Machine learning based prediction of production using real time data of a point bottom sealing and cutting machine

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ABSTRACT

The packaging sector utilizes polypropylene based flexible materials for diverse product packaging with customization options in size and design achieved through advanced flexographic printing and point bottom sealing and cutting machines. Accurately estimating production time and quantity is vital for efficient planning and cost estimation, with factors like material dimensions, thickness, and cutting machine speed influencing production output. Understanding the intricate relationship between these parameters is essential for comprehending their impact on production time and quantity. Predicting production quantity before production begins helps in determining machine runtime and associated costs. In large-scale production systems, machine learning (ML) has proven to be a useful tool for resource allocation and predictive scheduling. An attempt has been made in this paper to develop an intelligent model for predicting the yield of a cutting machine using artificial neural network (ANN), support vector regression (SVR), regression tree ensemble (RTE) and gaussian process regression (GPR). The most crucial features for prediction were identified and the hyperparameters of the ML models were optimized to create efficient models for prediction. A comparative analysis of the four models revealed that the GPR model was simple and effective with least training time and prediction error.

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1. INTRODUCTION

Packaging sector is among the fast-growing industries in India and worldwide. An integrated packaging material is a type of flexible packaging material that can be used to pack a variety of products. polypropylene (PP) based flexible packaging materials are extensively used for packaging various products by the unorganized and organized manufacturing sector. They are light weight and come with the advantages of durability, reusability and cost effectiveness. They can be manufactured in variety of sizes. Advanced flexographic printing machines can be used to print on these materials for appeal and branding. The continuous printed film is then sealed and cut using a point bottom sealing and cutting machine. The dimensions of the material like size and thickness are set as per the need of the customer. The speed at which the sealing and cutting operation can be performed is limited by the thickness of the material and the temperature rise in the machine.

Accurate assessment of production time and quantity is crucial for effective planning and cost estimation. The production quantity relies on factors such as the material dimensions, thickness, and operating speed of the cutting machine. The relationship between these parameters is fairly complex, as speed is again constrained by factors such as thickness and machine's temperature rise and the temperature setting of the machine is determined based on the material's thickness. Therefore, it is essential to comprehend the correlation between various parameters and how they impact production time and quantity. Cost effectiveness and run time management are imperative factors in a manufacturing set up and a prior knowledge of productivity can be a big leap towards attaining it. Having prior knowledge of the production quantity can aid in determining both the machine runtime and the associated costs. Hence there is a need to predict the production quantity in terms of number of pieces or kilograms prior to commencing production. This motivated the authors to collect real time data from a flexoprinting and cutting unit to understand the correlation between various parameters and to develop a suitable model for predicting the output of a point bottom sealing and cutting machine.

Proper management of data and its utilization for data driven decision making can give an edge to an industry over their competitors [1], [2]. The field of artificial intelligence (AI) has been successful in dealing with large amounts of data to draw meaningful conclusions [3]. Machine learning (ML) is a subdivision of AI that deals with algorithms that are capable of learning from the given data. In recent years the applications of ML have grown tremendously in all fields which include medicine, agriculture, and entertainment to name a few [4]-[7]. ML has also penetrated into the industrial field, and many works show promising results that would bring a transformation to the traditional manufacturing system [8]. ML has established itself to be a valuable tool in predictive scheduling and resource allocation in large scale manufacturing systems [9]. Most manufacturing systems operate in dynamic environments and ML can be used for effective scheduling under such circumstances [10]. Hence an attempt has been made in this work to develop four different ML models namely artificial neural network (ANN), support vector regression (SVR), regression tree ensemble (RTE) and gaussian process regression (GPR) aimed at predicting production quantity. The hyperperameters of these models have been optimized with five-fold cross validation and the optimized models have been assessed and compared based on their accuracy in prediction, training duration, and prediction speed.

