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Machine learning Classification algorithms for prediction of surface finish of Flatwork Ironing Machine.

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ABSTRACT

Flat-work Ironing Machine, also known as the Saree Roll Press machine, has become a prime calendaring process because of its high output fabric finish. Saree Roll Press is an arduous task, and hence, Surface Finish of Saree Roll press heavily depends on Feed Rate and Roller Temperature. Surface Finish information was gathered from Flat-work Ironing Machine by performing 49 tests for different Roller Speed and Roller Temperature. The several test on Saree Roll Press is costly and time consuming, hence it necessary to predict the surface finish. This paper describes the comparison of twenty-three machine learning (ML) classification models on surface finish prediction. The best algorithm obtained is Linear Discriminant, Quadratic Discriminant, and Bagged Tree with an accuracy of 100%. The best algorithm was selected on basis of Performance Metrics i.e. F-Score, Accuracy, Area under Curve (AUC) of Receiver operating characteristics curve (ROC).

Keywords:*Flat-work Ironing Machine, Supervised Machine Learning, Classification Algorithms.*

1. INTRODUCTION

The laundry industry has witnessed a revolution in automation and control with the advent of Saree roll press machines, Industrial Saree roll press machine or (calendaring machine) Flat work ironer belongs to ironing and pressing machines in laundries, extensively used for Saree roll pressing. The calendering rolls are invented as per its application likewise single, double, three heated rolls in the field of textile, paper etc. The main component of Saree roll press machine is the single heated roll which is electrically heated. Saree roll press machine is introduced for automatic roll press and polishing service to take care of the different sarees, dhotis, curtains, bed sheets etc. For this purpose, optimum feed rate and optimum temperature is needed to be predicted and optimized for highest surface finish. Saree roll press ma- chine or calendaring machine is the only solution for laundry services, as it is the most effective way to get the highest surface finish in shorter time duration without losing its actual polish and finish of the fabric used, silk at major. This is the most promising technology currently needed which gives maximum profit with less operating time and cost.

Saree Roll press and its Finishing is an inimitable laundry facility that aims to restore and preserve the inherent brightness and shine of the fabric by rolling it around rollers, deprived of heart-rending its robustness and innate splendour. It is a process of rolling all kinds of silk, cotton, fancy, designer Sarees and Handwork moti work, embroidered sarees. It can also be done for half sarees, skirts, blouses, shawls, light carpets, curtains, bed-sheets, and drapes. Roll polishing revives the look of the fabric, making it smooth and lustrous. Silk tends to be heirloom fabrics and has an emotional value quite incomparable to its purchase price. With that in mind Saree roll press machine is introduced for an automatic roll press and polishing service to take care of the different, dhotis, curtains, bed-sheets, etc. For this purpose, the optimum feed rate and the optimum temperature is needed to be predicted for the highest surface finish.

Data science developments have enabled the widespread using of machine learning (ML) for data analysis and prediction. ML is a part of the development of artificial intelligence and can be applied to the analysis of large amount of data, thus suitable, where abundant data are collected, stored, managed, and analysed with appropriate models [2]. Several ML methods are currently available, but they may have weaknesses in reliability such as generalization error, over fitting, and under fitting. Therefore, it is necessary to analyse and compare various methods when applied to specific purposes for selecting the one with the best performance [3]. To the best of our knowledge, no study has made a systematic comparison of different ML methods to determine suitability for surface finish prediction. We want to evaluate suit- able ML methods for this purpose using actual surface finish and determine the most appropriate one.

2. Materials and Methods

2.1. Data and modelling

Data were collected from Saree roll press machine consisting of Roller Speed (cm/sec), Roller Temperature (C), and Surface Finish (%). The roller speed and roller temperature were considered as input parameters, while surface finish is considered as output. The data is then scrutinized for surface finish values in “Good” and “Bad” category. These categorized values are considered as prediction output for machine leaning classification algorithms. We used the ML algorithms listed in Table 2 for pattern recognition and modelling. In this process, we adopted a five-fold cross-validation for modelling. The data set was randomly partitioned into five equal sized subsets. Four subsets were used as training set and the remaining sub-sample was used as testing set. The cross-validation process was repeated 5 times and each of the 5 subsets was used as validation data exactly once. Finally, we chose the model with the smallest test error [4].

