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Converting Apple Textural Parameters Obtained from Penetrometers and Their Relationships with Sensory Attributes

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Abstract: Textural attributes of apple impact consumers' acceptance of the fruit, and are frequently measured by researchers and industry experts to evaluate the fruit quality at different stages of production and marketing. Various instruments are used to conduct these textural evaluations in research and industry settings. The application of different instruments makes the comparison and integration of results extremely difficult. The main objectives of this study were to compare data obtained from three widely used textural instruments, investigate their relationships with each other and with sensory evaluations, and develop models to convert data among instruments. Three penetrometers were included in the study: (1) Fruit Texture Analyzer (FTA); (2) Mohr Digi-Test-2 (MDT-2); and (3) TA.XT*plus* Texture Analyzer (TA.XT*plus*). Eight apple varieties with a range of textural attributes were selected. Eleven sensory judges evaluated three apple slices (1/8 apple) from each variety. The instrumental measurements were conducted on 10 apples per instrument from each variety, with two measurements on each apple. Results of principal component analysis indicated that 95.82% of the variation in the texture data could be explained using only two principal components. Linear and nonlinear regression models were developed to convert data obtained from an instrument to those from other instruments.

Keywords: apple; fruit texture; penetrometer; model development; sensory evaluation

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1. Introduction

Apple texture is considered a very important quality factor by customers and impacts their purchase decisions, especially during repeat purchases [1–3]. Results of a conjoint analysis demonstrated the importance of the apple texture on the overall liking of the fruit [4]. As a result, apple textural attributes are considered in evaluating the quality of the products at different stages of the supply chain from production to marketing [5]. In addition, apple firmness and starch-iodine test are considered the best harvest time determinants [6]. Apple breeding programs also consider sensory and instrumental firmness in the selection of new varieties [7,8].

Genetic, agronomic, and environmental factors impact the internal and external apple quality parameters, including firmness [9]. Some of the pre-harvest factors affecting the apple firmness include: (i) differences among varieties and within their strains [10,11]; (ii) differences in the cell number, size and shape, and it was shown that fruits with greater cell numbers and smaller cell size were firmer while fruits with larger cell size had softer texture [5,10,12–15]; (iii) the number of seeds in fruit which was reported to be correlated negatively with firmness [13]; (iv) maturation which was reported to be correlated negatively with firmness [16]; (v) apple tree vigor factors including the crown diameter and height and the trunk girth which showed negative correlations with the fruit firmness [17]; (vi) thinned trees with a lower crop load produced heavier and firmer fruits with higher dry matter [18,19]; (vii) fruit nutrient concentrations, especially N, K, Ca, and Mn levels, were proven to be correlated with fruit firmness [19,20]; (viii) differences among rootstocks [21]; (ix) deficit irrigation reported to be positively correlated with apple firmness [22] and Reid [23] demonstrated the importance of the timing of water reduction on apple firmness; (x) different growth regulators showed different impacts on the firmness [24]; (xi) differences were reported in the texture of fruit harvested from various altitudes [25]; and (xii) long-term data demonstrated that climate change and global warming have resulted in earlier blooming in apples and the production of less firm apples [26]. In addition, different post-harvest practices can affect the texture quality of the fruit [27–30]. For example, storage type and duration can impact the perceived textural attributes of the fruit [27].

Different types of penetrometers have been used widely to measure the texture quality of fruits for decades [29]. Their instructions differ; for example, some of them require the fruit to be peeled for the test while others can conduct the evaluation on intact fruits [31,32]. The recommended probe size and penetration depth vary, and the generated data are not the same [31,32].

Flesh firmness is considered an important attribute in the evaluation of the performance of different varieties in apple selection programs [33]. The performance of different firmness penetrometers was evaluated in previous studies with the main objective of evaluating the influence of operators in the use of handheld penetrometers and earlier computerized instruments [34–36]. The use of digital penetrometers has been more common nowadays which eliminates the influence of the operator and provides more accurate and precise information about the fruit texture. Nevertheless, the use of different digital penetrometers across different research studies and settings has resulted in difficulties in the comparison, compatibility, and integration of the results from one laboratory to another one or from research to industrial laboratories and vice versa. This not only can cause challenges in the use of the available information but can also create dilemmas for the long-standing programs such as breeding programs, with decades of selection data [37], and fruit quality assessment programs in integrating data obtained from different fruit supply chain sectors.

The main objectives of this study were to compare the data obtained from three widely used textural instruments, investigate relationships between the obtained parameters, validate the instrumental measurements with sensory evaluations, and develop practical models to convert data among the studied instruments.

2. Materials and Methods

2.1. Apple Varieties

Eight apple varieties with a broad range of textural attributes were selected for the purposes of this study (see Table 1). The broad range of the studied textural attributes permits the application of the results to many established and new varieties [31].

All fruit was produced based on commercial practices and harvested at commercial maturity [38]. The apple varieties were sourced from either an experimental orchard at Summerland Research and Development Centre (SuRDC) or orchards in the same region, not retail outlets [31]. All fruits were "orchard run" and had not been sorted, waxed, or packaged using commercial packinghouse practices. The fruit was sorted at the Sensory Laboratory to minimize size and color variations within each variety and to remove any damaged fruit [31,32]. The apples were stored in air at 1 ± 0.5 °C and 72 ± 2% RH for 2–4 weeks, grouped into two lots of four varieties considering the harvest time, and were warmed to room temperature overnight prior to testing. Testing for one lot was completed all within one week and the other lot was completed all within the subsequent week.

Table 1. Apple varieties included in the study, information about their harvest timing and visual appearance.

Variety	Harvest Timing Group	Appearance of Sorted Fruit
McIntosh	Early	25–75% red over-color with green ground-color
Silken	Early	0–5% red over-color with yellow/green ground-color, and russet filled stem bowl
SuRDC2 [1]	Early	60–90% red over-color with slight greenish to yellow ground-color, and russet filled stem bowl
Aurora Golden Gala	Early	Slightly greenish to yellow color, and russet filled stem-bowl
Ambrosia	Mid/late	60–90% red over-color with yellow ground-color
Fuji	Mid/late	80–95% red over-color with yellow ground-color, and russet
Red Delicious	Mid/late	95% red over-color with yellow ground-color, and slight stripe
Pink Lady®	Mid/late	70–95% red over-color with slight greenish to yellow ground-color

[1] SuRDC2 is a new unnamed selection from the Tree Fruit Breeding and Germplasm Development Program at Summerland Research and Development Centre (SuRDC) in Summerland, BC, Canada.

2.2. Sensory Assessments

Investigating the relationships of the instrumental measurements with sensory attributes can assist in the interpretation of the instrumental data [30–32]. Sensory judges (n = 11) were recruited from the staff at SuRDC based on their interest, availability, and previous experience. The panel consisted of four men and seven women ranging in age from 19 to 56 years. The attributes were selected and defined based on ballot training techniques [39]. The panelists were either experienced in conducting the apple texture evaluations or received training before conducting the experiments [31,32]. In addition, prior to the formal assessments, all judges practiced scoring each of the apples in an orientation session. Ten apples per variety were available for the training sessions.

