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Fault Diagnosis of a Single Point Cutting Tool using Statistical Features by Simple CART Classifier

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Abstract

Objective: Tool condition monitoring is an important aspect of the modern day manufacturing system. It plays a significant role in increasing the efficiency of machining operation by identifying defects at a very early stage. Tool wear decreases the life of the tool considerably, increases the length of the machining process, also affects the surface finish and the dimensional accuracy of the product. To identify whether the tool is in a good or faulty condition, a monitoring system is essential. **Method/Analysis:** The fault diagnosis of the single point cutting tool was accomplished with the vibration signals obtained from auniaxial accelerometer attached to the cutting tool in a lathe machine. In this study, three different spindle speeds, feed rates and depth of cuts and four different wear levels of cutting tool are considered. Statistical data obtained from the signals is classified using a decision tree algorithm to get substantial features. The recognized features are considered in classifying data by using Simple CART classifier. **Findings:** The accuracy of the classifier was found to be 73.38% for the model with all the signals combined. The classification accuracy was observed to improve with the reduction in complexity of the model. The classification accuracy obtained for the model with only varying feed rate and depth of cut was in the range of 81–87 %. On further reduction of the model to have varying depth of cut was found to have a classification accuracy in the range of 81.5–91 %. The model with all the parameters independent yielded classification accuracy in the range of 81–100 %. **Applications/Improvements:** This study broadly analysed the use of simple CART classifier to diagnose fault in the cutting tool during machining. It can be used to increase productivity and reduce machine downtime. The improvements can be made to this study by considering different feature extraction techniques for more reliability.

Keywords: Decision Tree, Feature Extraction, Simple CART, Statistical Features, Tool Condition Monitoring

1. Introduction

Manufacturing industries produce finished goods from raw materials on a large scale. These finished goods are further used to make more complex products. Manufacturing industries have a key role in the economy as they are the major wealth producing sectors in any economy. Researchers have observed the factors affecting the key areas of manufacturing and highly recommend condition monitoring to improve efficiency of the machining operation. Manufacturing includes the traditional metal cutting processes like milling, turning, grinding, boring, etc.

The life of a cutting tool in these machining operations is determined by the extent of wear that has occurred on the tool. The most common wear type is the flank wear which occurs due to friction between the tool flank surface and the machined surface. Tool wear often leads to poor surface finish, less dimensional accuracy of the finished product, increased tool temperature and increased time of manufacturing. Thus, the tool wear should be perceived at an early stage to prevent machine downtime.

To predict tool failure at an early stage, engineers and researchers are developing condition monitoring system for cutting tools. Condition monitoring is a process of monitoring the mechanical parameters of a machine

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such as vibration, temperature, sound, etc. and even a small change in these parameters indicates a developing defect. The different stages in diagnosing a fault include choosing of sensing techniques, feature extraction, feature reduction and feature classification. In[1] discussed the use of bayes classification algorithm to diagnose the fault of single point cutting tool with statistical and histogram features. In[2] utilized vibrations from the cutting tool during machining process to classify the fault using decision tree algorithm. In[3] deliberated utilization of condition monitoring in a manufacturing industry to maximise the machine productivity, minimise downtime, improve machine life, improve product quality and reduce product cost. In[4] measured the flank wear caused due to machining hard martensitic stainless steel. In[5] studied the performance of acoustic sensor to monitor a single point cutting tool to identify fault. In[6] surveyed different decision tree approaches used in data mining. In[7] analysed different data mining algorithms including REPTree, Simple CART and Random tree algorithms for classification of Indian news. In[8] used Classification and Regression Trees (CART) algorithm for mining public health applications. In[9] compared many different classification algorithms. In this study, vibration signals from the accelerometer sensor are used to monitor the condition of the cutting tool. Statistical data obtained from the vibration signals is used in the classification.

2. Experimental Arrangement

The experimental investigation was conducted in a lathe machine by performing the conventional turning operation. The Figure 1 and Figure 2 shows the experimental set-up comprising of a data acquisition device attached to a laptop, an accelerometer, single point cutting tool and the specimen. A 25 mm diameter steel bar was used as the workpiece that was machined using a brazed carbide tipped single point cutting tool. The vibration signals generated during the machining process was recorded by using Dytran Uniaxial accelerometer which was mounted over the cutting tool with the assistance of glue. National Instruments USB Data Acquisition device NIVIB 4432 was attached to the accelerometer output which converts the analog signal output to digital signal. The LABVIEW software provided by National Instruments assisted in the capturing of the digital signal.

