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Prediction of Control Valve Stem Position using Machine Learning with Image Feature Extraction Algorithm

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Abstract

Control valves are a continuously crucial component of ongoing modern instrumentation all around the world since these control valves are essentially pneumatic gadgets made out of all mechanical parts their presentation is less contrasted with the best one and because of steady moving parts mileage corrupts over the long run. Control valves generally called the last control component in any cycle are utilized to control persistent stream, level, pressure, and temperature. The sign got from the customary regulator makes a motion for opening the CV (Control Valve) to some degree, completely open, or completely shut. The control signal is corresponding to the size of blunder regarding time. The control valve is opened and shut naturally by giving the strain to open and close utilizing I/P converters in overflow with Pneumatic, Water driven, or electrical actuators with positioners. A plant can perform ideally on the off chance that the presentation of the control valve is checked and kept up with. The point of this article is to start the examinations toward getting precision in stem situating through picture inputs and to show this yielding result as control valve stem position utilizing AI calculations, some portion of computerized reasoning empowers recognizing the stem position significantly quicker utilizing advanced picture handling. The proposed frameworks involve pictures of various stem positions is taken care of to the Weka programming apparatus, pre-processed utilizing Pyramid Histogram of Arranged Slopes (PHOG) include channel and prepared utilizing pre-arranged classifiers, the exhibition exactness of stem levels by analyze based characteristic choice, emphasis on positioning limits and Destroyed with triple emphasess on class levels is determined. The outcomes show the presentation with the most extreme precision of 92.4051% and weighted normal Collector Administrator Qualities (ROC) upsides of 0.978. Thus such brilliant estimations utilizing AI calculations which is a piece of man-made brainpower give us a crucial job in anticipating the CV stem position significantly quicker utilizing picture handling channels.

1. INTRODUCTION

As the key terminal equipment in the automation system, the pneumatic control valve is widely used in industrial control fields such as metal smelting, petrochemical, nuclear power, and sewage treatment [1,2]. Due to its inherent properties such as sealing performance, friction force, and flow characteristic curve, the pneumatic control valve inevitably has nonlinear characteristics such as hysteresis and dead zone [3]. In the industrial production process, if the valve position is not properly controlled and the vibration is too large, it will increase the wear of the valve stem, and, in severe cases, it will cause surge and reduce the life of the regulating valve. If the adjustment time is too long, it is not conducive to production efficiency. Pneumatic control valves not only need to reach the specified valve position quickly and smoothly, but also need to have high accuracy.

For the modeling of the pneumatic actuator of the pneumatic control valve, different objects have been investigated, including the modeling and analysis of soft pneumatic actuator based on a soft robot gripper [4], dynamic modeling of bidirectional pneumatic actuator based on the dynamic balance equation [5], and modeling of soft pneumatic actuators with different orientation angles using echo state networks for irregular time series data [6], which are of great help in modeling pneumatic control valves. Many scholars have also conducted studies on the valve position control of pneumatic control valves. Plestan et al. [7] designed a new adaptive sliding mode controller that ensures that the gain is not overestimated and reduces chattering during valve position control. Haslinda et al. [8] applied predictive control to the pneumatic control valve. Although the nonlinear factor interference of the control valve was solved in a certain sense, the problems of poor robustness and low stability still existed. Guo et al. [9] designed an active disturbance rejection controller according to the characteristics of the valve cylinder servo system. The co-simulation of AMESim and MATLAB verified that the controller has the advantages of strong anti-disturbance and high precision. In addition, fuzzy neural network-PID [10], PID-IMC (internal model control) [11], Expert-PID [12], etc. have been proposed for regulating valve position control, thus improving the control accuracy and response speed of the pneumatic control valve, control accuracy, and responsiveness. At present, most of the control strategies in engineering are still mainly integer-order PID or other control strategies based on integer-order PID, while traditional integer-order PID struggles to meet the increasing control demand.

In the existing literature, few researchers have applied the fractional-order control theory to the valve position control of pneumatic control valves. Because the fractional calculus operation has memory characteristics, compared with the integer-order PID, the differential order and the integral order are introduced. Second, the flexibility of controller design is increased, and the combination of fractional-order calculation and controller parameter tuning is one of the current research hotspots [13,14]. The main methods of fractional-order PID controller parameter tuning include intelligent optimization method [15], phase angle margin and amplitude margin method [16], dominant pole method [17], and transfer function design method based on ideal bode [18]. Some scholars have introduced intelligent optimization algorithms to adjust fractional-order PID parameters, showing good results [19,20,21]. For example, the biogeography-based optimization algorithm, as an intelligent optimization algorithm, has been proven to have fast convergence and high accuracy.

For some current optimization algorithms applied to valve positioner opening control, there are still too many iterations, and the problem of jumping out of the local optimal ability is poor. In order to effectively realize the valve position control of the regulating valve, this paper proposes an improved biogeography-based optimization algorithm, which improves the optimization ability by introducing chaotic mapping initialization, adjusting the migration model, and improving the migration operator and mutation operator. The model is not accurate enough because it does not consider the air pressure fluctuation, system viscosity, and dead zone. Although previous researchers have conducted some forward-looking work on the pneumatic control valve, the current pneumatic control valve still has the problems of inaccurate valve position control, a considerable amount of overshoot, and long adjustment time.

2. LITERATURE SURVEY

This part shows that the connected works of issue distinguishing proof. Serrano, J et al. introduced a computationally effective AI model for shortcoming discovery in a mDSF motor utilizing a three-class Strategic Relapse arrangement in view of regularly accessible motor regulator signals. Preparing and testing precision surpassed 98% in light of consistent state motor dyno information with valve deficiencies prompted at a 1% rate[22]. Dangut et.al. [23] Proposed model is contrasted with other comparative profound learning draws near. The outcomes showed a 18% expansion in accuracy, a 5% increment in review, and a 10% increment in G-mean qualities. It likewise exhibits dependability in expecting uncommon disappointments inside a foreordained, significant time span. [24-33]. Lawrence et.al. [34] the organization of Straight Relapse as an AI strategy for expectation of cavitation in light of observational information gathered from detecting instruments checking the cycle condition and the control valve under study. The AI calculation carried out for the ID of different disappointments in the control valve and can say that the prescient examination is more proficient than fluffy rationale as the fluffy rationale expects information to be gathered for all the disappointment occasions and characterize participation capabilities for each kind of disappointment. [35-37]. By utilizing an AI approach during the activity of a well with numerous ICV settings, it would be practical to gauge the lateral- by- lateral yield at concealed situations. Subsequently, it becomes conceivable to augment the all around yield by utilizing a streamlining calculation to decide the ideal ICV settings.[38]

3. PROPOSED SYSTEM

3.1 Data Preparation And Description

The below lying information happens to be a set of pictures showing essentially the Stem positions with variable lighting background. The image dataset obtained therefore inevitably contains imprecise, strident pixels to be regulated to preserve the mensuration accuracies. Stem position measurement is finished by employing a completely different approach to victimization image processing.