Apple varieties were assessed in triplicate in individual sensory booths under red light using Compusense five® (Compusense Inc., Guelph, ON, Canada) software. The triplicate assessments of four apple varieties were completed in one sitting based on descriptive analysis techniques with selected attributes [40]. Fifteen sorted apples per variety were available for the sensory tests (i.e., five apples per replication per variety). Two apple slices (1/8 apple) were excised from each sun/shade transition zone of an apple (i.e., four slices per apple), coded with three-digit numbers, and presented in random order on white trays [31,32]. Judges received one slice but were free to ask for more samples if required. Food standards were presented in 1 oz. plastic cups simultaneously. Attribute intensities were scored on 100-unit unstructured line scales with low, high, and mid-point marked as identified in Table 2.

Table 2. Sensory attributes, definitions, and food standards for sensory profiling.

Attribute	Definition	Food Standard
Crispness	The amount of sound produced by the apple flesh when the sample is first bitten with the front teeth.	Banana at 0 units; celery at 90 units
Hardness	The resistance to compression by the apple flesh when the sample is placed on the back teeth and the teeth are compressed. Assess after repeated chewing.	Medjool date at 10 units; carrot at 90 units
Skin toughness	The relative ease of breakdown of skin in the mouth during chewing with the back teeth to prepare the apple for swallowing.	Green pepper at 50 units

The study was conducted according to the guidelines of the Tri-Council Policy Statement, Ethical Conduct for Research Involving Humans, and approved by the Human Research Ethics Committee of Agriculture and Agri-Food Canada (HERC Reference Number: Amendment to 2018-F-003 Bejaei). Informed consent was obtained from all panelists involved in the study.

2.3. Instrumental Measurements

The texture of eight apple varieties was assessed using three instruments: (1) Fruit Texture Analyzer or FTA (Güss Manufacturing Ltd., Strand, South Africa); (2) Mohr Digi-Test-2 or MDT-2 (Mohr and Associates Inc., Richland, WA, USA); and (3) TA.XT*plus* Texture

Analyzer or TA.XT*plus* (Stable Micro Systems Ltd., Godalming, UK). Ten apples per variety per instrument were used in this study (i.e., 240 apples from eight varieties).

Following each instrument's instructions, measurements using FTA and MDT-2 were conducted on peeled samples while the TA.XT*plus* measurements were conducted on unpeeled samples. Two penetrations were conducted with each instrument in the sun/shade transition zones at the equatorial region of an apple.

The maximum firmness was measured on peeled fruit using the FTA fitted with an 11.1 mm diameter Magness-Taylor probe, penetrated to a depth of 10 mm and reported in pound-force (Table 3). The MDT-2 was also equipped with an 11.1 mm Magness-Taylor probe, and eight parameters were reported (Table 3) from region 1 (between 0–~8 mm) and region 2 (from 8 to ~15 mm between region 1 and the core) [32,41]. The TA.XT*plus* instrument was fitted with an 8 mm stainless steel probe which penetrated to a depth of 10 mm [31]. Then, Exponent software (Stable Micro Systems Ltd., Godalming, UK) was utilized to calculate five texture parameters [31] as shown in Table 3. All three instruments used cylindrical probes and were operated in compression mode with a load cell of 30 kg and a trigger force of 0.1 N.

Table 3. List of parameters, abbreviations, and units of measure associated with the instrumental measurements.

Instrument	Parameter	Unit	Description
Fruit Texture Analyzer (FTA) [1]	*MaxForce*	Pound-force (lbf)	The maximum flesh firmness
Mohr Digi-Test-2 (MDT-2) [2]	*M1*	lbf	Maximum firmness for region 1 [2]
	A1	lbf	Average force for region 1
	M2	lbf	Maximum firmness for region 2 [2]
	A2	lbf	Average force for region 2
	E2	lbf	Average force of last 20 readings in region 2
	C0	Inch (in)	Creep deformation or relaxation rate of fruit material measured at the beginning of region 2
	Cn	Unit less	Crispness measurement (a composite variable)
	QF	Unit less	Quality factor (weighted some of several MDT-2 parameters)
TA.XT*plus* Texture Analyzer [3]	*Fs*	Newton (N)	The maximum force required to rupture apple skin and flesh
	Ws	Nmm	Work to rupture skin and flesh
	Grad	N/mm	The gradient on the force-distance curve between 20% and 80% of *Fs* to measure the slope of the firmness
	D	mm	The probe position at *Fs*
	Ff	N	The average force required to puncture the flesh between 4.5 mm and 9.5 mm a

[1] FTA (Güss Manufacturing Ltd., Strand, South Africa) measurements were conducted on peeled fruit; [2] MDT-2 (Mohr and Associates Inc., Richland, WA, USA) measurements were conducted on peeled fruit, and region 1 refers to the first ~8 mm of the puncture and region 2 refers to an area between ~8 mm and ~15 mm; and [3] TA.XT*plus* (Stable Micro Systems Ltd., Godalming, UK) measurements were conducted on intact fruit.

2.4. Data Analysis

All statistical tests in the current study discussed below were conducted using JMP software (JMP® PRO, Version 16.1.0, SAS Institute Inc., Cary, NC, USA), at $\alpha = 0.05$ significance level.

Two penetrations per fruit were conducted with each instrument. As a result, before analyzing the data, a mean value was calculated for each instrumental parameter per apple sample, and the results were included in Dataset #1 ($n = 80$ per instrument). Then, standardized values for the instrumental measurements (from Dataset #1) and the sensory evaluations (i.e., Dataset #2 with $n = 264$) were screened to identify outliers per parameter. Only one z-value above $|3.21|$ was identified, from the TA.XT*plus* *Grad* parameter, and removed from the instrumental Dataset #1 before calculating the descriptive statistics and mean standardized values per parameter.

Dataset #3 was created from the mean variety averages of Datasets #1 and #2. Then, it was utilized in conducting a principal component analysis (PCA) test to explore the main tendencies of variation among the studied parameters. Instrumental measurements and sensory evaluations were considered as the output and supplementary variables in the PCA test in JMP software, respectively. PCA treats all variables simultaneously and models the data to develop a few significant principal components and residuals. PCA made it possible to study the relationships among the parameters with the principal components on a biplot. The principal components contain the systematic variability present in the data [42].

The centering and scaling options for PCA are selected by default in the JMP software. As a result, all variables are centered and scaled to have the mean of 0 and standard deviation of 1 and are placed on an equal basis relative to their variation [43]. This is important to make sure that the differences in the units of measurement do not affect the results.

At the next stage, models were developed to convert each instrument type's parameters to each other using Dataset #1 by considering data from an instrument as the predictor (i.e., X variable) and measurements from another instrument as the output (i.e., Y variable). Appropriate regression tests were selected considering the number of X variables, and the nature of the relationship between the studied variables (i.e., linear or nonlinear). Outliers were identified before finalizing the models based on the Studentized residuals, and multicollinearity problems were avoided by considering the variance inflation factor (VIF) scores. Nevertheless, VIF scores were not reported for single linear regression (SLR) models because there is only one X variable in the model. However, they were reported for multiple regression models.

The best fit models were selected considering coefficient of determination or R^2, $R^2_{Adjusted}$, F-ratio, root mean square error (RMSE), coefficient of variation (CV), VIF, 95% confidence intervals (CI), and 5-fold cross-validation R^2. CV is indicative of the model fit, and the higher the CV, the greater the dispersion in the variable [44]. In model development, CV is calculated by replacing the standard deviation term with the root mean square deviation (RMSD) in the CV equation. In addition, a 95% CI for regression coefficients means that there is a probability of 95% that the CI range contains the true value of the coefficient estimates. If the range between the upper limit and lower limit of CI for regression coefficients does not include zero, that indicates that the impact of the parameter is consistent and reliable.

