Chapter 1

PREAMBLE

1.1 Introduction

Parameters of the paper for quality enhancement through machine learning have become essential for the optimal functioning and control of the parameters.

Paper manufacturing is divided into eight steps that are sequentially performed as shown in figure below.

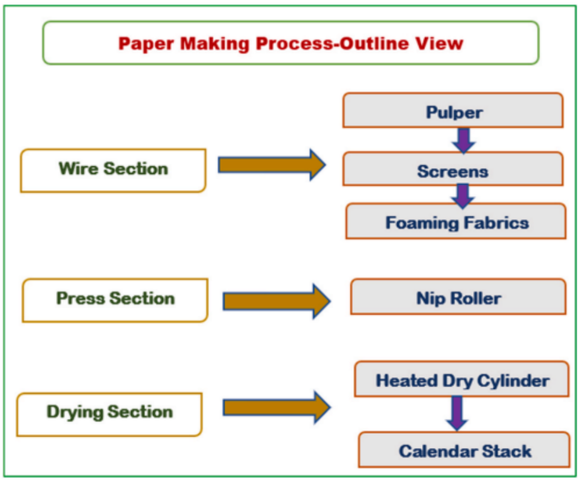


Fig. 1. Paper making process

The paper-making machine has a width of 10–15 feet and a length that varies from half a football field to a full football field, which is 100 yards. The wet end and the dry end make up the main components.

An endless belt of plastic or wire screen moves continuously.

Pulp and water are received at the screen end, and the excess water drains off to form a continuous sheet.

The sheet is then dried by suction, pressure, and heat.

There are three sections in the paper industry which are the wire section, the press section, and the drying section.

The paper process involves three sections, each with an internal subsection.

Water, caliper, and weight are the basic parameters to measure in the drying section of the paper industry.

They determine the amount of steam used in the dryer section, which in turn affects the production cost, so these parameters are primarily used for measurement and control

In the paper industry, moisture control is essential to maintain paper quality and to conserve energy. It is important to monitor the moisture level when the paper comes out of every section of the industry. When the paper comes out of the dryer section, it should have a moisture content of only 5%–10%. Moisture content is measured as relative humidity (RH).

The paper is designed to remain stable at 45%–55% relative humidity in an environment of 72◦ Fahrenheit. The static electricity generated when the humidity level is below 45% RH can shock the staff if there is no moisture present .

Additionally, it causes the paper to shrink, curl, and lose dimensional stability. Hence, the quality of the paper should be continuously monitored to reduce waste and to prevent risk to the staff. All papers should have a uniform caliper or thickness.

A deviation in the caliper could affect some properties, including formation, drying, strength, stiffness, optical quality, etc. Furthermore, the cutter machine has to deal with the accumulation of bad mother rolls. Variations in calipers affect the quality of printing and the ability to run the press.

Weight of the paper is very important for paper production, productivity and quality of paper. If the basis weight fluctuates, it can affect the quality of the paper, resulting in uneven drying, blackish development, and other issues.

The moisture control in the drying section of the aper machine is performed using a Genetic Algorithm (GA). Conventional PID controller is used in the process where tuning of the gain parameters like Kp, Ki, Kd are done using a Genetic Algorithm .

The mathematical model for the single-tier cylinder-based paper drying process is focused which is used widely with high-speed paper-making machines. The mathematical model is prepared based on real-time data .

The dynamic modeling in the drying process of the paper which is done using a multi-cylinder in the drying section with mass and heat balancing around the drying cylinders .

The removal of water from the thin film during the paper making process using the Volume of Fluid (VOF) model is performed in the final stage of the drying process.

1.2 Literature Survey

The research is done using various soft computing techniques like Genetic Algorithms, Evolutionary Programming, Particle Swarm Optimization, and Bacterial Foraging Optimization for the controlling of moisture in the paper industry . The sensing of multi parameters in the paper industry using terahertz radiation is used along with a highly accurate material characterization approach.

The sensing of parameters was found to be better by terahertz radiation which has evolved from stratified dispersive model approach to spatial in the homogeneity of the sample.

The estimation of energy efficiency using firm-level data in the paper industry employed a slack-based method with variable returns to scale as flexible to perform analysis. The stack-based method revealed no significant improvement in energy efficiency level with an energy-saving potential of 40% .

While competing in the market with low-cost pulp and paper goods, pulp and paper mills are under enormous pressure to continue operating profitably in the face of escalating expenses connected with lumber, energy and process chemicals.

There has never been a more crucial time to enhance paper quality asset productivity while also optimizing your mill processes to prevent waste wherever it may be emerging as each new cost increase cuts into bottom line.

