DIFFERENTIATION OF RUBBER CUP COAGULUM THROUGH MACHINE LEARNING

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A support vector machine classification algorithm was formulated to differentiate rubber cup coagulum according to the type of acid coagulant used. Two classification models were established, a binary classification algorithm and a model that can identify if formic, acetic, sulfuric acid, or no acid was used to induce coagulation. The models were based on the properties of the rubber cup coagulum that are easy to measure, such as tensile strength, water contact angle, and density. The binary classification model, which differentiates the industry-accepted formic acid-coagulated rubber cup coagulum from those which are not, exhibited satisfactory reliability, as evidenced by a 92% overall prediction accuracy and 71.4% cross-validation accuracy. Moreover, it was also determined that the rubber properties density, and water contact angle were important contributors for the classification. Acid-induced rubber coagulation is an important post-harvest process that influences the resulting rubber quality. Thus, the accurate differentiation of the rubber samples is useful for quality assurance purposes, as well as in policy enforcement.

support vector machines, rubber post-harvest, acid-induced coagulation

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INTRODUCTION

Rubber is a globally important agricultural commodity, widely used in various applications such as healthcare, automobiles, and construction, among others. Rubber processing begins at harvesting the natural rubber latex (NRL) through a process called tapping. Coagulation of the collected NRL represents a vital post-harvest processing step, wherein coagulation is usually carried out with the aid of acids. Acid-mediated NRL coagulation involves the neutralization of negatively charged protein complexes that leads to aggregation, and the eventual coagulation (Gidrol et al. 1994; De Oliveira Reis et al. 2015). Formic acid has long been used to induce NRL coagulation (Ditmar, 1908), although other acids have already been reported to facilitate coagulation such as hydrochloric acid (Karunaratne, Piyadasa, 1973), sulfuric acid (Best, Morrell, 1955), and biomass-derived acids (Baimark, Niamsa, 2009). The type of acid used to drive coagulation is known to influence the physical properties of the coagulated rubber (Chukwu et al., 2010). Thus, the differentiation of coagulated rubber based on the coagulant used is not only important in terms of practicality, but also in trade and regulatory considerations.

Rubber is one of the top agricultural crops in the Philippines (Philippine Statistics Authority, 2017), wherein majority of the Philippine rubber industry is located in the southern part of the

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Philippine archipelago. Locally, the coagulated NRL is referred to as 'cuplumps', the equivalent of cup coagulum. Cuplumps represent the earliest rubber products that are traded and sold. In order to ensure the quality of the sold cuplumps, the Philippine government has strongly recommended the use of formic acid to induce coagulation (DOST-PCAARRD, 2014). However, due to logistics reasons and/or problems related to the supply of formic acid, widespread use of acids other than formic acid has been rampant. These 'non-standard acids' include vinegar-derived acetic acid, and automobile battery-derived sulfuric acid. The resulting 'non-standard cuplumps' are then sold claiming to be formic acid-coagulated. This fraudulent activity stems from the fact that formic acid-coagulated cuplumps are priced higher compared to the non-formic acid-coagulated cuplumps. Considering that the overall quality of the rubber products produced is dependent on the quality of the cuplump (Wisunthorn et al., 2015), ensuring the consistency and quality of the produced cuplumps is vital in safeguarding the competitiveness of the Philippine rubber industry. Thus, the differentiation of formic acid-coagulated cuplumps from non-formic acid-coagulated cuplumps is critical in enforcing compliance and maintaining trade standards. However, such method of classifying cuplumps according to the acid coagulant used remains to be created. Against this backdrop, this study aims to utilize machine learning in differentiating formic acid-coagulated cuplumps from non-formic acid-coagulated cuplumps using properties that are easy to measure.

MATERIAL AND METHODS

Rubber coagulation

The Department of Agriculture – Zamboanga Peninsula Integrated Agriculture Center (DA-ZAMPIARC) provided the rubber cuplumps. The NRL was harvested from rubber trees (*Hevea brasiliensis*) and was coagulated using 5% (v/v) formic acid, acetic acid, and sulfuric acid. Naturally coagulated rubber cuplumps (no acid) were also prepared.

Surface wetting property

The interaction of the cuplumps with water was evaluated using contact angle measurements using ThetaLite100 (Biolin Scientific, Germany). Cuplumps were sliced into strips and dabbed before testing. At room temperature, the capillary of the device was filled with distilled water that runs through the syringe thereby producing a 5 µl sessile drop. The resulting maximum contact angles were measured. The analysis was conducted in triplicates for each cuplump sample.

Vertical tensile strength

Samples were sliced until the dimensions of 1 cm width × 5 cm length × 2 mm thickness were reached. The samples were then vertically clipped and stretched at 500 mm min^{-1} with the capacity of 100 N using the Universal Testing Machine (UTM) Autograph AGS-X (Gester Instruments, China). The analysis was conducted in triplicates for each cuplump sample.