ML can be used for classification and regression tasks. The relevant literature works are presented here to bring out the significance of the proposed work. Predictive model-based quality inspection using ML and Edge Cloud Computing has been proposed with a case study in electronics industry [11]. Naïve Bayes, decision tree (DT), logistic regression, support vector machine (SVM) and gradient boosted tree (GBT) have been used for the classification task. A modified nomadic based Lion algorithm has been used for predicting the optimal scheduling in flexible manufacturing systems [12]. A manufacturing system wide balanced random survival forest algorithm has been used to predict breakdown in machines 30 minutes ahead [13]. Ensemble based method has been used for dynamic scheduling in flexible manufacturing systems [14]. An ANN based model has been developed for prediction of failure in a production line for predictive maintenance of industrial packaging robots [15]. A comprehensive review of various ML techniques used for industrial applications is presented in [16], [17]. Table 1 presents a survey of literatures using regression models for prediction in various applications [18]-[25]. As seen from the table, the ML models used are linear regression (LR), ANN, space vector regression (SVR) using PP and/or radial bias function (RBF) kernel, K nearest neighbor (KNN), DT, random forest (RF), gradient boosting (GB), ensemble learning (EL), light gradient boosting machine (LGBM) and extreme gradient boosting (XGBoost). LR is the simplest model for prediction that is easy to develop. SVR with RBF kernel is the most frequently used regression model for prediction. GB and other ensemble-based methods use a combination of weak learners for prediction to avoid overfitting. The performance parameters considered for the evaluation of models include R-squared value, mean absolute error (MAE), root mean squared error (RMSE), percentage error (PE), correlation, training time and computation time. Based on these parameters, the best models identified for each application is also shown in Table 1. Based on the survey presented in Table 1, the regression models giving good results are identified as SVR, ANN and Ensemble based methods using trees.

GPR is yet another regression model with promising results for small datasets, which is relatively new and has not been used for many applications [26]-[28]. Hence an attempt has been made in this paper to develop an intelligent model for predicting the yield of a cutting machine using ANN, SVR, RTE and GPR. The aim of this paper is to determine the most important parameters for predicting production, develop high-performing ML models with optimized hyperparametersfor prediction utilizing these selected input parameters, and perform a comparative analysis of the results to find the optimal model.

This paper is organized as follows. A review of recent literatures with similar work has been presented in the next section. The methodology, comprising of a detailed account of the dataset used for training the ML models and a description of the four regression models is presented in the section 3. It is followed by the results and discussion section where the visualization results of the dataset have been presented to understand the inherent relations between the parameters and the results of the four ML models developed. Results have also been provided comparing the performance of the four regression models and using the best performing model to predict output for unseen data. Lastly, the conclusion section summarizes the work and concludes with the final contribution and future scope of the work.

Table 1. Survey of regression models developed for prediction

Regression model	ML techniques	Performance parameter	Best model identified
Prediction of photovoltaic energy production [18]	SVR (RBF)	MAE, R-Squared, RMSE	SVR (RBF)
Prediction of micrometeorological data [19]	SVR (RBF)	RMSE	SVR (RBF)
Prediction of CNC tool ware compensation offset [20]	SVR (RBF)	RMSE	SVR (RBF)
Estimation of manufacturing cost of jet engine components [21]	LR, ANN, SVR, GB	R-squared, MAE, RMSE, correlation, computation time	GB
Estimation of effort in a sprint [22]	LR, KNN, DT, RF, SVR	Correlation, MAE, RMSE	ANN
Estimation of crop production [23]	GB, RF, DT, SVR	Train accuracy, test accuracy	DT
Prediction of tool ware in milling operations [24]	ANN, SVR, RF	MSE, R-squared, training time	RF
Estimation of steel quality control [25]	LR, SVM, KNN, EL, RF, GB, LGBM, XGBOOST	R-squared, RMSE, PE	EL

2. METHOD

The methodology adopted in the development of prediction model is illustrated in Figure 1. Data was collected from the production record books of the flexoprinting unit. The data was further cleaned by removing data with missing values to generate final labeled data. The data was then used to compute the optimized hyperparameters of four different regression models namely ANN, SVR, RTE and GPR with five-fold crossvalidation. The models were then trained and evaluated with cross validation to prevent overfitting of data. The model was further used for prediction of production output for new unseen data. The following subsections include a description of the flexoprinting, cutting, and dataset construction processes. The dataset itself is then described. The four regression models trained and used for prediction are briefed in the further subsections.

