \begin{cases} 1, & \text{if } F_{0j} < F_{\text{separation}} < F_{1j} \\ 0, & \text{if } F_{\text{separation}} > F_{0j} \text{ or } F_{\text{separation}} < F_{1j} \end{cases}$$

If the calculated separation force is larger than the upper bound threshold F_{0j} or smaller than the lower bound threshold F_{1j} , then the printing part is failed, and a 0 label will be assigned to the data. The number of instances of 0 label and 1 label are close in the simulated dataset. Therefore, the dataset is balanced, and no oversampling and under-sampling is needed. Machine learning techniques are trained on this simulation generated dataset and the learned models provide some prior knowledge before designed experiments are carried out. To test the effectiveness of the machine learning models trained on this synthetic dataset, the learned models are evaluated on experimental obtained data.

2.2.2 Experimental data collection

Experiments are carried out to test different speeds for continuous printing. The schematic of the setup is given in Fig. 3. The image of the continuous projection SL system is shown in Fig. 4. A precision position stage from Velmex is used as the Z stage. A process control testbed has been developed using C++ language, as shown in Fig. 4 (a). It integrates the geometry slicing, image projection, and motion controlling. DLP® LightCrafter™ 4500 from Texas Instrument is used as the image projection unit in this setup, as shown in Fig. 4 (b). A KMotion control board from DYNAMOTION is implemented to control the Z stage motion, light projection and synchronized the motion and projection. An online force monitoring unit has been developed in Matlab/Simulink for measuring the separation force. A load cell (LRM 200 from Futek) is utilized to collect the force signals, together with a data acquisition (DAQ) device (USB 6008 from National Instruments). The online force monitoring system reads and processes data from the load cell, and records separation force measured in real time during the continuous manufacturing processes. Two commercial photopolymers, Perfactory™ LS600M from EnvisionTEC Inc. and G+ (green) from MakeJuice Labs are used as the materials in the experiments.

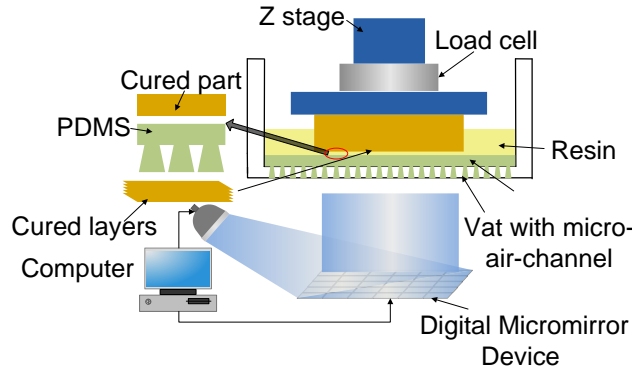


Fig. 3 Schematic of the experiment setup

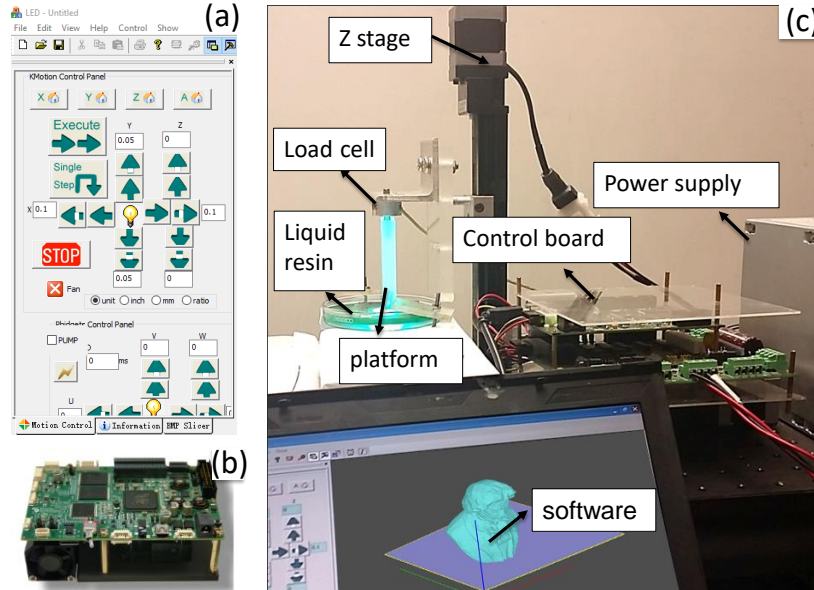


Fig. 4 Continuous printing experiment setup

Parameters described in the mathematical model, which are readily accessible through measurements, are selected as the variables in the experiments and the other conditions are fixed.

For simplicity, cylinders of different diameters and heights are printed. Each set of process parameters and the corresponding outcomes are recorded and summarized to generate an experimental dataset. The label is 1 if the part is successfully printed (without consideration of the surface roughness) and 0 otherwise. An initial experimental dataset of 180 instances is collected. Machine learning algorithms are trained and tested on this experimentally obtained dataset to find the proper manufacturing speed for different sets of process parameters. The collected experimental dataset is balanced with the same number of successful and failed prints (positive and negative labels). Fig. 5 gives an example of samples continuously printed with various speed.

