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Decision Tree-Based Classification of Guimaras Mango Varieties Using Fruit and Stone Attributes with the J48 Algorithm

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Abstract

Guimaras mango varieties have overlapping physical characteristics that complicate manual identification. This exploratory study compares three J48 decision-tree configurations using 11 recorded observations (one per variety) and 17 candidate predictors describing fruit and stone attributes in WEKA. Model A uses pruning with a confidence factor of 0.25 and a minimum leaf size of two; Model B uses the same confidence factor with a minimum leaf size of one; Model C is unpruned with a minimum leaf size of one. The trees contain 7, 19, and 22 nodes, with 5, 13, and 15 leaves, respectively. Peel color is the root attribute in all three configurations; subsequent splits also use fruit weight, flesh color, peel thickness, shape, and, in Model C, peel texture. Evaluation on the training observations produces 45.45% accuracy (5/11) for Model A and 100% (11/11) for Models B and C. These are resubstitution results, not validated estimates of performance on unseen specimens. Stone predictors were available but were not selected in the fitted trees. This study demonstrates interpretable, parameter-sensitive descriptions of the recorded classes; independently replicated fruit samples are needed before generalization or practical varietal authentication can be established.

Keywords: Guimaras Mango; J48 Algorithm; Decision Tree; Variety Classification; Machine Learning.

1. INTRODUCTION

Mango (Mangifera indica L.) is an economically important horticultural commodity, and Guimaras mangoes are closely associated with production practices and livelihoods in the Philippine province of Guimaras. Research on mango farming in the Philippines has documented the social and labor conditions underlying this agricultural value chain [1]. Guimaras mangoes were registered as a Geographical Indication (GI) in the Philippines on 13 May 2023, according to the official Intellectual Property Office of the Philippines register (IPOPHL, https://www.ipophil.gov.ph/geographical-indications/registered-geographical-indications/). GI registration concerns a specified product, production area, and requirements; it should not be confused with proof that every named sample in a classification dataset satisfies the GI specification. A transparent means of describing recorded mango characteristics may nevertheless support future research on variety documentation and produce sorting.

Identifying mango varieties is difficult when several cultivars share visible characteristics. The general fruit-classification literature highlights the importance of color, shape, texture, and maturity in visual assessment [2], while defect and quality image classification is also affected by image representation and dataset preparation [3]. For mango varieties specifically, recent work combines deep feature extraction with machine-learning classifiers to address cultivar identification [4]. Studies using near-infrared spectra have also demonstrated approaches to distinguishing visually similar fruit varieties [5]. These findings motivate an examination of whether recorded physical descriptors can distinguish the limited set of Guimaras mango observations examined here.

Recent computer-based fruit evaluation covers different tasks that should not be equated. Worasawate et al. used machine-learning models for mango ripeness-stage classification [6], whereas Tai et al. developed a mango grading and sorting system using external features and machine-learning algorithms [7]. Mustaffa et al. explored TensorFlow Lite for mango image recognition [8]. Ripeness, quality grading, and cultivar identification involve different class labels and validation settings. They offer relevant methodological precedents, but their reported accuracies cannot be treated as directly comparable with the present 11-variety classification task.

Several studies focus more directly on mango variety identification. Fitri et al. developed a digital encyclopedia for mango varieties using morphological image parameters and backpropagation [9]. Aulia and Husna investigated convolutional neural networks for mango-type classification from digital images [10], and Ahmad et al. compared transfer-learning feature extractors integrated with classical classifiers for mango variety recognition [4]. The aim of these image-oriented methods is predictive classification from suitable training and evaluation datasets. By contrast, the present research analyzes a tabular record of fruit and stone characteristics and prioritizes inspection of the learned decision rules.

Developments in other fruit-classification tasks further demonstrate the diversity of available feature representations. Tapia-Mendez et al. applied deep learning to fruit and vegetable recognition and ripeness assessment [11], and Duan et al. examined a language–image model combining complementary visual cues for fruit quality classification [12]. Taner et al. used machine learning and deep image features for apple variety recognition [13]. Work on Alphonso mango ripening has examined comprehensive color features [14], while Muchtar and Muchtar compared

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KNN and SVM using HSV and statistical features for mango ripeness classification [15]. These studies support the relevance of observable fruit traits, without demonstrating that a classifier trained on the present small sample will generalize.

An interpretable alternative to image-heavy pipelines is a decision-tree model built from nominal and numeric descriptors. Decision trees recursively split data by attributes, yielding traceable conditions that can be expressed as if–then rules. Charbuty and Abdulazeez reviewed decision-tree classification for machine learning [16]. Applications of J48 include categorization of research abstracts [17] and comparative classification alongside CART and Naïve Bayes [18]. Related applications of C4.5 demonstrate how explicit rules can be inspected by users [19]. These references support the suitability of rule-based interpretation; they do not imply that the method is automatically superior to other learners on fruit data.

Machine learning is also increasingly used beyond fruit classification. Saleem et al. reviewed automation in agriculture through machine-learning and deep-learning approaches [20], and Botero-Valencia et al. synthesized the role of machine learning in sustainable agriculture [21]. Examples include prediction of plant growth stages with Random Forest [22] and agricultural land-fertility classification using ensemble methods [23]. Collectively, these studies situate interpretable models within agricultural decision support, where the meaning, provenance, and quality of the input data are as important as the reported fit.