Fig. 1: Final control Element Scenario for Stem position

Figure 1 shows the physical appearance of the 2-tank system with the control valve in the process station the data collection is done with this two-tank system and the different stem level images are acquired through a normal high-resolution camera. The collected images are labeled with its actual percentage of stem position and then modeling the 2-tank interacting tank system which is a second-order process system is done using the traditional method of running the process with mandatory controllers like PI, PID controllers with tuning parameters, and a steady-state is obtained after some prescribed interval of time. The images of the control valve for various positions are obtained and are tabulated, labeled for implementing machine learning algorithms using supervised learning. The data collection is done based on the stem positions as shown in figure 2 which describes the different stem positions as 0%, 5%, 50% and 100% openings of the control valve during the running of the process shown in figure 2. Using digital image processing and image filters like PHOG are used for preprocessing the image to the corresponding numeric values for classification of different classes in machine learning algorithms like rules bases, nearest neighborhood, lazy rules and Trees based algorithms.

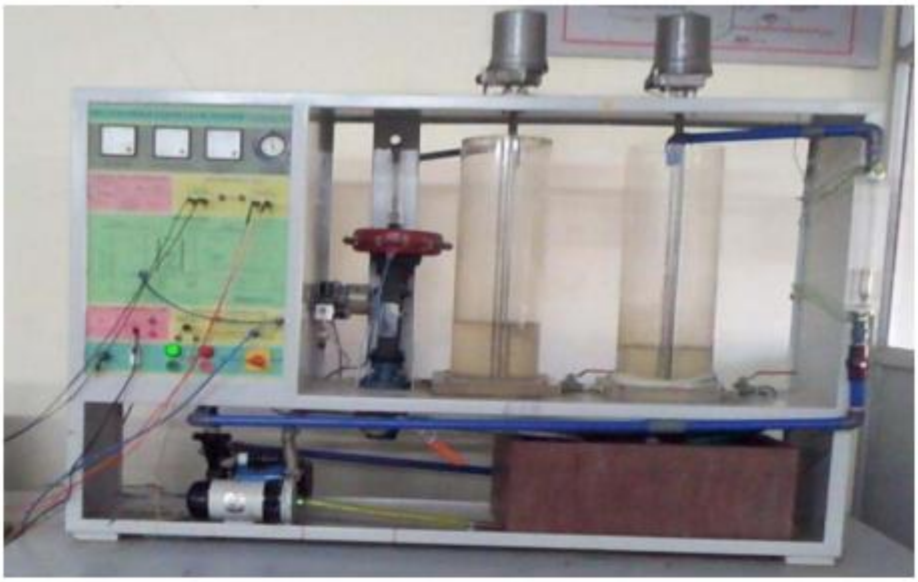

Fig. 2: Two interacting tank system set up

3.1 Mathematical modeling of two-tank system

The convention method of running the process with the general parameters and observed for the self-regulatory control of the system. The open-loop response with the given setpoint of 12 cm and the default controller's parameters are set and the process is run till it reaches the stable state that is plus or minus 5% of the set point

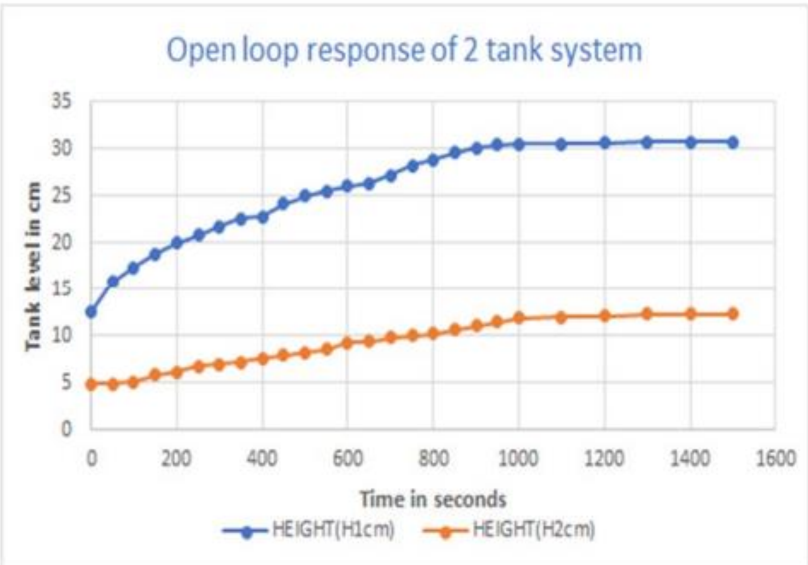

Fig. 3: open response of 2 interacting system

From the above, figure 3 it is observed that system reaches the stable state for the given set point for thousandth second in open loop condition. Mathematical modeling is done by finding the values of the time constants τ1 and τ2 by calculating the product of the rate of accumulation and resistances R1 and R2 at 63% of its final value. However, the values of R1 and R2 are evaluated to be 254,77 and 339.49. The resultant transfer function by substituting the values is:

$$\frac{H2(S)}{Qi(S)} = \frac{339.49}{85.28S2+29.32S+1}$$

The figure 5 illustrates the Simulink model of the above-mentioned open loop system. Simulated with the obtained transfer function and giving a step input and seeing the corresponding output in the scope.