Machine learning has the capability to support bundled products and services that position of future profitability year over year by converting adversity into opportunity as shown in figure below.

Fig. 2. Influence of ML and NN in manufacturing industry

More than automation and technological up-gradation are involved in reliability. Manufacturing processes might fall short of their dependability targets even when using the most advanced technologies and successful techniques if they are unable to properly change the way they operate. An overall manufacturing initiative, reliability affects purchasing, management, engineering, operations, maintenance, planning, and scheduling

From Fig. 2, the impact of machine learning is getting tremendous growth in the manufacturing sector mainly to enhance the production quality and downtime.

Especially from 2020 to 2022, the implementation of Machine learning has improved the overall efficiency to 11.5% by reducing the downtime to 2.7% to achieve the target cost greater than 1.2%.

Energy conservation in the paper and pulp industry to make it cost effective is done by operating an analytical framework to measure the marginal energy saving cost and construct an energy conservation model. It paved a way for the difference in the energy-saving in different provinces and the optimal energy is also saved based on the energy conservation supply curve .

Chapter 2

METHODOLGY

2.1 Method

In the present work, the development of paper quality enhancement using machine learning techniques is done based on different algorithms such as linear regression, decision tree, K-Nearest Neighbor, and Support vector Regressor. The variables used are moisture, caliper, grammage, and output is controlling of steam pressure. These three input variables play a crucial role in the reduction of steam pressure output for the paper industry. Hence, these are considered as the key performance indicators as shown in Fig. 3.

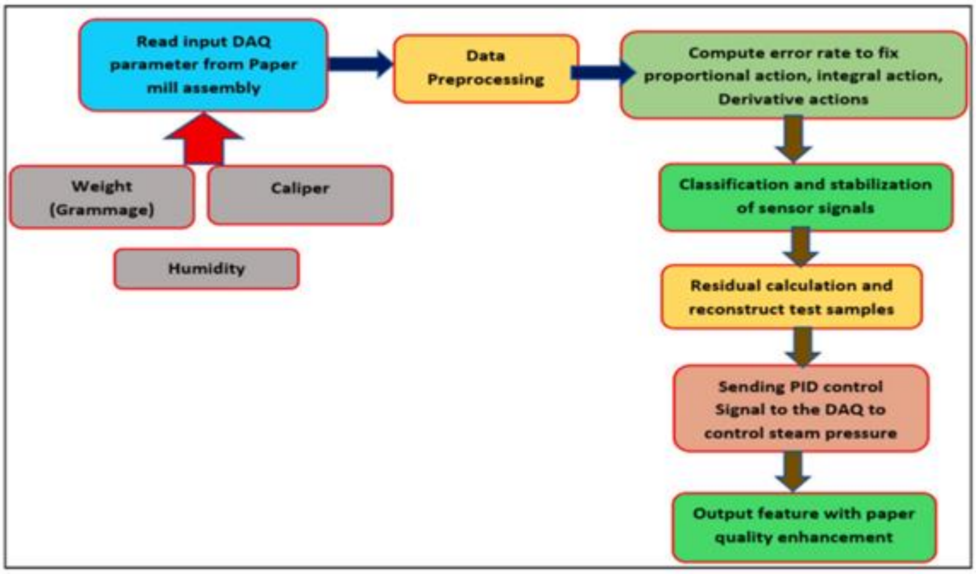


Fig. 3. PID control actuation

Advanced control is a broad word that covers anything from supervisory optimization systems to intricate PID-based control techniques. However, a regulatory level controller that can manage the lengthy response times and process disruptions better than standard PID control is required to fulfil the fundamental control requirements of the primary paper manufacturing processes.

Long process time delays can be overcome using the tried-and-true method of data predictive modeling. The same design process can also be used to solve multivariable systems, such as interacting control loops, and it also offers an elegant framework for including measurable disturbances as feed forwards in the control design .

The data model analysis control is able to regulate processes with long delay or response times (or quick response processes where the time delay is a key part of the response dynamics) better than is possible with PID type controllers by using these models as the foundation for a predictive control design.

By include them as feedforward variables in the control strategy, this method can also be used to automatically model and mitigate the impacts of observed disruptions.

The dataset of these parameters was collected from the paper industry.

Machine learning techniques with different algorithms were investigated and the results were compared. In addition, model interpretation, cross-validation, and error calculation have been performed by comparing with the existing models.

Fig. 4 shows the proposed model of paper quality enhancement. The dataset for moisture, caliper and weight are imported and the sample values are displayed for verification.