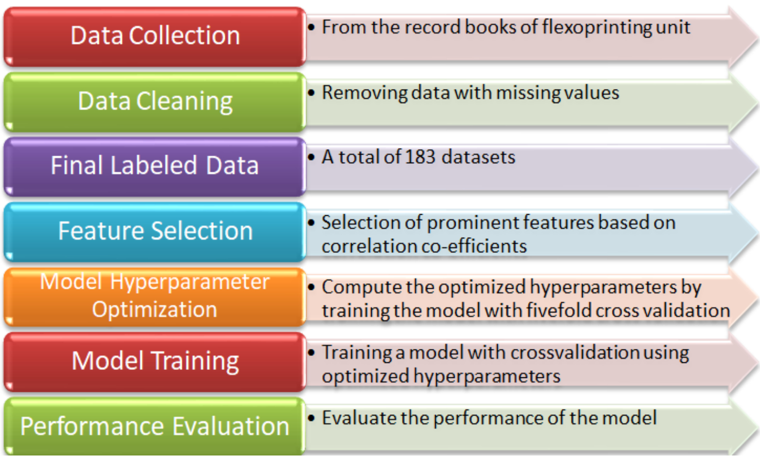


Figure 1. General framework of the proposed work

2.1. Process description and construction of dataset

The purpose of a package is to safeguard, contain, preserve and convey information about a product. Flexible packaging doesn’t have a set shape but takes the shape of the product it protects. Advanced flexographic printing methods facilitate brand owners to market their product and convey informations like source of the product, nutritional details, vital tracking data for product recall etc effectively. PP and low-density (LD) polyethylene resin based flexible packaging materials are extensively used for packaging various products by the unorganized and organized manufacturing sector. Often, these resins are extruded into a film form using PP or LD monolayer or multilayer blown film machine. The extruded film is corona treated and the treated film is wound in the form of a roll. Corona treatment increases the surface energy of films to improve wettability and adhesion of inks. The extruded treated film can be flexoprinted, bottom sealed and cut as per the requirement of the buyer. The sealing and cutting of the continuous flexoprinted film are done using point bottom sealing and cutting machine. The finished product is used as integrated packaging material to pack various products. The machine consists of unwinding section, a photo cell-based sensor to detect the print repeat, bottom sealing and a cutting section. The machine is equipped with temperature controllers which can provide the most accurate and fastest heating performance for sealing process. The operation of the machine is controlled by programmable logic controller (PLC). The machine is equipped with servo motor for indexing and accuracy and is ideal for the bottom sealing and cutting operation of flexoprinted PP or LD film rolls. The material is printed and cut in different dimensions as per the customer requirements. The production depends on the length, width, thickness (gauge) of the material and the cutting machine speed. Forecasting the production (pieces/kg) would be crucial for inferring the machine run time. Hence to develop a prediction model, a total of 183 datasets were collected from the production reports.

2.2. Dataset description

A prediction model can be developed to predict the production based on the input parameters length, width, gauge machine speed and temperature. The description of the dataset parameters collected from the production reports of cutting machine are presented in Table 2. The width of the film rolls and length of cutting the printed film is dependent on the dimensions of the packaging material. These dimensions are provided by the buyer. The film roll for printing will be extruded as per the width required. The repeat size for the printing process will be dependent on the length of the packaging printed material. The same length will be set in the cutting machine for sealing and cutting process. The thickness of the film is often expressed in gauge or micron. A film that has 100 gauge or 25.40 microns will have a thickness of 0.0254 mm (or 0.0010 inch). The gauge is given to the extruder for making film roll and the actual gauge of the film received for printing is cross-checked using gauge meter. The speed (strokes/minute) and temperature (°C) of the cutting machine is set by the cutting machine operator. Optimum speed and temperature is set with the criteria that a good sealing is obtained in the cut material. The material at the sealing must not open. The production (pieces/kilogram) is obtained by weighting 200 pieces of the cut material and converting to pieces per kilogram. A total of 183 datasets were selected for development of prediction model. The regression models used in this work for prediction are discussed next.

Table 2. Description of dataset parameters

Sl. No.	Parameter name	Description	Data type	Range	Mean	Variance
1	Gauge	Thickness of the product	Integer	[120,424]	219	2284.17
2	Width	Width of the product in inches	Float	[3, 18]	7	5.35
3	Length	Length of the product in inches	Float	[4, 22]	10	12.09
4	Speed	Number of strokes/minutes	Integer	[50, 185]	126	518.12
5	Temperature	Machine temperature setting	Integer	[142, 395]	267	1424.68
6	Production	Number of pieces/kg	Integer	[37, 1538]	310	71392.15

2.3. Regression models

Regression models use input-output pairs from the training dataset to determine the connection between a dependent variable and one or more independent variables. Four such models have been trained to learn the relationship between production and length, width, gauge, and speed. The details of the four models are presented in the following subsections.

2.3.1. Artificial neural network

An ANN is a powerful model that learns the non-linear mapping input-output. The input, hidden and output layers have neurons with activation function and are interconnected with weighted connections. The ANN is trained to interpolate data with high accuracy they can based on input-output data pairs.

2.3.2. Support vector regression

SVM is a supervised learning model that analyzes data for classification and regression. The SVM model used for regression is called SVR. It provides an efficient prediction model for small non-linear datasets. SVR tries to fit the error within a threshold, by finding the best fit line called hyperplane and approximating the predicted value within the given margin. A kernel function is used to map the data points to a higher dimension. The SVR is trained using input-output datasets to find the best fit hyperplane that fits as many data points as possible within the boundary lines.