Evaluation design is critical for such systems. Bernett et al. discuss how data dependencies and leakage can undermine biological machine-learning claims [24], while Kapoor and Narayanan document overoptimistic performance arising from methodological leakage in scientific machine learning [25]. Even when information does not leak between separately defined data partitions, measuring a model on observations also used for training gives a resubstitution score, not an independent generalization estimate. This distinction is especially important for datasets containing only one recorded specimen per target class.

The present dataset comprises 11 named Guimaras mango varieties, each represented by one recorded observation, with 17 candidate predictors spanning fruit appearance, flesh and sensory descriptions, and stone dimensions. Such a design allows exploratory assessment of how tree-induction settings partition the observed labels but cannot establish within-variety variation or prediction accuracy on new specimens. The present study therefore makes a deliberately limited methodological contribution rather than claiming an operational mango authenticator.

The central research gap lies between work seeking strong predictive performance on relatively larger image or spectroscopy datasets and the need to describe small morphological records transparently. Studies of mango variety recognition using images [4], shape-derived parameters [9], and spectral features [5] illustrate complementary approaches. The value of the present experiment is to show which recorded variables appear in J48 decision paths, how hyperparameter settings change the resulting structure, and why these observations must be distinguished from evidence of external predictive reliability.

Specifically, the analysis uses the WEKA implementation of J48, an algorithm in the C4.5 decision-tree family, and compares three settings while keeping the 11 observations and 17 predictors fixed. The first uses default pruning with a minimum of two instances per leaf; the second permits a minimum of one instance per leaf with pruning; and the third disables pruning while retaining the one-instance leaf setting. The resulting models are interpreted through their splitting attributes, tree sizes, number of leaves, decision rules, and training-set metrics.

Attribute selection has substantive as well as computational implications. A feature selected near the root gives an informative split in this particular data representation, not proof that it is the biologically dominant trait across trees, orchards, harvests, and stages of maturity. Moreover, the absence of a stone descriptor from a fitted tree does not demonstrate its lack of scientific value. With one sample per class, fitted thresholds are sample-dependent and require independent replication before being used as cultivar standards.

To make the evaluation auditable, the article reports the exact WEKA configurations, the training-set confusion patterns, model complexity, and descriptive rules. Class-specific metrics for a single observation must not be described as strong evidence of practical reliability. Future work requires several independently collected specimens of each variety and a validation design that prevents related samples from appearing in both training and test sets [24], [25].

The contribution is consequently threefold: first, a documented exploratory classification workflow for fruit and stone data; second, a comparison of parameter-dependent J48 tree structures; and third, an explicit distinction between in-sample separation and generalization. The study offers a reproducible starting point for later multi-sample cultivar recognition research rather than evidence of geographical-origin certification.

Compared with black-box classifiers, the main practical attraction of J48 in this setting is interpretability rather than an asserted accuracy advantage. A rule such as a peel-color test followed by a numerical fruit-weight cutoff is easy to inspect, measure, and challenge. That transparency can support dataset auditing and field-protocol refinement, but the reliability of each rule remains uncertain until tested against independent fruit.

For this reason, the study discusses both the observed success of highly specific trees in fitting all 11 known records and the limitation imposed by the absence of within-class replication. Parameter sensitivity is presented as a descriptive finding, not as a statistically validated model-selection exercise. This emphasis is consistent with published concerns about optimistic evaluation of machine-learning systems [25].

Accordingly, the objectives are (i) to construct J48 decision trees using recorded fruit and stone descriptors, (ii) to compare how minimum leaf size and pruning influence tree structure and training accuracy, and (iii) to identify the

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selected splitting attributes and representative classification rules. These objectives intentionally stop short of claiming reliable classification of unseen Guimaras mangoes or authentication of their geographical origin.

2. RESEARCH METHODOLOGY

2.1 Study design and research workflow

An exploratory supervised multiclass classification design was adopted. The study followed a staged workflow beginning with problem formulation and objective setting, continuing with dataset acquisition, data cleaning, attribute harmonization, ARFF preparation, J48 modeling, training-set evaluation, and comparative interpretation. Figure 1 summarizes the overall research stages.

The detailed stages were: (1) formulating the classification problem and the study objectives; (2) compiling the Guimaras mango dataset consisting of 11 labeled instances and 17 predictor attributes; (3) cleaning the data and harmonizing labels, units, and categorical spellings; (4) converting the curated dataset into WEKA-readable ARFF format and assigning Variety as the class attribute; (5) building three J48 configurations, namely Model A (C = 0.25, M = 2), Model B (C = 0.25, M = 1), and Model C (U = True, M = 1); (6) evaluating the resulting trees on the training dataset and extracting the decision rules; and (7) interpreting the rules, comparing tree complexity, and discussing the implications and limitations of the obtained models.



Figure 1. Research workflow for the classification of Guimaras mango varieties using J48

The first stage established the classification target as the named Guimaras mango variety and specified the analysis unit as one recorded mango observation. The next stage consolidated the tabular features and associated labels into a single dataset. The study then inspected attribute names, data types, measurement units, category spellings, and the placement of the class variable. Since nominal values are treated as distinct categories, textual variants such as “yellow orange” and “orange yellow” were retained as different observed levels rather than merged without substantive justification.

During preprocessing, measurement attributes were treated as numeric and morphological descriptions as nominal categories. Fruit_Weight_g and Stone_Weight_g represent masses, while Peel_Thickness_mm and stone dimensions represent lengths. The label Variety was assigned as the class attribute in WEKA Explorer. All 17 explanatory attributes remained eligible during J48 induction, allowing the algorithm itself to choose splitting variables; no post hoc manual exclusion was made merely to increase training accuracy.

