

1 **The prediction of cake texture during conventional baking based on AdaBoost**
2 **algorithm**

3
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5
6 **ABSTRACT**

7 The present study investigates the effect of baking temperatures (140, 160, 180, 200, and 220°C)
8 on texture kinetics. It also explores a statistical classification meta-algorithm, called Adaptive
9 Boosting (AdaBoost), to predict texture changes during conventional cake baking. The
10 experimental results indicated that texture properties were significantly affected by baking
11 temperature and time. As time and temperature increased, there was an increase in hardness,
12 cohesiveness, gumminess, and chewiness and a decrease in springiness. However, the impact of
13 time and temperature on resilience was inconsistent, as it was maximum in the last quarter of the
14 process. The predicted results revealed that the AdaBoost algorithm accurately predicted the
15 texture properties with a high coefficient of determination ($R^2 > 0.989$) and minimal root mean
16 square error (RMSE < 0.0019) across all textural properties. Therefore, it can serve as an efficient
17 tool for predicting the texture properties of cakes during baking. Furthermore, the proposed
18 methodology can be extended to predict the texture properties of other baked goods.

19 **Keywords:** Machine learning, Prediction, Texture Profile Analysis, Hardness, Cohesiveness.

20
21 **INTRODUCTION**

22 Cakes are bakery products that are widely consumed worldwide. Regardless of the variety of
23 cakes, which are attributed to various formulations and process conditions, achieving the desired
24 texture in the product is still challenging.

25 Understanding the textural characteristics of the cake improves quality control. However,
26 determining these properties requires expensive equipment and significant time (Crispín-Isidro et
27 al., 2015). The use of predictive algorithms based on mathematical models is recommended.

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28 Researchers have developed various algorithms to predict the texture of food materials. Some of
29 these approaches include Artificial Neural Network (ANN) (Abbasi et al., 2012; Ahmad et al.,
30 2014; Batista et al., 2021a; Khawas et al., 2016; Lee et al., 2024; Meng et al., 2012; Pan et al.,
31 2015; Qiao et al., 2007; Vásquez et al., 2018), Bayesian Extreme Learning Machine (BELM) (Lee
32 et al., 2024), Random Forest (RF) (Lee et al., 2024; H. Lin et al., 2024; Sun et al., 2021; Zhou et
33 al., 2024), Support Vector Machine (SVM) (H. Lin et al., 2024; Zhu et al., 2017), Genetic
34 Algorithm (GA) (Abbasi et al., 2012; H. Lin et al., 2024; Zhu et al., 2017), Partial Least Squares
35 Regression (PLSR) (Darnay et al., 2017; Polak et al., 2019; Sun et al., 2021; Vásquez et al., 2018;
36 Zhu et al., 2017), Monte Carlo Cross (MCC) (Darnay et al., 2017), Weighted Regression (WR)
37 (Zhu et al., 2017), Successive Projections Algorithm (SPA) (Zhu et al., 2017), Gaussian Process
38 Regression (GPR) (Barzegar et al., 2024), eXtreme Gradient Boosting algorithm (XGBoost) (Zhou
39 et al., 2024).

40 The AdaBoost is a powerful algorithm that can select properties during learning (Chuan et al.,
41 2021). Furthermore, since increasing the sample size requires reasonable speed and accuracy, this
42 method can be useful and efficient when dealing with large amounts of data. The AdaBoost
43 algorithm also offers numerous advantages, including ease of use, simple and interpretable
44 classification rules, and having only one regularization parameter (i.e., the number of algorithm
45 repetitions), resulting in a high level of automation. Also, this algorithm is compatible with
46 unbalanced training data and offers great flexibility compared to many other algorithms (Chen et
47 al., 2014; Freund & Schapire, 1997). In addition, it has various applications in food products,
48 including ripe fruit detection (G. Lin & Zou, 2018), sweetness prediction (Bouysset et al., 2020),
49 camellia oil fraud detection (Kuang et al., 2022), food glycemic index prediction (Khan et al.,
50 2022), wheat varieties, and mixing ratio detection and classification (Jiang et al., 2023).