Standardized coefficients (STd Betas) were also reported for each regression model. The studied parameters were standardized to a mean of 0 and a variance of 1 to calculate STd Betas. These values can be compared with each other as they lack a measurement unit.

The K-fold cross validation method (K = 5) was selected to validate the results of all developed regression models in the current study. In this method, the data are partitioned into K subsets (folds). Then, the model is developed using data from all subsets except one, and the developed model is tested on the subset that was not used in the development of the model to validate the model, fitting a total of K models [45]. The k-fold cross-validation method was selected to make efficient use of the dataset.

The achieved statistical power (1-β), the probability of rejecting a false null hypothesis, was also calculated using G*Power 3 software [46] for the developed regression models with the sample size of 80 and the type I error level (α) of 0.05. The accepted statistical power was set at 0.8 [47] to determine if the applied tests were able to identify genuine effects when they existed.

3. Results and Discussion

3.1. Descriptive Statistics

A summary of the instrumental (from Database # 1) and sensory (from Database # 2) parameters are presented in Table 4. Results indicated that the study included apple varieties with diverse textural profiles because the reported attribute ranges were broad.

The selection of appropriate varieties was important so that the models that were developed later to convert the data from one instrument to another one can be used for many different apple varieties that have textural characteristics within the range reported in Table 4. In addition, increasing the data range width is effective in increasing the certainty in regression slope [48].

Table 4. Minimum, maximum, mean, and standard deviation of the sensory evaluations and instrumental measurements.

Data Source	Parameter	Minimum	Maximum	Mean	SD
Sensory evaluations [1] (n = 264)	Crispness	11	87.5	53.18	20
	Hardness	2	87	40.84	23.23
	Skin toughness	16	94	49.73	14.81
Fruit Texture Analyzer (FTA) [2] (n = 80)	*MaxForce*	9.04	23.69	15.01	4.01
Mohr Digi-Test-2 (MDT-2) [3] (n = 80)	*M1*	7.59	20.07	12.95	3.27
	A1	5.54	13.72	9.07	2.1
	M2	11.27	27.84	18.39	4.9
	A2	9.66	22.41	15.1	3.75
	E2	9.35	25.64	16.7	4.7
	C0	0	0.09	0.02	0.02
	Cn	59.32	534.04	217.03	106.96
	QF	−102.44	145.14	30.88	66.94
TA.XT*plus* Texture Analyzer [4] (n = 80)	*Fs*	15.28	43.63	25.36	7.02
	Ws	43.89	100.66	64.57	15.43
	Grad	1.98	4.16	2.99	0.58
	D	51.11	198.8	95.47	34.13
	Ff	22.35	56.26	36.9	9.29

[1] Three sensory attributes with the definitions provided in Table 2; [2] one parameter (i.e., *MaxForce*) was measured using Fruit Texture Analyzer (FTA) as described in Table 3; [3] eight parameters (i.e., *M1*, *A1*, *M2*, *A2*, *E2*, *C0*, *Cn* and *QF*) were measured using Mohr Digi-Test-2 (MDT-2) as described in Table 3; and [4] five parameters (i.e., *Fs*, *Ws*, *Grad*, *D*, and *Ff*) were measured using TA.XT*plus* Texture Analyzer (TA.XT*plus)* as described in Table 3.

Standardized responses for the sensory attributes and instrumental measurements of texture for each variety are shown in Figure 1a–d. Standardized values were visualized in the radar charts to compare the parameters visually without the influence of their measurement units. The differences in the texture of different apple varieties were expected [10,11]. The charts demonstrated similarities between the sensory flesh hardness evaluations (Figure 1a) and the flesh firmness data measured using all three instruments. The only variable measured by FTA (i.e., *MaxForce*; Figure 1b) showed a very similar pattern to the sensory hardness data, and that was the same with six parameters reported by MDT-2 (i.e., *M1*, *A1*, *M2*, *A2*, *E2*, and *QF*; Figure 1c) and the *Ff* parameter measured by TA.XT*plus* (Figure 1d). Musacchi and Serra [9] discussed that the measurements obtained from the apple flesh (identified as region 2 by Mohr [41]) represent eating experience and are correlated with consumer acceptance of the fruit. FTA and MDT-2 samples were peeled, but intact samples were penetrated with TA.XT*plus* and the presence of the skin have probably resulted in obtaining diverse data compared to the data obtained from the other two instruments.

3.2. Principal Component Analysis (PCA)

The PCA was conducted using Dataset #3 which included means per variety for all studied variables to obtain an overview of the data and interpret the multi-source dataset [42]. Results of the PCA using 14 instrumental measurements indicated that 95.82% of the variation in the data could be explained using only two principal components (Figure 2), with 79.25% and 16.57% of the variation explained by PC 1 and PC 2, respectively.

