Leaf Mechanical Resistance: Effect of Leaf Geometry Shapes for Maturity Classification

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***Abstract*—The leaf mechanical resistance differs by species; leaf geometry shape, besides they are maturity-transition dependent. Despite the leaf developments being described extensively, different leaf geometry shapes and its maturity influence on its mechanical resistance is still vague. This paper discusses the statistical significance of the leaf mechanical resistance by geometry shapes for leaf maturity classification. Tensile tests were performed on ten samples from each of 20 species leaf lamina strips (5 x 50 mm) at three maturity states (young, adult, and old). The indicators used were the Tensile Strength (S_T), Work-to-Tear (W_T), and Specific Work-to-Tear (SW_T). Statistical and classification analyses, supported by SPSS and Waikato Environment for Knowledge Analysis (WEKA) tools, were performed to examine the leaf mechanical resistance indicators on the maturity states predictions. All S_T, W_T, and SW_T showed statistical significance were for the young-adult. The young-old was only significant for W_T which showed the better accuracy of 0.11% - 27.14% above S_T and SW_T for maturity classification. However, classification accuracy was higher for W_T attribute on significant leaf geometry shapes segregation, with enhancement of 33.63%. The study suggests that W_T measure on significant leaf geometry shapes is a useful indicator of leaf maturity state classification.**

***Index Terms*—Data Classification; Leaf Geometry; Leaf Maturity; Leaf Mechanical Resistance.**

I. INTRODUCTION

Plants mechanical resistance often relates to its functional bases such as photosynthesis rate, and metabolism level for growth–survival trade-offs. The mechanical resistance in leaves was identified as one of the key indicators on the plant's anti-herbivore defences. Diverse species demonstrates a different tolerance level towards destructive effects caused by herbivory and environmental stresses [1]. As the plant's age and become mature, their physical defence changes, leading to susceptibility to insect herbivores [2]. Leaf geometry size and shape factors have long been considered in the plant's growth [3, 4]. However, their relations with the toughness aspects were not discussed.

The fracture properties of plants determine the toughness of plants towards herbivore. Punching, tearing and shearing tests were typical approaches to quantify the biomechanical resistance of leaves [5]. The choice of testing approach was dependent on the research interests such as herbivory by insects or investigation plants sustain strategies [6]. Tearing and shearing tests were more commonly used to evaluate the leaf mechanical resistance [7].

The outcomes from these testing included 'structural' properties, for instance, leaf strength, flexural stiffness, as well as toughness (work to fracture) and 'material' properties such as specific strength, specific toughness and Young's modulus of elasticity [8]. The standard leaf mechanical resistance indicators reported in the literature included Tensile Strength (S_T), Work-to-Tear (W_T) and specific Work-to-Tear (SW_T), Work-to-Shear (W_S), Specific Work-to-Shear (SW_S), Punch Strength (S_P), Specific Punch Strength (SS_P), Work-to-Punch (W_P) and Specific Work-to-Punch (SW_P).

The leaf maturity state has a substantial influence on the plant's growth, nutrient content, yield, photosynthesis rate and physiochemical properties [9, 10, 11]. Although S_T, W_T, and SW_T indicators were widely studied on different leaf species across countries, the effect of different maturity states on leaf mechanical resistance was not clearly defined. Also, no previous works have considered leaf mechanical resistance by geometry shapes. As such, the leaf mechanical resistance indicators by geometry shape could provide some useful information for classifying the leaf maturity states.

The main objectives of this work are to examine the statistical significance of the leaf mechanical resistance indicators: S_T, W_T, and SW_T by different leaf geometry shape on its maturity classification. Tensile tests were conducted on 20 species (10 samples of each species at different maturity states) from the Development Department in USM Engineering Campus. Leaf geometry shapes and maturity level criteria were determined by protocols mentioned in Section III. The Statistical Analysis of Variance (ANOVA) followed by the post hoc tests were performed on S_T, W_T, and SW_T to investigate statistical differences between maturity levels. Leaf maturity classification was then performed on six different algorithms.

II. RELATED WORKS

Previous studies on leaf mechanical resistance concentrated on plant's self-support under the impacts of environmental factors and habitat variations [8, 12, 13, 14]. Some additional efforts also considered the leaf morphology for a better understanding of the leaf mechanical resistance [15]. Meanwhile, works related to leaf maturity were mainly performed on the plant's health and crops yield. For instance, Jahan et al. [16] evaluated the effect of leaf maturity on antioxidant activity on Moringa plant while Tyson et al. [17] evaluated the influence of leaf age on the plant's infection.