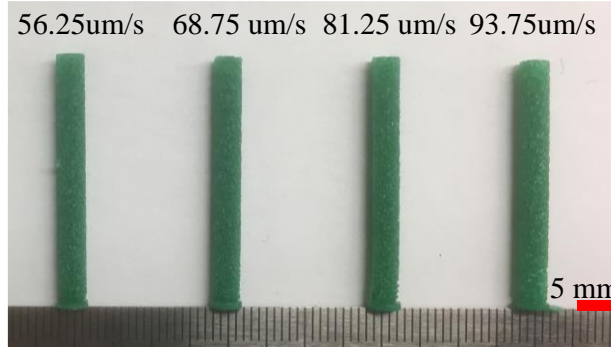


Fig. 5 Cylinder samples continuously printed under different speed

2.3 Machine Learning Models

To the best of authors' knowledge, there is no investigation on the feasibility of process planning and optimization for continuous printing using machine learning models. To close this knowledge gap, the most representative machine learning models in conventional and ensemble approaches are explored in this paper. Most of deep learning approaches require a large amount of data for training, hence cannot be applied in manufacturing process due to the small dataset. However, one state-of-the-art deep learning approach, Siamese network, which is conventionally used for signature verification, has been proved work well with small amount of data. However, its effectiveness in manufacturing process planning and optimization has never been investigated. Thus, in addition to the conventional and ensemble approaches, a customized Siamese network deep learning approach is also investigated in this study. The detailed configurations of conventional models, ensemble methods, and the Siamese network are elaborated in the following sections.

2.3.1 Conventional techniques

To classify the simulated data, conventional approaches, including K Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree, Logistic Regression, Quadratic Discriminant Analysis (QDA), Gaussian Processes (GP), Naive Bayes and Neural Network are implemented first with scikit-learn using Python. KNN implements 5-nearest neighbours vote and uniform weights are used for all points in each neighbourhood. The implementation of SVM is based on libsvm, commonly used radial basis function is selected as kernel function and all classes are supposed to have weight one. The split criterion for decision tree is Gini impurity and all classes are equally weighted to be one. The regularization utilized in logistic regression is l2 penalty, which adds "squared magnitude" of coefficient as penalty term to the loss function, and the tolerance for stopping criteria is $1e-4$. 'Liblinear' algorithm is applied in the optimization

problem. Quadratic Discriminant Analysis (QDA) is generated by fitting class conditional densities to the data and using Bayes' rule. Gaussian process classification (GPC) is based on Laplace approximation, in which the 'fmin_l_bfgs_b' algorithm from scipy.optimize is used as the optimizer. Naïve Bayes is implemented using the Gaussian Naive Bayes algorithm and the likelihood of the features is assumed to be Gaussian. The neural network model is implemented using multi-layer perceptron classifier.

2.3.2 Ensemble Methods

The goal of ensemble methods is to combine the predictions of several base estimators built with a given learning algorithm to improve the generalizability and robustness over a single estimator. This study implements a typical averaging approach, Random Forests, and two boosting methods, Ada Boost and Gradient Tree Boosting [18]. Random Forest is implemented with 25 trees. The split criterion for each tree is Gini impurity and all classes are equally weighted to be one. The base estimator for Ada Boost is decision tree. The maximum number of estimators is 50. For gradient boosting, 'deviance' is used as the loss function, the learning rate is 0.1 and the number of boosting stages to perform is 100.

2.3.3 Siamese Network

Deep neural networks are currently very popular in machine learning community because they can have arbitrarily large number of trainable parameters and usually achieve satisfactory results [19]. However, it requires a large amount of data to train the parameters, which is sometimes not available for manufacturing systems. This becomes more serious when it comes to collecting data obtained from relatively time consuming and expensive experiments. "Siamese" neural network, which was introduced by LeCun [20], only requires just one training example of each interested class. This network can still be trained with many data points, as long as they are in the similar domain to other training data points. Siamese Network was first developed for signature verification written on pen-input tablet. It consists of two identical sub-networks with shared weights jointed at their outputs, as illustrated in Fig. 6. Given a pair of signature images, these two sub-networks extract features from one image from the pair and pass the learned information through a contrastive loss function to measure their distance. The contrastive loss can capture the detailed difference between two inputs, and the loss function can be described as follows [21]:

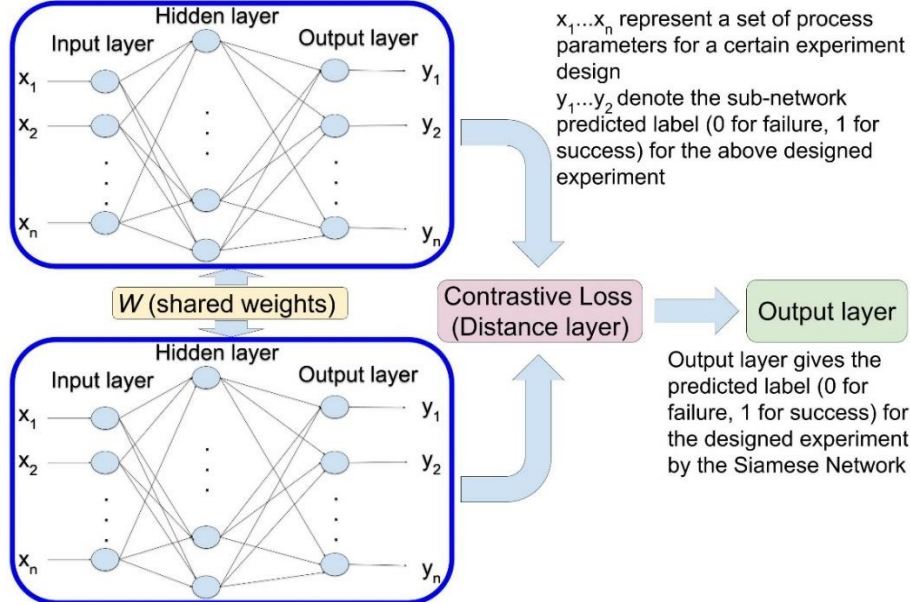
$$(1 - Y) \frac{1}{2} (D_w)^2 + (Y) \frac{1}{2} \{ \max(0, m - D_w) \}^2 \quad (1)$$