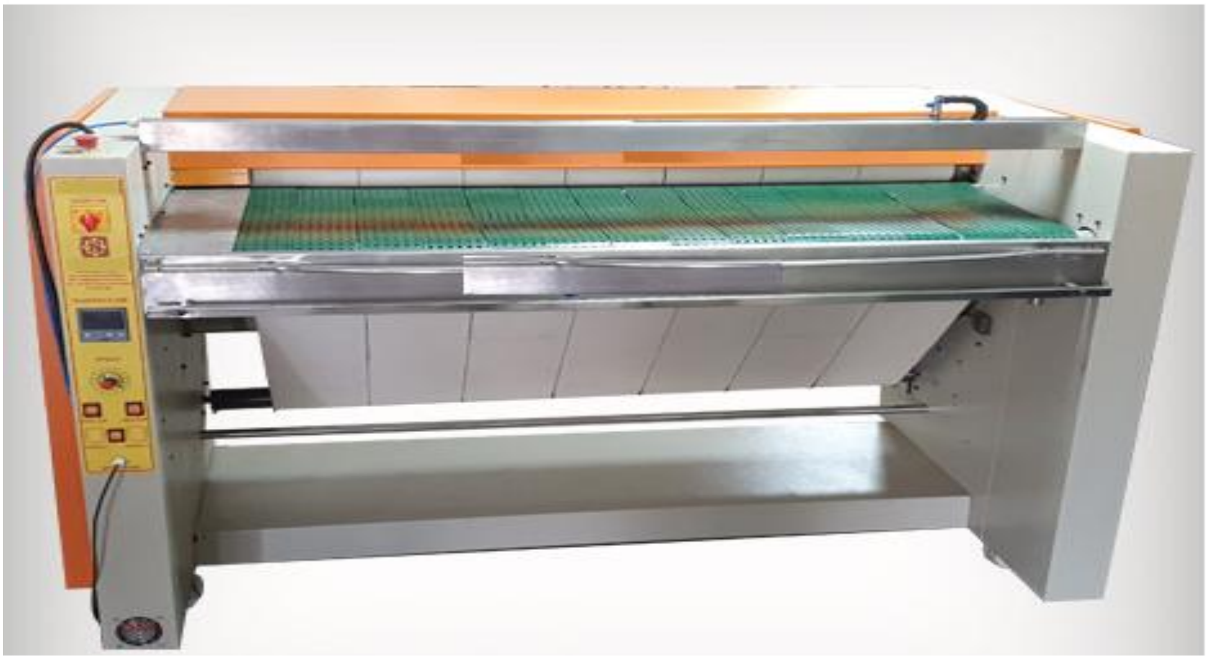

Fig 1: Saree Roll Press Machine (Flatwork Ironer).

2.2.Description of Saree Roll Press Machine (Flatwork Ironer).

1. Cylinder Dimensions: 400×1600 mm.
2. Supply Tension: 220×440.
3. Weight, Gross/Net: 285 kg.
4. Width: 6 feet
5. Speed: Adjustable speed range 0.8-3 m/min
6. Model: Electrical (size 6.5 feet x 2.2 feet)
7. Power: 12 KW
8. Heating coil Temperature with developments stop streetcar mounted for simple development one touch miniature regulator

2.3. Model performance evaluation

There are 5metrics commonly used in machine learning to evaluate the prediction performance [15, 16]: receiver operating characteristic (ROC) equal to area under curve (AUC), accuracy, precision rate (P), recall rate (R) and (F). The classification threshold was all 0.5 in this study [5]. The quality of surface finish is a binary classification problem, which is defined by the ground truth that determines the prediction performance. The prediction can retrieve true positive (TP), false positive (FP), true negative (TN), or false negative (FN). In this study, we identified the good surface finish and bad surface finish as the positive and negative cases, respectively, obtaining the classification matrix detailed in Fig. 2.

To obtain the ROC curve, we plotted the true positive rate (TPR) according to the false positive rate (FPR), which are given by

$$TPR=\frac{TP}{TP+FN} \quad \text{……………………………..} \ (1)$$

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$$FPR=\frac{FP}{FP+TN} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Note that higher values of the AUC corresponding to the ROC curve result in betterperformance.

2.4. 23 Algorithms used are:

1. Fine Tree 2. Medium Tree. 3. CoarseTree
4. Linear Discriminant. 5. Quadratic Discriminant 6. Logistic Regression
7. LinearSVM 8. Quadratic SVM 9. Cubic SVM
10. Fine Gaussian SVM 11. Medium Gaussian SVM 12. Coarse Gaussian SVM
13. Fine KNN 14. Medium KNN15. Coarse SVM
16. Cosine KNN. 17. Cubic KNN 18. Weighted KNN
19. BoostedTree 20. Bagged Tree 21. SubspaceDiscriminant
22. SubspaceKNN 23. RUS BoostedTree

(SVM, support vector machine, KNN, k-nearest neighbours.)