Three classifier runs were conducted under the same set of observations and predictor columns. The configurations were the default pruned tree, a pruned tree with minimum leaf size one, and an unpruned tree with minimum leaf size one. For all three, the supplied run logs explicitly identified “evaluate on training data” as the test mode. Consequently, the tables in this paper summarize the WEKA output as supplied, rather than estimates from an independent test set. Each tree was interpreted through its root, downstream decisions, terminal predictions, and reported coverage or errors.

2.2 Dataset and variables

The working dataset contains 11 rows with one labeled instance for each of the following varieties: Golez Strain (GES 73), GES 77, GES 84, GES 85, EFONDO, TANALEON, TALABAN, FRESCO, GUIMARAS SUPER GALILA, JTA SWEET, and BPI GOLDEN PICO. Its provenance is the spreadsheet supplied with the study; the specific orchard-level sampling dates, instruments, collection protocol, and independent verification of labels were not recorded in the supplied analysis files and therefore cannot be asserted here.

Table 1. Predictor variables and recorded units

Group	Variables	Data representation
Fruit—size and exterior	Fruit_Weight_g; Shape; Peel_Color; Peel_Texture; Peel_Thickness_mm; Peel_Weight_g	Numeric (g or mm) and nominal
Fruit—flesh and sensory	Flesh_Color; Flesh_Texture; Juiciness; Fibers; Aroma; Flavor; Edible_Portion_pct	Nominal and numeric (%)
Stone descriptors	Stone_Weight_g; Stone_Length_mm; Stone_Width_mm; Stone_Thickness_mm	Numeric (g or mm)
Target	Variety	Nominal: 11 distinct variety labels

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All 17 predictors were eligible to be selected by the tree induction procedure, rather than manually restricting the tree to a predefined group. Numeric features were retained as measured quantities, whereas color, shape, texture, juiciness, fibers, aroma, and flavor were treated as categorical descriptors. Color strings were harmonized to remove spelling inconsistencies. The category strings "yellow orange" and "orange yellow" were preserved as separate labels because the working dataset distinguished them; this semantic distinction requires confirmation against original observation records.

Table 2. Fruit Characteristics of Guimaras Mango Varieties

Mango Variety	Fruit Weight (g)	Shape	Peel Color	Peel Texture	Peel Thickness (mm)	Peel Weight (g)	Flesh Color	Flesh Texture	Juiciness	Fibers	Aroma	Flavor	Edible Portion (%)
Golez Strain (GES 73)	289.6	ellipsoid	yellow orang	smooth	1.88	32	dark yellow	smooth & firm	juicy	scanty	mild	sweet (19 brix)	79.25
GES 77	297.4	ellipsoid	yellow orang	smooth	2	35	yellow	smooth & firm	juicy	scanty	mild	sweet (18 brix)	79.34
GES 84	276.5	ellipsoid	yellow	smooth	1.8	32	dark yellow	smooth & firm	juicy	scanty	mild	sweet (18 brix)	79.91
GES 85	298.3	ellipsoid	yellow	smooth	1.8	30	light yellow	smooth & firm	juicy	scanty	mild	sweet (18 brix)	80.16
EFONDO	341.85	ellipsoid	yellow orang	smooth & firm	1.26	38.66	yellow orang	firm	juicy	scanty	mild	sweet (18,4 brix)	80.2
TANALEON	308.57	ellipsoid	yellow	smooth	0.95	34.84	orange yellow	firm	juicy	scanty	mild	sweet (19,46 brix)	80.12
TALABAN	289.7	ellipsoid	orange yellow	smooth	1	32.2	orange yellow	firm	juicy	scanty	mild	sweet (18 brix)	80.6
FRESCO	249.9	ellipsoid	orange yellow	smooth	1.2	24.2	orange yellow	firm	juicy	scanty	mild	sweet (19 brix)	80.2
GUIMARAS SUPER GALILA	364.64	ellipsoid	bright yellow	smooth	0.93	43.19	orange	smooth & firm	juicy	scanty	mild	sweet (22,3 brix)	79.56
JTA SWEET	331.78	oblong	orange yellow	smooth & leather	1.7	38.21	orange yellow	smooth & firm	juicy	none to scanty	mild	sweet (19,34 brix)	79.07
BPI GOLDEN PICO	264.88	ellipsoid	yellow orang	smooth	1.34	46.53	orange	smooth	juicy	scanty	mild	sweet (17,49brix)	67.56

Note: The recorded categorical labels follow the source worksheet (including "yellow orang"). TANALEON fruit weight was verified against the original reference display (Figure 2) and standardized as 308.57 g.

Table 3. Stone Characteristics of Guimaras Mango Varieties

Mango Variety	Stone Weight (g)	Stone Length (mm)	Stone Width (mm)	Stone Thickness (mm)
Golez Strain (GES 73)	28	100.16	37.2	14.8
GES 77	26.4	98.4	36.4	15.3
GES 84	28	98.6	40.3	14.6
GES 85	25.4	99.2	43.8	15.8
EFONDO	29.14	101.29	40.98	15.1
TANALEON	25.23	96.13	37.06	14.06
TALABAN	24.1	94	38	15
FRESCO	25.3	96	42	15
GUIMARAS SUPER GALILA	29.73	102.95	40.35	14.35
JTA SWEET	25.3	96	42	15
BPI GOLDEN PICO	38.23	106.05	37.66	16.2

Source: Guimaras mango dataset, 11 recorded varieties. Stone measurements are shown in their source units.