$Y=0$ if the pair of images are similar, and $Y=1$ if they are dissimilar. The parameterized Euclidean distance function between these two images D_w is defined as:

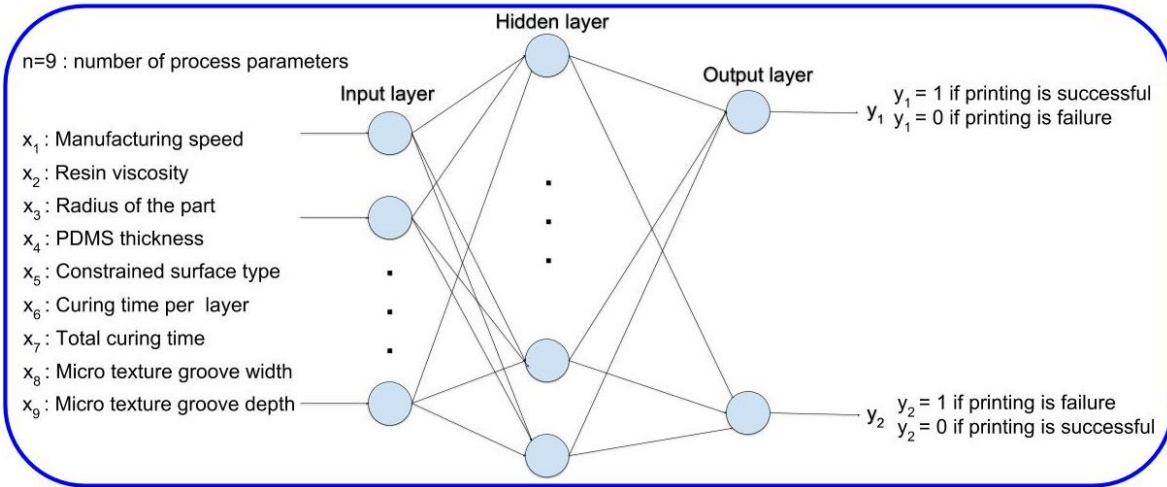
$$D_w(X_1, X_2) = \sqrt{G_w(X_1) - G_w(X_2)} \quad (2)$$

where X_1, X_2 are a pair of image instances and G_w is the output of each individual neural network.

Intuitively, Siamese Network trained two identical neural networks using pairs of signature images, extracted feature vectors and stored the learned weights. At test time, the distance between a test signature and a known signature is calculated. Similar signatures are accepted, and forgeries are rejected.



(a) General Siamese Network



(b) Subnetwork of a Siamese Network for continuous printing

Fig. 6 Diagram of Siamese Network

The sub-network for Siamese Network in above signature verification situation is a time delay neural network. In [21], convolutional neural networks are used as sub-networks of Siamese Network for dimensionality reduction by learning an invariant mapping. A variation of deep Siamese Networks is proposed in [22]. It consists of a sequence of convolutional layers, applies ReLU activation functions and imposes a regularized cross-entropy objective to the binary classifier for one-shot image recognition. In [23], 3-layer MLP (Multilayer Perceptron) is used as the sub-network. Tanh is the activation function and the loss function is modified to be Triangular Similarity Metric Learning (TSML) objective function for dimensionality reduction and face identification. To our best knowledge, all existing applications of Siamese Networks are related to image classifications. Since Siamese Network works well on small dataset which matches the typical size of our experimental collected dataset, a customized Siamese Network is created according to the characteristics of our dataset. To implement our own Siamese Network, base networks of 4 MLP with dropout rate 0.1 are created and ReLU is selected as the activation

function after comparing it with tanh and sigmoid. Various sets of process parameters are fed into the input layer and their corresponding outcomes are collected in the output layer in the form of predicted labels. There are 32 neurons in all hidden layers except the first and last ones, which have 8 neurons. After outperforming Adagrad and RMSprop, Stochastic gradient descent with a learning rate of 0.00035 is used as the optimizer. The network is initialized with 0 mean and 0.05 standard deviation.

3 Results and discussions

The problems of identifying the proper working speed range and the optimum printing speed are converted to classification tasks in this study. The input to the machine learning models is a vector of process parameters and the output is the prediction of whether the printing outcome is success for the problem of identifying the proper working speed range. For the problem of identifying the optimum printing speed, the same input is used while the output is the predicted surface quality level. If the model prediction agrees with the real manufacturing outcome, it represents the model is accurate. The evaluation metric in this study is accuracy, which is defined as the ratio of the amount of correct classifications to the total amount of classifications. The training accuracy is the accuracy of a model on examples it was constructed on (training dataset). The testing accuracy is the accuracy of a model on examples it has not seen (testing dataset).

3.1 Evaluation of Models Trained Using Synthetic Data

Theoretical modelling generated synthetic data can be useful when initiating a new set of experiments without any prior experimental data. The trained machine learning models on synthetic data can be used to give relatively simple while constructive predictions on designed experiments. To evaluate the performance of these models, experimental data is used for testing.

3.1.1 Evaluation of Conventional Techniques

Conventional machine learning models described in the section above are trained using the synthetic dataset. All the parameters such as learning rate, momentum, and batch size, etc., adopt the classifiers' default value. The results are shown in Table 2. Although the accuracy of these models on training set is high, their performance on testing dataset is relatively low. This cannot be explained by overfitting because no overfitting problem has been identified when training the models. The following causes may lead to the low testing accuracy: 1. The limitation of only using separation force as the evaluation metric of whether printing is successful or not; 2. The deficiency of extending the generalized separation force model developed for layer-by-layer printing to continuous printing; 3. The simulation data and experimental data are drawn from different distributions.