Table 1 shows the different spindle speeds, feed rates, depth of cuts and levels of tool wear which were considered in this experimental study. Experiments were performed for all different combinations of the above varying parameters.

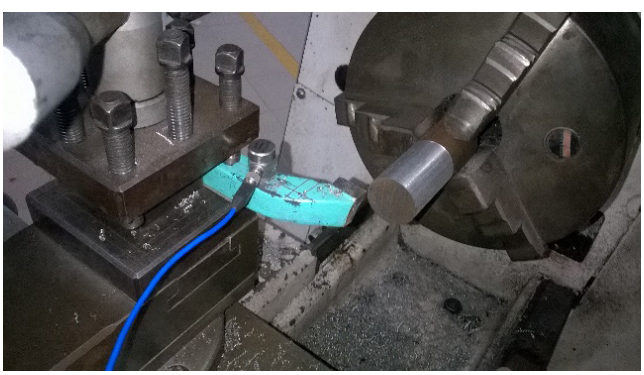

Figure 1. Experimental setup (accelerometer, cutting tool and specimen).

2.1. Experimental Procedure

2.1.1. Acquisition of Baseline Signal

Figure 1 shows the experimental setup with the accelerometer, cutting tool and the specimen. The new unused single point cutting tool has the Uniaxial Dytran accelerometer fixed to it and tool is held on the tool post.

Figure 2. Experimental setup (data acquisition device and computer).

Table 1. Variable process parameters

Variables	Unit	Levels			
		1	2	3	4
Spindle speed	rpm	510	770	900	
Feed rate	mm/rev	0.109	0.122	0.135	
Depth of cut	mm	0.5	0.8	1.0	
Flank wear	mm	0	0.2	0.4	0.6

Since 6 kHz is the maximum recorded frequency for the system, the sampling frequency is considered as 20 kHz as per the Nyquist sampling theorem which states that the sampling frequency should be at least two times the maximum recorded frequency. To remove the oxide layers over the surface of the specimen and to provide even surface, rough turning is carried out on the cylindrical mild steel specimen.

The acceleration signals are acquired after the machining process becomes stable using a data acquisition system. This is done to avoid the random variations recorded during the first few seconds of measurement.

2.1.2. Fault Simulation

Lines parallel to the nose radius of new single point cutting tool are drawn as reference lines. The initial length between the reference line and the topmost point on the nose radius is recorded. A 'tool and cutter grinder' is used to produce wear on the single point cutting tool and the final length between the reference line and the topmost point on the nose radius is determined. The wear level is calculated by measuring the difference between the newly recorded length and the previously recorded length.

2.1.3. Acquisition of Acceleration Signal

The sampling length and the sampling frequency are adjusted to 2000 and 20 kHz respectively and once the machining process becomes stable, the acceleration signal is acquired from the piezoelectric accelerometer fixed to the single point cutting tool. The time domain signals recorded for the different cutting tool conditions are as shown in Figure 3 – Figure 6.

3. Feature Extraction

Twelve statistical features extracted in this experiment include mean, mode, median, standard error, variance, standard deviation, kurtosis, maximum, minimum, skewness, sum and range. The statistical features are extracted from the time domain signals of the acceleration signals. Among the extracted features, not all possess the data required for the classification. Such features that do not contribute to the classification can be ignored. This method of neglecting the unwanted features can be understood in feature reduction. In this study, the features were reduced using decision tree classifier and classified using simple CART classifier.

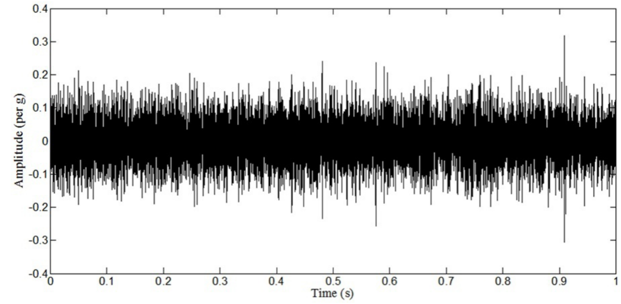

Figure 3. Time domain plot of good tool signal.