51 According to the studies presented in the research literature, no study was found that could predict
52 the texture profile analysis (TPA) characteristics of the cake using existing algorithms. Therefore,
53 we chose the AdaBoost algorithm to predict the cake's fundamental textural properties (i.e.,
54 hardness, springiness, cohesiveness, chewiness, gumminess, and resilience) during conventional
55 baking. Also, a split-plot based on complete block design was applied for TPA experiments.

56 Based on the mentioned points, the main contributions of this paper are as follows:

57 -For the first time, the AdaBoost algorithm is used to model the textural properties of food and
58 applied RMSE, R^2 , and QC

59 -Time and temperature are used simultaneously to enhance the model's accuracy.

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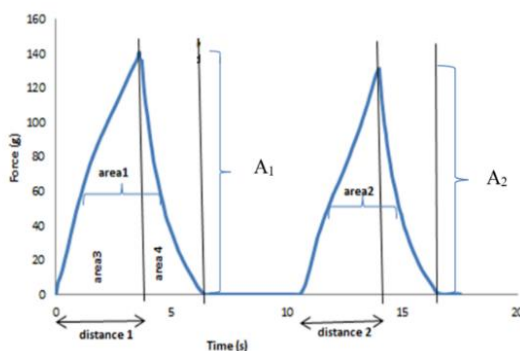
61 MATERIALS AND METHODS

62 a. Experimental Data

63 **Baking Procedure:** In this step, a vanilla cake batter including sugar (21.1 g), milk powder (1.6
64 g), emulsifier (0.25 g), salt (0.45 g), baking powder (1.35 g), flour (21.1 g), Vanilla (0.45 g), liquid
65 egg (24.7 g), vegetable oil (14.5 g), and water (14.5 g) was prepared by stirring the liquid egg using
66 a mixer (Bosch-CNCM57,1100 W, Slovenia) at high speed for 10 min and mixing with water and
67 vegetable oil. Finally, other ingredients of batter were added and mixed until uniformity in the cake
68 batter was obtained (Soleimanifard et al., 2024). The moisture content of the batter was 49% on a
69 dry basis.

70 About 100 g of vanilla batter was baked in a conventional oven (Butane MR-1, Iran) at 140, 160,
71 180, 200, and 220°C for 1.59, 0.81, 0.66, and 0.63 hour, respectively. The total process time at each
72 temperature was divided into 17 parts, where all textural parameters were measured.

73 **Texture Profile Analysis:** A texture analyzer (TA Plus, Lloyd Instruments, UK) with a 50 N
74 load cell was used to conduct double-compression TPA on cake crumbs. A cylindrical probe (40
75 mm in diameter) was used to compress cylindrical samples with a diameter of 24.5 mm and a height
76 of 20 mm to 50% compression at a speed of 60 mm (Bourne, 2002; Zareifard et al., 2009). TPA
77 was designed to simulate the mastication processes.



78

79 **Figure 1.** The textural parameters of the TPA curve.

80

81 As shown in Fig. 1, the force peak height on the first compression cycle is defined as hardness
82 (N). The ratio of the positive force areas under the first and second compressions (A_2/A_1) was used
83 to measure cohesiveness (N/N). This ratio indicates the extent to which a sample can be deformed
84 before it ruptures. Springiness (s/s) is defined as the time index it takes for the sample to return to

85 its original shape or size after being partially compressed. The parameter was calculated as
 86 $\text{distance}_2/\text{distance}_1$. Moreover, resilience (N.s/N.s), i.e., the degree to which the sample returns to
 87 its original shape and elasticity, was calculated as A_4/A_3 . Two additional parameters were derived
 88 from the measured parameters. Here, gumminess (N) was defined by multiplying hardness by
 89 cohesiveness, while chewiness (N) was calculated by multiplying gumminess by springiness
 90 (Bourne, 2002; Zareifard et al., 2009). All experiments were performed in five replications.