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The photographed reference display in Figure 2 presents NSIC-approved Guimaras mango strains with labeled fruit and stone characteristics. It is provided as visual context for the varieties considered; the image alone does not establish the specimen-level provenance of the dataset.

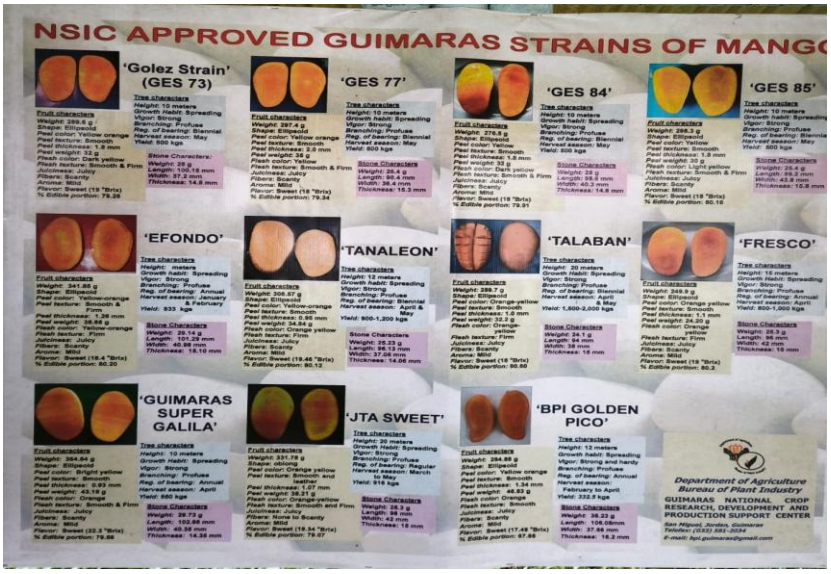


Figure 2. Photographed display of NSIC-approved Guimaras mango strains and their fruit and stone characteristics (source identified on display: Department of Agriculture, Bureau of Plant Industry, Guimaras National Crop Research, Development and Production Support Center).

The predictor inventory consists of fruit weight, shape, peel color, peel texture, peel thickness, peel weight, flesh color, flesh texture, juiciness, fibers, aroma, flavor, edible portion, stone weight, stone length, stone width, and stone thickness. These measurements span external appearance, internal fruit characteristics, sensory descriptions, and stone morphology. A multi-family predictor set allows the classifier to use whichever candidate feature best separates the classes at each node. Inclusion in the candidate set does not guarantee that a variable will appear in the final fitted tree.

Categories should be interpreted operationally as the labels appearing in the curated dataset, not universal botanical categories. For example, the categories “yellow orange” and “orange yellow” may be difficult to distinguish without a standardized photographic or colorimetric protocol. Future work should describe color scales, observer training, illumination, and measurement instruments. Likewise, measurement precision matters: a fitted threshold such as 1.34 mm for peel thickness may be sensitive to how an instrument is calibrated and how biological variation is sampled.

Although each supplied report confirms 11 observations and 18 total columns, the available model reports do not document the original field collection date, instrument calibration, number of trees sampled, or provenance of each fruit. These details must be completed from the primary dataset and field records before treating the manuscript as an independently reproducible field investigation. No undocumented random sampling scheme, external validation, or repeated measurements are asserted in this paper.

2.3 J48 algorithm and mathematical foundation

J48 is the WEKA implementation of the C4.5 decision-tree family. Decision-tree methods recursively partition observations through nominal tests and numeric thresholds to yield interpretable root-to-leaf rules [16], [18]. In this study the influence of leaf-size and pruning settings is treated as a descriptive comparison on fixed training data, not a validated search for an optimal predictive model. Entropy, information gain, split information, and gain ratio provide useful quantities for explaining attribute selection. For a node dataset S with class proportions p_i and a candidate attribute A, these are represented as:

$$\text{Entropy}(S) = -\sum_i p_i \ log_2(p_i) \quad (1)$$

$$\text{Gain}(S,A) = \text{Entropy}(S) - \sum_V (|S_V|/|S|) \ \text{Entropy}\ (S_V) \quad (2)$$

$$\text{SplitInfo}(S,A) = -\sum_V (|S_V|/|S|) \ log_2(|S_V|/|S|) \quad (3)$$

$$\text{GainRatio}(S,A) = \text{Gain}(S,A) \ / \ \text{SplitInfo}(S,A) \quad (4)$$

At the root, the eleven recorded varieties each appear once, giving Entropy(S) = $\log_2(11) \approx 3.4594$ bits. The observed Peel_Color root divides them into groups of 4, 3, 3, and 1 observations. The weighted post-split class entropy is [4 $\log_2(4)$ + 3 $\log_2(3)$ + 3 $\log_2(3)$ + 1 $\log_2(1)$]/11 ≈ 1.5918 bits. Thus, information gain is approximately 3.4594 − 1.5918 = 1.8676 bits. The split information for proportions 4/11, 3/11, 3/11, and 1/11 is also approximately 1.8676 bits, giving a gain ratio of approximately 1.0000. This hand calculation illustrates the observed partition, rather than reproducing all of WEKA's candidate-attribute selection procedures.