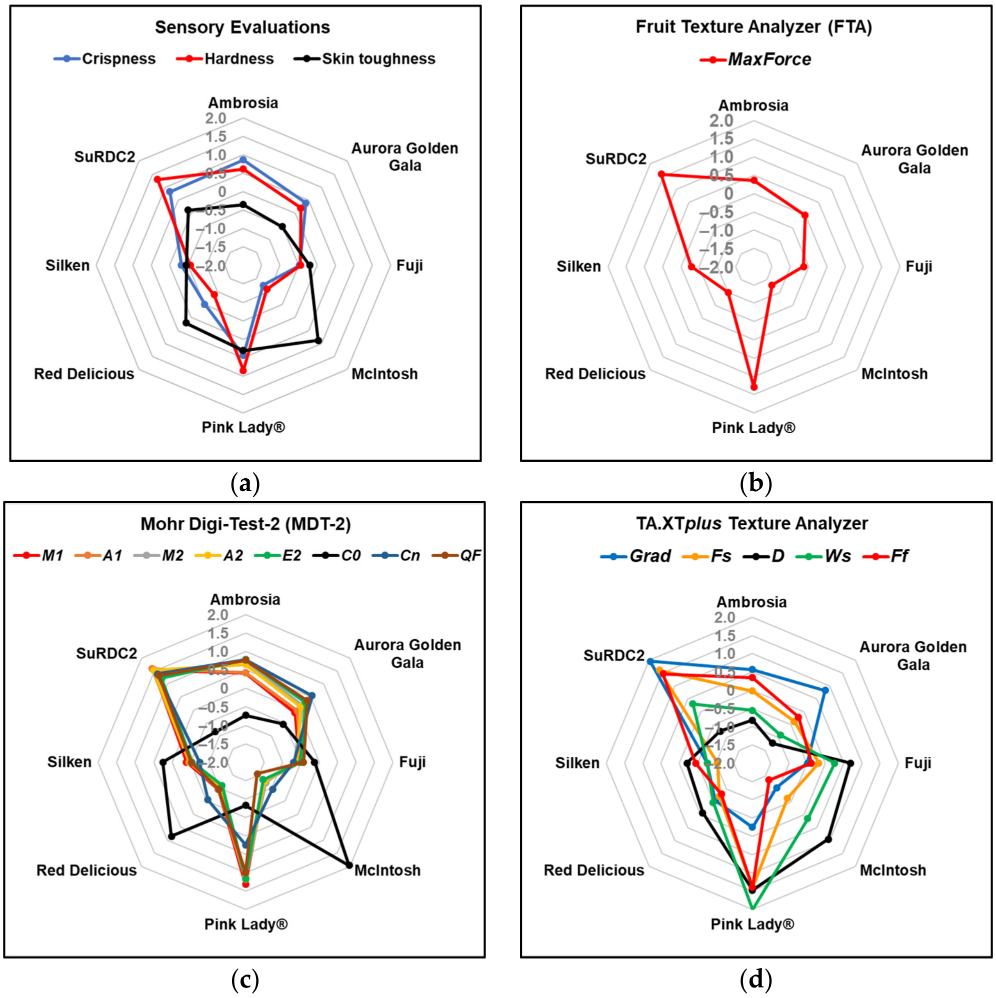

Figure 1. Standardized data for each of the apple varieties; (**a**) three sensory attributes with the definitions provided in Table 2; (**b**) one parameter from Fruit Texture Analyzer or FTA (i.e., *MaxForce*) as defined in Table 3; (**c**) eight parameters from Mohr Digi-Test-2 or MDT-2 (*M1*, *A1*, *M2*, *A2*, *E2*, *C0*, *Cn* and *QF*) as described in Table 3; and (**d**) five parameters from TA.XT*plus* Texture Analyzer or TA.XT*plus* (i.e., *Fs*, *Ws*, *Grad*, *D*, and *Ff*) as described in Table 3.

The vectors for MDT-2 *A2* (99.65%), MDT-2 *A1* (99.38%), MDT-2 *M2* (99.17%), MDT-2 *QF* (98.71%), MDT-2 *E2* (98.64%), MDT-2 *M1* (98.62%), FTA *MaxForce* (98.43%), TA.XT*plus* *Ff* (97.55%), MDT-2 *Cn* (90.84%), TA.XT*plus* *Fs* (88.67%), TA.XT*plus* *Grad* (81.95%), and MDT-2 M*C0* (−88.33%) were heavily associated with PC 1 (loadings inside parentheses), and explained the majority of the variation in the samples. PC 1 was positively and strongly correlated with sensory hardness (r = 0.996) and crispness (r = 0.92), as obvious from the correlation coefficients reported for the supplementary variables. All of the variables loaded heavily on PC 1 and the correlated sensory attributes refer to 'flesh firmness'. In comparison, the vectors for *D* and *Ws* were heavily associated with PC 2 (with loadings of 96.76% and 89.97%, respectively), and explained 16.57% of the variation in the samples. PC 2 was positively correlated with the sensory attribute of skin toughness (r = 0.63) and variables loaded on this component collectively described "skin strength". Bejaei et al. [31] also investigated the relationships between TA.XT*plus* parameters and sensory attributes of texture in a different study and reported similar PCA findings. MDT-2 and FTA did not contribute considerably in PC 2. The dimension was developed mainly based on the data from two TA.XT*plus* variables (i.e., *D* and *Ws*).

TA.XT*plus* measurements can represent consumer eating experience more closely because the samples are intact and the skin strength is considered in the measurements.

The MDT-2 *Cn* parameter was developed to explain crispness in apples [41] and it strongly correlated with the sensory crispness data in this study.

Figures 1 and 2 demonstrated differences in the texture of apple varieties included in this study. McIntosh and Red Delicious varieties had softer flesh while Pink Lady® and SuRDC2 varieties showed greater firmness than the remaining apple varieties in the present study. Other studies reported similar textural characteristics for the same apple varieties [31,32,49]. Fruit texture is considered a very important quality factor in determining consumer acceptance and is used in identifying fruit storability [1,50]. Consumers perceive the sensory textural attributes of fruits by hand or mouth [51].

Fruit firmness is mainly determined by cell size and shape, cell wall structure and composition, cell-to-cell adhesion, and turgor pressure status (i.e., the force exerted by the osmotic pressure of the protoplast) [52,53]. Lapsley et al. [10] reported differences in the cell size, shape, density, and degree of cell adhesion among apple varieties. Smaller cell sizes and more angular-shaped cells are associated with denser tissue and less airspace [10,54]. In addition, tricellular junctions in firm apples were rich in highly esterified pectin resulting in denser tissue, stronger cell adhesion, and smaller airspace [54]. Ng et al. [54] demonstrated that differences in the texture of apple varieties resulted from variations in the development of cell wall structures at the early stages of fruit growth (as early as the cell expansion phase). Cell adhesion and separation during ripening play a major role in the texture characteristics of apples [53]. Fruit texture softens as the fruit ripens, and the speed of softening varies in different apple varieties [52–54].

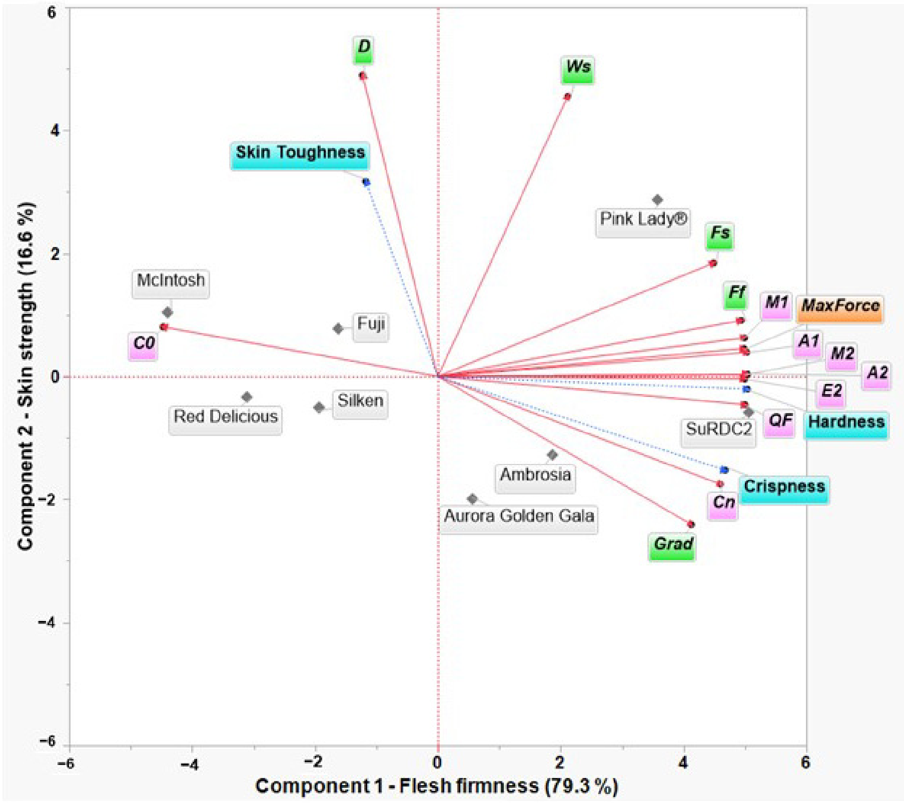

Figure 2. Principal component analysis (PCA) biplot calculated using standardized mean values of one Fruit Texture Analyzer (FTA) parameter (i.e., *MaxForce* in orange color), eight Mohr Digi-Test-2, MDT-2 (MDT-2) parameters (i.e., *M1*, *A1*, *M2*, *A2*, *E2*, *C0*, *Cn* and *QF* in pink color), and five TA.XT*plus* Texture Analyzer (TA.XT*plus*) parameters (i.e., *Fs*, *Ws*, *Grad*, *D*, and *Ff* in green color) as described in Table 3. All instrumental variables are identified by red lines. Sensory textural attributes (crispness, hardness, and skin toughness in blue color) are identified by blue lines and positioned on this plot using correlation analysis. Apple varieties are presented in grey color.