91 **Statistical Analysis:** The experimental data was analyzed by analysis of variance
 92 (ANOVA) using a split-plot design based on complete block design with the SAS statistical
 93 program (version 9.4). Means of treatment were separated using the Duncan test ($p \leq 0.05$).

94

95 **b- AdaBoost Modeling**

96 This research applies the AdaBoost algorithm to predict textural changes in cake samples during
 97 baking under various conditions. AdaBoost was chosen for its ability to improve productivity and
 98 address the problem of imbalanced categories in other learning algorithms. This algorithm can
 99 upgrade a weak classifier with a better classification effect than random classification to a strong
 100 classifier with high classification accuracy (Chuan et al., 2021).

101 This algorithm integrates many weak classifiers (e.g., simple decision trees and neural networks)
 102 and transforms them into strong ones (Tharwat et al., 2018a) during both the training and testing
 103 phases. The process was performed in the following steps:

104 In the training step, observation weights were initialized to be equal and were used for the first
 105 classifier $w_j^1 = \frac{1}{N}$, $j=1, \dots, N$. The weights of the first classifier (w_j^1). Afterward, they were
 106 determined through the error rates of weak learners (C_t), as:

$$107 \quad \epsilon_t = \sum_{j=1}^N w_j^t l_j^t \text{ and } l_j^t = \mathbf{1}$$

108 where training samples were misclassified; otherwise, $l_j^t = \mathbf{0}$. If $\epsilon_t \geq \mathbf{0.5}$, the weights were
 109 readjusted so the misclassified samples were classified more accurately in the next learning step
 110 by increasing their weights. Therefore, weak learner weights (α_t) were calculated as:

$$111 \quad \alpha_t = \frac{\epsilon_t}{1-\epsilon_t}. \text{ (Gaber et al., 2016)}$$

112 Finally, the previous steps were repeated until the best classifier was achieved (Li & Li, 2020).

113 In the testing step, all weak learners of the algorithm were used to classify the testing sample
 114 (X_{test}) as follows:

$$115 \quad \mu_t = \sum_{C_t(x_{test})=\omega_t} \ln\left(\frac{1}{\alpha_t}\right), \quad \forall t = 1, 2, \dots, T,$$

116 where μ_t is the score of a class ω_t . Moreover, T , N , and ϵ_t are the total number of iterations,
117 the total number of samples in the training set, and the minimum error, respectively.

118 Eventually, the unknown sample was devoted to the highest score class (Gaber et al., 2016;
119 Tharwat et al., 2018b).

120

121 c Validation Criteria

122 The model was validated using statistical parameters such as $R^2 = 1 - \frac{\sum_i^N (x_{i_exp} - x_{i_pre})^2}{\sum_i^N (x_{i_exp} - \bar{x}_{exp})^2}$, root

123 mean square error as $RMSE = \sqrt{\frac{\sum_{i=1}^N (x_{i_exp} - x_{i_pre})^2}{N}}$, and quality coefficient as $QC =$

124 $\frac{R_{train}^2 + R_{test}^2}{RMSE_{train}^2 + RMSE_{test}^2}$ (Batista et al., 2021b; Niu et al., 2020).

125 where N , x_{i_pre} , x_{i_exp} , and \bar{x}_{exp} represent the number of data sets, the predicted values, the
126 experimental values, and the average experimental data, respectively. Generally, a model with the
127 maximum R^2 value (close to 1) and the minimum RMSE value (close to 0) would exhibit the best
128 relative performance.