2.3.3. Regression tree ensemble

A non-parametric model called a DT can be trained to predict an output variable by deriving basic decision rules from the training set of data. Regression trees are DTs that are utilised for regression; they are conceptualised as piecewise constant approximations. Regression trees tend to over fit and do not generalize well on unseen data. A RTE is a regression model built using weighted combination of multiple regression trees. Combining multiple regression trees improves the predictive performance of the model. Regression tree models are trained in a process called "boosting," where each model aims to outperform the one before it in the sequence.

2.3.4. Gaussian process regression

A probabilistic supervised model for regression and classification applications is the gaussian process (GP) model [26] that uses Bayesian method for fitting the training data over possible over possible functions. GPR model is a non-parametric kernel-based model that uses the training data and the prior knowledge for prediction and computes predictive posterior distribution on the testing data. It yields good results on datasets which are small also providing uncertainty measures over predictions.

3.1. Data visualization

The histogram of the input and the response variable is presented in Figure 2. From the histogram, we observe that maximum frequency of gauge during production is between 180 to 275, width between 3 and 10 inches, length between 4 and 12 inches, speed between 100 and 150 strokes/min, temperature between 200 and 300 °C and production between 100 and 1,400 pieces. The correlation matrix of the input and the response variable is presented in Table 3. It shows there is a high to moderate correlation between input variables width, length, gauge and speed on response variable production. As the variable temperature has a weak correlation with response variable, it will not contribute significantly in predicting the production quantity and hence is not used for model training.

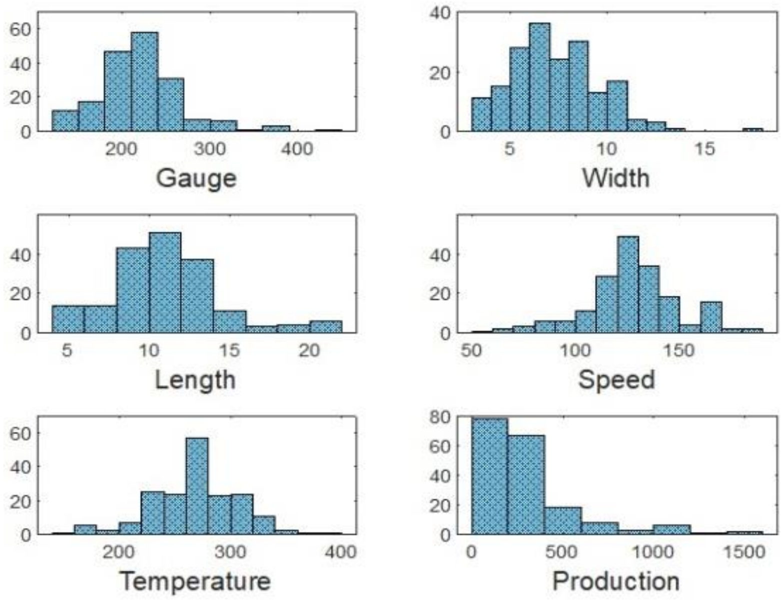


Figure 2. Visualization of input and output features

Table 3. Correlation matrix showing correlation between data features

Parameter	Gauge	Width	Length	Speed	Temperature	Production
Gauge	1					
Width	0.0130	1				
Length	-0.0632	0.8982	1			
Speed	-0.1500	-0.7908	-0.8409	1		
Temperature	0.0819	-0.0592	-0.0338	-0.0114	1	
Production	-0.5742	-0.7566	-0.7377	0.7270	0.0376	1

3.2. Regression model training and performance evaluation

Four regression models namely ANN model, SVR model, RTE model and GPR model were developed to predict production based on the values of width, length, gauge and speed. The parameter temperature was not used in model training due to its weak correlation with output variable. The models were first optimized using Bayesian optimization method with five-fold cross validation to find the optimized values of hyperparameters for each model with the five-fold crossvalidation loss as the objective function of optimization. The variation of the five-fold crossvalidation loss as a function of iteration number during optimization is shown in Figure 3 for the four models. Six hyperparameters were optimized for ANN, SVR and RTE models and five hyperparameters for GPR model. As seen from Figures 3(a) to 3(d), the parameters of GPR model were optimized with minimum cross validation loss value in minimum number of iterations. The hyperparameters that were optimized in each model and their values after optimization are shown in Table 4. Further the models were cross validated to avoid overfitting of the data and the K fold loss was obtained.