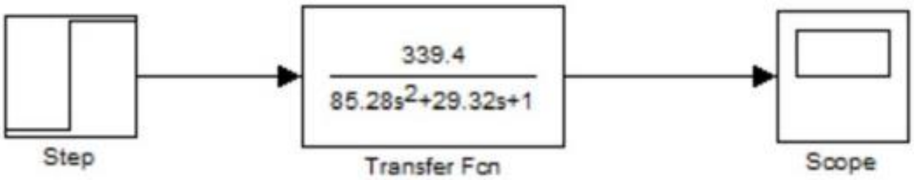

Fig. 4: Simulink diagram for open loop

The output of this Simulink for completing the mathematical modeling is given in the below figure 4 for a step input to the obtained transfer function is:

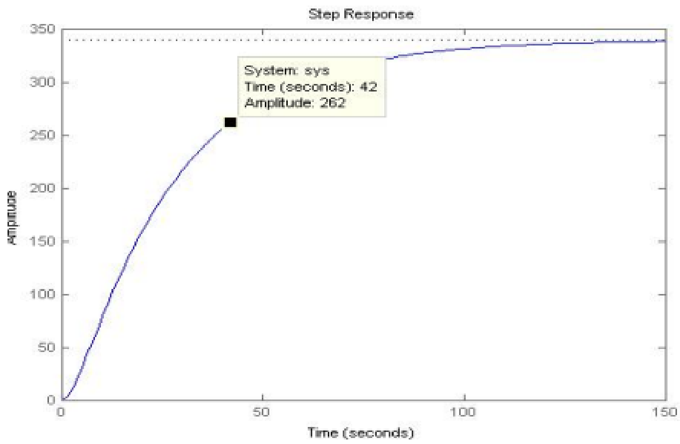

Fig. 5: Step input response to the Transfer function obtained.

Figure 5 is the response achieved for the obtained transfer function, which is the time versus output amplitude characteristics. The process control system is run in the conventional method to get the image data of the control valve to progress to build a model in feedback to predict the control valve stem position using machine-learning algorithms. The Control valve images are collected by running the process with the default controllers and the CV images are collected under three different classes and tabulated by labeling the level values. The true value of the collected CV images is compiled in the given format with the output CV stem positions. For example, CV1.jpeg = Low, CV6.jpeg = Medium, CV14.jpeg = High and so on for all the 58 distinct images obtained. Then the file format must be changed for further processing. The filter section is used for which the file format supported is ARFF format i.e., Attribute relation file format, combining the image and the class in one single file and converting it into a single file for further processing.

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3.2 Major seven steps in data preprocessing are:

- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set

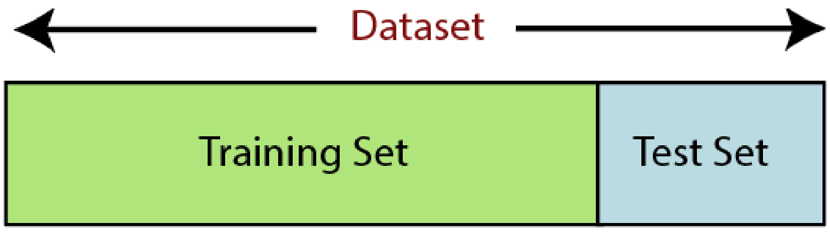
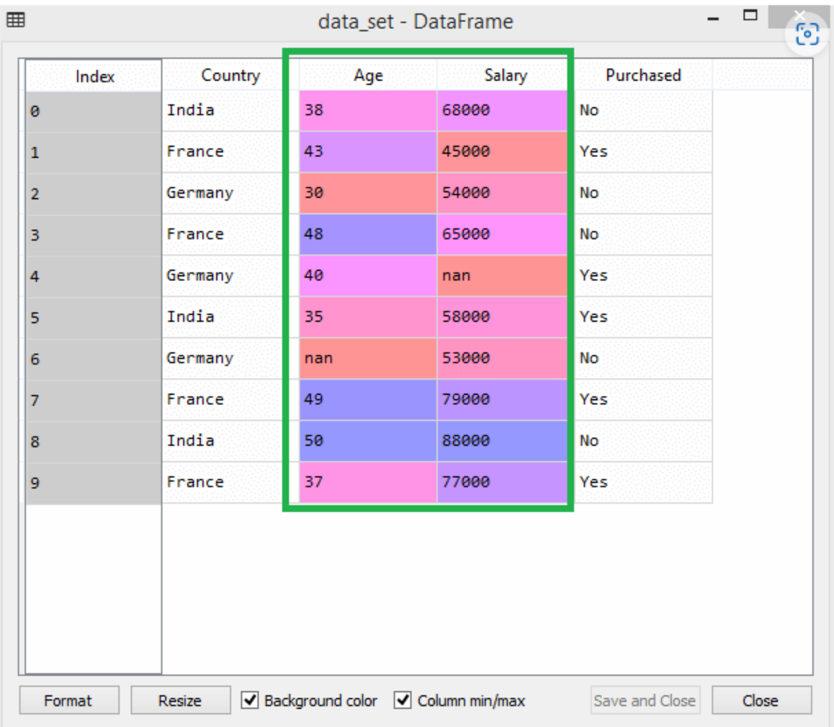


Fig. 6: Partitioning the dataset during training

- Feature scaling

Consider the below dataset:



data_set - DataFrame

Index	Country	Age	Salary	Purchased
0	India	38	68000	No
1	France	43	45000	Yes
2	Germany	30	54000	No
3	France	48	65000	No
4	Germany	40	nan	Yes
5	India	35	58000	Yes
6	Germany	nan	53000	No
7	France	49	79000	Yes
8	India	50	88000	No
9	France	37	77000	Yes

Format Resize Background color Column min/max Save and Close Close

As we can see, the age and salary column values are not on the same scale. A machine learning model is based on Euclidean distance, and if we do not scale the variable, then it will cause some issue in our machine learning model.