129

130 RESULTS

131 a. Experimental Analysis

132 **Hardness:** Fig. 2(A) illustrates the effects of baking time and temperature on the hardness of the
133 baked cakes. As can be seen, hardness increased by increasing the baking time. This behavior is
134 attributed to the role of water as a plasticizer. By reducing the amount of moisture content during
135 the process, hardness will increase accordingly. In other words, when the moisture content
136 decreases, the gelatinization or retrogradation of starch and protein interactions are accelerated,
137 resulting in a harder texture. Hence, the moisture content had a negative correlation with hardness.
138 During the baking process, the evaporation of water from the surface creates a crust that increases
139 hardness. This increase may explain the surge in hardness observed after the crust (around 1,000
140 to 2,000 s, depending on temperature). As the baking temperature rises, water evaporation and
141 pressure gradients increase considerably, leading to rapid moisture loss. In this respect, many
142 studies have reported an increase in hardness in bread (Das et al., 2012; İçöz et al., 2004; Matos &

143 Rosell, 2012), cake (Al-Muhtaseb et al., 2013a), and Chhana Podo (Kumari et al., 2015) with an
144 increase in baking time and temperature.

145 **Cohesiveness:** Fig. 2B illustrates the effects of baking time and temperature on the cohesiveness
146 of the cake during baking. As also reported by Clarke & Farrell (2000), the cohesiveness of the cake
147 increased by prolonging the baking time. Furthermore, this parameter increases with the
148 temperature rise at a constant time. Final mean cohesiveness values ranged from 0.48 to 0.63 in the
149 temperature range of 140 to 220°C. During the baking process, a stronger and more cohesive
150 structure will develop by decreasing the moisture content, thereby increasing the hardness. In
151 addition, as the temperature increases, the sample absorbs more energy over time, reducing the
152 processing time needed to achieve the final strong structure.

153 While cohesiveness increased slowly during the baking process at lower temperatures, this
154 behavior was significantly different at higher temperatures, showing rapid growth initially and then
155 reaching a plateau over time.

156 **Springiness:** Springiness is the time index to which the cake returns to its original state after
157 removing the compression force. This parameter, which is controlled by the crumb network's
158 strength, is thought to be a good predictor of staling initiation (Cauvain & Young, 2009).
159 Springiness significantly increased with time and decreased with temperature during baking using
160 a conventional oven (Fig. 2C). One of the most significant changes at the beginning of baking is
161 the increase in dough temperature. This factor fills the pores and transforms the product from a
162 liquid batter or semi-viscous dough into a solid alveolar structure by the end of the baking process,
163 thereby increasing springiness. Similar results have been reported by Gond et al., (2023), and
164 Osman et al., (2018).

165 By increasing the temperature from 140 to 220°C, the cake hardness negatively correlated with
166 the cake's springiness, where higher hardness led to lower springiness. As the temperature
167 increases, the cake absorbs more heat during baking. Consequently, it increases water evaporation
168 inside the cake batter and the pressure gradient between the dough surface and core, resulting in
169 crumb softening (Shahapuzi et al., 2015). This outcome is probably the reason for the decrease in
170 springiness. Moreover, As the processing time increases at a constant temperature, porosity
171 exhibits an upward trend. Consequently, as porosity increases and the sample swells, the formation
172 of additional air pore during baking enhances the return to the initial state. Therefore, the observed
173 increase in springiness appears reasonable, despite the rise in hardness. In this respect, similar

174 results have been reported in a study on pizza (Clarke & Farrell, 2000) and Chhana Podo (Kumari
175 et al., 2015).