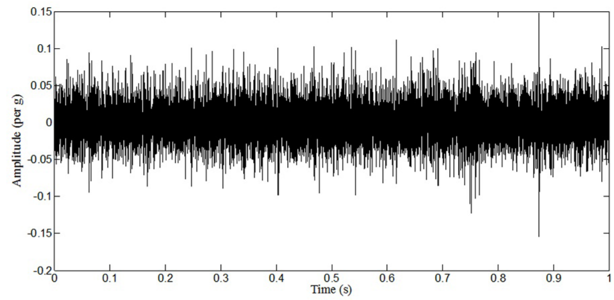

Figure 4. Time domain plot of 0.2 mm worn tool signal.

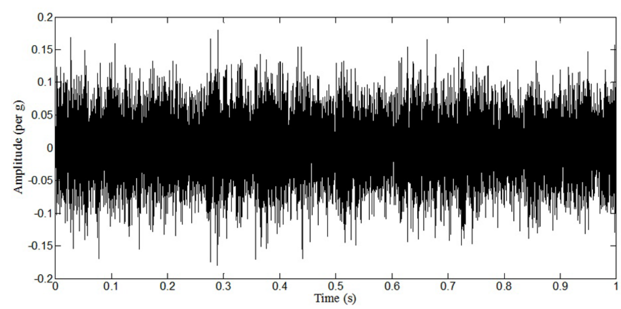

Figure 5. Time domain plot of 0.4 mm worn tool signal.

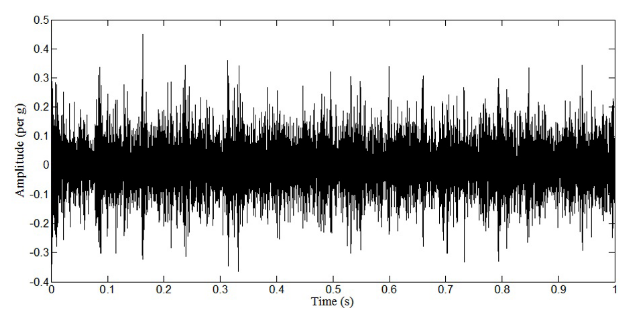

Figure 6. Time domain plot of 0.6 mm worn tool signal.

3.1. Feature Reduction using Decision Tree

The decision tree algorithm was used for feature reduction with the twelve extracted statistical features as input. The location of the feature in the decision tree is used to categorize the importance of that feature. The feature that is at the topmost level of the decision tree has the most information about the classification, whereas the feature that is at the bottommost level of a decision tree has the least information about that classification. The classification accuracy can be improved by eliminating such redundant features.

3.2. Simple CART Classifier

CART (Classification and Regression Trees) or Simple CART classifier is an important tool for building prediction models from a dataset in the modern data mining. CART constructs either classification or regression trees. The simple CART tree divides the data recursively into smaller and smaller branches to get the best fit.

In classification trees, the tree is used to predict a set within which the target value is expected to lie whereas in regression trees, the tree is used to predict the value of the target variable. The classification and regression tree produces a binary output. Hence, a node can be split only into two subsets, like 0/1, yes/no, truth/lie. It generally indicates whether the event will occur or not. The sample space is first divided into two branches. For each of these branches formed, the process is repeated. In CART classifier, entropy is used to calculate the measure of impurity or homogeneity. The tree grows until a stage is reached when there is no significant decrease in the entropy when an additional branch is added. At this stage, the node is called a terminal node which is not divided further.

3.3. Decision Tree Classifier

Decision tree is a knowledge design approach where trees are used to exemplify classification rules. J48 is a decision tree classifier which uses C4.5 algorithm to generate the decision tree. The C4.5 algorithm creates recursive partitioning of data to form a decision tree. The depth first approach is used to grow decision here. A typical decision tree comprises one root, numerous branches, leaves and nodes. A decision is taken in the tree at every node. The selection of the most noteworthy feature for classification can be found using appropriate estimation criteria. The standards involved in choosing the best feature is based on the concept of information gain and entropy reduction. Information gain is the predicted decrease in the entropy due to separating samples according to the specified attribute. Entropy is the categorization of impurities of a random collection of occurrences. By adding additional information, the ambiguity can be reduced. Information gain evaluates the alteration in entropy beforehand and after adding information to the system. Information gain o(***s***,***x***)f a feature ***x*** relative to piling of instances ***s*** is given by:

$$Gain(s,x) = Entropy(s) - \sum_{v \in Value(x)} \frac{|s_v|}{|s|} Entropy(s_v)$$

Where $Value(x)$ is the group of all possible values for attribute x and s_v is the subset of s for which feature x has value of v.