Table 1: Configuration parameters for Machine Learning Classification

Sr. No	**Roller.Speed (cm/sec)**	**Roller Temperature (^{o}C)**	**Surface.Finish (%)**	**Quality**
1	20	35	40	Bad
2	20	40	50	Bad
3	20	60	75	Bad
4	20	80	84	Bad
5	20	100	88	Good
6	20	130	92	Good
7	20	160	95	Good
8	25	35	37	Bad
9	25	40	45	Bad
10	25	60	73	Bad
11	25	80	83	Bad
12	25	100	87	Good
13	25	130	90	Good
14	25	160	94	Good
15	30	35	34	Bad
16	30	40	42	Bad
17	30	60	69	Bad
18	30	80	80	Bad
19	30	100	85	Good
20	30	130	91	Good
21	30	160	94	Good

22	35	35	37	Bad
23	35	40	45	Bad
24	35	60	73	Bad
25	35	80	83	Bad
26	35	100	85	Good
27	35	130	87	Good
28	35	160	91	Good
29	40	35	33	Bad
30	40	40	41	Bad
31	40	60	67	Bad
32	40	80	79	Bad
33	40	100	83	Bad
34	25	130	86	Good
35	40	160	89	Good
36	45	35	31	Bad
37	45	40	39	Bad
38	45	60	65	Bad
39	45	80	76	Bad
40	45	100	81	Bad
41	45	130	85	Good
42	45	160	90	Good
43	50	35	28	Bad
44	50	40	30	Bad
45	50	60	63	Bad
46	50	80	76	Bad
47	50	100	81	Bad
48	50	130	85	Good
49	50	160	89	Good

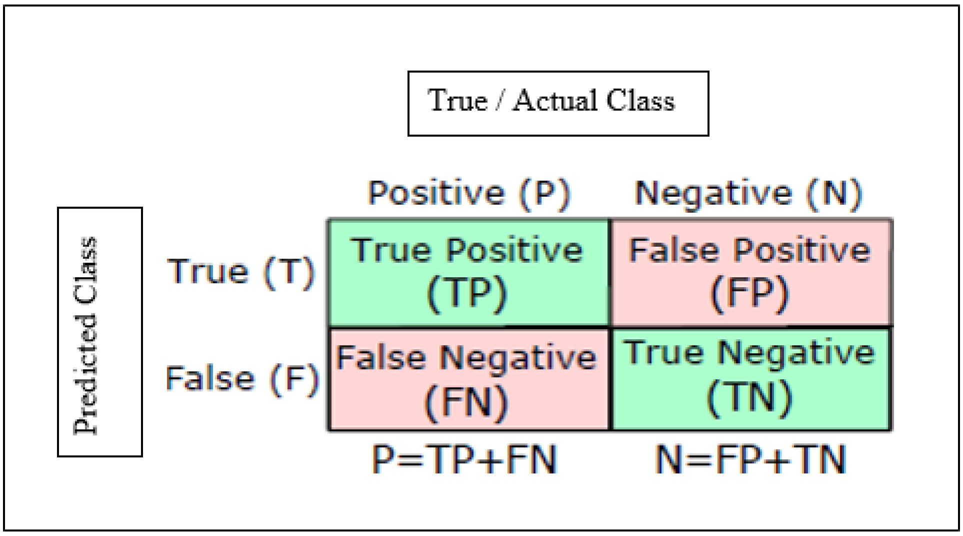

Fig 2: Classification Matrix.

In addition, we determined the accuracy, which is the proportion of correct predictions for both good and bad over the total number of experiments. Besides the correct discernment of good surface finish, we considered the amount of predicted good surface finish who were truly good by using precision rate 'P' and the number of good surface finish predicted by using recall rate 'R'. The precision and recall rates are respectively defined as

$$P=\frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$R = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

We also used the comprehensive performance index given by the F score to describe the effectiveness of each algorithm, with values closer to1indicating better performance. The F score is defined as

$$F = \frac{2 \times P \times R}{P + R} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

We implemented every evaluated method and calculated all the performance parameters selected for this study using MathWorks MATLAB (R2018a) running on Microsoft Windows 10. Cross-validation analysis on the performance of models is performed by matching, learning models with good predictive performance were selected and computed repeatedly for 10 times.