Lowman and Box [18] presented the variation in leaf toughness at different maturity states. In [18], punching test with penetrometer was used on five species of Australian rainforest trees. Leaf samples were collected from the same branch and segregated by five leaf ages for each species. It has been agreed in the literature that leaves can vary significantly by distinctive features such as outline shape, texture, venation, and colours.

Lee et al. [19] had identified plant using the deep learning approach by considering their features. Their findings proved that the venation showed better representative features than the outline shape. Dyrmann et al. [20] identified plant species using a combination of the leaf and plant outline. In Harrison et al. [21], the tropical tree species were recognised from the leaf spectral. Mahlein et al. [22] developed specific spectral disease indices for diseases detection in crops; while Zhang et al. [23] conducted plant diseased leaf segmentation and recognition by K-means with superpixel and orientation gradient. Regarding leaf maturity state, Hang et al. [24] studied the tobacco leaf by using spectral feature parameters with the Support Vector Machine (SVM) approach.

Previous researchers have confirmed that the variations in leaf mechanical resistance were dependent on its species and the surrounding variables such as nutrient and water supply, light intensity and competition among the neighbourhood. While the leaf outline shape was considered in many classification studies, the impact of its different shapes on leaf mechanical resistance is still vague. The knowledge about the leaf mechanical resistance classification by maturity level is also lacking. Thus, this paper attempts to fill up this knowledge gap.

III. Methodology

A. Sample Preparation

All the leaves samples were collected from terrestrial potted plants grown and nursed at the Development Department in USM Engineering Campus (5°08'59.8" N 100°29'27.8" E, approximately 4 m above sea level) between September to October 2017. Five leaf samples from each species, for 20 different plant species at three maturity states (young, adult, and old) were collected. The determination of leaf maturity criteria was based on the preliminary field observations by a number of leaves on branches, its colour or size; whichever is prevalent with reference to [18] and [25] as shown in Figure 1.

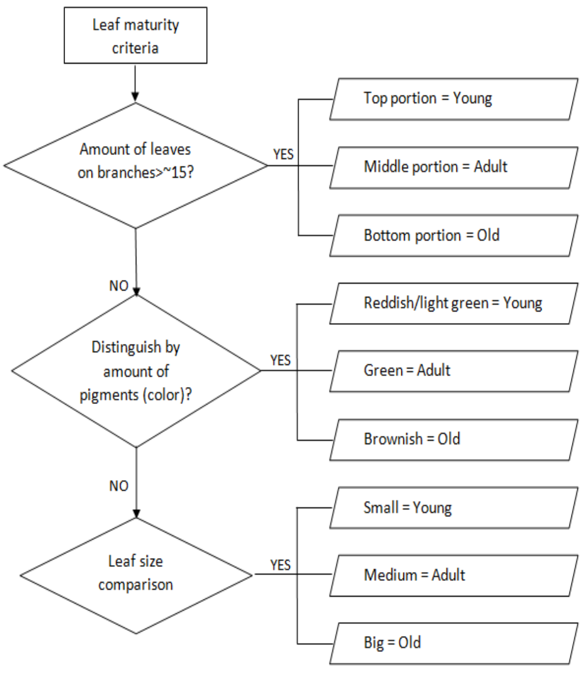

Figure 1: Leaf maturity state determination criteria

Leaf images were captured using Mi3 Smartphone camera (Sony IMX135 sensor, 13-megapixel 1/3.06-inch chip) in a light-controlled condition. The leaf geometry dimensions (longest width and length) were measured using the ImageJ 1.51n software. The leaves were subsequently stored in a plastic bag with moist towels until deemed ready for the tensile test, within 24 hours of each species leaf collection.

There were nine leaf geometry shapes (cordate, elliptical, irregular, lanceolate, linear, oblanceolate, obovate, ovate, peltate) compiled and characterised based on [26, 27, 28].