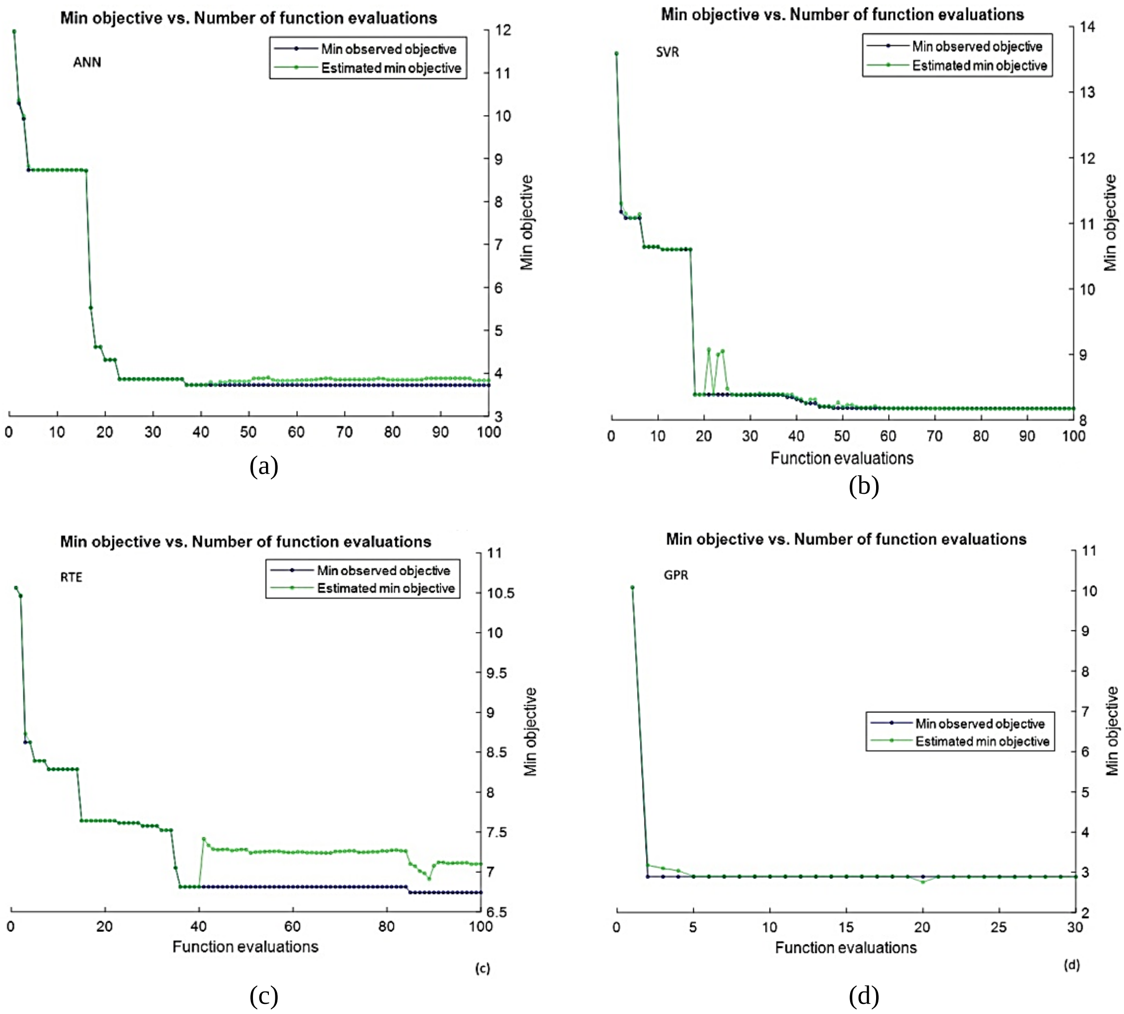
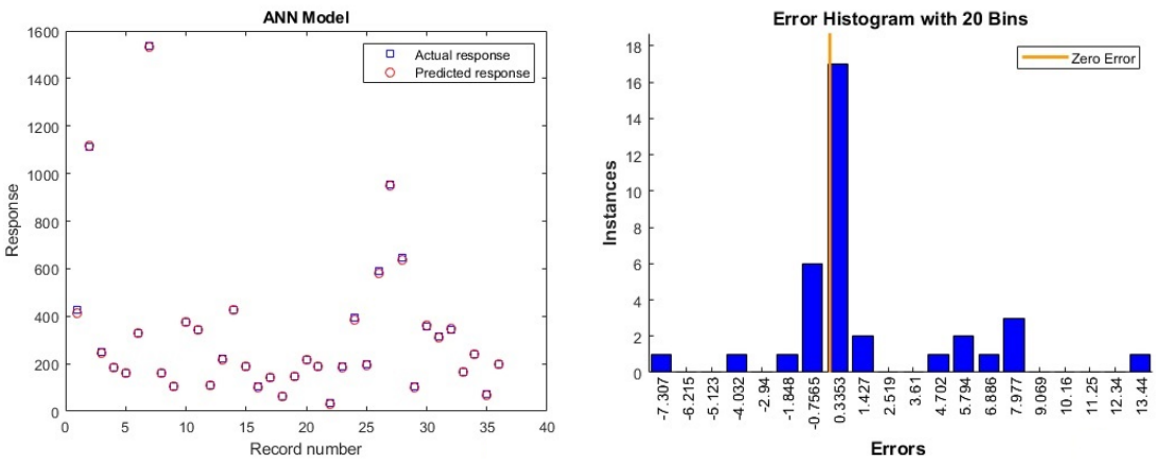