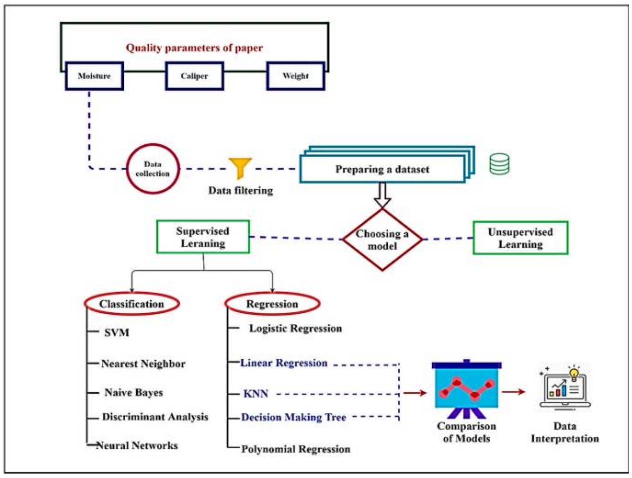


Fig. 4. Proposed model of paper quality enhancement

The dataset is divided into training data and testing data and they are provided for performing linear regression, KNN, decision tree, and support vector regression. The execution time is noted and the predicted values are found for calculating errors like mean squared error, mean absolute error, root mean squared error, and R squared score.

The error graph is plotted based on mean absolute error and the line plot graph is also plotted. Finally, model interpretation is done to identify the best model to enhance the paper quality.

2.2 Machine learning algorithms

In Fig. 5 the dataset is imported and the sample values are displayed for verification.

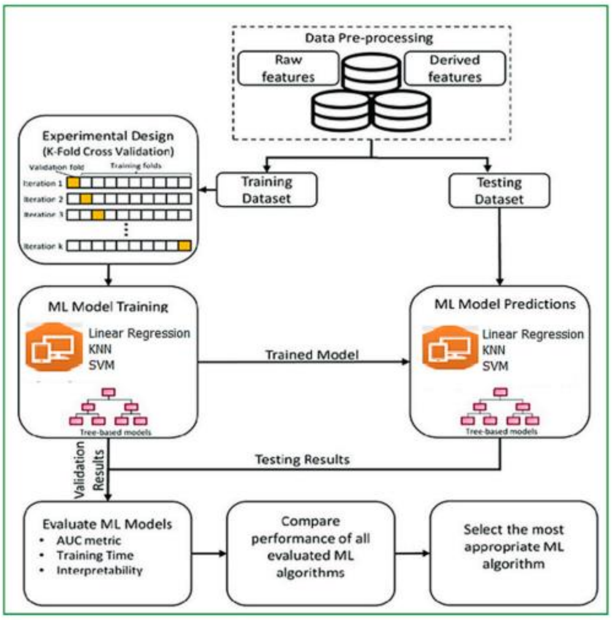


Fig. 5. Implementation steps of Machine Learning Algorithm

The data is divided into training data (80%) and testing data (20%) and it is provided for performing linear regression, KNN, decision tree and support vector regression. The execution time is noted and the predicted values are found for calculating errors like mean squared error, mean absolute error, root mean squared error and R squared score. The error graph is plotted based on mean absolute error and the line plot graph is also obtained.

In the proposed work, both supervised machine learning algorithms are utilized for better result statistics of paper quality enhancement.

Hence, in the present work, under supervised machine learning both classification and regression category algorithm are applied and compared with each other for better enhancement. So, under classification category Support Vector Regressor (SVR) is undertaken and compared with regression techniques like Linear Regression (LR), KNN and Decision Tree (DT).

Finally, model interpretation is also done and it is observed that KNN model is best suited for practice.

2.3 Linear regression

Linear regression provides the relationship between two variables that is a dependent variable and an independent or explanatory variable.

It is used in prediction; forecasting and error reduction using Equation (1).

$$Y = m(x-1 + x-2 + x-3) + c \quad (1)$$

From the above expression,

y – Steam pressure ; x 1 – Moisture; x 2 – Caliper; x 3 – Grammage, c - Intercept of the line; m - Linear regression coefficient.

2.4 K-NN (k nearest neighbors)

KNN algorithm is used to solve both regression and classification problems. It attempts to determine what a group of data points is based on how closely it matches the members of one group or other in the training set. It is used in image and video detection, handwriting recognition, etc. The equation for KNN regression model is shown in Equation (2).

$$(\sum(i = 1)\ k\ (|x-i - y-i|Nq\ ))1/q \quad (2)$$

Where, x i - Point 1; y i - Point 2 with N pointing Neighborhood count**.**

2.5 Decision tree algorithm

Decision tree algorithm is used to solve both regression and classification problems using Equation (3). It is a flowchart like structure in which each branch represents the outcome of the node, and each leaf node represents Decision tree algorithm is used to solve both regression and classification problems using Equation (3).