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2.4 Parameter configurations and evaluation

Three J48 parameter settings were compared using exactly the same observations and predictor columns. Model A uses the standard pruned configuration; Model B lowers minimum instances per leaf from two to one; Model C disables pruning while keeping that minimum at one. These choices provide an exploratory comparison of tree complexity and training fit [16], not evidence of optimal generalization. All three WEKA outputs explicitly use "evaluate on training data."

Table 4. Compared WEKA J48 parameter settings

Model	WEKA options	Meaning
A	-C 0.25 -M 2	Pruned; default confidence and minimum leaf size
B	-C 0.25 -M 1	Pruned; minimum leaf size reduced to one
C	-U -M 1	Unpruned; minimum leaf size one

Reported measurements were training accuracy, error rate, Cohen's kappa, mean absolute error (MAE), root mean squared error (RMSE), number of leaves, and tree size. Accuracy was calculated as correctly classified observations divided by 11, multiplied by 100%. The confusion matrix tallies actual labels by predicted labels. Because each class appears only once, ordinary k-fold validation would omit the held-out class from the corresponding training partition, making such estimates unsuitable for claims about recognition of all 11 known varieties. No externally validated accuracy is reported.

For a valid comparison of the three settings, the observations, class definitions, and candidate attributes must remain fixed. The difference between Models A and B is the minimum number of training instances allowed for leaf formation, whereas the difference between Models B and C is the pruning switch. These comparisons constitute a controlled sensitivity exercise on the supplied dataset, not statistical model selection. Because the parameter choices were not chosen on a held-out validation set, ranking models by training accuracy alone would exaggerate their predictive credibility.

The evaluation output includes accuracy, kappa, error indicators, and class-level metrics. With one sample per class, a confusion matrix entry of one on the diagonal simply means that the sole training observation of the corresponding variety is correctly classified. A per-class recall of 1.000 under these conditions has very high sampling uncertainty and is not equivalent to robust recognition of a cultivar. Further, model complexity should be assessed together with empirical fit: a larger tree may reduce training error without adding a defensible basis for extrapolation.

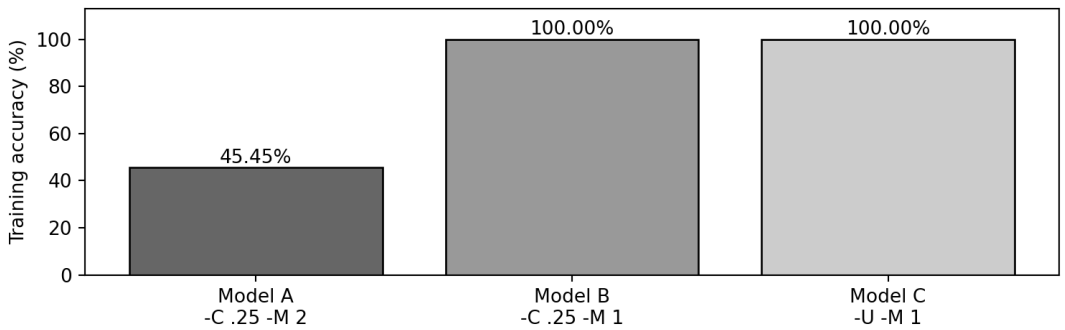
3. RESULT AND DISCUSSION

3.1 Comparison of the three J48 models

The supplied WEKA run reports for Models A, B, and C were analysed without recomputing or changing their classifier outputs. Table 5 presents the primary results. Accuracy improved sharply from Model A to Model B, while both B and C reached perfect fit to the 11 training cases. The unpruned model required a larger tree without improving this in-sample accuracy.

Table 5. Training-set evaluation and tree complexity

Indicator	Model A	Model B	Model C
Correct / total	5 / 11	11 / 11	11 / 11
Training accuracy	45.45%	100.00%	100.00%
Training error	54.55%	0.00%	0.00%
Kappa	0.400	1.000	1.000
MAE	0.0992	0.0000	0.0000
RMSE	0.2227	0.0000	0.0000
Leaves	5	13	15
Total nodes	7	19	22



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Figure 3. Training accuracy under three J48 configurations

As illustrated in Figure 3, the two configurations allowing a one-instance leaf attained identical training accuracy, with distinct model complexities. With M = 2, J48 grouped multiple distinct varieties under the same predicted labels. For example, the yellow peel-color group was assigned to GES 84, causing GES 85 and TANALEON to be misclassified. With M = 1, the algorithm formed finer subgroups and separated every observed training instance. Moving from B to the unpruned C added two leaves and three nodes but did not improve training accuracy. Thus, among the two configurations with equal training fit, B is the smaller tree; it is not established as the superior predictor on new fruit.

The confusion-matrix patterns complement the overall score. In Model A, GES 85 and TANALEON were assigned to GES 84, EFONDO to GES 77, FRESCO and JTA SWEET to TALABAN, and BPI GOLDEN PICO to GES 73. The six errors cluster among peel-color groups with overlapping categories. These are not necessarily biologically indistinguishable varietal pairs; the errors arise from the decision boundaries of a tree constrained by its settings and this particular sample.

3.2 Interpretation of Model A

In the baseline pruned tree, Peel_Color was the root and Fruit_Weight_g was the only subsequent splitting attribute. The yellow-orange branch used a cutoff of 289.7 g, predicting GES 73 below or at the cutoff and GES 77 above it. Other peel-color groups were assigned directly to GES 84, TALABAN, and GUIMARAS SUPER GALILA. The resulting tree consisted of seven nodes and five leaves and correctly classified only five observations, confirming that this coarse partition was insufficient to separate the named classes in the training data. The visual structure of the baseline tree is shown in Figure 4.