Table 2 Results of conventional techniques trained on synthetic dataset

Models	Testing accuracy
Nearest Neighbours	0.53
QDA	0.53
Gaussian Process	0.53
Logistic Regression	0.53
Naive Bayes	0.53

Decision Tree	0.52
SVM	0.51
Neural Net	0.50

3.1.2 Evaluation of Ensemble Methods

Similar problems happen to the ensemble methods. The testing accuracy on experimental data are listed in Table 3. The Ada boost method outperforms other ensemble methods on the experimental dataset with an accuracy of 55.8%.

Table 3 Results of ensemble methods trained on synthetic dataset

Models	Testing accuracy
Random Forest	0.52
Ada Boost	0.56
Gradient Boosting	0.54

3.1.3 Evaluation of Siamese Network

Although Siamese Network also suffers from the aforementioned problems, the average training accuracy of our Siamese Network on the synthetic dataset is 84.24 and the average testing accuracy on experimental dataset is 64.29, which outperforms all conventional approaches and ensemble methods mentioned above. Therefore, Siamese Network is relatively reliable for providing basic experimental guidance when only synthetic dataset is available, thus it is more suitable for designing and initializing experiments.

3.1.4 Overall Comparison of Models Trained Using Synthetic Dataset

The performance of best conventional K Nearest Neighbors model and Ada Boost model, which represent the highest accuracy of conventional models and ensemble models trained on synthetic dataset, is compared with that of Siamese Network. Results are plotted in Fig. 7. It is apparent that Siamese Network can extract more information from and make better use of the synthetic dataset. This is mainly because of the contrastive loss used in Siamese Network, which can better capture the discrepancy between data from distinct classes. Therefore, Siamese Network can provide more prior knowledge when only the synthetic dataset is available.

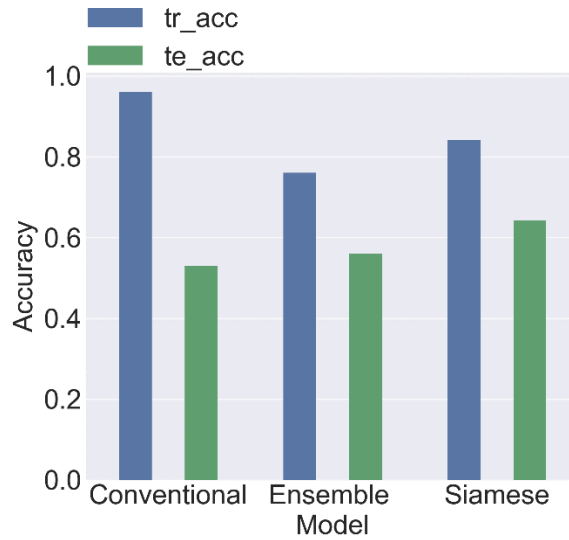


Fig. 7 Comparison of conventional methods, ensemble approaches and Siamese Network trained using synthetic dataset

3.2 Evaluation of Models Trained Using Experimental Data

3.2.1 Evaluation of Conventional Techniques

Similar to the cases using synthetic dataset, conventional approaches including K Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree, Logistic Regression, Quadratic Discriminant Analysis (QDA), Gaussian Processes (GP), Naïve Bayes, and Neural Network are implemented with scikit-learn using Python. All the parameter settings are set to obtain the models' best performance. To avoid overfitting, 10-fold stratified cross validation is applied to all the classifiers. The average accuracy of conventional models on testing data is shown in Table 4. It can be seen that K Nearest Neighbors works the best among all the conventional techniques with a testing accuracy of 85.87% and Gaussian Process also works well with a testing accuracy of 85.29%.

Table 4 Results of conventional methods on experimental dataset

Models	Testing accuracy
K Nearest Neighbours	0.86
QDA	0.75
Gaussian Process	0.85
Logistic Regression	0.72
Naïve Bayes	0.61
Decision Tree	0.81
SVM	0.83
Neural Network	0.82

The overall performance of all conventional techniques on the testing dataset is shown in Fig. 8. The error bars depict the mean and variation of training and testing accuracy for each model on all the 10 folds of data. The blue bars show the training accuracy and the green bar denotes the

testing accuracy. On the x axis, Neural N., Gaussian P., QDA, Logistic R., D. Tree, SVM, N. Bayes and N. N. represent Neural Network, Gaussian Process, Quadratic Discriminant Analysis, Logistic Regression, Decision Tree, Support Vector Machine, Naïve Bayes, and Nearest Neighbours, respectively. The same abbreviations are used in the following sections.