3.3. Models to Convert MDT-2 and TA.XTplus Data to FTA Data

SLR, MLR, and nonlinear regression models were considered to convert MDT-2 and TA.XT*plus* data to FTA data.

3.3.1. Converting MDT-2 Data to FTA Data

Standardized results in Figure 1 indicated that six parameters reported by MDT-2 were almost similar to those reported by the FTA *MaxForce* parameter. Thus, each one of those MDT-2 variables could be used in an SLR model as an X variable to convert MDT-2 data to FTA *MaxForce* data. The best fit model was developed using the *M1* variable, and the multicollinearity problems were avoided by including only one predictor variable in the model. No outliers were detected using the Studentized residual plot.

The linear effect of the MDT-2 *M1* parameter explained a significant proportion of the variance in the FTA *MaxForce* variable: F(1, 78) = 394.25, $p < 0.0001$, $R^2 = 0.83$, $R^2{}_{Adjusted} = 0.83$, RMSE = 1.64, Power = 1.00. The CV score in this test was considered good (10.93%), and 5-fold cross-validation R^2 for the model was 0.82. Table 5 shows the developed model, standard errors of parameter estimates, Std Beta, and their t-statistics and *p*-values.

Table 5. Model to convert MDT-2 data to FTA *MaxForce* data.

Output [1]	Predictor [1]	Model	Standard Error	Std Beta [2]	t-Statistics	Prob > |t|	Lower 95% CI [3]	Upper 95% CI
MaxForce	Intercept	0.51 +	0.75	0	0.68	0.5	−0.99	2.01
	M1	(1.12 × *M1*)	0.06	0.91	19.86	<0.0001	1.01	1.23

[1] *MaxForce* and *M1* parameters as described in Table 3; [2] Std Beta: standardized beta coefficient; and [3] CI: confidence intervals for regression coefficients.

The probe sizes and shapes of these two instruments were the same, and both required peeled samples and recorded the *MaxForce* and *M1* data in lbf. Considering the high R^2, lower RMES, satisfactory power of the test, good CV, high cross-validation power and the fact that the reported CI range for *M1* did not include zero, the model presented in Table 5 for the conversion of MDT2 data to FTA data is considered highly reliable, consistent and reproducible. As a result, it is recommended for practical applications.

3.3.2. Converting TA.XT*plus* Data to FTA Data

In calculating the FTA data with TA.XT*plus* variables using forward stepwise regression, *Ff* variable had the lowest *p*-value and was selected and then the *D* parameter with the second-lowest *p*-value was selected to be included in an MLR model. The other three parameters were not significantly contributing to the model after the inclusion of the first two variables. As observed from the PCA results these two variables were loaded on two different dimensions (Section 3.2). The *Ff* parameter was heavily loaded on the flesh firmness dimension similar to the *MaxForce* parameter, however, the *D* parameter was loaded on the skin strength dimension. The considerable contribution of the skin toughness on the overall apple firmness was demonstrated by Grotte et al. [55] by conducting penetration tests with peeled and unpeeled apples.

An outlier was detected based on the Studentized residual plot, and as a result, the data were reanalyzed after the removal of the outlier.

The linear effect of TA.XT*plus Ff* and *D* parameters explained a significant proportion of the variance in the FTA *MaxForce* variable: F(2, 76) = 542.44, $p < 0.0001$, $R^2 = 0.87$, $R^2{}_{Adjusted} = 0.86$, RMSE = 1.45, Power = 1.00. The *Ff* parameter explained more variation in the output variable than the *D* parameter. The CV was also considered very good (9.6%), and 5-fold cross-validation R^2 for the model was 0.86. Table 6 shows the parameter estimates, and considering the reported statistics, the model is considered highly reliable, consistent, and reproducible. As a result, it is recommended for practical applications.

Table 6. Model to convert TA.XT*plus* data to FTA data.

Output [1]	Parameter [1]	Model	Standard Error	Std Beta [2]	t-Statistics	Prob > |t|	Lower 95% CI [3]	Upper 95% CI	VIF [4]
MaxForce	Intercept	3.00 +	1.09	0.00	2.81	0.006	0.89	5.21	
	D (mm)	$(-0.86 \times D)+$	0.28	−0.12	−3.00	0.004	−1.41	−0.28	1.00
	Ff (N)	$(0.40 \times Ff)$	0.02	0.92	22.47	<.0001	0.36	0.43	1.00

[1] *MaxForce*, *D* and *Ff* parameters as described in Table 3; [2] Std Beta: standardized beta coefficient; [3] CI: Confidence intervals for regression coefficients; and [4] VIF: variance inflation factor.

3.4. Models to Convert FTA Data to MDT-2 Data

Table 7 shows the parameter estimates to convert FTA *MaxForce* data to the data that can be obtained from six MDT-2 parameters (i.e., *M1*, *A1*, *M2*, *A2*, *E2,* and *C0*). All these parameters refer to flesh firmness (Section 3.2). Models for the conversion of the MDT-2 *Cn* and *QF* parameters were not developed because both of these parameters are composite variables developed by the manufacturer (see Table 3).

Table 7. Models to convert FTA data to MDT-2 data.

Output [1]	Parameter [1]	Model	Standard Error	Std Beta [2]	t-Statistics	Prob > |t|	Lower 95% CI [3]	Upper 95% CI
M1	Intercept	1.76 +	0.58	0	3.01	0	0.59	2.92
	MaxForce	(0.75 × *MaxForce*)	0.04	0.91	19.86	<0.0001	0.67	0.82
A1	Intercept	2.03 +	0.41	0	5	<0.0001	1.22	2.84
	MaxForce	(0.47 × *MaxForce*)	0.03	0.9	17.92	<0.0001	0.42	0.52
M2	Intercept	1.83 +	0.93	0	1.98	0.05	−0.01	3.67
	MaxForce	(1.10 × *MaxForce*)	0.06	0.9	18.5	<0.0001	0.98	1.22
A2	Intercept	2.33 +	0.68	0	3.41	0	0.97	3.69
	MaxForce	(0.85 × *MaxForce*)	0.04	0.91	19.34	<0.0001	0.76	0.94
E2	Intercept	1.50 +	1.03	0	1.45	0.15	−0.56	3.56
	MaxForce	(1.01 × *MaxForce*)	0.07	0.86	15.2	<0.0001	0.88	1.15
C0	Intercept	0.2065 +	0.0251	0	8.22	<0.0001	0.1565	0.2565
	MaxForce	(−0.0207 × *MaxForce*) +	0.0033	−3.48	−6.24	<0.0001	−0.0273	−0.0141
	$(MaxForce)^2$	$(0.0005 \times MaxForcex^2)$	0.0001	2.76	4.95	<0.0001	0.0003	0.0007

[1] *M1*, *A1*, *M2*, *A2*, *E2*, *C0* (presented with 4 digit decimals because of the measurement scale) and *MaxForce* parameters as described in Table 3; [2] Std Beta: standardized beta coefficient; and [3] CI: confidence intervals for regression coefficients.