3. RESULTS

The ROC curve and its AUC along with the accuracy of the evaluated algorithms on surface finish data were shown in Table 2 and Fig.3 respectively. The AUC value is typically between 0.5 and 1.0, where 0.5 indicates an algorithm performance similar to the probabilities of coin tossing. The AUC values were low in following models: boosted trees, cosine k-nearest neighbours (KNN); indicating sensitivity and specificity of these models are low. The accuracy of linear discriminant, quadratic discriminant, and Bagged Tree (100%) was the highest among all models. Algorithms such as (fine, medium, coarse) Trees, KNN, SVM, LR, (fine, medium and coarse) Gaussian SVM resulted in accuracy of approximately in range of 93% TO 98%, while fine KNN shows 87% accuracy.

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Table2:AUCoftheROCcurve,accuracy,Fscore,precisionPandrecallRofevaluated algorithms on surface finishdata.

Algorithm	AUC	Accuracy	F-score	P	R
Fine Tree	0.93	93.9	0.923	0.8571	1
Medium Tree	0.93	93.9	0.923	0.8571	1
Coarse Tree	0.93	93.9	0.923	0.8571	0
Linear Discriminant	1	100	1	1	1
Quadratic Discriminant	1	100	1	1	1
Logistic Regression	1	98	0.9729	0.9473	1
Linear SVM	0.99	93.9	0.9091	1	0.8334
Quadratic SVM	1	98	0.9729	0.9473	1
Cubic SVM	1	98	0.9714	1	0.9445
Fine Gaussian SVM	1	83.7	0.7142	1	0.5556
Medium Gaussian SVM	1	93.9	0.9091	1	0.8334
Coarse Gaussian SVM	1	93.9	0.9091	1	0.8334
Fine KNN	0.87	89.8	0.8485	0.9334	0.7778
Medium KNN	1	91.8	0.875	1	0.7778
Coarse KNN	0.45	63.3	0	0	0
Cosine KNN	1	98	0.9714	1	0.9445
Cubic KNN	1	93.9	0.9091	1	0.8334
Weighted KNN	1	95.9	0.9411	1	0.8809
Boosted Tree	0.4	63.3	0	0	0
Bagged Tree	1	100	1	1	1
Subspace Discriminant	0.99	93.9	0.9091	1	0.8334
Subspace KNN	0.97	71.4	0.3637	1	0.2223
RUS Boosted Tree	0.94	77.6	0.5926	0.8809	0.4445

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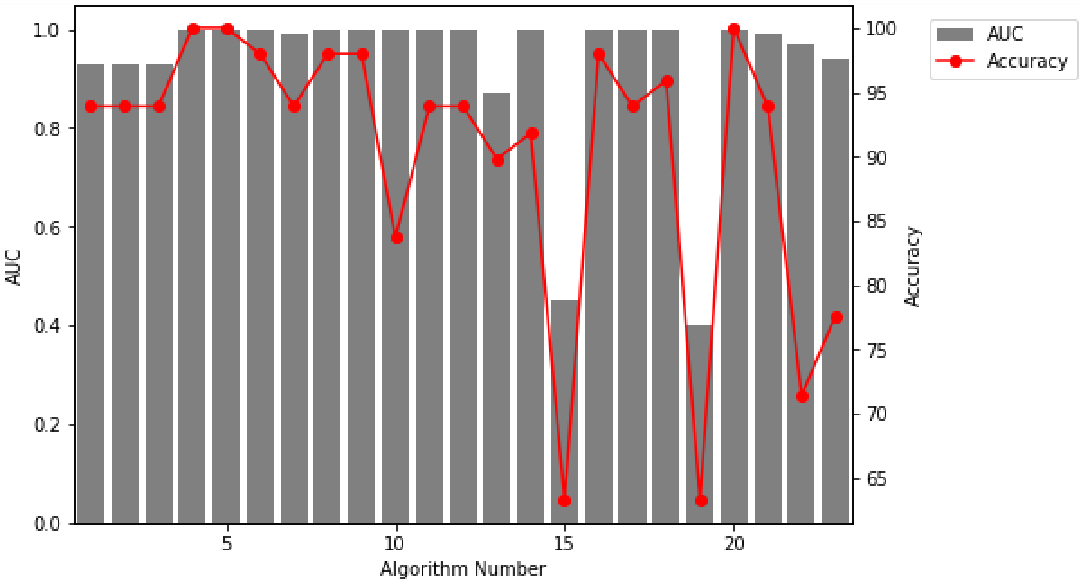

Figure3:AUC of the ROC curve and accuracy of evaluated algorithms on surface finish data.