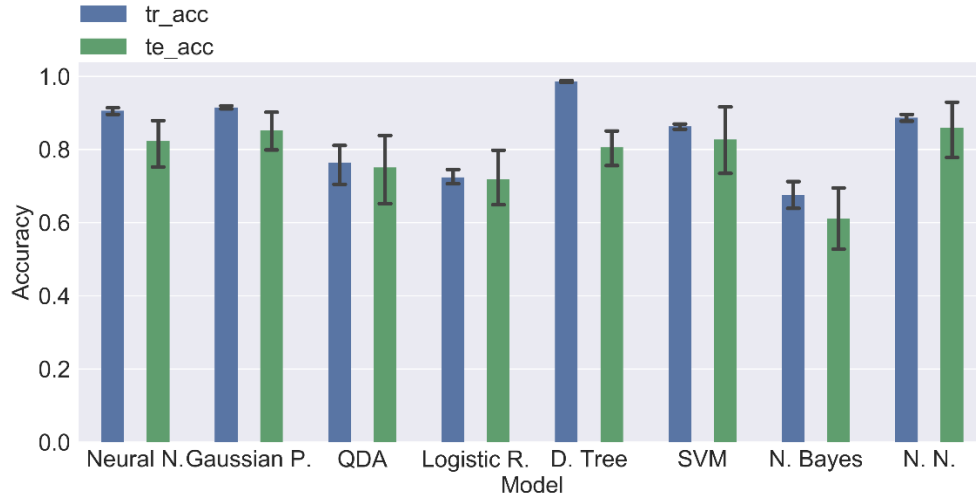


Fig. 8 Overall performance of all conventional techniques

The training and testing accuracy of K Nearest Neighbors model, which works best among all conventional approaches, on each of the 10 folds of data is illustrated using blue bars and green bars respectively in Fig. 9.

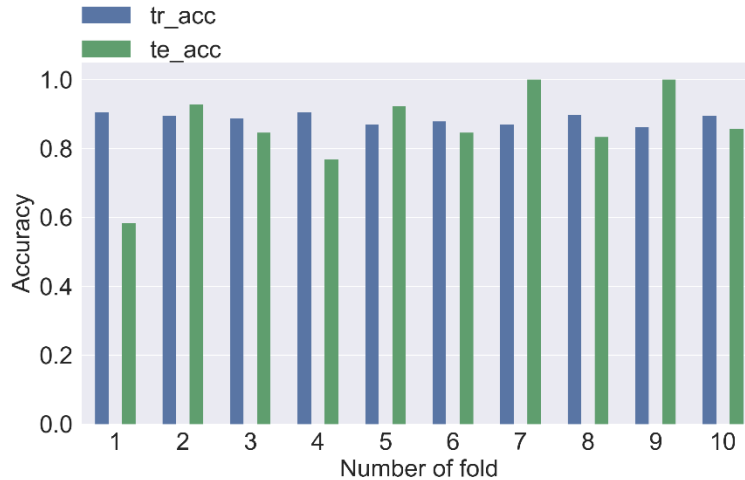


Fig. 9 Training and testing accuracy of K Nearest Neighbors model on all the 10 folds of data

3.2.2 Evaluation of Ensemble Methods

Ensemble methods including Random Forests, Ada Boost, and Gradient Tree Boosting are tested on the experimental dataset. These methods are adjusted to achieve their best performance. 10-fold stratified cross validation is applied to all the classifiers. The average accuracy of conventional models on testing data is shown in Table 5. Random Forest works the best among all the ensemble methods with a testing accuracy of 83.02%.

Table 5 Results of ensemble methods trained on synthetic dataset

Models	Testing accuracy
Random Forest	0.83
Ada Boost	0.82
Gradient Boosting	0.80

The overall performance of all ensemble methods on each fold of the dataset is shown in Fig. 10. The error bars depict the mean and variation of training and testing accuracy for each model on all the 10 folds of data. The blue bars show the training accuracy and the green bars denote the testing accuracy. On the x axis, G. Boosting, R. Forest, and AdaB. denote Gradient Boosting, Random Forest, and Ada Boost, respectively. The same abbreviations are implemented in the following sections.

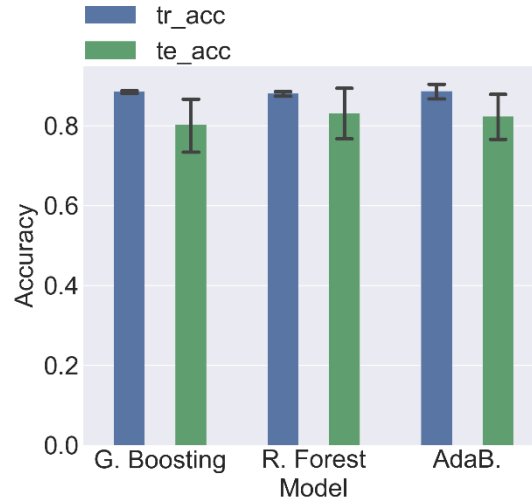


Fig. 10 Overall performance of ensemble methods

The training and testing accuracy of Random Forest model, which performs the best among the ensemble models, on each of the 10 folds of data is illustrated in Fig. 11 using blue bars and green bars respectively.

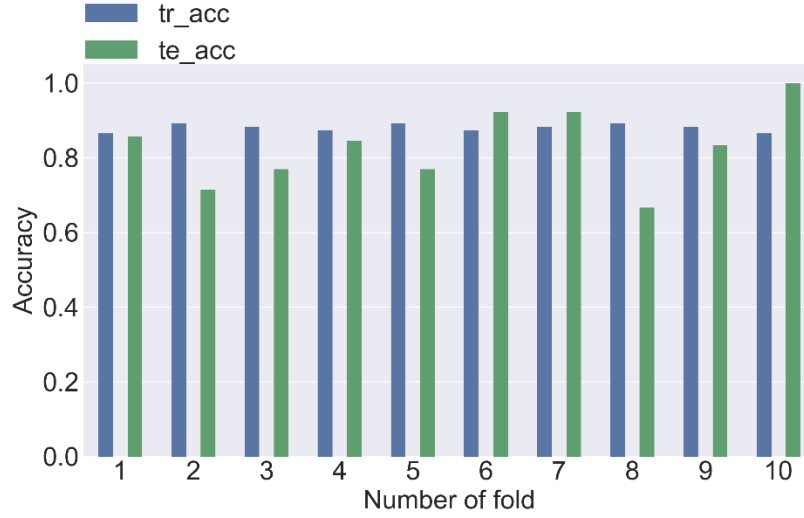


Fig. 11 Training and testing accuracy of Random Forest on all the 10 folds of data

3.2.3 Evaluation of Siamese Network

Siamese Network is also evaluated on the same experimental dataset. 10-fold stratified cross validation is also implemented. The training and testing accuracy of Siamese Network on each of the 10 folds of data is plotted in Fig. 12 using blue bars and green bars, respectively. The average training accuracy is 90.17% and the testing accuracy is 88.42%.