3.4.1. Converting FTA MaxForce Data to MDT-2 M1 Data

The SLR model developed to convert the FTA *MaxForce* parameter to the MDT-2 *M1* parameter (i.e., maximum firmness for region 1) was significant and explained the majority of the variation in the output variable: $F(1, 78) = 394.25$, $p < 0.0001$, $R^2 = 0.83$, $R^2_{Adjusted} = 0.83$, RMSE = 1.34, Power = 1.00. The CV was also considered good (10.34%), and the five-fold cross-validation R^2 for the model was 0.83. The results indicated that the model is highly reliable, consistent, reproducible, and recommended for practical applications.

3.4.2. Converting FTA MaxForce Data to MDT-2 A1 Data

The SLR model developed to convert the FTA *MaxForce* parameter to the MDT-2 *A1* parameter (i.e., average force for region 1) was significant and explained the majority of the variation in the output variable: $F(1, 78) = 320.98$, $p < 0.0001$, $R^2 = 0.80$, $R^2_{Adjusted} = 0.80$, RMSE = 0.93, Power = 1.00. The CV was also considered good (10.29%), and the five-fold cross-validation R^2 for the model was 0.79. The results indicated that the model was highly reliable, consistent, reproducible, and recommended for practical applications.

3.4.3. Converting FTA MaxForce Data to MDT-2 M2 Data

The SLR model developed to convert the FTA *MaxForce* parameter to the MDT-2 *M2* parameter (i.e., maximum firmness for region 2) was significant and explained the majority of the variation in the output variable: $F(1, 78) = 342.13$, $p < 0.0001$, $R^2 = 0.81$, $R^2_{Adjusted} = 0.81$, RMSE = 2.13, Power = 1.00. The CV was also considered good (11.56%), and the five-fold cross-validation R^2 for the model was 0.80. The results indicated that the model was highly reliable, consistent, reproducible, and recommended for practical applications.

3.4.4. Converting FTA MaxForce Data to MDT-2 A2 Data

The SLR model developed to convert the FTA *MaxForce* parameter to the MDT-2 *A2* parameter (i.e., average force for region 2) was significant and explained the majority of the variation in the output variable: $F(1, 78) = 374.02$, $p < 0.0001$, $R^2 = 0.83$, $R^2_{Adjusted} = 0.83$, RMSE = 1.57, Power = 1.00. The CV was also considered good (10.39%), and the five-fold cross-validation R^2 for the model was 0.82. The results indicated that the model was highly reliable, consistent, reproducible, and recommended for practical applications.

3.4.5. Converting FTA MaxForce Data to MDT-2 E2 Data

The SLR model developed to convert the FTA *MaxForce* parameter to the MDT-2 *E2* parameter (i.e., average force of last 20 readings in region 2) was significant and explained about three fourths of the variation in the output variable: $F(1, 78) = 231.08$, $p < 0.0001$, $R^2 = 0.75$, $R^2_{Adjusted} = 0.74$, RMSE = 2.38, Power = 1.00. The CV was 37.09%, and the five-fold cross-validation R^2 for the model was 0.74. Even though the model explained about 75% of the variation in the data but the CV level was not acceptable [42]. As a result, the developed model for the conversion of the *MaxForce* data to the *E2* data is not recommended for practical applications.

3.4.6. Converting FTA MaxForce Data to MDT-2 C0 Data

A nonlinear model was developed to convert the FTA *MaxForce* parameter to the MDT-2 *C0* parameter. The model was significant: $F(1, 77) = 73.39$, $p < 0.0001$, $R^2 = 0.66$, $R^2_{Adjusted} = 0.65$, RMSE = 0.01, Power = 1.00. The mean of the *C0* parameter was close to zero (0.02), and as a result, it was expected to have a high value (70.47%) for CV [56]. The 5-fold cross-validation R^2 for the model was 0.62.

The nonlinear relationship showed that MDT-2 *C0*, or creep deformation, was greater with the softer flesh apples ($C0_{\text{maximum}}$ = 0.09 in and $MaxForce_{\text{minimum}}$ = 9 lbf), and as the apple firmness increased *C0* reached its lowest value (around 0 in) when the FTA *MaxForce* parameter was around 17 lbf. The *C0* parameter remained without change while the *MaxForce* parameter increased. It is expected from biological relationships to reach a natural limit [57], and in this case, it is considered to be related to the number and size of cells and cell structures [10,12,58]. Considering the fact that *C0* remains around 0 in apples with *MaxForce* above 17 lbf, extra care is recommended in the application of the model.

3.5. Models to Convert FTA Data to TA.XTplus Data

Results of the PCA test indicated that the relationship between *D* and *Ws* parameters and FTA *MaxForce* were not strong and they were loaded on a separate dimension (Figure 2). As a result, SLR models were only developed for the remaining three TA.XT*plus* parameters (i.e., *Grad*, *Fs* and *Ff*), and Table 8 shows the parameter estimates for the developed models.

Table 8. Models to convert FTA data to TA.XT*plus* *Grad*, *Fs* and *Ff* data.

Output [1]	Parameter [1]	Model	Standard Error	Std Beta [2]	t-Statistics	Prob > |t|	Lower 95% CI [3]	Upper 95% CI
Grad	Intercept	7.71 +	2.29	0.00	3.37	0.001	3.15	12.28
	MaxForce	(1.18 × *MaxForce*)	0.15	0.67	7.97	<0.0001	0.89	1.48
Fs	Intercept	18.78 +	4.12	0.00	4.56	<0.0001	10.58	26.99
	MaxForce	(3.05 × *MaxForce*)	0.27	0.79	11.50	<0.0001	2.52	3.58
Ff	Intercept	4.25 +	1.57	0.00	2.70	0.01	1.12	7.38
	MaxForce	(2.16 × *MaxForce*)	0.10	0.93	21.45	<0.0001	1.96	2.36

[1] *Grad*, *Fs*, *Ff* and *MaxForce* parameters as described in Table 3; [2] Std Beta: standardized beta coefficient; and [3] CI: confidence intervals for regression coefficients.

3.5.1. Converting FTA Data to TA.XT*plus* Grad Data

The SLR model developed to convert the FTA *MaxForce* parameter to the TA.XT*plus* *Grad* parameter (i.e., the gradient on the force-distance curve between 20% and 80% of *Fs*) was significant but explained less than half of the variation in the output variable: F(1, 77) = 63.46, $p < 0.0001$, $R^2 = 0.45$, $R^2_{Adjusted} = 0.44$, RMSE = 5.23, Power = 1.00. The CV was considered acceptable (20.62%), and five-fold cross-validation R^2 for the model was 0.42. The model explained only 45% of the variation in the output data, and as a result, it is not recommended for practical applications.

3.5.2. Converting FTA Data to TA.XT*plus* Fs Data

The SLR model developed to convert the FTA *MaxForce* parameter to the TA.XT*plus* *Fs* parameter (i.e., the maximum force required to rupture apple skin and flesh) was significant and explained about two-third of the variation in the output variable: F(1, 78) = 132.26, $p < 0.0001$, $R^2 = 0.63$, $R^2_{Adjusted} = 0.62$, RMSE = 9.46, Power = 1.00. The CV was also considered good (14.65%), and five-fold cross-validation R^2 for the model was 0.58. This model is acceptable but it only explains 63% of the variation in the data. The main reason for the difference between the *MaxForce* and *Fs* parameters is related to the presence of skin in the measurement of *Fs* and the influence of skin toughness on the force required to rupture the samples [58].