Euclidean distance is given as:

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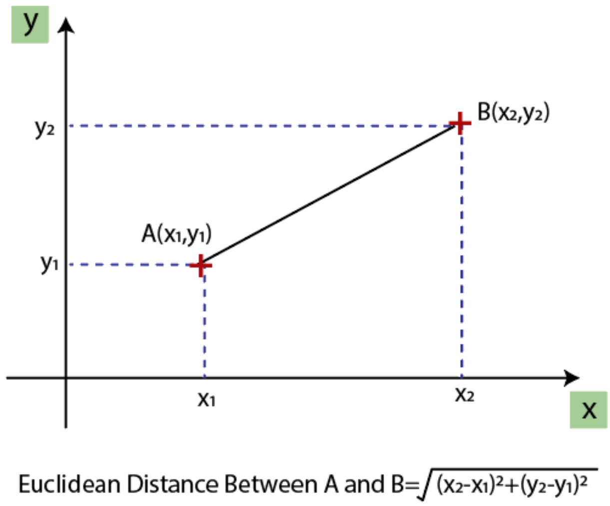

Fig. 7: Calculate the distance between A and B

If we compute any two values from age and salary, then salary values will dominate the age values, and it will produce an incorrect result. So to remove this issue, we need to perform feature scaling for machine learning.

There are two ways to perform feature scaling in machine learning:

Standardization

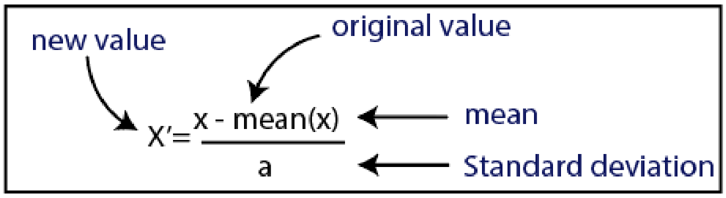

Fig. 8: Feature extraction Pre-processing steps in standardization

Normalization

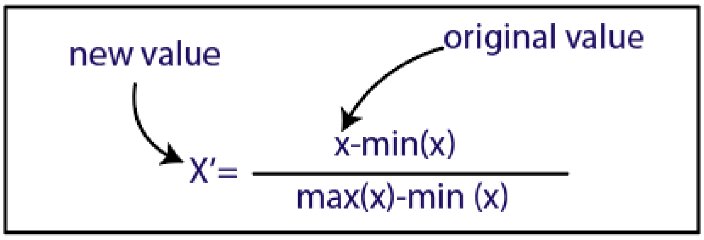

Fig. 9: Feature extraction Pre-processing steps in Normalization.

SMOTE

Synthetic Minority Oversampling Technique (SMOTE) is a statistical technique for increasing the number of cases in your dataset in a balanced way. The component works by generating new instances from existing minority cases that you supply as input. This implementation of SMOTE does not change the number of majority cases.

The new instances are not just copies of existing minority cases. Instead, the algorithm takes samples of the feature space for each target class and its nearest neighbors. The algorithm then generates new examples that combine features of the target case with features of its neighbors. This approach increases the features available to each class and makes the samples more general. SMOTE takes the entire dataset as an input, but it increases the percentage of only the minority cases. For example, suppose you have an imbalanced dataset where just 1 percent of the cases have the target value A (the minority class), and 99 percent of the cases have the value B. To increase the percentage of minority cases to twice the previous percentage, you would enter 200 for SMOTE percentage in the component's properties.

Table 1 Lookup image data set with and without applying SMOTE

	Class 0	Class 1	total
Original dataset	570	178	748
(equivalent to SMOTE percentage = 0)	76%	24%	
SMOTE percentage = 100	570	356	926
	62%	38%	
SMOTE percentage = 200	570	534	1,104
	52%	48%	
SMOTE percentage = 300	570	712	1,282
	44%	56%	

Fig. 10: Example of SMOTE.

3.3 BLOCK DIAGRAM OF 2 TANK SYSTEM WITH SMART POSITIONER

The block diagram clearly establishes the optimum model in the closed loop for governing the system by measuring the stem position optimally as shown in figure 11. This also shows some enhancement in the earlier prediction of stem position and thereby maintaining the plant to run continuously without any breakdown and early prediction of failures like backlash and stiction problems.

It is a cascade loop having primary and secondary loop with two controllers one monitoring the flow and the other the level in the process. The secondary controller undergoes the problem of continuously varying setpoint and tuning a controller for settling the process become very difficult task hence implemented an optimum controller using machine learning algorithms.

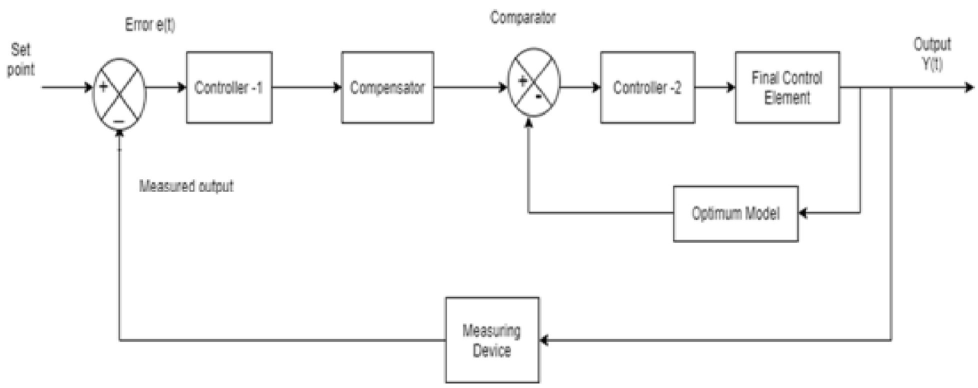

Fig. 11: Designed optimum model in the feedback.

4. PROPOSED SYSTEM FLOW FOR SMART POSITIONER FOR CONTROL VALVE

WEKA or Waikato Environment for Knowledge Analysis the University of Waikato Hamilton, New Zealand is an open-source data mining software issued under GNU public license software that provides freedom to its users in performing all these data mining works. It is a collection of many machine learning algorithms for data mining tasks. It is a pack of a tool consisting of various operations called document preparation, clustering, regression, data preprocessing, classification, Association rules, instance-based classifying, and picturing. The methodology involved in establishing the task is carried out using this software called WEKA for modeling the above said smart positioning using image processing.