The determination of leaf shapes proposed in this study was according to the hierarchy of “leaf outline”, “the location of broadest width” and “width-to-length ratio” criteria as shown in Figure 2. The leaf lamina outline could directly determine the ‘cordate’ and ‘irregular’ shapes on visual inspection. The remaining seven shapes falls under the convex shape outline were distinguishable by the location of broadest width; ‘Top’, ‘Middle’, and ‘Bottom’. The ‘Top’ location refers to the region above middle line of the leaf lamina; the ‘Middle’ location refers to the region at the middle line while the ‘Bottom’ location refers to a region below middle line.

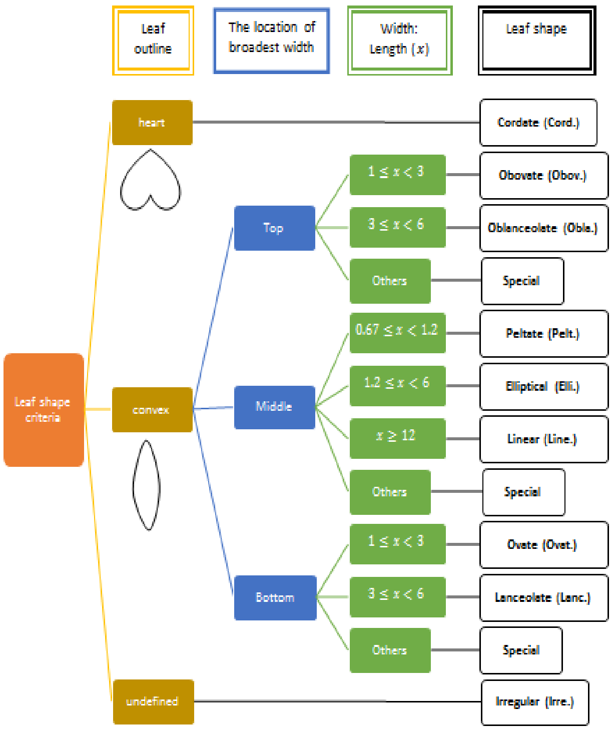

Figure 2: Criteria for leaf geometrical shape determination

This is further refined by different categories of width-to-length ratio measurement [27] into ‘elliptical’, ‘lanceolate’, ‘linear’, ‘oblanceolate’, ‘obovate’, ‘ovate’, and ‘peltate’ shapes. The dimensions which were not detected on any of these criteria were categorised as ‘Special’ and discarded from the study as indicated in Figure 2. Two parallel-sided intercostal lamina strips (50 x 5 mm) with an aspect ratio (length: width), 10:1 were used to avoid the potential effects of necking [29]. Therefore, the highly dissected, needle-type or twisted leaves, palmate compound leaflet and small leaves of size < (10.4 x 50) mm were avoided. Strips were cut within 2 mm away from both sides of the midrib using HIPPO SS650 6.5” scissors.

Approximately 5-10 mm of the leaf strip’s surface from each end was attached to an aluminium plate using cyanoacrylate compound (super glue) and strengthened with cloth tape to mount within tensile equipment clamp as presented in Figure 3. This is to ensure the test strips did not break at the ends and to prevent direct grip effect that potentially damages the leaf tissue.

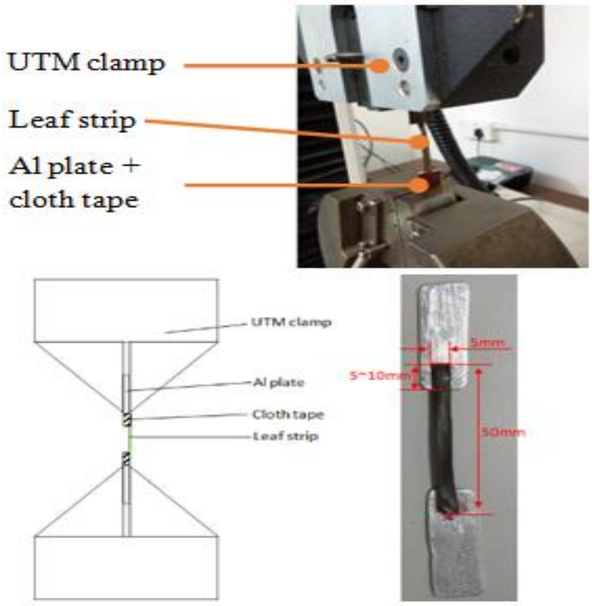

Figure 3: Photos and illustrative diagram of the leaf strip setup mounted on Instron UTM for the tensile test

B. Tensile Testing

Axial tensile tests were conducted using the Instron Universal Testing Machine (UTM), model 3367 equipped with a 500N static load cell. The crosshead extension speed was kept constant at 0.45 mm/s, and the resulting load (N) applied with the displacement (mm) were recorded to a personal computer at every 100 ms. Three leaf mechanical resistance properties were measured and derived, S_T, W_T, and SW_T.