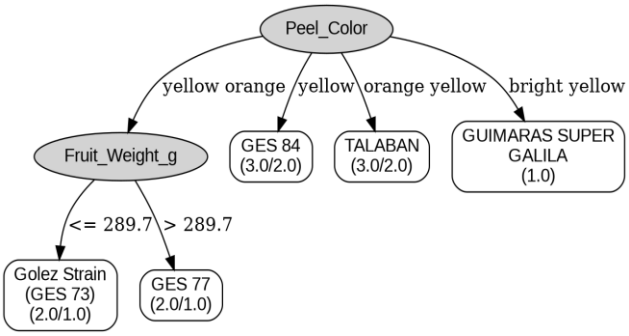


Figure 4. Decision-tree structure of Model A (J48, C = 0.25, M = 2)

Figure 4 shows a compact five-leaf tree in which Peel_Color alone separates most observations, while Fruit_Weight_g is required only for the yellow-orange branch. This compact structure explains why Model A has the smallest tree size, but it also reveals why several varieties are merged into the same terminal nodes, leading to six misclassifications.

Table 6. Model A misclassifications from the confusion matrix

Actual variety	Predicted variety
GES 85	GES 84
EFONDO	GES 77
TANALEON	GES 84
FRESCO	TALABAN
JTA SWEET	TALABAN
BPI GOLDEN PICO	Golez Strain (GES 73)

3.3 Interpretation of tree simplification in Model A

The baseline model has five terminal leaves across four root categories. The yellow-orange class branch uses weight but still assigns two observations to GES 73 and two to GES 77, each with one error. The yellow branch assigns all three observations to GES 84, with two errors, and the orange-yellow branch similarly assigns all three to TALABAN, also with two errors. Only GUIMARAS SUPER GALILA has a single-observation terminal decision without an error. These node annotations reconcile exactly to five correct and six incorrect resubstitution predictions.

This result illustrates the trade-off between structural parsimony and empirical separation. The relatively compact tree is easy to describe but does not achieve a unique terminal prediction for every distinct variety. Since the analysis has just one representative of each variety, however, no scientifically justified claim can be made that this default tree would necessarily have lower true external accuracy than a larger tree.

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3.4 Interpretation of Model B

Model B selected five distinct predictors across its tree: Peel_Color, Flesh_Color, Peel_Thickness_mm, Fruit_Weight_g, and Shape. Peel_Color was again the root. For the yellow-orange peel group, different flesh-color categories separated GES 73, GES 77, EFONDO, and BPI GOLDEN PICO. For yellow peel, peel thickness first separated TANALEON at ≤1.34 mm, followed by a fruit-weight split at 276.5 g distinguishing GES 84 from GES 85. For orange-yellow peel, shape distinguished the oblong JTA SWEET from ellipsoid fruits, after which a 264.88 g threshold distinguished FRESCO from TALABAN. Bright-yellow peel led directly to GUIMARAS SUPER GALILA. The corresponding pruned tree is presented in Figure 5.

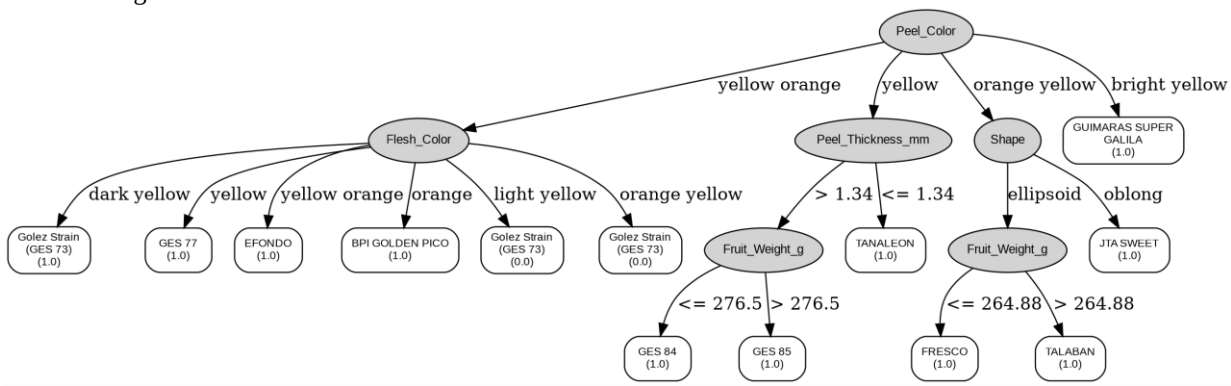


Figure 5. Decision-tree structure of Model B (J48, C = 0.25, M = 1)

As shown in Figure 5, reducing the minimum leaf size to one allows the tree to separate all 11 training instances. Within the yellow-orange peel group, Flesh_Color distinguishes GES 73, GES 77, EFONDO, and BPI GOLDEN PICO. Within the yellow group, Peel_Thickness_mm and Fruit_Weight_g distinguish TANALEON, GES 84, and GES 85. Within the orange-yellow group, Shape and Fruit_Weight_g separate FRESCO, TALABAN, and JTA SWEET. The resulting tree is more complex than Model A but achieves perfect resubstitution accuracy on the available data.