3.5.3. Converting FTA Data to TA.XT*plus* Ff Data

An outlier was identified and removed from the dataset before developing the final model to convert FTA *MaxForce* data to the TA.XT*plus* *Ff* parameter (i.e., the average force required to puncture the flesh between 4.5 mm and 9.5 mm). The developed SLR model explained the majority of the variation in the output variable: F(1, 77) = 460.32, $p < 0.0001$, $R^2 = 0.86$, $R^2_{Adjusted} = 0.85$, RMSE = 3.56, Power = 1.00. The CV was also considered very good (9.65%), and 5-fold cross-validation R^2 for the model was 0.85. The results indicated that the model is highly reliable, consistent, reproducible, and recommended for practical applications.

3.6. Models to Convert TA.XTplus Data to MDT-2 Data

Table 9 shows the parameter estimates and the models developed to convert TA.XT*plus* data to six MDT-2 parameters (i.e., *M1*, *A1*, *M2*, *A2*, *E2* and *C0*). All these parameters refer to flesh firmness. Models are not developed for the MDT-2 composite variables (i.e., *Cn* and *QF*).

Table 9. Models to convert TA.XT*plus* data to MDT-2 data.

Output [1]	Parameter [1]	Model	Standard Error	Std Beta [2]	t-Statistics	Prob > |t|	Lower 95% CI [3]	Upper 95% CI	VIF [4]
M1	Intercept	$1.02 +$	0.68	0	1.51	0.14	−0.33	2.37	
	Grad	$(0.08 \times Grad) +$	0.03	0.17	2.68	0.01	0.02	0.13	1.68
	Ff	$(0.27 \times Ff)$	0.02	0.78	12.18	<0.0001	0.22	0.31	1.68
A1	Intercept	$1.37 +$	0.47	0	2.91	0.00	0.43	2.32	
	Grad	$(0.05 \times Grad) +$	0.02	0.18	2.65	0.01	0.01	0.09	1.64
	Ff	$(0.17 \times Ff)$	0.02	0.77	11.38	<0.0001	0.14	0.20	1.64
M2	Intercept	$0.12 +$	1.12	0	0.11	0.91	−2.11	2.35	
	Grad	$(0.15 \times Grad) +$	0.05	0.22	3.23	0.00	0.06	0.25	1.64
	Ff	$(0.39 \times Ff)$	0.04	0.74	10.90	<0.0001	0.32	0.46	1.64
A2	Intercept	$0.98 +$	0.80	0	1.22	0.23	−0.62	2.58	
	Grad	$(0.12 \times Grad) +$	0.03	0.23	3.54	0.00	0.05	0.19	1.64
	Ff	$(0.30 \times Ff)$	0.03	0.74	11.69	<0.0001	0.25	0.35	1.64
E2	Intercept	$5.22 +$	1.85	0	2.82	0.01	1.54	8.91	
	D	$(-1.37 \times D) +$	0.48	−0.17	−2.85	0.01	−2.33	−0.41	1.00
	Ff	$(0.42 \times Ff)$	0.03	0.83	14.09	<0.0001	0.36	0.48	1.00
C0	Intercept	$0.1965 +$	0.0270	0	7.27	<0.0001	0.1427	0.2504	
	D	$(0.0080 \times D) +$	0.0024	0.1896	3.28	0.0016	0.0031	0.0128	1.15
	Ff	$(-0089 \times Ff) +$	0.0013	−3.4347	−6.98	<0.0001	−0.0115	−0.0064	83.65
	Ff^2	$(0.0001 \times Ff^2)$	0.0000	2.6733	5.43	<0.0001	0.0001	0.0001	83.87

[1] *M1*, *A1*, *M2*, *A2*, *E2*, *C0* (presented with 4 digit decimals because of the measurement scale), *Grad*, *D* and *Ff* parameters as described in Table 3; [2] Std Beta: standardized beta coefficient; [3] CI: confidence intervals for regression coefficients; and [4] VIF: variance inflation factor.

3.6.1. Converting TA.XT*plus* Data to MDT-2 M1 Data

An outlier was detected and removed before developing the final model. The best fit MLR model developed to convert the TA.XT*plus* data to the MDT-2 *M1* parameter (i.e., maximum firmness for region 1) included two predictors (i.e., *Grad* and *Ff*) with acceptable VIF scores. The model was significant and explained the majority of the variation in the output variable: $F(1, 75) = 165.58$, $p < 0.0001$, $R^2 = 0.82$, $R^2_{Adjusted} = 0.81$, RMSE = 1.37, Power = 1.00. The CV was also considered good (10.71%), and 5-fold cross-validation R^2 for the model was 0.79. The results indicated that the model was reliable, consistent, reproducible, and recommended for practical applications.

3.6.2. Converting TA.XT*plus* Data to MDT-2 A1 Data

The best fit MLR model developed to convert the TA.XT*plus* data to the MDT-2 *A1* parameter (i.e., average force for region 1) included two predictors (i.e., *Grad* and *Ff*) with acceptable VIF scores. The model was significant and explained the majority of the variation in the output variable: $F(1, 76) = 143.03$, $p < 0.0001$, $R^2 = 0.79$, $R^2_{Adjusted} = 0.78$, RMSE = 0.96, Power = 1.00. The CV was also considered good (10.62%), and 5-fold cross-validation R^2 for the model was 0.79. The results indicated that the model was highly reliable, consistent, reproducible, and recommended for practical applications.

3.6.3. Converting TA.XT*plus* Data to MDT-2 M2 Data

The best fit MLR model developed to convert the TA.XT*plus* data to the MDT-2 *M2* parameter (i.e., the maximum firmness for region 2) included two predictors (i.e., *Grad* and *Ff*) with acceptable VIF scores. The model was significant and explained the majority of the variation in the output variable: $F(1, 76) = 142.37$, $p < 0.0001$, $R^2 = 0.79$, $R^2_{Adjusted} = 0.78$, RMSE = 2.27, Power = 1.00. The CV was also considered good (12.40%), and the five-fold cross-validation R^2 for the model was 0.79. The results indicated that the model was highly reliable, consistent, reproducible, and recommended for practical applications.

3.6.4. Converting TA.XT*plus* Data to MDT-2 A2 Data

The best fit MLR model developed to convert the TA.XT*plus* data to the MDT-2 *A2* parameter (i.e., the average force for region 2) included two predictors (i.e., *Grad* and *Ff*) with acceptable VIF scores. The model was significant and explained the majority of the variation in the output variable: $F(1, 76) = 165.03$, $p < 0.0001$, $R^2 = 0.81$, $R^2_{Adjusted} = 0.81$, RMSE = 1.57, Power = 1.00. The CV was also considered good (10.83%), and the five-fold cross-validation R^2 for the model was 0.79. The results indicated that the model was highly reliable, consistent, reproducible, and recommended for practical applications.

3.6.5. Converting TA.XT*plus* Data to MDT-2 E2 Data

The best fit MLR model developed to convert the TA.XT*plus* data to the MDT-2 *E2* parameter (i.e., the average force of last 20 readings in region 2) included two predictors (i.e., *D* and *Ff*) with acceptable VIF scores. The model was significant and explained about three fourths of the variation in the output variable: $F(1, 77) = 104.37$, $p < 0.0001$, $R^2 = 0.73$, $R^2_{Adjusted} = 0.72$, RMSE = 2.47, Power = 1.00. The CV was good (14.79%), and the five-fold cross-validation R^2 for the model was 0.70. The results indicated that the model was reliable, consistent, reproducible, and recommended for practical applications.