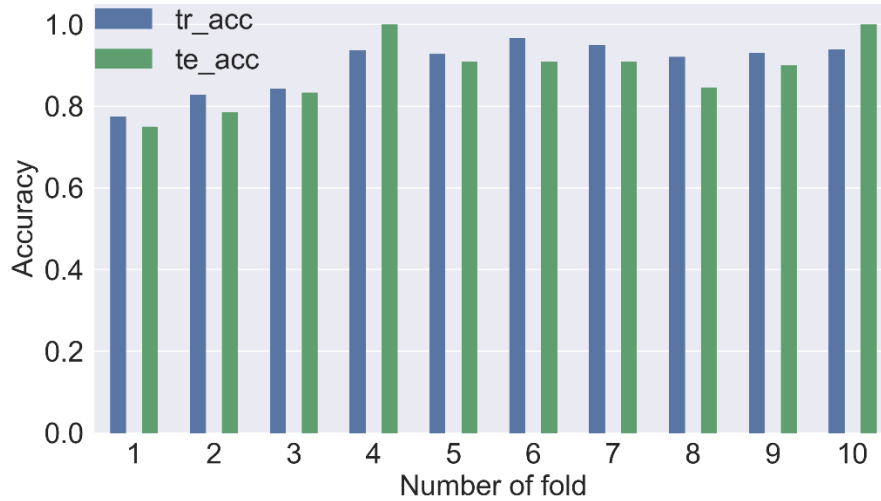


Fig. 12 Training and testing accuracy of Siamese Network on all the 10 folds of data

3.2.4 Overall Comparison of Models Trained Using Experimental Dataset

To make a better comparison, K Nearest Neighbors model, which works best among all conventional approaches, is selected as the representative of conventional models. Random Forest is picked on behalf of ensemble methods. Their training and testing accuracy are compared with Siamese Network and the comparison is shown in Fig. 13. Siamese Network outperforms all the

other mentioned approaches. It is verified that the trained model can be used for predicting the outcome of future trials to guide the design of experiments.

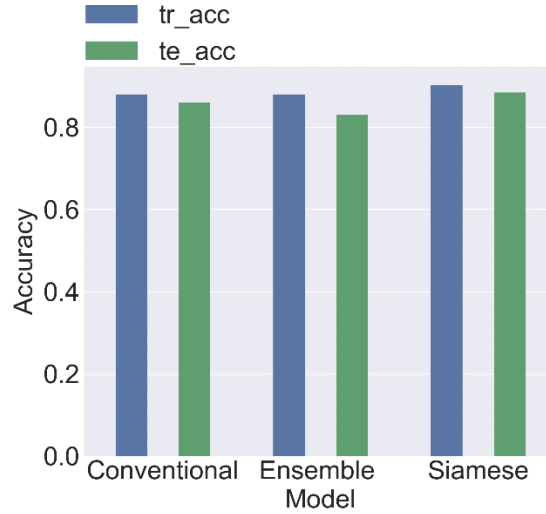


Fig. 13 Overall comparison of the models on experimental data

3.3 Printing Speed Optimization

The learned machine learning models in Section 3.2 can more accurately predict whether the printing speed is appropriate to print a part continuously. However, the surface quality of the printed parts varies with the continuous printing speed. the printed surface is much coarser if the filling resin is rapid when a higher continuous elevation speed is used. A tradeoff between the printing speed and the printed surface quality needs to be made. This section investigates the application of machine learning models on identifying the optimum continuous printing speed that can produce an acceptable surface quality.

3.3.1 Data collection

To collect data, squares with the same area while different aspect ratios are continuously printed using different continuous elevation speed. The data is labeled 0 if the printing fails. The successfully printed parts are observed under microscope to check the surface quality. Since there are only a few optimum speeds for each geometry, to avoid unbalanced data, the printing with an optimum speed is labeled 3 and the rest unlabeled data are rated 1 or 2 by concerning both the surface quality and manufacturing speed. Microscopic images of some surface of printed samples are shown in Fig. 14. The average size of the pores on the printing surface is used as the surface quality evaluation metric. In this example, Fig. 14 (b) is graded as 3, (a) and (c) are rated to be 2 and (d) is marked as 1. Therefore, there are four classes in the dataset and the task becomes more challenging than previous. Due to the high cost and time-consuming characteristics of continuous printing experiments, limited data (~80) is collected.