Table 7. Representative decision rules for Model B

Rule	If conditions	Predicted variety
B1	Peel_Color = yellow orange; Flesh_Color = dark yellow	GES 73
B2	Peel_Color = yellow orange; Flesh_Color = orange	BPI GOLDEN PICO
B3	Peel_Color = yellow; Peel_Thickness_mm ≤ 1.34	TANALEON
B4	Peel_Color = yellow; Peel_Thickness_mm > 1.34; Fruit_Weight_g ≤ 276.5	GES 84
B5	Peel_Color = yellow; Peel_Thickness_mm > 1.34; Fruit_Weight_g > 276.5	GES 85
B6	Peel_Color = orange yellow; Shape = ellipsoid; Fruit_Weight_g ≤ 264.88	FRESCO
B7	Peel_Color = orange yellow; Shape = oblong	JTA SWEET

The WEKA display includes two terminal branches in Model B annotated (0.0). These branches contain no training observations and are counted in the 13-leaf model structure; they should not be construed as additional successful samples. All 11 observed labels appear on the diagonal of the training confusion matrix. This proves separation of observed rows only, a relatively weak result when a leaf can contain a single observation.

Model B introduces different kinds of condition at different levels of the tree. Nominal decisions test category membership, while numeric decisions compare a measurement to a fitted threshold. For example, a mango categorized as yellow with a peel thickness greater than 1.34 mm enters a subsequent Fruit_Weight_g test. An observation weighing 276.5 g or less is assigned to GES 84, whereas an observation above that threshold is assigned to GES 85. The threshold is an empirical partition between observations, not an agronomic standard defining the two varieties.

Likewise, Model B uses a 264.88-g cutoff inside the orange-yellow, ellipsoid branch. Neither value should be rounded or generalized without examining instrument precision and biological variation. The remaining yellow-orange branch uses flesh color to separate specific sample labels, including GES 73, GES 77, EFONDO, and BPI GOLDEN PICO. Notably, the output also lists leaves with zero covered training observations. These are legitimate structural branches generated by the software but do not provide additional evaluated specimens.

The reported count of thirteen leaves is therefore not equivalent to thirteen correctly classified mangoes. Eleven unique observed instances were correctly reproduced, and the remaining terminal nodes represent unoccupied category branches. This distinction should be explained wherever the figure is reproduced, so that readers do not confuse the number of theoretical rules with dataset size.

3.5 Interpretation of Model C

Model C used -U -M 1. Its unpruned tree retained the same peel-color root and the downstream yellow and orange-yellow splits seen in Model B. In the yellow-orange group it added Peel_Texture before Flesh_Color, allowing a direct branch

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for EFONDO with "smooth & firm" texture. With 15 leaves and 22 nodes, this tree was larger than Model B but obtained the same 100% training accuracy. Peel_Texture is therefore present only in the unpruned tree among these outputs; the additional branching offers no demonstrated predictive benefit without external evaluation. Its visual tree structure is displayed in Figure 6.

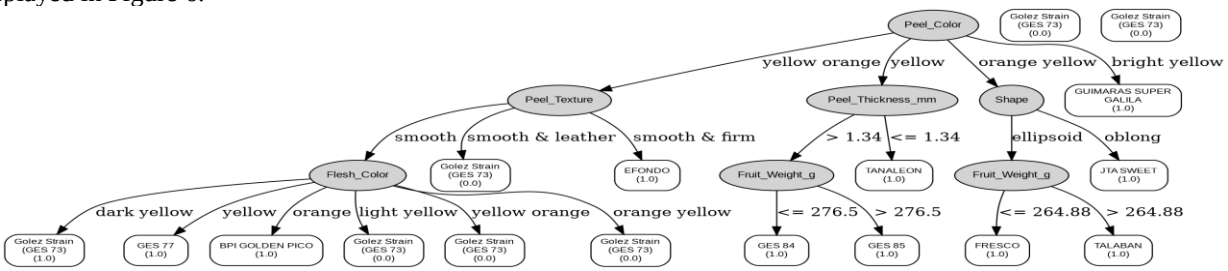


Figure 6. Decision-tree structure of Model C (J48, U = True, M = 1)

Figure 6 indicates that disabling pruning retains additional intermediate branches, especially in the yellow-orange peel subgroup where Peel_Texture is inserted before Flesh_Color. This makes Model C the largest tree among the three configurations. Although Model C and Model B both achieve 100% training accuracy, the extra nodes in Model C represent a less parsimonious structure and further increase the risk of overfitting.

Table 8. Attribute selection by configuration

Selected predictor	Model A	Model B	Model C
Peel_Color	Yes	Yes	Yes
Fruit_Weight_g	Yes	Yes	Yes
Flesh_Color	—	Yes	Yes
Peel_Thickness_mm	—	Yes	Yes
Shape	—	Yes	Yes
Peel_Texture	—	—	Yes

The unpruned Model C adds Peel_Texture above Flesh_Color in the yellow-orange group. Its fifteen leaves and twenty-two nodes exceed Model B by two leaves and three nodes, yet there is no difference in the number of correctly fitted training instances. Therefore, the additional structure supplies descriptive detail about how the training examples can be partitioned but no measured incremental benefit in training accuracy. Comparing Model B and Model C demonstrates why accuracy alone is an incomplete criterion for choosing an interpretable tree.

In a conventional prediction study, whether pruning is beneficial should be determined on independent validation data. The present study cannot perform that comparison reliably because the dataset contains one observation for each of eleven classes. Thus, the smaller Model B tree is structurally more parsimonious than Model C while equally accurate on training cases, but it cannot be declared the empirically best generalizing model. The result is a descriptive comparison of inductive bias under controlled settings.