3.6.6. Converting TA.XT*plus* Data to MDT-2 C0 Data

The best fit nonlinear model developed to convert the TA.XT*plus* data to the MDT-2 *C0* parameter included three predictors (i.e., *D*, *Ff* and Ff^2). The model was significant: $F(1, 75) = 90.29$, $p < 0.0001$, $R^2 = 0.78$, $R^2_{Adjusted} = 0.77$, RMSE = 0.01, Power = 1.00. As discussed before, the nonlinear relationship between the force required to puncture the samples and the MDT-2 *C0* parameter (i.e., or creep deformation) indicated the *C0* value is greater with softer flesh apples. The CV was 56.14% (because of a very low mean), and the five-fold cross-validation R^2 for the model was 0.68. The model should be applied with extra care considering the nonlinear relationship between the studied variables and the fact that it only explained about two-third of the variation in the output data.

3.7. Models to Convert MDT-2 Data to TA.XTplus Data

When converting seven MDT-2 parameters to five parameters obtained from the TA.XT*plus* instrument, the MDT-2 parameters were considered as the X variables while TA.XT*plus* parameters were considered as the Y variables.

Six MDT-2 parameters (i.e., *M1*, *A1*, *M2*, *A2*, *E2* and *C0*) were considered in the development of conversion models for three TA.XT*plus* parameters (i.e., *Grad*, *Fs* and *Ff*). The selected parameters were all loaded on the first component of the PCA plot and none of the was a composite variable. Table 10 shows the parameter estimates for the developed models.

Table 10. Models to convert MDT-2 data to TA.XT*plus* *Grad*, *Fs* and *Ff* data.

Output [1]	Parameter [1]	Model	Standard Error	Std Beta [2]	t-Statistics	Prob > |t|	Lower 95% CI [3]	Upper 95% CI	VIF [4]
Grad	Intercept	5.76 +	2.41	0.00	2.39	0.02	0.96	10.56	
	A2	(1.30 × *A2*)	0.16	0.69	8.37	<0.0001	0.99	1.61	1.00
Fs	Intercept	−2.62 +	8.30	0.00	−0.32	0.75	−19.15	13.91	
	M1	(4.90 × *M1*) +	0.54	1.04	9.08	<0.0001	3.82	5.97	3.02
	C0	(189.65 × *C0*)	73.99	0.29	2.56	0.01	42.32	336.98	3.02
Ff	Intercept	4.16 +	1.94	0.00	2.14	0.04	0.29	8.03	
	M1	(2.53 × *M1*)	0.15	0.89	17.37	<0.0001	2.24	2.82	1.00

[1] *Grad*, *Fs*, *Ff* and *A2*, *M1* and C0 parameters as described in Table 3; [2] Std Beta: Standardized beta coefficient; [3] CI: confidence intervals for regression coefficients; and [4] VIF: variance inflation factor.

3.7.1. Converting MDT-2 Data to TA.XT*plus* Grad Data

The best fit SLR model developed to convert the MDT-2 data to the TA.XT*plus* *Grad* parameter (i.e., the gradient on the force-distance curve between 20% and 80% of *Fs*) included one predictor (i.e., *A2*). The model was significant but explained less than half of the variation in the output variable: $F(1, 77) = 70.04$, $p < 0.0001$, $R^2 = 0.48$, $R^2_{Adjusted} = 0.47$, RMSE = 5.11, Power = 1.00. The CV was considered acceptable (20.16%), and 5-fold cross-validation R^2 for the model was 0.37. The model explained less than half of the variation in the output data, and as a result, it is not recommended for practical applications.

3.7.2. Converting MDT-2 Data to TA.XT*plus* Fs Data

The best fit MLR model developed to convert the MDT-2 data to the TA.XT*plus Fs* parameter (i.e., the maximum force required to rupture apple skin and flesh) included two predictors (i.e., *M1* and *C0*). The model was significant and explained about two-third of the variation in the output variable: $F(1, 77) = 76.96$, $p < 0.0001$, $R^2 = 0.67$, $R^2_{Adjusted} = 0.66$, RMSE = 9.02 Power = 1.00. The CV was also considered good (13.98%), and 5-fold cross-validation R^2 for the model was 0.65. This model is acceptable; however, it only explains about two-third of the variation in the *Fs* variable. The reason for the difference in the forces required to rupture the samples in the two instruments is related to the presence of apple skin in TA.XT*plus* samples as discussed previously.

3.7.3. Converting MDT-2 Data to TA.XT*plus* Ff Data

The best fit SLR model to convert MDT-2 data to the TA.XT*plus Ff* parameter (i.e., the average force required to puncture the flesh between 4.5 mm and 9.5 mm) was developed using one predictor (i.e., *M1*). The model explained the majority of the variation in the output variable: $F(1, 78) = 301.87$, $p < 0.0001$, $R^2 = 0.79$, $R^2_{Adjusted} = 0.79$, RMSE = 4.23, Power = 1.00. The CV was also considered good (11.48%), and 5-fold cross-validation R^2 for the model was 0.79. The results indicated that the model was highly reliable, consistent, reproducible, and recommended for practical applications.

4. Conclusions

The use of diverse apple texture testing instruments makes the comparison and integration of the results very challenging, especially for long-term research and fruit quality assessment programs when the assessments occur at different sectors/stages using different instruments. Results of this study indicated that there are similarities among some of the parameters measured, and all three instruments were able to track the flesh firmness or the sensory hardness attribute in apple varieties regardless of the type of sample (i.e., peeled or unpeeled) they required. For example, the MDT-2 *M1* parameter and the TA.XT*plus Ff* and *D* parameters can be converted reliably to the FTA *MaxForce* parameter; the MDT-2 *M1*, *A1*, *M2*, and *A2* parameters can be calculated consistently by the FTA *MaxForce* parameter, and the MDT-2 *M1*, *A1*, *M2*, *A2,* and *E2* parameters can be calculated reliably by the TA.XT*plus* data. In addition, results indicated that the use of unpeeled samples generates other parameters that correlate with the skin toughness sensory perception [31]. It was also shown that differences existed among the measured variables even when the applied probe size and shape, and measurement units were the same (and other settings were tried to be kept similar considering the manuals published by each manufacturer). This emphasizes the importance of proper data handling when the data are generated from different instruments, and the need for the application of reliable models to convert data when required.

Three sensory attributes were included in the current study to focus only on the textural characteristics of apples. This may have introduced a limitation in the sensory results because the panel did not have an opportunity to evaluate other sensory attributes of the fruit (e.g., flavor and color) [59]. However, the decision was made to reduce the number of the evaluated attributes considering the samples size per session (i.e., 12) to avoid panel fatigue.

The strength of this research lies, in part, with the development of cross-validated practical models that can be applied by researchers and industry experts to integrate data obtained using different instruments in their research and analysis. In addition, the models make it possible for apple quality assessment programs at different sectors of a fruit supply chain to exchange data when they are using one of the three instruments investigated in this study. The broad range of textural traits in the selected apple varieties in this study also makes it possible to apply the models to many different apple varieties [31].

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Institutional Review Board Statement: The study was conducted according to the guidelines of the Tri-Council Policy Statement, Ethical Conduct for Research Involving Humans, and approved by the Human Research Ethics Committee of Agriculture and Agri-Food Canada (HERC Reference Number: Amendment to 2018-F-003 Bejaei).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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