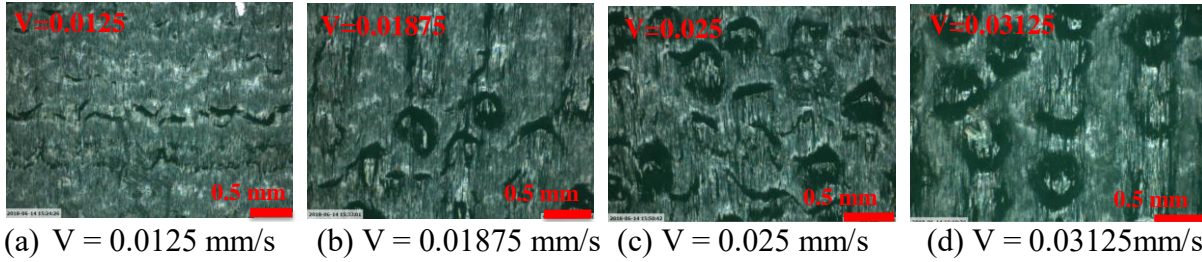


Fig. 14 Microscopic images of surface of printed 2mm x 8mm square

3.3.2 Evaluation of Conventional Techniques on Optimizing Printing Speed

Conventional approaches including K Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, Logistic Regression, Gaussian Processes (GP) and Neural Network are tested on the dataset. To avoid overfitting, 10-fold stratified cross validation is utilized. The average accuracy of conventional models on testing data is shown in Table 6. Nearest Neighbours works the best among all the conventional techniques with a testing accuracy of 59%.

Table 6 Results of conventional methods on optimizing printing speed

Models	Testing accuracy
Nearest Neighbours	0.59
Gaussian Process	0.53
Logistic Regression	0.46
Naive Bayes	0.53
Decision Tree	0.46
SVM	0.50
Neural Net	0.49

The overall performance of all conventional techniques on each fold of the dataset is shown in Fig. 15. The error bars depict the mean and variation of training and testing accuracy for each model on all the 10 folds of data. The blue bars show the training accuracy and the green bars the testing accuracy.

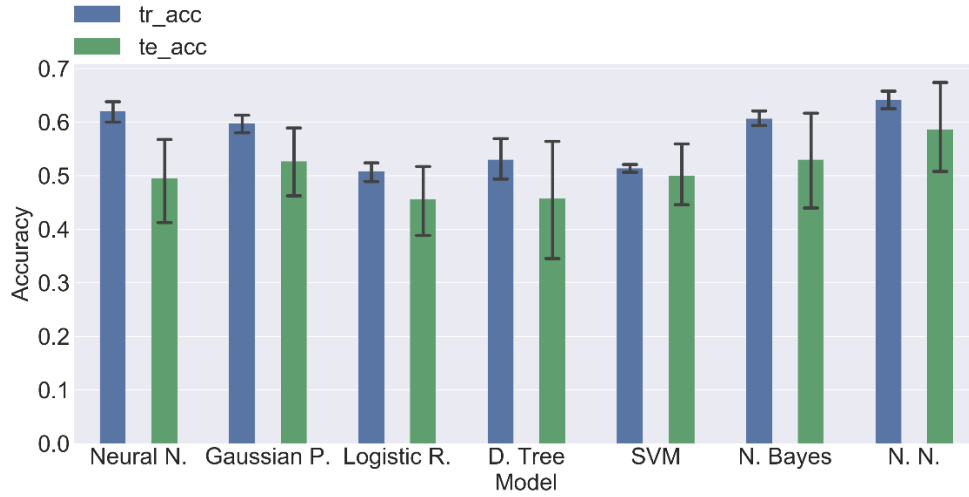


Fig. 15 Overall performance of all conventional techniques

The training and testing accuracy of Nearest Neighbours model on each of the 10 folds of data is plotted in Fig. 16 using blue bars and green bars, respectively.

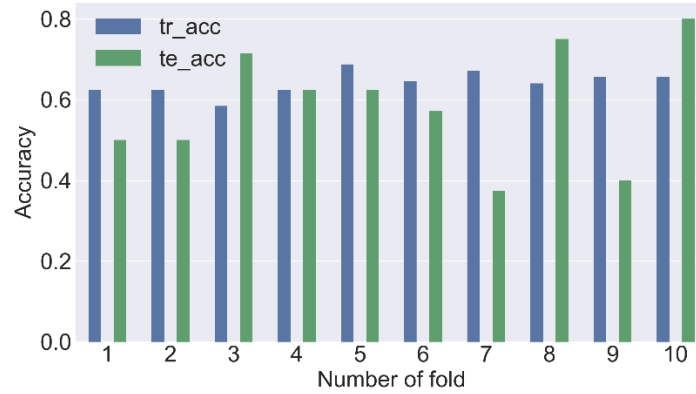


Fig. 16 Training and testing accuracy of K Nearest Neighbors model on all the 10 folds of data

3.3.3 Evaluation of Ensemble methods on Optimizing Printing Speed

Ensemble methods are also tested for optimizing the printing speed. The settings of these methods are modified to achieve the best accuracy. 10-fold stratified cross validation is applied to all the classifiers. The average accuracy of ensemble methods on testing data is shown in Table 7. Random Forest works the best among all the ensemble methods with a testing accuracy of 73%.

Table 7 Results of ensemble methods trained on synthetic dataset

Models	Testing accuracy
Random Forest	0.73
Ada Boost	0.60
Gradient Boosting	0.68

The overall performance of all ensemble methods on all 10 folds of the dataset is shown in Fig. 17. The error bars depict the mean and variation of training and testing accuracy for each model on all the 10 folds of data. The blue bars show the training accuracy and the green bars denote the testing accuracy.