The F score, precision, and recall of the evaluated algorithms were listed on Table 3. Precision and recall are contradictory variables; as high precision usually retrieves a low recall [5]. Table 3 showed that the recall of trees, LR, discriminants, quadratic SVM, bagged tree of the algorithms was 100%, which was higher than that of all other algorithms. Trees, LR, Linear and cubic SVM, and RUS Boosted trees had lower precision, indicating their low prediction performance.

Both the precision and recall can be described by the F score. In Table 3, the F score of most of the algorithms was less than that of linear discriminant, quadratic discriminant, and bagged indicating that these algorithms can outperform the prediction. This relation can be confirmed by comparing the precision and recall. The algorithms like coarse KNN and Boosted trees has no predictions i.e. no Recall, Precision and F-score.It was not difficult to see that linear discriminant, Quadratic discriminant and bagged trees achieved best performance in the above metrics. Therefore, we plotted their ROC curve in Fig. 3 and it became more obvious that their prediction performances are better than other algorithms.

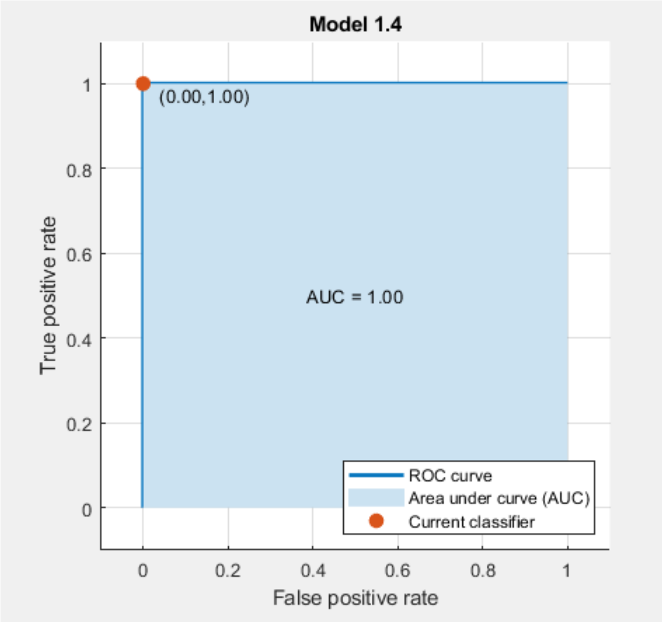

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Figure4:ROC Plot for Good Surface Finish: Linear Discriminant, Quadratic Discriminant, Bagged Trees.

4. DISCUSSION

Accurately estimating the probability of surface finish is key because it plays a crucial role in Saree roll press. We found that ML algorithms generally outperform linear regression for determination of surface finish values. ML represents a new generation of multivariate statistical methodologies. ML models can handle higher-dimensional factors more robustly than conventional methods. This capability can reduce the dependence on the practitioner's experience and ensure objective outcomes. Our study on surface finish prediction was the first to compare 23 ML algorithms for establishing the corresponding models based on different roller speeds and roller temperatures.

Based on the analysis above, coarse KNN and boosted trees are clearly not suitable to predict the surface finish, as most ML algorithms retrieve better prediction performance. In a wider sense, ML can provide tools for the development of high-performing surface finish prediction models. However, the large number of ML algorithms complicates the proper selection. A retrospective study by Liu et al. [6] analyzed varying sizes of training and test sets and different factors that can severely affect the sensitivity and specificity of the same algorithm. Given that our study uses the same dataset and set of factors to evaluate the predictive performance of different algorithms, the results are more objective and present reduced variability.

Thus, our work presented here is just an early pilot in this field. In the future, we will continue to enroll more parameters for future evaluations to verify further the results from this study. In addition, we are still working on the methodology to evaluate the best input parameters for higher surface finish using optimization.

5. CONCLUSION

For predicting the Surface finish for Flatwork Ironing machine, the 23 different supervised ML classification algorithms were tested on Saree roll press machine data, this the outcome foe the best algorithm for prediction of surface finish. In conclusion, linear discriminant, quadratic discriminant, and bagged tree ML algorithms have better performance in predicting the outcome of surface finish of Saree roll press and are best suitable algorithms with accuracy of 100% is found in our research.

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