$E(T, X) = \sum(C \in X)P(c)E(c)$ (3)

Where, T - Current state. X - Selected attribute. P(c)- Individual observation. E(c)- Entropy of individual observation.

It is a flowchart like structure in which each branch represents the outcome of the node, and each leaf node represents a class label. In this, the data is continuously split according to a certain parameter a class label. In this, the data is continuously split according to a certain parameter.

2.6 Support Vector Regression

Support Vector Regression (SVR) algorithm solves both regression and classification problems using Equation (4).

It creates a hyperplane or a line that separates the data into classes. It divides the datasets into classes to find a maximum marginal hyperplane. Support vectors are the data points that are closest to the hyperplane.

$Y = a- 0 + a- 1x$ (4)

Where, a 0 - Intercept of the lin ; a 1 - Linear regression coefficient; Y–Dependent variable; x – Independent variable SVR is similar to linear regression equation. Here, straight line is referred to as hyperplane.

Caliper ranges from 0.0032 inches to 0.0078 inches, Weight is limited between 59 and 178 g/m2 . The moisture content varies from 3.5 to 5.45 RH. The steam pressure is to be maintained between 0.01 and 4 bars. Caliper, weight, grammage are the input values; steam pressure is the output in Table 1.

Table 1
Input and output Parameters Range.

Parameters	Starting values	Ending values
Weight (g/m^2)	59	178
Caliper (inch)	0.0032	0.0078
Moisture (RH)	3.5	5.45
Steam Pressure (bar)	0.01	4

Chapter 3

IMPLEMENTATION

3.1 Error calculation

Error Calculation 1 - Root mean squared error takes the square root of difference between the predicted value and the actual value for all samples in the data set from which average is calculated.

Equation (5) is the root mean square mathematical formula :-

RSME = (∑(𝑖 = 1) N(({Predicted− i} − {Actual− i})) / N) (5)

Error Calculation 2 – Mean squared error takes difference between the predicted value and the actual value for all samples in the data set from which the average is calculated.

Equation (6) shows mean square error mathematical formula :-

MSE = 1 / n ∑(i = 1) n {yi − (y) i } {yi − (y) i }2 (6)

1/n ∑(i = 1) n - Test set; yi–Predicted value; (y) i – Actual Value

Error Calculation 3 - Mean absolute error finds absolute error difference between predicted values and actual values.

Equation (7), is the mean absolute error mathematical formula :-

MAE = 1 / n ∑(i = 1) n |yi − (y) i | (7)

1/n ∑(i = 1) n - Test set; yi–Predicted value; (y) i – Actual Value R Squared Score is calculated in order to find the correlation values.

Equation (8) gives the R2 Score mathematical formula :-

R2 = (1 − [SSE / SSW]; SSE = ∑(y − ŷ) 2 ; SSW = ∑(y − y) 2 (8)

Where parameters like y is the actual value; yˆis the predicted value of y; yis the mean of the y value.

Errors such as root mean squared error, mean squared error, mean absolute error are calculated along with execution time between linear, KNN, Support Vector, and Decision Tree models as shown in Table 2.

The one with minimum error is said to be more efficient.

Table 2
Comparison between machine learning models.

Components	Machine learning Algorithms			
	Linear Regression	KNN	SVR	Decision making Tree
Execution time	0.582 ms	0.352 ms	0.859 ms	0.855 ms
Root mean squared error	0.1744	0.05700	0.1245	0.2283
Mean squared error	0.0304	0.0032	0.0155	0.0521
Mean absolute error	0.0094	0.0087	0.0267	0.0165
R Squared score	0.979	0.997	0.9894	0.9644

Table 2 shows how much deviation is between KNN regression and other models. The deviation is represented as the percentage difference between KNN and other models. The execution time shows a slight difference when compared with KNN regression. The root mean squared error of linear regression deviates 39% with KNN, 6.7% with SVR and 10% with Decision Tree.

The mean squared error of linear regression deviates 2.7% with KNN, 1.2% with SVR and 4.8% with Decision Tree. The mean absolute error of linear regression deviates 0.07% with KNN, 1.8% with SVR and 0.07% with Decision Tree.

The R Squared Score of linear regression deviates 1.8% with KNN, 0.83% with SVR and 3.3% with Decision Tree. Since there is a major deviation of values with the other models and KNN, KNN is best suited for practice.

3.2 Model Interpretation

Model Interpretation explains the decisions taken by the response function by answering questions like what, why, and how. It helps to debug the model and builds trust between humans and the model. It understands the model in a better manner.

Fig. 6 explains the contribution of each input parameter such as Grammage, caliper and moisture in order to get the desired output parameter steam pressure.