Figure 3. Hyperparameter optimization using fivefold cross validation loss as the objective function: (a) ANN model, (b) SVR model, (c) RTE model, and (d) GPR model

Table 4. Optimized hyperparameters

ANN	SVR	RTE	GPR
Activations: ReLU	Box constraint: 33.28	Method: LSBoost	Sigma: 0.52295
Standardize: true	Kernel scale: 1.85	Num learning cycles: 365	Basis function: zero
Lambda: 3.7e-06	Epsilon: 31.575	Learn rate: 0.178	Kernel function: ardmatern5/2
Layers weights initialize: glorot	Kernel function: polynomial	Min leaf size: 4	Kernel scale: -
Layers bias initialize: zeros	Polynomial order: 4	Max num splits: 4	Standardize: false
Layer sizes: 24-17-11	Standardize: true	Num variables to sample: 4	

The ANN model that was developed had a total of five layers, one input, three hidden and one output layer. The number of neurons in each layer was 4-24-17-11-1. The number of neurons in the input and output layer are decided by the number of inputs and outputs respectively. The number of hidden layers and number of neurons in each hidden layer depends on the nonlinearity in the input output relationship and was obtained by hyperparameter optimization. Rectified linear unit (ReLU) activation function was used in the hidden layers and limited-memory broyden–fletcher–goldfarb–shanno (LBFGS) solver in the output layer. The results of ANN model is shown in Figure 4. The actual and predicted response of the model is shown in Figure 4(a) and the error histogram in Figure 4(b). The K fold loss in the ANN model was 14.73. A SVR model with a Polynomial kernel was developed for prediction. The kernel function applies nonlinear transformation to the data before the model is trained. The optimum value of box constraint and epsilon were found to be 33.28 and 31.575 respectively. Prediction errors smaller than epsilon are considered as zero. A kernel scale of 1.85 was used in the model to control the scale of the predictors on which the kernel fluctuates considerably. The sequential minimal optimization (SMO) algorithm was used as solver during the training. The results of SVR model is shown in Figure 5. The actual and predicted response of the model is shown in Figure 5(a) and the error histogram in Figure 5(b). The K fold loss in the SVR model was 2921.9. A RTE model was developed by training ensembles of regression trees and combining their results to obtain a ensemble model with high performance. The ensemble method used for regression fitting was Least Squares Boosting with shrinkage with a learning rate of 0.178. During training, at every step, the ensemble trains a new learner to reduce the difference between the observed response and the cumulative prediction of all learners in the existing model. In the optimized model, the minimum leaf size, maximum number of splits and number of variables to sample were set to 4. The number of learning cycles was set to 365. It limits the number of training data samples used to compute the output of each leaf node. The results of RTE model is shown in Figure 6. The actual and predicted response of the model is shown in Figure 6(a) and the error histogram in Figure 6(b). The K fold loss in the RTE model was 495.55. The GPR model with a zero-basis function and ARD Matern5/2kernel with a scaling factor of 2.01 was developed. The basis function indicates the shape of the prior mean function of the model. The kernel function finds the correlation in the output variable as a function of the distance between the values of input variables keeping the correlation length scales same for all the variables. Sigma is the initial value of the observation noise standard deviation and its value is set to 0.523. The results of GPR model is shown in Figure 7. The actual and predicted response for the model is shown in Figure 7(a) and the error histogram in Figure 7(b). The K fold loss in the GPR model was 6.46.