$Entropy(s)$in the equation indicates the entropy of theoriginalgroup$s$and$\sum_{v \in Value(x)} \frac{|s_v|}{|s|} Entropy(s_v)$ indicates the predicted value of the entropy after s is separated using the feature x. Entropy is the amount of regularity of the set of occurrences.

$$Entropy(s) = \sum_{i=1}^{n} -p_i \cdot log_2 p_i$$

Where p_i is the partition of s belonging to class i and n is the number of classes.

4. Results and Discussions

The study on classification of single point cutting tool condition with simple CART classifier is discussed in the coming sections as follows:

- Choosing the noteworthy features to ease the computing effort of the classification i.e., Feature reduction.
- Classification accuracy of simple CART classifier.
- Justification of simple CART classifier.

4.1. Feature Reduction

The reduction of extracted features was done using J48 decision tree classifier. The classification accuracy of 71.11% was observed for the J48 decision tree classifier. The decision tree contains 680 leaves and size of the tree was 1359. 72.86% classification accuracy was observed with reduced error pruning in J48 decision tree. The tree had 186 leaves and size of the tree was 371. When enhancing the minimum number of objects in the classification, the classification accuracy was observed to be 72.31% with 34 leaves and size of the tree as 67.

Table 2 shows the influence of features in classification accuracy. The features which are not listed in the Table 2 does not contain adequate information for classification. Therefore, those unwanted features can be removed for further calculation. Thereby, reducing the computing effort required to classify the signal. The maximum classification accuracy was witnessed from the graph shown in Figure 7 with five features. The five features which contributed for the maximum classification accuracy was taken for the further classification.

4.2. Classification Accuracy of Simple CART Classifier

The classification accuracy of the simple CART classifier for all the signals of 108 experiments combined was observed to be 73.38%.

Table 2. Feature combination and their classification accuracy

No. of features	Features	Classification accuracy (%)
1	Standard deviation	64.34
2	Standard deviation + skewness	68.35
3	Standard deviation + skewness + variance	68.74
4	Standard deviation + skewness + variance + sum	72.07
5	Standard deviation + skewness + variance + sum + kurtosis	72.42
6	Standard deviation + skewness + variance + sum + kurtosis + range	72.21
7	Standard deviation + skewness + variance + sum + kurtosis + range + maximum	72.21

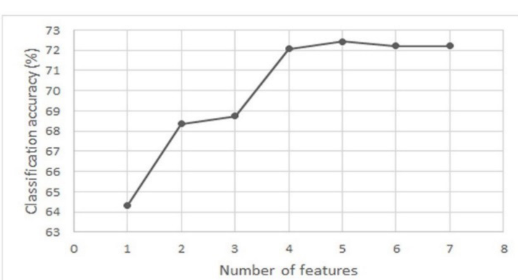

Figure 7. Number of features vs. classification accuracy.

The complexity of the experiment can be reduced by considering the spindle speed as a separate factor. The classification accuracy of simple CART classifier is shown in Table 3 and Figure 8 shows the comparison without considering the depth of cut and feed rate as separate factors. The classification accuracy on considering the spindle speed as a separate factor was found out to be in the range of 81% to 87%.

On taking both the feed rate and spindle speed as separate factors, the complexity of the experiments is further reduced. Table 4 shows the classification accuracy of a Simple CART classifier for this case and Figure 9 shows the comparison of accuracy for different combinations. The accuracy in this case is found to vary between 81% and 91%. A lesser value of classification accuracy was recorded for a few combinations of feed rate and spindle speed in contrast to the values obtained when only the spindle speed was considered as a distinct factor, however an overall increase of 8–18 % is found in the classification accuracy by considering the spindle speed and feed rate as separate factors as compared to the case with all signals combined.