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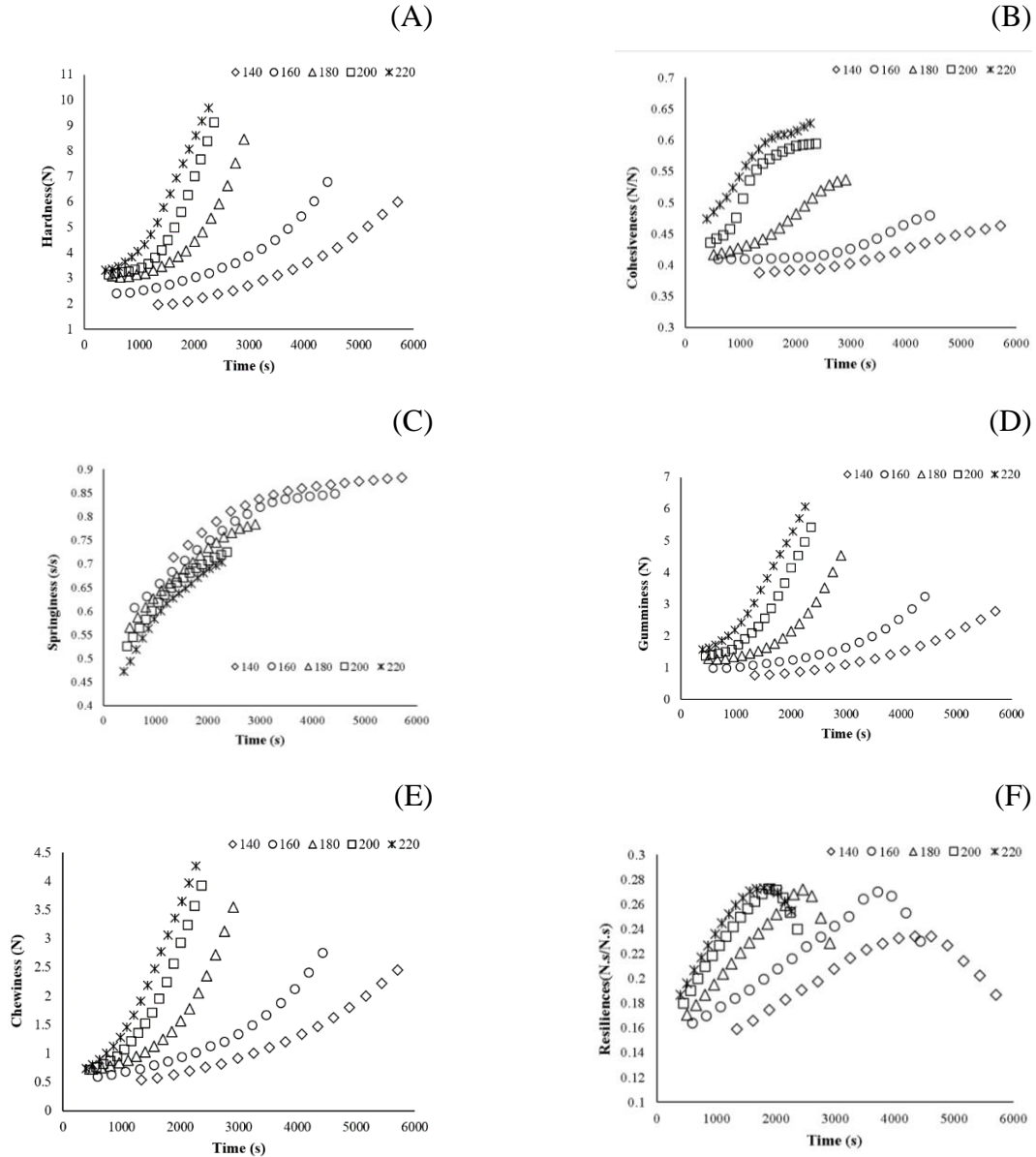


Figure 2. The effect of temperature and time on hardness (A), cohesiveness (B), springiness (C), chewiness (D), gumminess (E), resilience (F).

177 **Chewiness and Gumminess:** Cake baked in the conventional oven showed an overall increase
178 in chewiness and gumminess by prolonging the baking time (Figs. 2D and 2E). One possible
179 explanation for this result could be the rise in cake hardness over time and with temperature (Fig.