- S_T is defined as the work to tear the leaf per unit leaf thickness. It indicates the maximum stress to break the leaf reflecting the measure of resistance against crack initiation [12].
- W_T is defined as the absolute amount of work done to tear the leaf per unit leaf width [12]. This attribute designates the energy required to break the leaf.
- SW_T indicates the specific toughness (work to break/tear) influenced by the leaf thickness [12].

S_T, W_T, and SW_T were evaluated according to Equations (1) to (3).

$$Tensile\ strength, S_T\ (Nm^{-1}) = \frac{F_T}{cross-section} \quad (1)$$

$$Work-to-tear, W_T\ (Jm^{-1}) = \frac{F_T \times displacement}{2} \quad (2)$$

$$Specific\ work-to-tear, SW_T\ (Jm^{-2}) = \frac{W_T}{cross-section} \quad (3)$$

where: F_T = tearing force (N), the maximum force exerted to break apart leaf strip on UTM.
cross-section = area (mm^2) of which leaf strip is broken into pieces (thickness × width).

C. Statistical Analysis

The statistical analysis was performed using IBM SPSS software version 22. Pearson correlation analysis was used to investigate associations among S_T, W_T, and SW_T. One-way ANOVA was used to test the differences among the leaf maturity states (young, adult and old) for a 95% confidence interval.

We tested two hypotheses relating to the leaf mechanical resistance indicators (S_T, W_T, and SW_T) across species: (i) The statistical significances of mechanical resistance indicators differ by maturity states (young, adult, and old), (ii) Leaf mechanical resistance by maturity states differ better in terms of leaf geometry shapes. The basic assumptions for one-way ANOVA including independent observations, normal distribution, and equal variances in each data group were carefully studied [30].

Any outlier and extreme values detected were filtered to ensure that qualitative data remains for reliable statistical analyses. The independent data between maturity levels and geometry shapes has confirmed the unrelated independent observations. Due to this study large sample size data ($n = 600$), the Central Limit Theorem supports the convergence to a normal distribution.

Following Ghasemi and Zahediasl [31], the ANOVA is robust to violations of normality and tiny adverse effects on results. In the event of non-homogeneity of variance analysis, the Welch's ANOVA test was used instead of one-way ANOVA. Tukey HSD post hoc test was performed to further investigate the differences in mechanical resistance within the three maturity states: young, adult and old. Games-Howell post hoc test was applied when non-homogeneity of variance was violated.

D. Classification Analysis

The classification analyses were conducted using NaiveBayes, SMO, IBK, KStar, J48, and REPTree algorithms in Waikato Environment for Knowledge Analysis WEKA (WEKA) tool version 3.8.1. The inputs were 600 instances featured by the mechanical resistance S_T, W_T, and SW_T and their corresponding maturity state: young, adult and old were the class attribute outputs. All the classifications were conducted under a 10-fold cross-validation test option to maximise information gained (ensuring all instances were used for both training and testing) and prevent overfitting phenomena.

The default parameters for each classifier were used without optimisation since we focus on the impact of study attributes instead of the algorithm's performance. ZeroR algorithm which always predicts the class with most observations was used as the performance reference baseline for comparisons among classifiers [32]. The classification analyses were considered on each attribute S_T, W_T, and SW_T and their combinations for the entire collective samples. The better classification performance was further analysed by segregating the dataset into nine geometry shapes accordingly.

IV. Results and Discussion

S_T, W_T, and SW_T were the attribute indicators, experimentally measured to determine the leaf mechanical resistance. Associations among S_T, W_T, and SW_T were evaluated on the Pearson correlation.