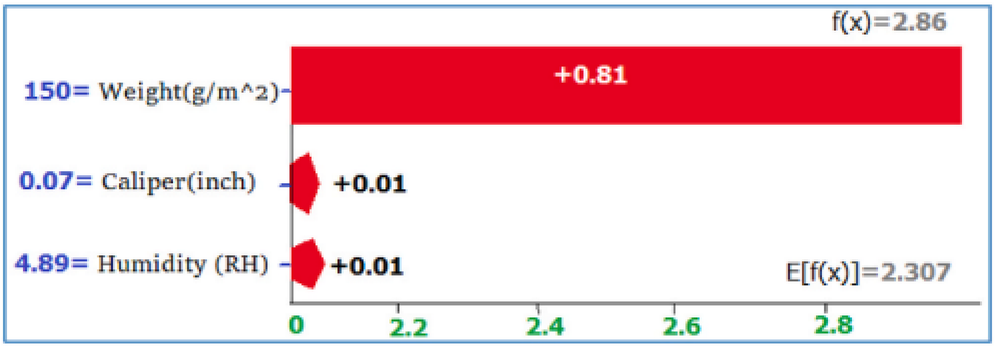


Fig. 6. Parameter Contribution Graph

Table 3 shows the Shap values which stand for SHapley Additive explanations. The shap values represent the contribution of that particular data point in predicting the outputs. Shap values [0] shows the first prediction of steam pressure.

Table 3
Model interpretation with Shap_values ().

Shap_values ()	Grammage	Caliper	Moistur
Shap_values [0]	0.81	0.01	0.01
Shap_values [1]	−1.99	0	0
Shap_values [2]	1.1	0	0
Shap_values [3]	−0.04	0	0
Shap_values [4]	−0.62	0	0
Shap_values [5]	1.08	0	0

The contribution of grammage (0.81), caliper (0.01) and moisture (0.01) are very less since the values lie close to zero. In shap [1] which is the second prediction, the contribution of grammage is high (− 1.99) and caliper and moisture do not contribute to predict the outputs.

In the third, fourth and fifth predictions, caliper and moisture do not contribute for the prediction but grammage contributes − 0.04, − 0.62 and 1.08 respectively for the prediction.

The steam supply in the drying section constitutes nearly 80% of the energy used in this paper manufacturing process. The level of moisture and grammage decides the amount of steam to be supplied in the drying section.

If these are calculated using the machine learning technique with lesser calculation time, the supply of the steam to the drying section can be adjusted with the moisture level in the paper.

The proposed method satisfies the necessities of reducing the usage of steam by around 1.5% in the drying section and also improves the efficiency of the dryer. When n is the total number of samples in the paper-pulp manufacturing unit monitoring data, m is the dimension size, and yi j and ̂yi j denote the ith dimension of the jth paper quality monitoring samples objectives and outputs, respectively.

$$E = \frac{1}{2} \sum_{j=1}^{n} \sum_{i=1}^{m} (y_{ij} - \hat{y}_{ij})^2 \quad (9)$$

The weight of the predicted steam pressure in Equation (9) is crucial for improving the efficiency outcomes. When the input characteristics are significantly different, Tanh is preferred; otherwise, the sigmoid function is used. The input needs to be normalised when using Sigmoid and Tanh as shap functions, but not when using ReLu.

A nonlinear shape function and a highly nonlinear decoder have been added to the auto-encoder.

3.3 Cross Validation

Cross validation is a statistical method for evaluating and comparing machine learning algorithms by dividing data into two segments: one is used to learn or train a model and the other is to test the model.

To do cross-validation as shown in Figs. 7 and 8, the predict and score packages are imported initially.

The computational cost and cross-validation procedure runtime for big k values. By training 5 separate models using K-fold cross validation, where each model uses one speaker from the training dataset and the rest from the testing dataset.

Cross validation will not affect the parameter value k you select for the knn model, but the performance will change because you're essentially training and testing on slightly different "sets" of train/test splits. Since the best method out of comparison is KNN, cross-validation is done only to that method. df. head () returns the first 5 rows from the data frame.

The cross_val_score () function is used to perform evaluation, taking the dataset and cross-validation configuration and returns scores.

The most common choices for k are 5 or 10, however there is no set rule. However, the size of the dataset affects the value of k. Strong protection against overfitting is provided by cross-validation.

The entire dataset is divided into sections. It is vital to divide the data into k folds in order to perform the usual K-fold cross-validation. Then, using the last holdout fold as the test set, we iteratively train the algorithm on k-1 folds. The model produced by kNN is essentially just the available labelled data arranged in some metric space.

To put it another way, there is no training phase for kNN because there is no model to create. All that is happening in kNN is template matching and interpolation.