Table 5 shows the values of classification accuracy recorded for a Simple CART classifier when all the three

Table 3. Classification accuracy of simple CART without considering feed rate and depth of cut as distinct factors

spindle speed (rpm)	Classification accuracy of simple CART (%)
510	81.03
770	81.92
900	87.00

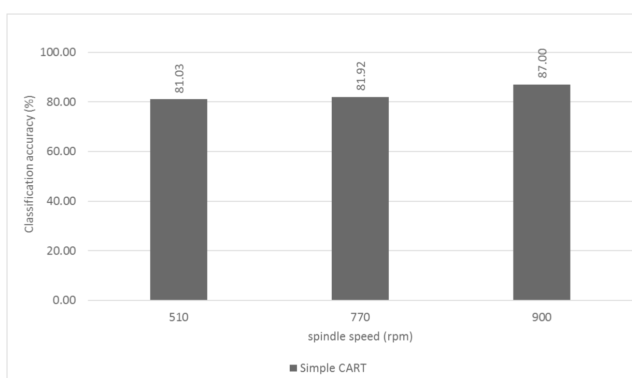

Figure 8. Comparison of classification accuracy without considering depth of cut and feed rate as separate factors.

Table 4. Classification accuracy of simple CART without considering depth of cut as a separate factor

spindle speed *(rpm)*	Feed rate *(mm/rev)*	Classification accuracy of simple CART *(%)*
510	0.109	91.00
510	0.122	85.00
510	0.135	83.75
770	0.109	85.75
770	0.122	91.33
770	0.135	81.75
900	0.109	81.50
900	0.122	88.33
900	0.135	90.75

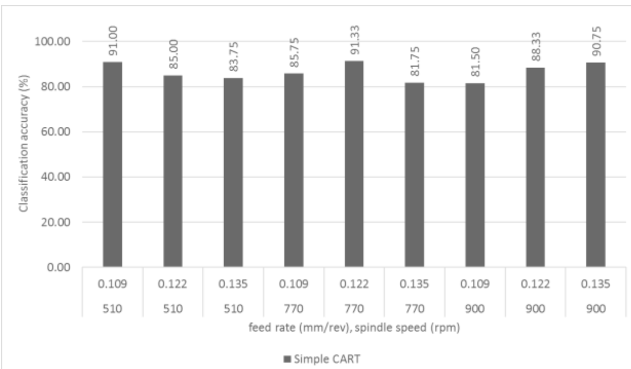

Figure 9. Comparison of classification accuracy without considering depth of cut as a separate factor.

Table 5. Classification accuracy of simple CART considering depth of cut, feed rate and spindle speed as distinct

spindle speed *(rpm)*	Feed rate *(mm/rev)*	Depth of cut *(mm)*	Classification accuracy of simple CART *(%)*
510	0.109	0.5	98.75
510	0.109	0.8	96.50
510	0.109	1	98.00
510	0.122	0.5	95.00
510	0.122	0.8	91.25
510	0.122	1	89.50
510	0.135	0.5	92.75
510	0.135	0.8	86.50
510	0.135	1	97.75
770	0.109	0.5	83.25
770	0.109	0.8	100.00
770	0.109	1	89.50
770	0.122	0.5	97.50
770	0.122	0.8	98.75

factors namely the spindle speed, feed rate and the depth of cut are taken as distinct features. The comparison for every signal at 510 rpm speed is as shown in Figure 10. The classification accuracy in this case lies from 81% to 100%. Thus there is an increase of 8-27 % in the classification accuracy as compared to the value obtained for all signals combined. Thus the accuracy of classification can be further increased by reducing the complexity by taking all the spindle speed, depth of cut and feed rate as separate factors.

Hence, it can be said that the classification accuracy for a Simple CART classifier increases, when considering discrete models. However, the time to set up the condition monitoring system is directly proportional to the number of models. Therefore, the setting up time for the system increases with the increase in the number of models.

4.3. Classifier Validation

The representation of the confusion matrix is further explained for better understanding. The confusion matrix for the classification is shown in *1*. The good condition of the cutting tool is depicted in the uppermost row of the confusion matrix. The first element in the confusion matrix denotes the number of signals that are in good condition and categorized as good followed by the number of signals which are in good condition and categorized by 0.2 mm flank wear (FLW1), denoted by the second element in the confusion matrix. The third element in the confusion matrix represents the number of signals in good condition and categorized by 0.4 mm flank wear (FLW2). Similarly, the number of signals in good condition which are categorized by 0.6 mm flank wear (FLW3) are represented by the fourth element in the confusion

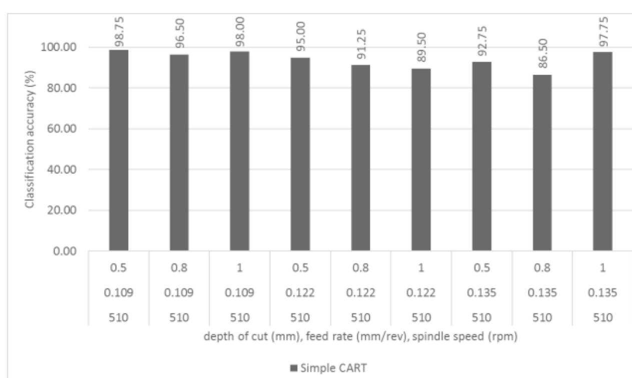

Figure 10. Comparison of classification accuracy of every signal with 510 rpm spindle speed.