These attributes were statistically assessed on their mean differences within group samples across species. One of the issues identified was the existence of outliers. A remedy was taken in which 15% outliers from the original dataset consisting of 600 instances data were trimmed down to 509 instances. An assumption for the one-way ANOVA has not met; unequal sample size effect upon the outliers' removal and the violation of the homogeneous variance. This was adjusted on Welch's ANOVA with the follow-up Games-Howell post hoc test to determine the mean differences between maturity states.

The maturity state classifications were dependent on S_T, W_T, and SW_T attributes. Classification results on the cleaned dataset (outliers' removal) (n=509) were demonstrated on NaiveBayes, SMO, Ibk, KStar, J48, REPTree algorithms using 10-fold cross-validation. The cleaned dataset classification was considered to deduce the results obtained from statistical significance analysis. The baseline classifier (ZeroR) was included to indicate the minimum acceptable performance thresholds for comparisons among algorithms. As observed in Figure 4, classification accuracies achieved were low on each S_T, W_T, and SW_T and their combinations, within the range 30.25% - 44.01% for all algorithms.

The findings from statistical and classification analyses were discussed within entire collective samples and subsequently segregated by the leaf geometrical shapes.

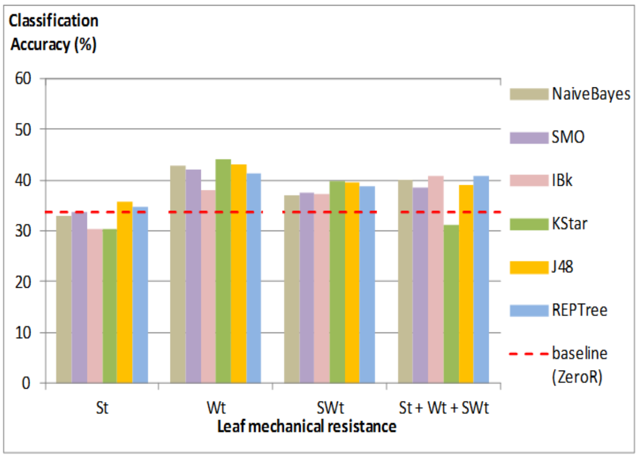

Figure 4: Classification accuracy by leaf mechanical resistance for the collective sample cleaned data

A. Collective Samples

All the leaf mechanical resistance attributes: S_T, W_T, and SW_T were strongly inter-correlated to each other as listed in Table 1. According to Edwards et al. [33], even though the indicators were strongly correlated, it is risky to assume that either attribute by itself could sufficiently represent the leaf mechanical resistance. It is therefore essential to take a step further to investigate the attributes' impacts on the mean differences between the leaf maturity states.

Table 1
Pearson Correlation Among S_T, W_T, and SW_T (Statistically Significant, p < 0.05*)

	S_T	W_T	SW_T
S_T			
W_T	0.836*		
SW_T	0.911*	0.919*	

The results from Table 2 manifested that there were major significances between the young-adult as agreed in S_T, W_T, and SW_T attributes showing all tests were statistically significant (p<0.05). Meanwhile, significant differences were observed between young-old maturity states only for W_T. Conversely, no significant results were observed for adult-old in all S_T, W_T, and SW_T.

As reported in [18], old leaves were found four times tougher than the young leaves, since the adult leaves have higher leaf tissue density, toughness, leaf thickness and Leaf Mass per Area (LMA) as compared to the sapling leaves [8]. Past studies had merely focused on the comparisons between young (juvenile or sapling) and adult leaves. An early prediction observed at this level was that there was not much amplification in the leaf mechanical resistance after maturity. Therefore, the adult and old leaves were hardly distinguishable by the mechanical resistance measures.

On the other hand, there was a slight variation effect between the young-old states which was seen through significant results for W_T attribute while the results were insignificant in S_T and SW_T attributes as shown in Table 2. The insignificant findings on young-old on S_T and SW_T attributes shall cause the tendency of cancelling effects leading to a non-distinguishable mean difference in young-old leaf maturity states.