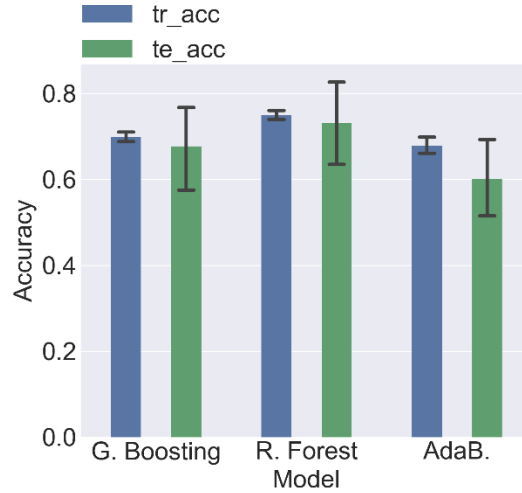


Fig. 17 Overall performance of ensemble methods

The training and testing accuracy of Random Forest model, which performs the best among the ensemble models, on each of the 10 folds of data is plotted in Fig. 18 using blue bars and green bars, respectively.

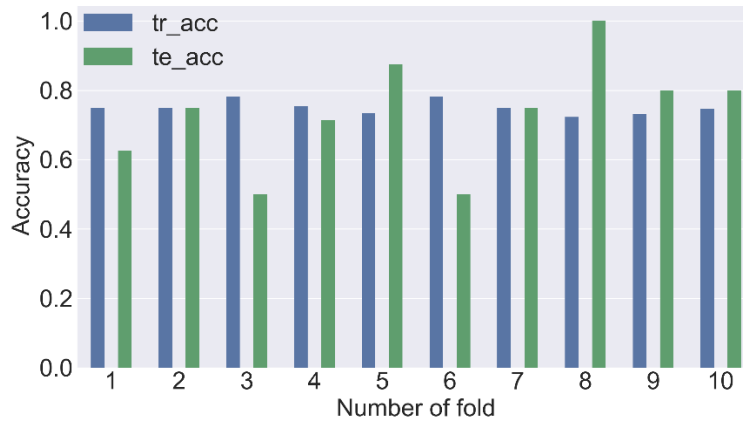


Fig. 18 Training and testing accuracy of Random Forest model on all the 10 folds of the dataset

3.3.4 Evaluation of Siamese Networks on Optimizing Printing Speed

Siamese Network is evaluated on the same experimental dataset, with a 10-fold stratified cross validation. The related training and testing accuracy on each of the 10 folds of data is plotted in Fig. 19 using blue bars and green bars, respectively. The average training accuracy is 80.14% and the testing accuracy is 82.67%, which outperforms all above mentioned approaches. Thus, it is also verified that Siamese Networks is effective on optimizing printing speed.

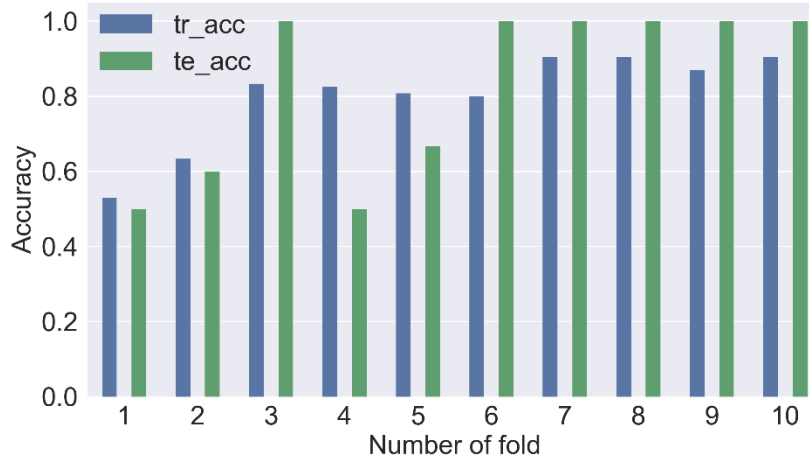


Fig. 19 Training and testing accuracy of Siamese Network on all the 10 folds of the dataset

3.3.5 Overall Comparison of Models for Speed Optimization

A comparison of conventional models (Decision Tree is used as a representative), ensemble methods (Gradient Boosting is selected as a representative), and Siamese Network for printing speed optimization is shown in Fig. 20. Siamese Network exceeds all the other approaches. The overall relatively low accuracy may due to the small size of the dataset. Nonetheless, the Siamese Network performs the best and shows a great potential for predicting the outcome of future trials to guide the design of printing jobs.

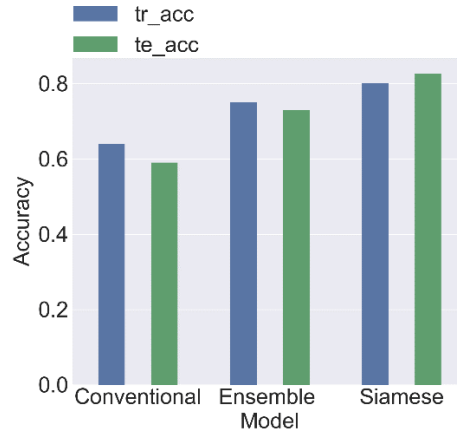


Fig. 20 Overall comparison of the models for printing speed optimization

4 Conclusions

This paper investigates the application of machine learning models in predicting feasible printing speed for CLIP process. Conventional techniques, ensemble approaches, and the state of the art Siamese Networks are investigated and compared. Siamese Network works the best among all the investigated models. It can effectively extract useful information from mathematical model generated synthetic dataset. Given an experimental dataset, Siamese Network can more accurately classify the data and give relatively more reliable guidance for future experimental design,

compared to all other models. Experimental results also validated that Siamese Network is more effective on capturing features for identifying the optimum manufacturing speed. With the help of Siamese Network, a dynamically growing dataset for continuous printing can be enriched effectively, and the continuous printing process can be planned efficiently. The effectiveness of Siamese Network has first been validated in continuous printing process planning. Due to its capability of dealing with small dataset, Siamese network can also be extended to other additive manufacturing systems or some general manufacturing systems.

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