Density

Cuplumps with dimensions of 1 cm^3 were weighed. The volume occupied by the cuplumps was determined through water displacement. A 10 ml graduated cylinder was filled with 5 ml of water for the initial volume. A cuplump sample was then placed inside the graduated cylinder, and the new volume was recorded. The density of the samples was then obtained by using the

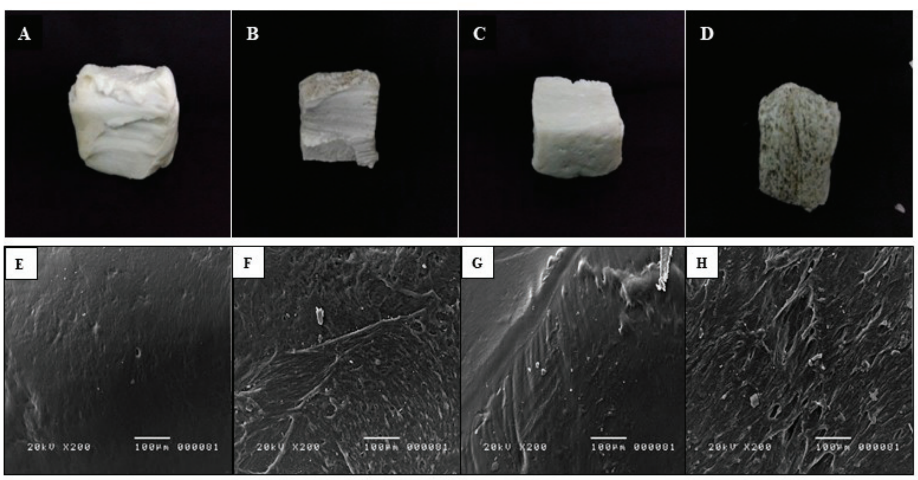

Fig. 1 The top images represent the macroscopic picture of the rubber cuplumps coagulated with A) formic acid, B) acetic acid, C) sulfuric acid, D) no acid. The bottom images are the surface morphologies obtained through scanning electron microscopy of the cuplumps coagulated with E) formic acid, F) acetic acid, G) sulfuric acid, H) no acid.

Table 1. Average ± standard deviation of measurements for each cuplump type that will serve as the continuous predictors for the SVM classification

Cuplump type	Vertical tensile strength (MPa)	Density (g ml^{-1})	Contact angle (°)
Formic acid	3.89 ± 0.86	1.01 ± 0.04	61.3 ± 9.9
Acetic acid	3.64 ± 0.49	0.94 ± 0.01	56.5 ± 1.6
Sulfuric acid	2.53 ± 0.78	0.92 ± 0.04	55.5 ± 10.4
No acid	9.20 ± 3.8	0.91 ± 0.11	55.2 ± 22.1

formula: density = mass/volume. The analysis was conducted in triplicates for each cuplump sample.

Classification using machine learning

The obtained data from the aforementioned measurements were used to formulate a classification algorithm using support vector machine (SVM) as implemented in TIBCO Statistica (Version 13.3, 2017). The results were validated by applying a 10-fold cross validation. Specific details of the classification algorithm are provided in the text.

RESULTS

The four cuplump types analyzed in this study were inspected visually (Fig. 1). Macroscopic and microscopic features were similar, indicating that cuplump differentiation based on visual attributes is difficult. Thus, other properties of the cuplumps that can be measured easily were used for classification and differentiation. The selected properties are the vertical tensile strength, surface wetting in the form of water contact angle, and density (Table 1). The measurements were used as the continuous descriptors for SVM classification in order to formulate a classification algorithm. Two SVM classification models were formulated. Model A is a binary classification model wherein the differentiation is limited to formic acid-coagulated cuplump and non-formic acid-coagulated cuplump. On the other hand, model B is a more thorough classification model, which differentiates the cuplumps into classes based on the acid used to induce coagulation. Table 2 shows the specifications and classification performances of both models. The performance of the model is measured in terms of accuracy, which refers to the successful classification done by the algorithm. The SVM classification results presented are typical showing the optimal weights assigned to the support vectors that gave rise to the hyperplanes or decision boundaries used in the classification. The performances of the two SVM classification models were satisfactory, as revealed by their respective class accuracy ratings (Table 2). Model A, the binary classification model, showed reliable classification ability, with an overall class accuracy of 92%, and cross-validation accuracy of 71%. Model B likewise exhibited an acceptable classification ability, although lower than model A. Thus, derivative models from model A were formulated in order to identify the individual contributions of each rubber property in the classification algorithm. One rubber property was systematically removed from the binary classification algorithm, while evaluating the performance. Table 3 summarizes the results, indicating that rubber density and contact angle were essential for the classification models.