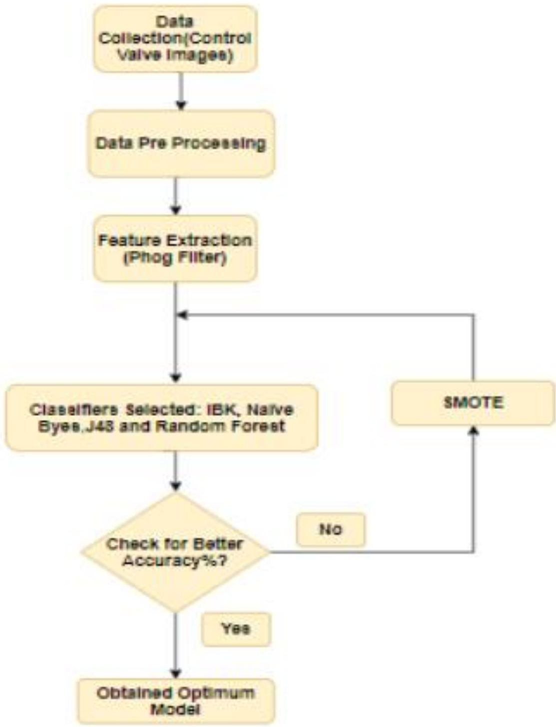

Fig. 12: Experimental set up to obtain Optimum model.

Figure 12 shows the experimental set up for predicting the Control valve stem position in the following steps:

- Data collection as raw images that has to cropped, format changed and framed the ground truth values
- to the corresponding images
- Data preprocessing using PHOG filter and the image to numeric values is processed for further
- classification and building the model using selected classifiers
- Classified and built the model for training and obtained performance results
- Inferring the results for better accuracy percentage and area of curve called weighted receiver operator

- characteristics is better or not for repeating the above process by applying SMOTE to the minority class
- to improve the overall performance of the built model.
- Attainment of the optimum model to predict the control valve stem position using machine-learning algorithms.

The control valve images for various stem positions namely 0%,25%, 50%,75%, and 100% are formed into a lookup table and converted into a comma-delimited file in excel, and the data preprocessing, feature extraction is carried out using PHOG filter in Weka software in functions tab. Then the classifying process is done using the classifiers namely instance base classifiers, Naive Byes, Decision tree classifiers (J48, Random Forest). Tabulating the results and checking for its accuracy level percentage. A synthetic minority imbalance in the dataset is overcome by a tool called SMOTE to get better accuracy performance. This SMOTE will give us better evaluation criteria in performance accuracy by balancing a low-resolution image also. Description of preprocessing using SMOTE image filter: Synthetic Minority Oversampling Technique common strategies for dealing with unbalanced class in classification problems. SMOTE is an oversampling technique where the synthetic samples are generated for the minority class. If the unbalanced data is not taken care of beforehand it may degrade the performance of the classifier model. Most of the predictions will be made with the majority class wherein the minority will be treated as noise and disturbance and will be ignored by the classifier algorithm resulting in a high bias in the model. SMOTE is used to increase the classifier performance despite the imbalance in the data set. The effect of 'SMOTE' clearly shows a uniform increment in the decision rule classifier.

4.1 Procedure for validation of classification

The preprocessing is done with a PHOG filter with 631 attributes and 58 distinct instances, having a mean value of 9.397 and Standard deviation equals 1.35.

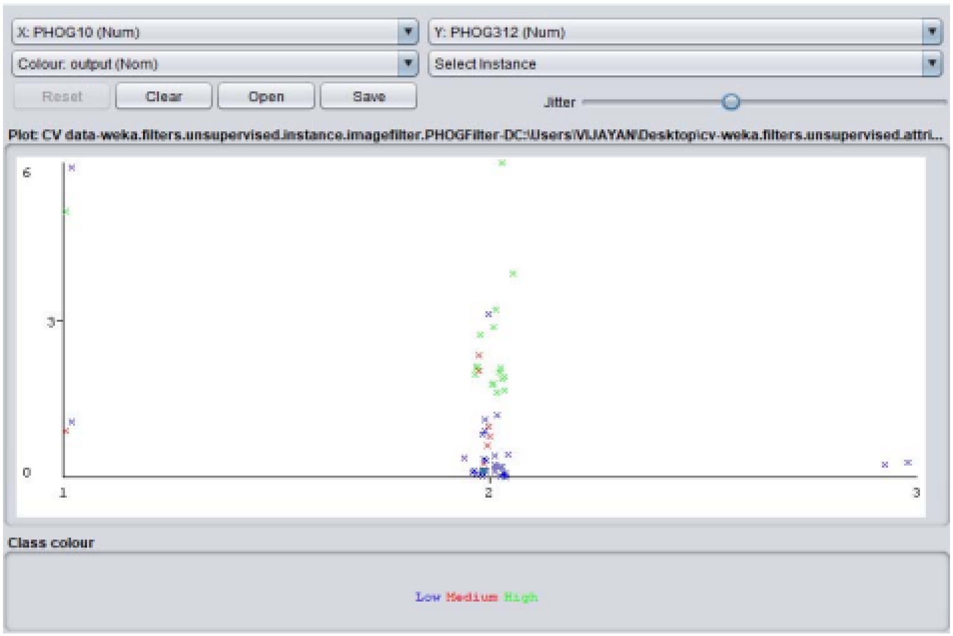

Fig. 13: Pre-Processing using image Filter (PHOG).

PHOG Filtering: Pyramid Histogram of Oriented Gradients (PHOG) features have been employed to discriminate between different stem positions. The proposed shape discriminator counts occurrences of gradient orientation in the localized portion of an image. To improve the recognition rate Pyramid Histogram of Oriented Gradients (PHOG) is used for feature extraction. As an example of the feature after filtering by PHOG scheme, its (PHOG10) distribution is shown in Figure13. The PHOG features are mined from the given input (Control valve stem Position) related to the stem position. It is basically a three-dimensional shape descriptor applied to image sorting. The PHOG features are mined from the region of interest (Control valve stem position) are focused by its local feature that is captured over edge positioning within a region and three-dimensional layout of the image. The three-dimensional distribution of edges is formulated as a vector image by tiling the image into a region at multiple resolutions. Pyramid histogram of orientation gradients over each image sub-region at each resolution.