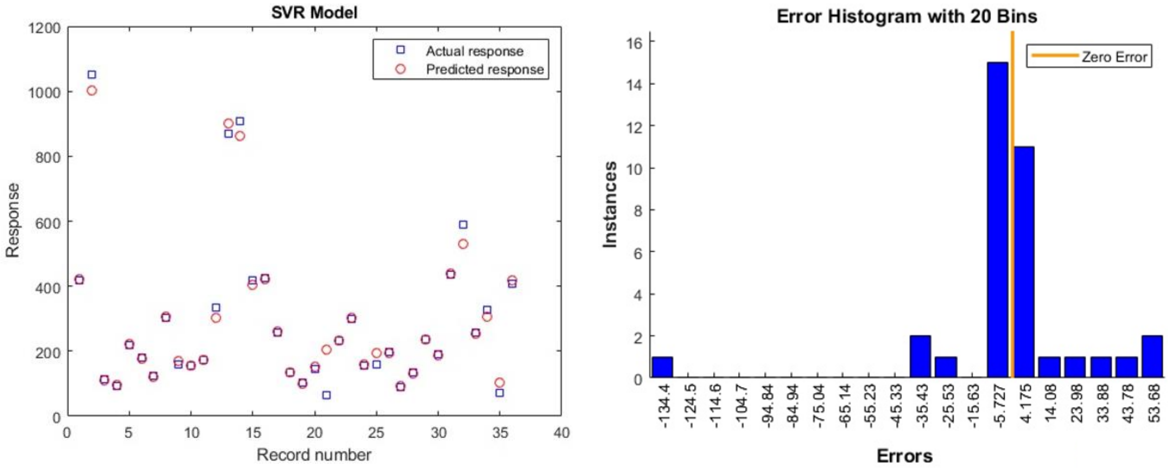


(a) (b)

Figure 4. ANN model (a) actual and predicted response and (b) error histogram with 20 bins

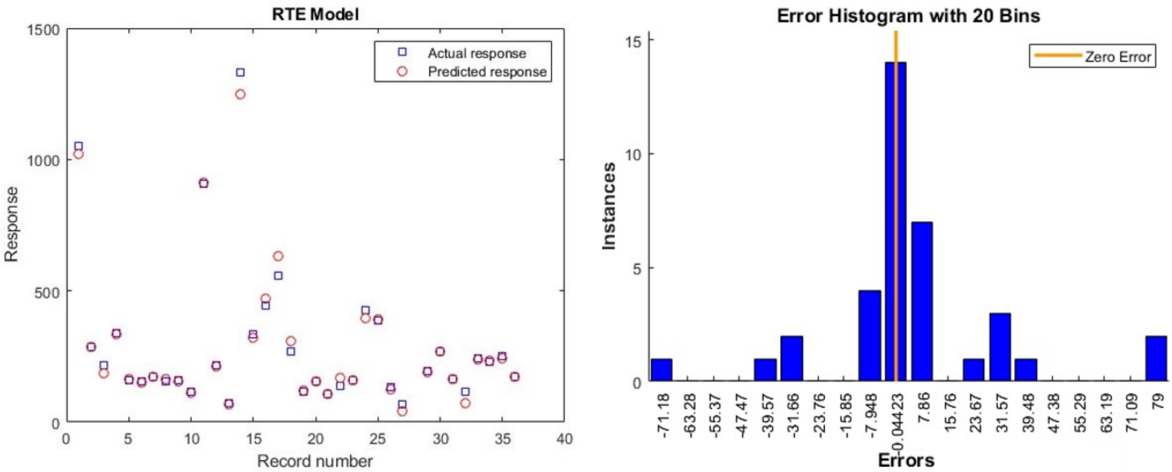
3.3. Comparison of regression models

The results of the four optimized models are compared in this section. The performance parameters considered for comparison are the training K Fold loss, Number of iterations of optimization, the function evaluation time, mean squared error (MSE), R-Squared, and MAE. The training K fold loss is the minimum value of objective function obtained at the end of maximum iterations and function evaluation time is the time taken for evaluation of the objective function during hyperparameter optimization. MSE was the performance parameter used during training. R-Squared value gives the coefficient of determination by comparing the trained model with the model where the response is constant and equals the mean of the training response. MAE is another performance parameter that is similar to MSE but less sensitive to outliers. The values of these parameters are tabulated in Table 5 for each model. The Training time of the model in seconds and the Prediction speed expressed as number of observations per second are also tabulated for comparison. As seen from the table, the GPR model is the best performing model with minimum MSE value of 6.4633, and MAE value of 1.321. It is followed by ANN model, RTE model and SVR model. Training time is a vital parameter during model development and it is seen that the GPR model also takes minimum time for training.