There is no validation process either. The predicted values are stored in variable preds and the Mean squared error for the same is calculated: 0.0184 in Fig. 6.

```
[ ] preds=cross_val_predict(model,X_test,y_test)

[ ] print(f"Mean Squared Error : {mean_squared_error(y_test,preds)}")
```

Fig. 7. Predicted values and error correction

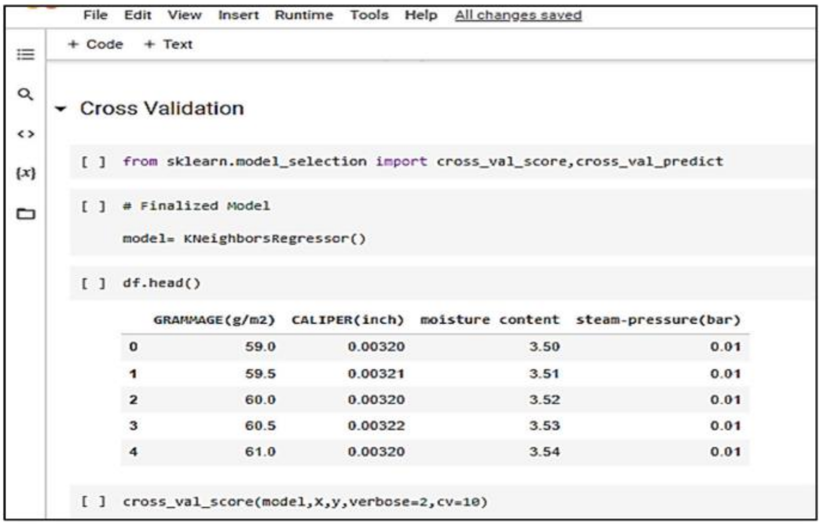


Fig. 8. Importing cross validation packages

To do cross-validation as shown in Figs. 7 and 8, the predict and score packages are imported initially.

Chapter 4

RESULTS AND DISCUSSIONS

4.1 Results

In order to analyze the efficiency on the ML on the undertaken datasets, RMSE value of k-NN algorithm seems to be 4.57 at the minimum case as compared with other algorithms with execution time of 2.58 ms. The best fit model rate of maximum R2 value of 90.78 is attained by K-NN followed by SVR, DT and minimum of 72.38 score retained for the statistical comparison analysis.

The deviation is represented as the percentage difference between KNN and other models. The execution time shows a slight difference when compared with KNN regression. The root mean squared error of linear regression deviates 39% with KNN, 6.7% with SVR and 10% with Decision Tree. The mean squared error of linear regression deviates 2.7% with KNN, 1.2% with SVR and 4.8% with Decision Tree. The mean absolute error of linear regression deviates 0.07% with KNN, 1.8% with SVR and 0.07% with Decision Tree. The R Squared Score of linear regression deviates 1.8% with KNN, 0.83% with SVR and 3.3% with Decision Tree. Since there is a major deviation of values with the other models and KNN, KNN is best suited for practice.

It is seen that the KNN model (represented by plus) is nearer to zero whose values range between 0.2 to maximum of 0.4 and minimum of − 0.2 while the Linear regression (represented by dot) values range from 0 to 0.2 maximum and minimum of − 0.6, decision tree (represented by inverted green triangle) values range from 0 to 0.8 and minimum of − 0.2 and support vector regression model (represented by inverted red triangle) the values range is from 0 to 0.5 maximum and minimum of − 0.4.

The better a regression model fits a dataset, the lower the residual standard error. On the other hand, a regression model fits a dataset worse the bigger the residual standard error. The residual square sum may equal 0. A model fits the data more accurately the smaller the residual sum of squares; conversely, the larger the residual sum of squares, the worse the model fits given data. Zero indicates that their model fits the data perfectly. The values of LR, Decision tree and SVR deviate away from zero indicating more errors which makes KNN model best suited for practice. In Straight line $y = mx + c$ where KNN model occupies most of the straight line whose values are ranging between 0 and 4 based on the steam pressure and represented by the symbol +. The values of the other models also lie between 0 and 4 based on steam pressure which are represented by blue circle for linear regression, inverted green triangle for decision tree and inverted red triangle for SVR. These models fail to fall on the straight line and deviate from the line. Changes in the machine learning model using different portions of the training data set are identified using a variance.