3.6 Interpretation, related studies, and implications

Allowing single-observation leaves can improve fit to the training data and increase model complexity; this should not be interpreted as evidence of out-of-sample reliability [16], [18]. Related research has classified mango ripeness, quality, and varieties using machine learning, image features, and other sensing approaches [6], [7], [8], [4], [5]. Unlike studies supported by independent evaluation, the present analysis shows only that the observed nominal and numeric descriptors can produce explicit rules for the eleven known records. This limitation is consistent with methodological warnings about optimistic estimates and model evaluation [24], [25].

An important finding is that none of the four stone predictors appears in the learned trees for these three parameter configurations. This does not imply that seed or stone traits have no taxonomic value: they were supplied to J48 but were not chosen for the fitted splits. The available sample is too small to determine whether their omission persists across maturity stages, trees, harvests, or independently measured fruit. Similarly, the preference for Peel_Color at the root is a property of this particular data representation and cannot establish causal primacy.

Altough, the full candidate set contains five stone-related and edible-yield variables: stone weight, stone length, stone width, stone thickness, and edible portion, although the latter describes edible yield rather than the stone directly. None of the stone dimension or mass variables was selected in the three reported final trees. This result should not be described as evidence that stone traits are irrelevant for Guimaras mango morphology. Rather, the observed peel, flesh, weight, shape, and texture variables were sufficient for the algorithm to fit the available cases under the examined settings.

Because the title explicitly names fruit and stone attributes, it is important to report this negative selection finding transparently. A classifier may reject a variable because of redundant information, low apparent split advantage, limited sample variation, or interaction with other predictors.

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3.7 Detailed interpretation of classifier error measures

Accuracy summarizes the proportion of correct decisions but should not be interpreted without the associated evaluation protocol. In Model A, five of eleven labels are reproduced, giving an observed re substitution accuracy of 45.45%. The remaining six mismatches produce an error rate of 54.55%. For Models B and C, the same eleven cases are fitted perfectly, giving zero training error. These numbers are exact descriptions of the supplied run logs, not confidence bounds for performance in the source population of mangoes.

Cohen's kappa complements accuracy by describing agreement between observed and predicted labels after accounting for agreement expected from the observed marginal distributions. Model A reports 0.40, whereas Models B and C report 1.00. Although a kappa of one is conventionally labeled perfect agreement, here it is calculated from only eleven already-seen observations. No biological repeatability or reproducibility across harvest conditions follows from this index alone.

Mean absolute error and root mean squared error in WEKA's classification output summarize errors of the probabilistic class estimates rather than simple errors measured in grams or millimeters. Consequently, the Model A values of 0.0992 and 0.2227 should not be mistaken for measurement deviations of physical attributes. The corresponding zeros for Models B and C reflect their exact fitted class probabilities on the supplied training records. Relative error measures compare those estimates with a baseline predictor and are similarly conditional on the same training sample.
In the detailed accuracy output, the class-level precision and recall of Model B and Model C are both one for each recorded variety. Yet there is only one observed positive example for each class. One correct prediction suffices to produce recall equal to one, and additional incorrect predictions to that class did not occur during resubstitution evaluation. In this setting, reporting the entire array of perfect class metrics without a caveat could lead readers to confuse apparent fitting with tested classification capability. This distinction is emphasized in research on evaluation pitfalls [25].

The confusion matrix provides a more transparent presentation than a single mean score. A diagonal matrix for Models B and C states that every observed sample is assigned to its given label; it does not say how the model handles an unseen sample whose feature values fall between the recorded thresholds. Decision-tree branches corresponding to unseen category combinations may follow default or majority-class paths. Thus, rule completeness on one tabular dataset is not equivalent to exhaustive coverage of biological variability.

3.8 Limitations and directions for validation

The dataset contains one instance for each class, with no within-variety replication. As a result, the reported performance measures are resubstitution or training-set measures and are optimistically biased as estimates of deployment accuracy. A straightforward stratified 10-fold cross-validation would not resolve this problem: the held-out variety would have zero representatives in that fold's training set. Further work should acquire several independently sampled fruits per variety, document tree and orchard sources, standardize ripeness and measurement protocols, and reserve independent specimens for testing. If multiple specimens originate from the same tree or batch, group-aware validation should avoid train–test leakage. Future comparisons can include alternative feature subsets and learners only after an adequate validation design exists. Avoiding dependent observations across train and test groups is also important [24].

4. CONCLUSION

This study constructed and compared three J48 configurations for exploratory classification of 11 Guimaras mango varieties using 17 fruit and stone predictors. The default pruned model (C = 0.25, M = 2) correctly classified 5/11 training instances (45.45%) and produced a seven-node, five-leaf tree. Reducing minimum leaf size to one (C = 0.25, M = 1) yielded 11/11 correct training classifications (100%) in a 19-node, 13-leaf tree, whereas the unpruned configuration (U, M = 1) achieved the same 100% training fit with 22 nodes and 15 leaves. Peel color was the root in all models, and the fitted branches also used combinations of flesh color, peel thickness, fruit weight, shape, and peel texture; no stone attribute was selected in these specific trees. These findings establish the interpretability and parameter sensitivity of the observed classification rules, not their reliability on unseen fruits. More independent observations per variety and an appropriate validation strategy are required before making claims about predictive generalization or practical authentication.

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