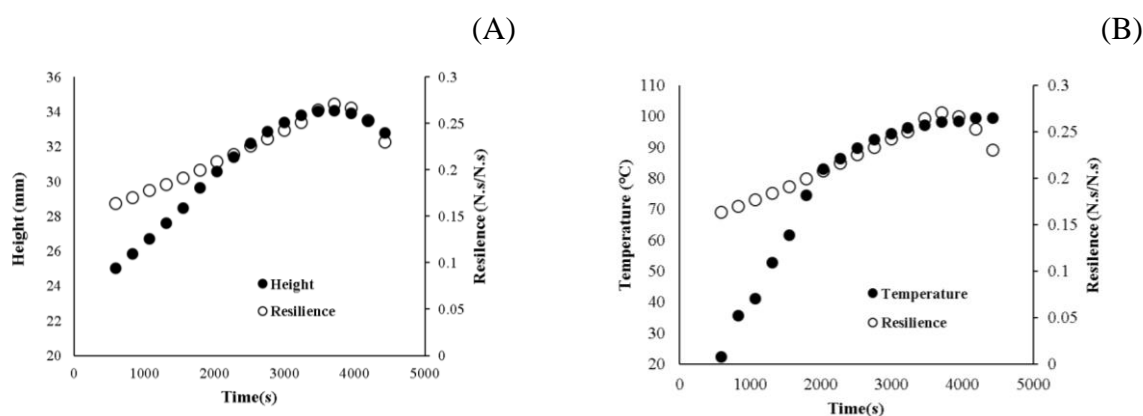
180 2A). Therefore, the energy required to break down and chew the samples would increase. The
 181 decrease in moisture content might be another reason for the increase in gumminess during baking.
 182 Similar conclusions have been proposed for cake Al-Muhtaseb et al., (2013b) and for Chhana Podo
 183 Kumari et al., (2015).

184 **Resilience:** Fig. 2F shows the changes in resilience during cake baking in a conventional oven.
 185 As can be seen, resilience increased and then decreased, reaching a peak at about the last quarter
 186 of the process time.

187 The cohesiveness and hardness of the cake increased during baking (Figs. 2A and 2B). These
 188 modifications, along with the differences in height as shown in Fig. 3A, led to favorable results
 189 that improved the formation and stability of the structure. Hence, they ultimately increased the
 190 cake's resilience and height, allowing it to return to its original state. After a while, when the center
 191 temperature of the cake reaches starch gelatinization and protein coagulation (85-90°C), expansion
 192 stops, but evaporation continues. The end of the cake's expansion can be demonstrated by the open
 193 structure of the cake, which occurs due to the formation of bubbles and the significant release of
 194 gases. Finally, the cake shrinks at the end of its expansion due to water evaporation (Lostie et al.,
 195 2002). The texture would be so hard that it could not recover to its original shape after removing
 196 the compression. As a result, resilience would decrease (Fig. 3B).

197 Results showed that the resilience increased as the temperature rose from 140 to 220°C. Also, the
 198 increase in the slope of the hardness curve in the final steps had a positive correlation with its
 199 resilience.

200



201 **Figure 3.** Relationship between height (A) and center temperature (B) with resilience of the cake
 202 at 180°C.

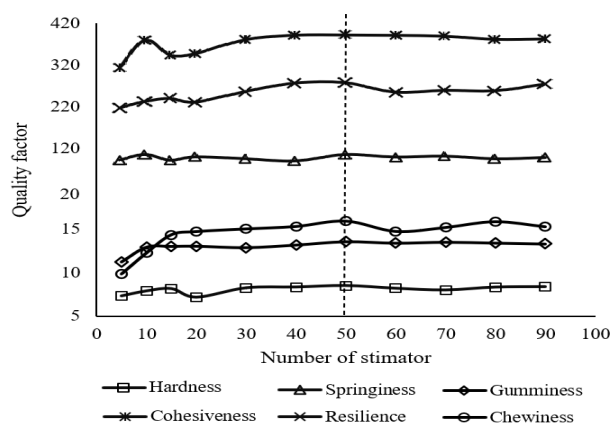
203 **b. Model Analysis**

204 The cake texture properties during conventional baking were predicted by performing AdaBoost
 205 modeling in Python (version 3.6). The selected estimator must have the highest R^2 and the lowest
 206 RMSE for the mean values of each temperature in both the training and validation phases (Table
 207 1), resulting in a higher quality coefficient value. Here, the best-estimated number was 50, with the
 208 highest quality coefficient among all textural properties (Fig. 4).