Table 2
Statistical Analyses Result for S_T, W_T, and SW_T on Mean Difference between the Maturity States (Statistically Significant, p < 0.05*)

Response variable	Welch's ANOVA	Post hoc test (Games-Howell) young-adult	young-old	adult-old
S_T	0.033*	0.031*	0.251	0.540
W_T	<0.001*	<0.001*	0.005*	0.133
SW_T	0.013*	0.009*	0.431	0.129

B. Leaf Geometry Shape

On discrimination by nine leaf geometrical shapes, results showed statistically significant differences among maturity states for S_T, W_T, and SW_T in three shapes: Lanceolate, Linear and Oblanceolate while non-significant for the remaining as indicated in Table 3. The young-adult and young-old were observed significant for Lanceolate's on S_T, young-adult, and adult-old for both W_T and SW_T measures. In Linear, young-old was more variable for S_T, while young-old and adult-old indicated more differences for W_T and SW_T. No significant effects were observed in S_T, W_T, and SW_T for young-adult.

While in Oblanceolate, young-adult and young-old were observed significant for S_T, W_T, and SW_T. It may be argued that the three significant shapes were dominant over the non-significant ones, to distinguish leaf maturity states better for classification analyses, as compared to the collective samples.

Genetic, biotic and abiotic components play a role in leaf shape diversity [34] while the specific properties of cell walls, vein networks, and epidermis properties could be important aspects in determining leaf mechanical resistance [35].

However, no study relates leaf maturity states to leaf geometry shapes. One of the explanations could be due to the limitation of leaf maturity determination criteria and protocols used. Seedling leaves and small size leaves were inappropriate to be used; while most of the old leaves might easily drop-off or defected. These conditions gave constraint to the sample leaves collection to sufficiently represent leaf maturity states across species.

Table 3
Statistical Significance Results, p < 0.05* for S_T (W_T) SW_T between Maturity States by Leaf Geometry Shape

Shape	No. of sample, $\boldsymbol{n}$	ANOVA/Welch's ANOVA$^{\&}$	Post hoc test (Tukey HSD/Games-Howell$^{\&}$) young-adult	young-old	adult-old
Lanc.*	30	<0.001* (*0.002*$^{*,\&}$) 0.005$^{*,\&}$	0.001* (0.004$^{*,\&}$) 0.009$^{*,\&}$	0.002* (0.996$^{\&}$) 1.000$^{\&}$	0.897 (0.003$^{*,\&}$) 0.006$^{*,\&}$
Irre.	30	0.809 (0.522) 0.774	0.981 (0.599) 0.812	0.802 (0.570) 0.807	0.895 (0.999) 1.000
Obov.	112	0.339$^{\&}$ (0.112$^{\&}$) 0.073$^{\&}$	0.633$^{\&}$ (0.734$^{\&}$) 0.864$^{\&}$	0.321$^{\&}$ (0.654$^{\&}$) 0.204$^{\&}$	0.846$^{\&}$ (0.098$^{\&}$) 0.141$^{\&}$
Ovat.	90	0.340 (0.250) 0.212$^{\&}$	0.318 (0.252) 0.187$^{\&}$	0.606 (0.933) 0.908$^{\&}$	0.873 (0.431) 0.321$^{\&}$
Elli.	176	0.680 (0.753$^{\&}$) 0.947	0.693 (0.937$^{\&}$) 0.982	0.772 (0.960$^{\&}$) 0.988	0.992 (0.735$^{\&}$) 0.942
Line.*	30	0.018* (0.002*) 0.004*	0.321 (0.960) 0.925	0.265 (0.004*) 0.007*	0.013* (0.008*) 0.017*
Cord.	60	0.410 (0.389) 0.511	0.436 (0.356) 0.583	0.986 (0.813) 1.000	0.532 (0.723) 0.565
Obla.*	40	0.005* (<0.001*) 0.000$^{*,\&}$	0.022* (<0.001*) 0.022$^{*,\&}$	0.012* (<0.001*) <0.001$^{*,\&}$	0.997 (0.977) 0.983$^{\&}$
Pelt.	30	0.296 (0.150) 0.379	0.275 (0.267) 0.382	0.854 (0.166) 0.551	0.563 (0.957) 0.953

C. *Leaf Maturity Classification*

Since the leaves' maturity differ by its mechanical resistance on statistical analyses, the maturity state classifications with collective samples were presented. Classification accuracies range between 30.25% - 44.01% on collective sample cleaned data as listed in Figure 4. Moreover, Figure 4. shows that S_T, W_T, and SW_T alone achieved better classification accuracy, whereby, the combinations of S_T, W_T, and SW_T attributes has weakened the performance. W_T was the best attribute of all for maturity state classification. When comparing the before and after cleaned (without outliers and extreme values) data, W_T showed the highest accuracy enhancement of all, 4.90% - 30.03% (Table 4). Considering only reliable results shown above the baseline, the best classification accuracies were on W_T attribute: 44.01% with KStar, 43.03% with J48 and 41.26% with REPTree. Low accuracies were indicated on S_T attribute: 35.76% with J48 and 34.77% with REPTree (Figure 4).