4.2 Procedure for selected base classifiers

- Naïve Bayes
- IBK instance base Classifiers (KNN)
- Random Forest
- J48

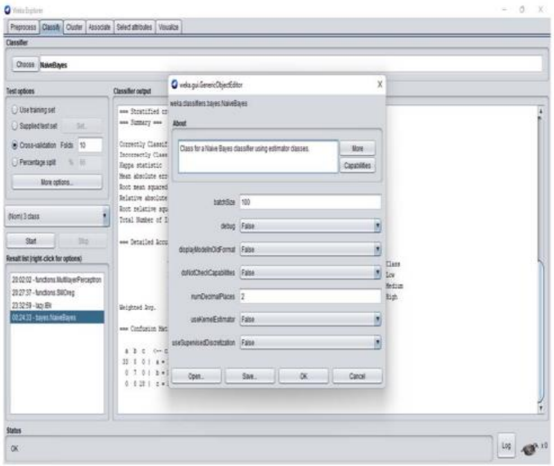

Fig. 14: Weka parameter tuning option panel for Naïve Bayes Classifier.

Bayes' theorem (BT) is defined as the probability of an event that occurs in the given probability of another event which has already occurred. BT is stated mathematically:

$$P\left(\frac{A}{B}\right) = \frac{P(B/A)P(A)}{P(B)}$$

Where A and B are the events and P(B) not equals to 0. In this regard the dataset is applied BT in the following way

$$P\left(\frac{y}{X}\right) = \frac{P(X/y)P(y)}{P(X)}$$

Where y is the class variable and X is a dependent feature vector with n elements: $X = (x_1 + x_2 + x_3 + x4 \ldots\ldots + x_n)$

Figure 14 shows the Weka parameter tuning option panel for Naïve Bayes Classifier which is in the Bayes category in Weka.

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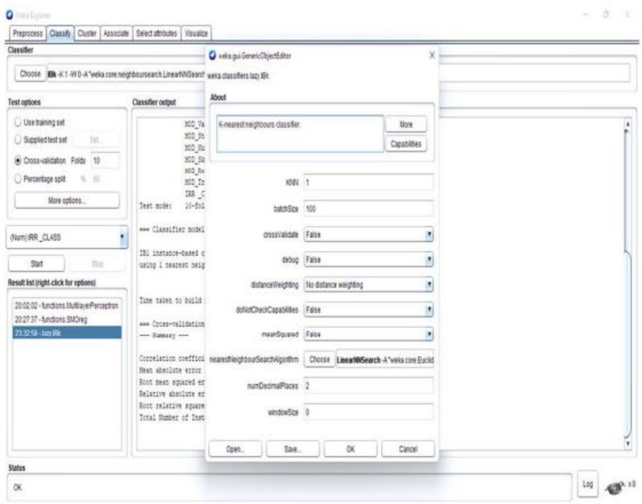

Fig. 15: KNN Classifier in parameter tuning option panel For any point of data y, the Euclidean Distance from another data point x is given by ,

$$ED = \sqrt{\sum_{i=1}^{n}(x_i + y_i)}\,{}^\wedge 2$$

where n is the number of features.

Figure 15 KNN Classifier in parameter tuning option panel in Weka and this classifier has opted lazy category and the option panel is utilized for varying the neighbor hood values.

The value of neighbors that is k value is chosen depending upon the performance as shown in figure 16, required accuracy, and the correlation Coefficient accepted for the built model. The advantage of this KNN algorithm is it is very simple to implement, Robust to the noisy training data, and it can be more effective on the training data of very large size. The drawback of this algorithm is it always needs to determine the value of k which may be Complex in some cases, the computational cost is high because of calculating the distance between the data points for samples.

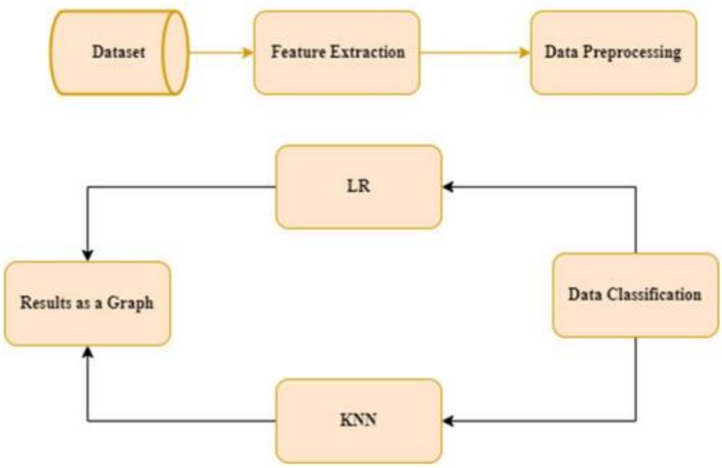

Fig. 16: Analysis of KNN algorithm

Random Forest classifier and J48 are from tree based category and the implementation procedure is as follows:

- Data preprocessing procedure

- Fit the Random Forest algorithm to the training set
- Prediction of test results
- Test the accuracy of the result (creating a confusion matrix)
- Visualization of test series results.

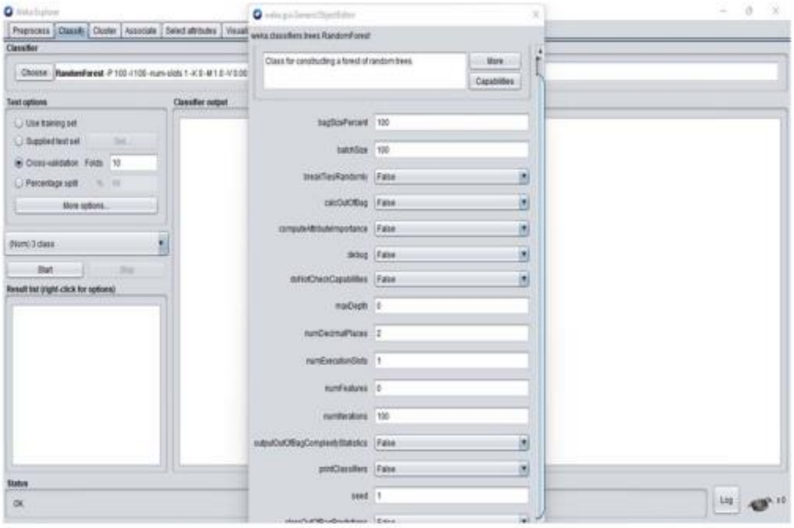

Fig. 17: Option panel for parameter tuning Random Forest classifier.