The parameters selected for comparison are execution time, rise time, settling time, the error and accuracy calculation. In other grammage. In BFO–PSO, while taking moisture only as parameter, the rise time and settling time of the model are 0.1462 s and 0.8 s and in Particle Swarm Optimization method, while considering weight and moisture as the parameters, they were 0.156s and 0.638 s respectively. In the other model where they have used Adaboost machine learning model, the precision was 0.972 ms. In our proposed model, the execution time of KNN model, the execution time was only 3.5 ms where we have considered three parameters such as moisture, caliper and weight, which is very less when compared with the other models considering only one or two parameters only. In other models, the ISE were 1.1122 and 0.001111, and the accuracy of Adaboost machine learning model was 0.97. In our model, we have calculated root mean squared error which is 0.06, mean squared error which is 0.004, mean absolute error as 0.0007 and R2 score as 0.996 which shows a better performance than the other methods.

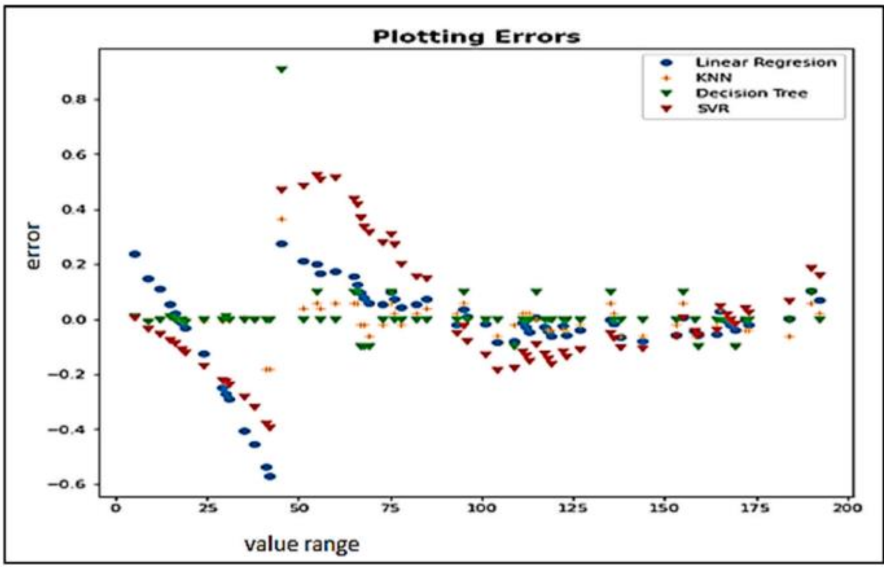
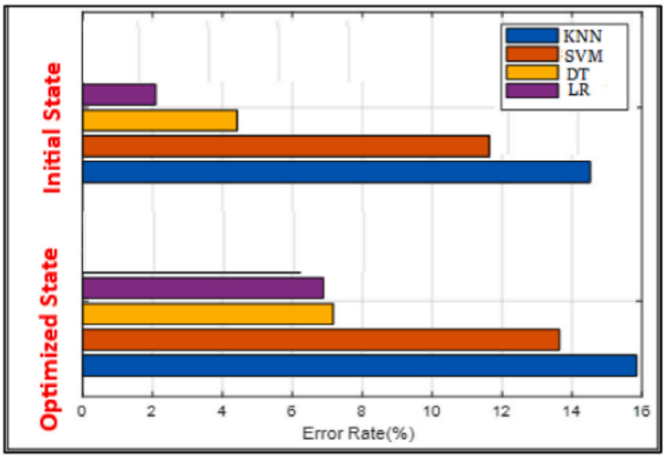


Fig. 9. Plotting of Error based on Mean Absolute Error

Based on the mean absolute error, a graph is plotted in Fig. 9. It is seen that the KNN model (represented by plus) is nearer to zero whose values range between 0.2 to maximum of 0.4 and minimum of − 0.2 while the Linear regression (represented by dot) values range from 0 to 0.2 maximum and minimum of − 0.6, decision tree (represented by inverted green triangle) values range from 0 to 0.8 and minimum of − 0.2 and support vector regression model (represented by inverted red triangle) the values range is from 0 to 0.5 maximum and minimum of − 0.4.



TFig. 10. Residual Error analysis for better interpretation

The difference between a group of observed data and their mathematical mean is known as residual error is given in Fig. 10. The better a regression model fits a dataset, the lower the residual standard error.

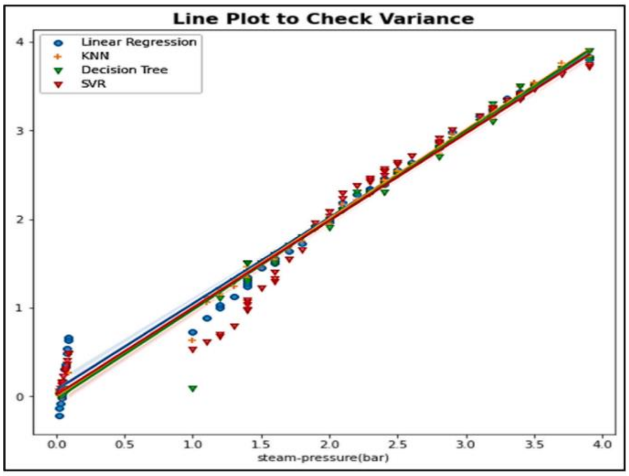


Fig. 11. Line plot to check variance

A line plot to check the variance of linear regression model, KNN model, decision tree and support vector regression is plotted in Fig. 11.