Table 4
Classification Accuracy Changes on Cleaned Data from the Original by Classification Algorithm

Algorithm	Leaf mechanical resistance indicator S_T	W_T	SW_T	$S_T+W_T+SW_T$
NaiveBayes	-3.98%	29.12%	9.90%	16.17%
SMO	0.87%	30.03%	7.20%	14.96%
Ibk	-5.97%	4.90%	4.59%	-6.14%
KStar	-3.45%	3.97%	8.74%	-3.00%
J48	7.29%	12.73%	-0.45%	2.89%
REPTree	10.98%	6.26%	6.03%	3.44%

Additional information about the geometry shape significance was used to classify the maturity states via mechanical resistance indicators. NaiveBayes, SMO, Ibk, and KStar algorithms were excluded at this level based on the performances indicated below the baseline in collective sample classifications. As the W_T feature alone has proven the best classification accuracy, the maturity state classification analyses by leaf geometry shape were only executed with W_T attributes as shown in Figure 5.

All classification accuracies in each geometry shape were above the performance baseline except for 'irregular', 'cordate' and 'peltate' shape. As expected from the statistical analyses outcome, the better classification accuracies were reflected in significant shapes; 57.50% for 'oblanceolate' on the J48 algorithm and 50.00% on the REPTree algorithm, 56.67% and 53.33% on the J48 algorithm and REPTree for 'linear' shape respectively and 43.33% for 'lanceolate' on J48 algorithm. Apparently, good classification results tie with the significant shapes: 'oblanceolate', 'linear' and 'lanceolate' as reported in statistical analysis (Section IV. B).

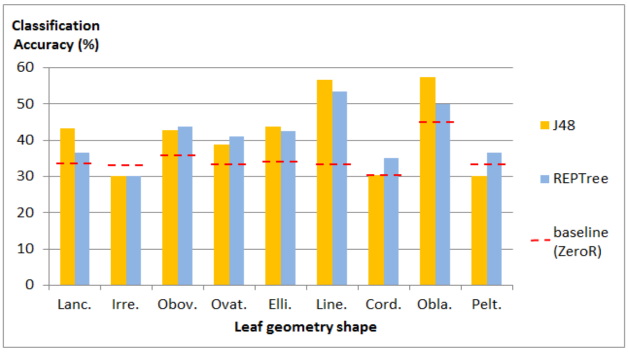

Figure 5: Classification accuracy considering leaf geometry shape on W_T attribute of J48 and REPTree algorithms

The classification analyses performed better by leaf geometry shape compared to the entire collective samples. The performances tally with the outcomes of the statistical significance tests showing significant differences observed for W_T on young-adult and young-old while S_T and SW_T showed significances on young-old only. On further breakdown into leaf geometry shapes, the statistically significant shapes showed better classification accuracy into corresponding maturity states.

V. Conclusion

On average, the leaf mechanical strength by maturity state varied considerably by the S_T, W_T, and SW_T indicators. Despite the apparent significance of S_T, W_T, and SW_T among species, there is relatively little known about the variation by maturity state across species. This study presents leaf maturity classification by its mechanical resistance attributes. Two study hypotheses were accepted, the statistical significances of mechanical resistance indicators differ by maturity states, and the leaf mechanical resistance by maturity states differ better in terms of leaf geometry shapes. Significant differences on S_T, W_T, and SW_T between the young against adult or old maturity states were observed. Based on the results, S_T, W_T, and SW_T were correlated strongly with each other. Findings also showed that the W_T is the best predictive attribute to classify the leaf maturity state. Classification accuracy is higher when entire collective samples further segregated by geometry shapes, in particular, on lanceolate, linear and oblanceolate shapes. An improvement of 33.63 % for W_T could be attained on leaf geometry shapes classification. Other mechanical resistance influences could be taken into consideration.

Future improvements in the classification accuracy could be targeted on other leaf geometrical measures and textures like length, perimeter, mass and the leaf venation.

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