(a) (b)

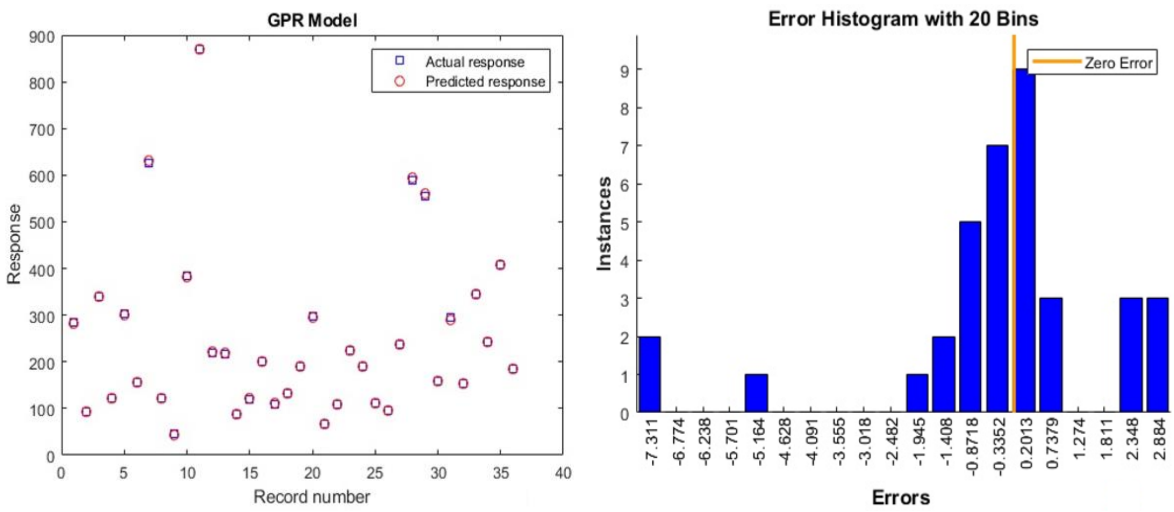
Figure 5. SVR model (a) actual and predicted response and (b) error histogram with 20 bins



(a) (b)

Figure 6. RTE model (a) actual and predicted response and (b) error histogram with 20 bins

The proposed model would prove to be very useful in creating reference charts for assessing production for different input parameters. A major part of packaging materials is manufactured in standard dimensions (width and length). Predicting the production for the standard dimensions for varying gauge and speed would provide a readymade reference tool for the industry for efficient estimation of run time and cost before the start of bulk production. Sample prediction results using GPR model for a standard dimension of 3x4 is presented in Table 6 for varying gauge and speed.



(a) (b)

Figure 7. GPR model (a) actual and predicted response and (b) error histogram with 20 bins

Table 5. Comparison of performance parameters

Model	ANN	SVR	RTE	GPR
Training K fold loss	3.7235	0.15682	6.7414	0.90323
Iterations	100	100	100	30
Function evaluation time	19.5253	8.1748	6.918	2.8904
MSE	14.7250	2921.9	495.5476	6.4633
R-squared	0.9998	0.9817	0.9948	0.9999
MAE	4.674	18.532	9.255	1.321

Table 6. Sample prediction results for 3x4 dimension

Gauge	Width	Length	Speed	Production
180	3	4	172	1501
200	3	4	172	1355
220	3	4	172	1239
240	3	4	172	1141
260	3	4	172	1045
180	3	4	165	1212
200	3	4	165	1085
220	3	4	165	987
240	3	4	165	904
260	3	4	165	832
180	3	4	158	1172
200	3	4	158	1040
220	3	4	158	931
240	3	4	158	840
260	3	4	158	777

3. CONCLUSION

The objectives of this paper were to determine the input parameters most suitable for the prediction of production, develop best performing ML models for prediction using the selected input parameters with optimized hyperparameters, and compare the results obtained to identify the best model. Five input parameters were considered namely gauge, width, length, speed and temperature. Based on the correlation coefficients it was concluded that the influence of temperature in the production quantity was insignificant and hence it was eliminated in the model development. The real-time data collected from production reports of a flexoprinting unit was used to train four distinct regression models: ANN, SVR, RTE, and GPR. The hyperparameters of the models were optimized by Bayesian optimization with fivefold cross validation. The performance of the modelswerethen evaluated with cross validation to obtain the performance metrics MSE, R-squared value, and MAE. Based on the analysis of results it was observed that the GPR model stood out in several aspects. Firstly, it required the least amount of time for training, indicating efficiency in model development. The results also highlighted the superiority of the GPR model, showcasing the lowest MSE, highest R-squared value, and minimal MAE value. Following closely was the ANN model, indicating its effectiveness in predicting production output as well. This versatility demonstrated the model's capability to provide accurate estimations of runtime and associated costs, makes it a valuable tool for production planning and optimization.

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