GOOD	FLW1	FLW2	FLW3	< classified as
2004	0	415	281	GOOD
4	2369	119	208	FLW1
288	200	1814	398	FLW2
308	184	470	1738	FLW3

Figure 11. Confusion matrix of simple CART classifier for all signals combined.

matrix. In the same way, the second row of the confusion matrix corresponds to 0.2 mm flank wear in the cutting tool. Likewise, the distribution can be explained for the other elements of the confusion matrix. The diagonal elements in the matrix indicate the cases which are appropriately classified whereas the wrongly classified cases are indicated by the off diagonal elements of the confusion matrix.

Many GOOD condition signals are wrongly classified as FLW2 and FLW3 which can be seen from the confusion matrix in Figure 11. Some signals acquired for some machining considerations are analogous to FLW2 and FLW3 conditions, which can be the reason for the misclassification. The FLW2 and FLW3 conditions contribute to a higher quantity of misclassifications whereas the FLW1 condition records a very few mistakes in the classifications. The resemblance of signals for flank wear between FLW2 and FLW3 condition could be the reason for the high misclassification. The resemblance in the values of the FLW2 and FLW3 signals could be due to the identical cutting edge for both FLW2 and FLW3 condition.

5. Conclusion

The objective of this study was to find the efficiency of the Simple CART classifier for a single point cutting tool condition monitoring. For all the signals combined, the accuracy of classification for the simple CART classifier was found out to be 73.38%. The classification accuracy ranges between the values 81% and 87% for different combinations of depth of cut. For different combinations of the depth of cut as well as the feed rate involved in machining the workpiece, the accuracy of classification was found to increase, ranging from 81.5% to 91%. On considering different combinations of feed rate, spindle speed as well as the depth of cut, the classification accuracy was found to increase significantly, ranging from 81% to 100%. Thus, for obtaining high classification accuracy with simple CART classifier, the operator has to adjust the settings of the condition monitoring system for every combination of feed rate, spindle speed and depth of cut.

6. References

1. Elangovan M, Ramachandran KI, Sugumaran V. Studies on Bayes classifier for condition monitoring of single point carbide tipped tool based on statistical and histogram features. Expert Systems with Applications. 2010 Mar; 37(3):2059–65.
2. Gangadhar N, Kumar H, Narendranath S, Sugumaran V. Fault diagnosis of single point cutting tool through vibration signal using decision tree algorithm. Procedia Materials Science. 2014 Dec; 5:1434–41.
3. Grote KH, Antonsson EK. Springer handbook of mechanical engineering. Berlin Heidelberg: Springer; 2009.
4. Thamizhmanii S, Hasan S. Measurement of surface roughness and flank wear on hard martensitic stainless steel by CBN and PCBN cutting tools. Journal of Achievements in Materials and Manufacturing Engineering. 2008 Dec; ,31(2):415–21.
5. Sundaram S, Senthilkumar P, Kumaravel A, Manoharan N. Study of flank wear in single point cutting tool using acoustic emission sensor techniques. ARPN Journal of Engineering and Applied Sciences. 2008 Aug; 3(4):32–6.
6. Teli S, Kanikar P. A survey on decision tree based approaches in data mining. International Journal of Advanced Research in Computer Science and Software Engineering. 2015 Apr; 5(4):613–7.
7. Kalmegh S. Analysis of WEKA data mining algorithm REPTree, Simple CART and RandomTree for classification of Indian news. International Journal of Innovative Science, Engineering and Technology. 2015 Feb; 2(2):438–46.
8. Gordon L. Using classification and Regression trees (CART) in SAS® Enterprise Miner™ for applications in public health. SAS Global Forum; 2013. p. 1–8.
9. Aher SB, Lobo LM. Comparative study of classification algorithms. International Journal of Information Technology. 2012 Jul-Dec; 5(2):307–10.