The general capability of the Random Forest classifier is the Binary class, Missing class values, and

Nominal class.

- The attribute that it uses is Binary attributes, Date attributes, Empty nominal attributes, Missing values, Nominal attributes, Numeric attributes, and Unary attributes.

The classifier object takes the following parameters as shown in figure 17: n_estimators = Number of trees required for Random Forest. The default value is 10. You can choose any number, but you have to deal with the problem of overfitting.

Criteria = A function that analyzes the accuracy of division. Here, we used "entropy" to get the information.

The need for confusion matrices in machine learning

- Evaluate the performance of the classification model when making predictions about test data and show how good the classification model is.
- It shows the nature of the error as well as the error caused by the classifier. B. Is it a Type I or Type II error?
- You can use the confusion matrix to calculate various parameters of your model, such as accuracy and accuracy.

5. RESULTS

We can use this matrix to perform various calculations on your model, such as model accuracy. These calculations are shown below.

Classification accuracy: This is one of the important parameters to determine the accuracy of the classification problem. Defines how often the model predicts the correct output. This can be

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calculated as the ratio of the number of correct predictions made by the classifier to the total number of predictions made by the classifier. The formula is:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

- Where TP and TN are the True positive and True Negative.
- FP and FN and False positive, False Negative Classification

Misclassification rate: Also known as the error rate, it defines how often the model makes false predictions. The error rate value can be calculated as the number of false predictions out of all the predictions made by the classifier. The formula is:

$$Error\ rate = \frac{FP + FN}{TP + FP + FN + TN}$$

Table 2 results clearly show the classification, of the stem position of the final control element is correctly classified by the above-mentioned classifiers are above 69%accuracy and the Receiver operator characteristics is also having a weighted average above 0.763 and the approximate time taken to build the models is also very less.

Table 2 Experimental results of the first iterated model

S.NO	Category	classifier	Accuracy (%)	Weighted Avg ROC
1	Bayes	Naive Bayes	82.7586	0.850
2	Lazy	IBK	79.3103	0.816
3	Trees	J48	69.9655	0.763
4	Trees	RF	82.7586	0.952

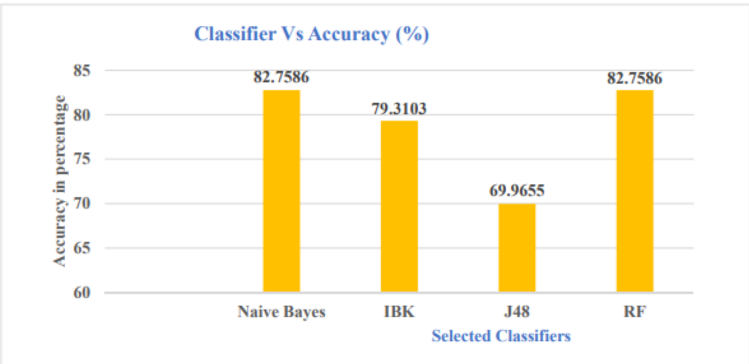

Fig. 18: Classified data performance analysis1

We observed from figure 18 the accuracy starts from 69% to 82.7586% for J48 and Naïve Bayes classifier, Random Forest.

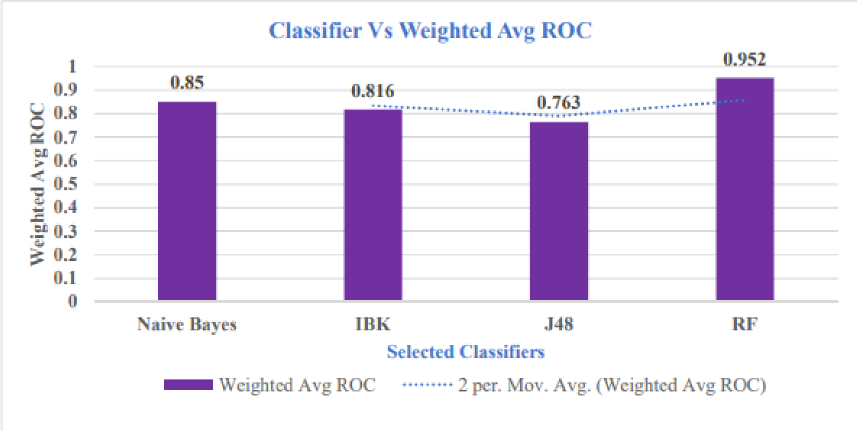

Fig. 19: Classifier Vs Receiver Operator Characteristics1

ROC is observed from figure 19 varies from 0.796 to 0.952 for J48 and Random forest, both belonging to the same tree category. The second iterated model is built by preprocessing using SMOTE (Synthetic Minority Oversampling TEchnique) by increasing the data of minority by in Weka tool followed by the classification is done.

The experimental results of the second iterated model from table 3 show a decrease in accuracy performance for Naïve Bayes and an increasing percentage for the remaining IBK, J48, and Random Forest algorithms. The selected classifier versus Accuracy performance is shown in figure19. The ROC for the selected classifiers also observed increasing area attained as shown in figure 20.

Table 3 Experimental results of the Second iterated model

S.NO	Category	classifier	Accuracy (%)	Weighted Avg ROC
1	Bayes	Naive Bayes	80	0.821
2	Lazy	IBK	89.2308	0.919
3	Trees	J48	69.2308	0.796
4	Trees	RF	87.6923	0.952

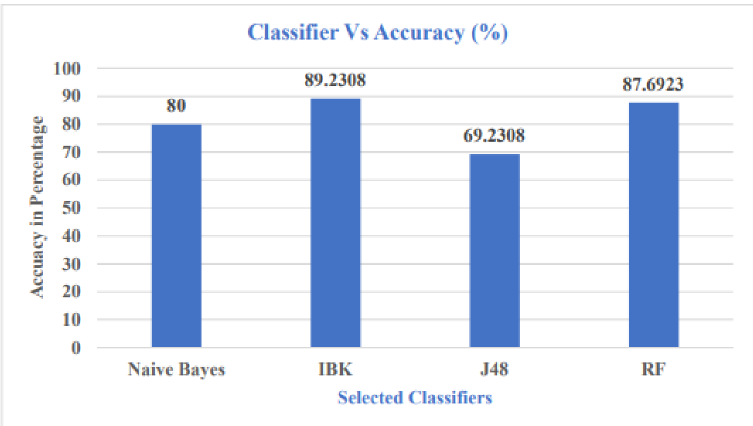

Fig. 20: Classified data performance analysis2

The Second iterated model is built using preprocessing using SMOTE in Weka which is used for increasing the classifier performance despite imbalance data. We detect the accuracy starts from 69% to 89.2308% for J48 and Naïve Bayes.