209 Therefore, a model of textural properties containing two inputs (i.e., time and temperature), 50
 210 estimators, 5 folds, and 6 outputs was selected (Fig. 5).

211 The efficiency of the composite models was verified using AdaBoost. As it turned out, the
 212 maximum differences between hardness, cohesiveness, springiness, resilience, chewiness, and
 213 gumminess were 0.38, 0.01, 0.05, 0.02, 0.26, 0.21, and 0.41, respectively, suggesting the
 214 effectiveness of the proposed model. Fig. 6 compares the experimental and predicted values to
 215 demonstrate the efficacy of models in predicting texture properties. These graphs indicate the
 216 proximity of the values obtained by the models to the TPA data.

217



218

219 **Figure 4.** The effect of estimator number on AdaBoost algorithm performance in the training
 220 and testing phase.

221

222

Table1. R^2 and RMSE values in the training and validation phase.

	Training		Validation	
	R^2	RMSE	R^2	RMSE
Hardness	0.99	0.068	0.99	0.074
Cohesiveness	0.99	0.002	0.98	0.003
Springiness	0.99	0.005	0.98	0.013
Resilience	0.99	0.002	0.97	0.005
Chewiness	0.99	0.035	0.99	0.089
Gumminess	0.99	0.043	0.99	0.103