DISCUSSION

Rubber coagulation under acidic conditions is known to affect various physical properties of rubber, such as tensile strength, and cross-linking density (Siti Maznah et al., 2008). Thus, one of the parameters measured in response to acid coagulant used is the cuplump tensile strength. It was found that the rubber cuplumps coagulated naturally (no acid) had a statistically higher tensile strength than the acid-coagulated cuplumps. This result resonates with the observation that at a certain lower pH, rubber tensile strength decreases due to the denaturation of proteins that are implicated in rubber toughness (Siti Maznah et al., 2008). Other rubber attributes measured include density, and surface wetting, wherein it was found that

Table 2. Optimum support vector machine (SVM) classification specifications and results for the two models. Model A is a binary classification model that differentiates formic acid-coagulated cuplumps from non-formic acid-coagulated cuplumps. Model B differentiates no acid, formic acid, acetic acid, and sulfuric acid-coagulated cuplumps

	Model A	Model B
SVM type	classification type 1, capacity = 3.0	classification type 1,capacity = 8.0
Kernel type	linear	radial basis function, gamma = 0.333
Number of support vectors	6 (4 bounded)	9 (0 bounded)
Training set	65%	75%
Class accuracy (%)	train = 100, test = 80, overall = 92, cross-validation = 71.4	train = 89, test = 67, overall = 83, cross-validation = 44.44

Table 3. Performance of the binary classification models when one descriptor was removed from the algorithm

	Model A-1	Model A-2	Model A-3
SVM type	classification type 1, capacity = 1.0	classification type 1, capacity = 8.0	classification type 1, capacity = 7.0
Kernel type	linear	linear	linear
Continuous descriptors	vertical tensile strength, density	vertical tensile strength, contact angle	density, contact angle
Number of support vectors	7 (5 bounded)	7 (5 bounded)	5 (3 bounded)
Training set	65%	65%	65%
Class accuracy (%)	train = 71.4, test = 80, overall = 75, cross-validation = 57.1	train = 71.4%, test = 60, overall = 66.7, cross-validation = 42.9	train = 100, test = 80, overall = 91.7, cross-validation = 85.7

there was no statistical difference among the samples examined. These three rubber physical properties were used as continuous descriptors for the classification and differentiation algorithm founded on machine learning. SVM classification has been utilized for agricultural applications such as crop classification (Mathur, Foody, 2008; Guerrero et al., 2012), and plant disease identification (Rumpf et al., 2010). In the current scenario, the SVM classification (type 1) algorithm is more appropriate than the other classification methods for categorical dependent variables, such as discriminant analysis or logistic regression. SVM does not require a large sample size, and the usual normality assumption of the numerical predictors in discriminant analysis.

The formulated classification models rely on the SVM classification function rooted on nonlinear decision boundaries that are based on the combination of the measured physical properties of the rubber cuplumps. These models generally attempt to identify if formic acid was used as the coagulant, since this acid is widely used and accepted. While any acid can induce latex coagulation, the resulting rubber quality can vary. For instance, using excessive amounts of sulfuric acid to induce coagulation can bring significant softness deviations (Best, Morrell, 1955), leading to an overall poor rubber quality (Othman, Lye, 1980). Hence, the ability to identify the coagulant used for cuplump processing based on simple rubber properties is a valuable tool in cuplump quality assessment. Model A differentiates formic acid-coagulated rubber cuplumps from those that are not, while Model B identifies if the cuplump was coagulated using formic acid, acetic acid, sulfuric acid, or if no acid was used. Suffice to say, the selected rubber physical attributes are enough to differentiate one class from the other since the constructed classification models exhibited reliability, as evidenced by their overall prediction accuracy. Models A and B have a high practical potential considering that only three rubber properties that are easy to measure are needed to identify the coagulant used. However, considering that Model A performs better than model B, model A was subjected to further optimizations in order to identify the influence of each descriptor on the overall predictive performance of the algorithm. This was achieved through a systematic removal of one descriptor, thereafter the model performance was evaluated. As demonstrated in Table 3, the descriptors density and contact angle were essential for the accurate classification. When either descriptor was removed, the performance of the model decreased (Models A-1 and A-2). But when the two descriptors were utilized, the performance improved, as well as the cross-validation accuracy.

The current work represents a pioneering endeavour in rubber cuplump quality assessment based on acid coagulant identification. Other assessment and measurement tools essential for regulatory purposes have mainly focused on contaminant detection (Somwong et al., 2017), rubber moisture (Suchat et al., 2015), isoprene units (Tuampoemsab et al., 2015), viscosity (Ehabe et al., 2005), among other properties. Thus, the presented method is a welcome addition to the repertoire of quality monitoring methodologies that can further enhance and improve rubber processing.