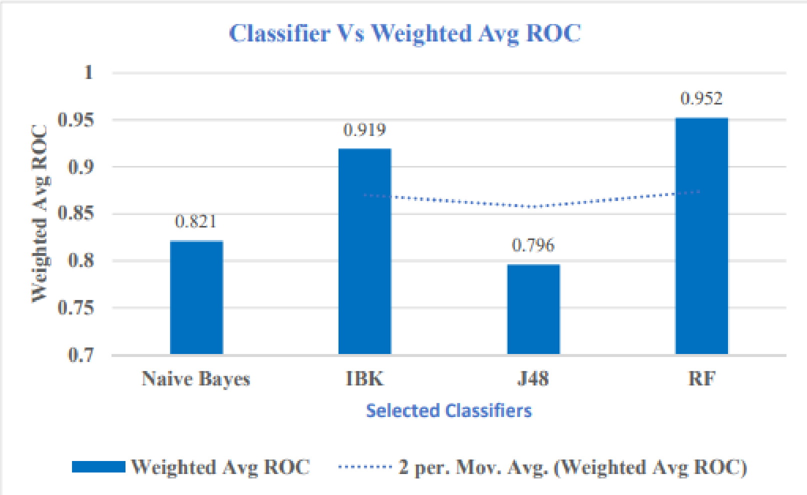

Fig. 21: Classifier versus Receiver Operator Characteristics2

The ROC in figure 21 shows a weighted average of 0.952 for Random Forest.

The third iterated model is built using preprocessing using SMOTE in Weka which is used for increasing the classifier performance despite imbalance data as shown in table 4.

We detect the accuracy starts from figure 22 shows 78.481% to 92.4051% for J48 and Random Forest.

Table 4 Experimental results of the third iterated model

S.NO	Category	classifier	Accuracy (%)	Weighted Avg ROC
1	Bayes	Naive Bayes	87.3418	0.912
2	Lazy	IBK	86.0759	0.881
3	Trees	J48	78.481	0.827
4	Trees	RF	92.4051	0.978

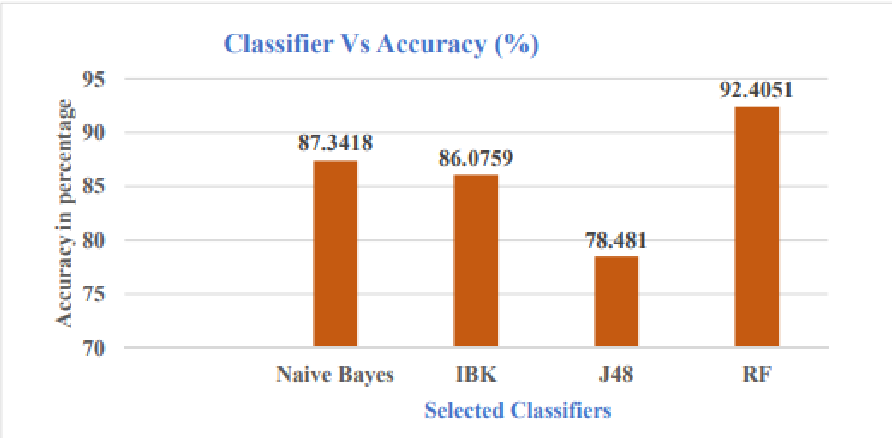

Fig. 22: Classified data performance analysis3

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The ROC gives a weighted average of 0.978 as shown in figure 22. With these results, we conclude that we have attained an optimum model in the feedback loop.

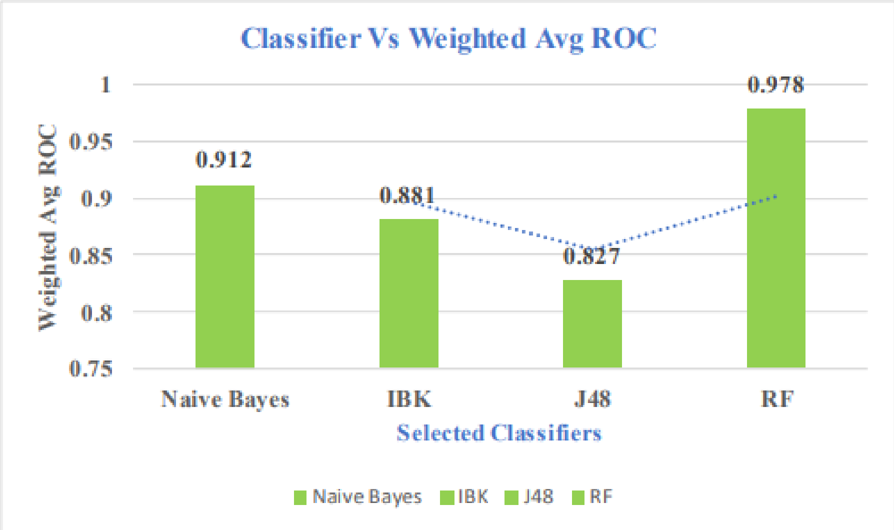

Fig. 23: Classifier versus Receiver Operator Characteristics3

6. CONCLUSION AND FUTURE SCOPE

Currently, this article work is a start-up in predicting the stem position of a control valve using image processing techniques and machine learning algorithms. The combination of the two has helped in getting an optimum model in the feedback loop of a second-order system and also help in decreasing the problems related to control valve positioning issues. The accuracy of the system is 92.405% by a selected classifier random forest and 0.978 is the receiver operator characteristics. The future possible improvements in future work can extend the usability in measuring other parameters like level, flow, and Pressure.

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