In Straight line y = mx + c where KNN model occupies most of the straight line whose values are ranging between 0 and 4 based on the steam pressure and represented by the symbol +. The values of the other models also lie between 0 and 4 based on steam pressure which are represented by blue circle for linear regression, inverted green triangle for decision tree and inverted red triangle for SVR. These models fail to fall on the straight line and deviate from the line. Changes in the machine learning model using different portions of the training data set are identified using a variance.

Table 4
KNN comparison with other Machine Learning Models.

Parameters Validation	Machine Learning Algorithms			
	k-NN	LR	DT	SVR
Execution Time (ms)	2.58	9.56	7.66	5.89
RMSE	4.57	13.56	9.62	7.89
MSE	16.29	183.37	92.54	62.25
MAE	34.58	249.31	112.89	98.67
R^2	90.78	72.38	85.91	88.34
Results (%)	Machine Learning Algorithms			
	k-NN	LR	DT	SVR
PRECISION	91.18	72.21	74.14	80.91
RECALL	92.46	73.14	75.12	79.83
F-MEASURE	91.77	74.67	77.13	80.27
ACCURACY	90.04	72.28	74.15	79.66
ERROR	8.69	27.55	18.85	16.94

Table 4 ndicate the deviation between KNN regression, Linear, SVR, and Decision-making tree. The deviation is represented as the percentage difference between KNN and other models.

Table 5
Comparison of proposed work with Existing Models.

S. No	Title of the previous work	Adopted Methods	Examined Parameters	Execution time, rise and settling time	Error and Accuracy
1	Paper Quality Enhancement using Machine Learning Techniques	Machine Learning- Linear, KNN, SVR, Decision Tree	Moisture, Caliper, Weight	K-Nearest Neighbor Execution time: 0.352 ms	RSME-0.066 MSE-0.0044 MAE-0.007 R^2 – 0.98
2	Tuning of a PID using Soft Computing Applied to Moisture Control in Paper Machine [4]	Tuning of a PID Controller using Soft Computing Technique – Genetic algorithm, PSO	Moisture	BFO–PSO Rise time: 0.1462s Settling time: 0.8s	ISE: 1.1122
3	Tuning of a PID using evolutionary multi objective optimization in the pulp and paper industry [6]	Tuning of a PID controller using multi objective optimization - Bacterial foraging optimization	Weight, Moisture	Particle Swarm Optimization Rise time:0.156 s Settling time: 0.63	ISE: 0.00111
4	Machine Learning for Paper Grammage Prediction Based on Sensor Measurements [21]	Machine Learning - AdaBoost	Grammage	Precision: AdaBoost: 0.972 ms	Accuracy:0.9741

Table 5 shows the comparison of the proposed work with existing methods. The parameters selected for comparison are execution time, rise time, settling time, the error and accuracy calculation.

4.2 Benefits of seminar

1.Presentation Skills

2. Discussion Skills

3. Listening Skills

4. Argumentative Skills and Critical Thinking

5. Questioning

6. Interdisciplinary Inquiry

7. Engaging with Big Questions

8. Studying Major Works

Chapter 5

CONCLUSION

This paper presents a machine learning model which meets the requirement of increasing the paper quality by adjusting the steam pressure applied to the paper at the drying section.

The model proposes the use of techniques which are Linear regression, KNN, Support vector regressor and Decision tree for moisture, caliper, grammage which decide the amount of steam to be used.

It also verifies the errors in different models which are mean squared error, root mean squared error, mean absolute error and R squared score.

The proposed method satisfies the necessities of reducing the usage of steam in the drying section.

Tried machine learning models show that the use of KNN model is best suited for practice that performs both regression and classification, it is easy for obtaining the values, has quick calculation time, has less error compared with linear regression, and has a high R squared score.

The proposed model indicates the root mean squared error which is 0.06, mean squared error which is 0.004, and mean absolute error as 0.0007 and R2 score as 0.996 which shows a better performance than the other methods.

From the analysis of the machine learning algorithms, it is found that the reduction in 0.5% of moisture in the drying section then results in reduction of 0.09% in steam pressure which is found in the cross validation.

This suggests that the efficiency of the system increases with 1.34% of energy recovery.

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