CONCLUSION

The present work has demonstrated the utility of machine learning in differentiating rubber cuplumps according to the acid used for coagulation. Two SVM classification models were formulated, wherein both models exhibited reliable classification ability. The first model can distinguish formic acid-coagulated cuplumps from non-formic acid-coagulated cuplumps, with an overall accuracy of 92% and cross-validation accuracy of 71.4%. The second model can identify if formic, acetic, sulfuric acid, or no acid was used to induce rubber coagulation, with an overall accuracy of 83%, and cross-validation accuracy of 44.4%. The better model, which implements binary classification, was determined to be heavily influenced by the rubber properties of density and water contact angle. The results presented can potentially improve the local rubber industry by aiding policy enforcement, and strengthening regulatory standards.

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REFERENCES

Baimark Y, Niamsa N (2009): Study on wood vinegars for use as coagulating and antifungal agents on the production of natural rubber sheets. Biomass and Bioenergy, 33, 994–998.

Best LL, Morrell SH (1955): Effect of sulfuric acid coagulation on properties of natural rubber. Rubber Chemistry and Technology, 28, 1185–1192.

Chukwu MN, Idiagha, JA, Ihuezor MO (2010): Effect of acid coagulation level on the plasticity retention index (PRI) of natural rubber. Multidisciplinary Journal of Research Development, 15, 1–4.

De Oliveira Reis G, Menut P, Bonfils F, Vaysse L, Hemar Y, Sanchez C (2015): Acid-induced aggregation and gelation of natural rubber latex particles. Colloids and Surfaces A: Physicochemical and Engineering Aspects, 482, 9–17.

Ditmar R (1908): Formic acid as a coagulant for the latex of *Hevea brasiliensis* (para rubber). Zietschrift fur Chemie und Industrie der Kolloide, 3, 104.

DOST-PCAARRD (2014): The Philippines recommendations for rubber. Department of Science and Technology – Philippine Council for Agriculture, Aquatic and Natural Resources Research and Development, Laguna.

Ehabe E, Bonfils F, Aymard C, Akinlabi AK, Sainte Beuve J (2005): Modelling of Mooney viscosity relaxation in natural rubber. Polymer Testing, 24, 620–627.

Gidrol X, Chrestin H, Tan H-L, Kush A (1994): Hevein, a lectin-like protein from *Hevea brasiliensis* (rubber tree) is involved in the coagulation of latex. Journal of Biological Chemistry, 269, 9278–9283.

Guerrero JM, Pajares G, Montalvo M, Romeo J, Guijarro M (2012): Support vector machines for crop/weeds identification in maize fields. Expert Systems with Applications, 39, 11149–11155.

Karunaratne S, Piyadasa K (1973): Coagulation of natural rubber latex with hydrochloric acid (HCl). Rubber Research Institute of Sri Lanka (Ceylon), 50, 151–156.

Mathur A, Foody GM (2008): Crop classification by support vector machine with intelligently selected training data for an operational application. International Journal of Remote Sensing, 29, 2227–2240.

Othman ABIN, Lye CB (1980): Effect of pH coagulation and sulphuric acid as a coagulant on natural rubber properties. Journal of the Rubber Research Institute of Malaysia, 28, 109–118.

Philippine Statistics Authority (2017): Selected statistics on agriculture 2017. Philippine Statistics Authority, Quezon City.

Rumpf T, Mahlein A-K, Steiner U, Oerke E-C, Dehne H-W, Plumer L (2010): Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. Computers and Electronics in Agriculture, 74, 91–99.

Siti Maznah K, Baharin A, Hanafi I, Azhar ME, Mas Rosmal Hakim MH (2008): Effect of acid treatment on extractable protein content, crosslink density and tensile properties of natural rubber latex films. Polymer Testing, 27, 823–826.

Somwong S, Wounchoum P, Chongcheawchamnan M (2017): Contamination detection in fresh natural rubber latex by a dry rubber content measurement system using microwave reflectometer. Biosystems Engineering, 164, 181–188.

Suchat S, Theanjumpol P, Karrila S (2015): Rapid moisture determination for cup lump natural rubber by near infrared spectroscopy. Industrial Crops and Products, 76, 772–780.

Tuampoemsab S, Nimpaiboon A, Sakdapipanich JT (2015): Quantitative analysis of isoprene units in natural rubber and synthetic polyisoprene using 1H-NMR spectroscopy with an internal standard. Polymer Testing, 43, 21–26.

Wisunthorn S, Chambon B, Sainte-Beuve J, Vaysse L (2015): Natural rubber quality starts at the smallholdings: farmers' cup coagulum production in Southern Thailand. Journal of Rubber Research, 18, 87–98.

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