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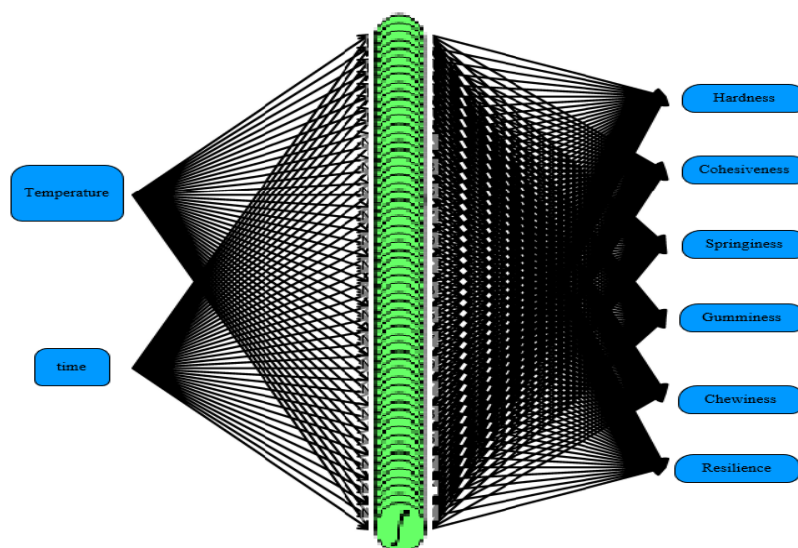
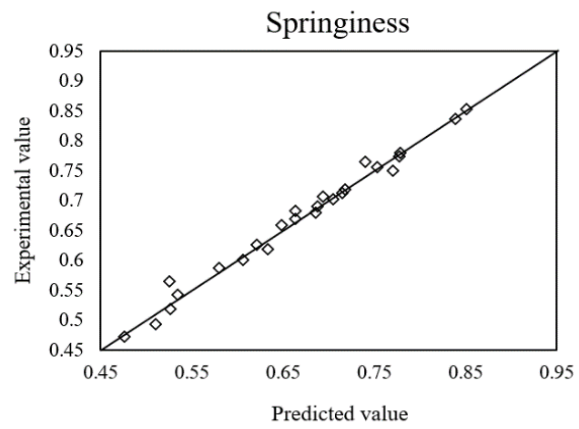
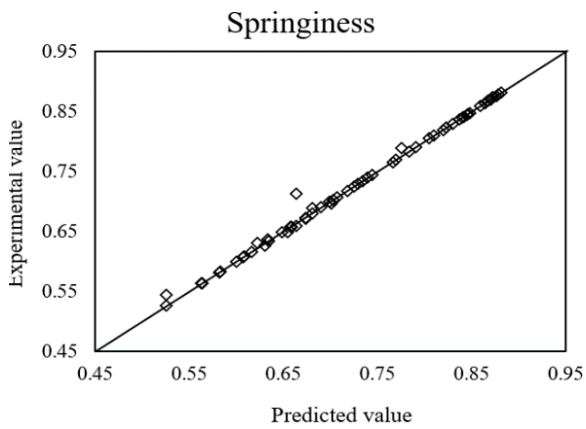
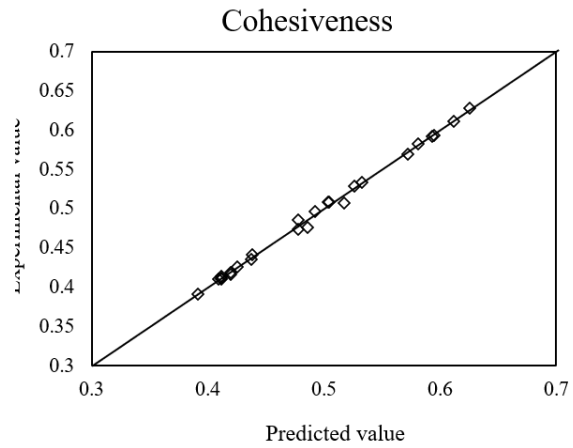
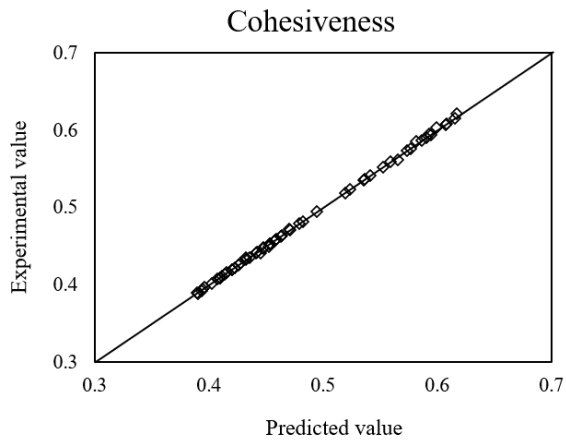
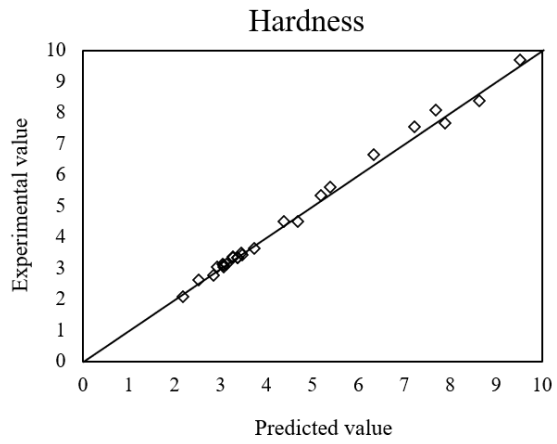
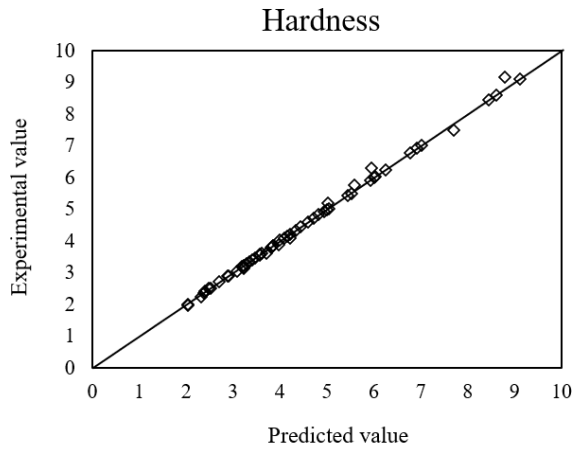
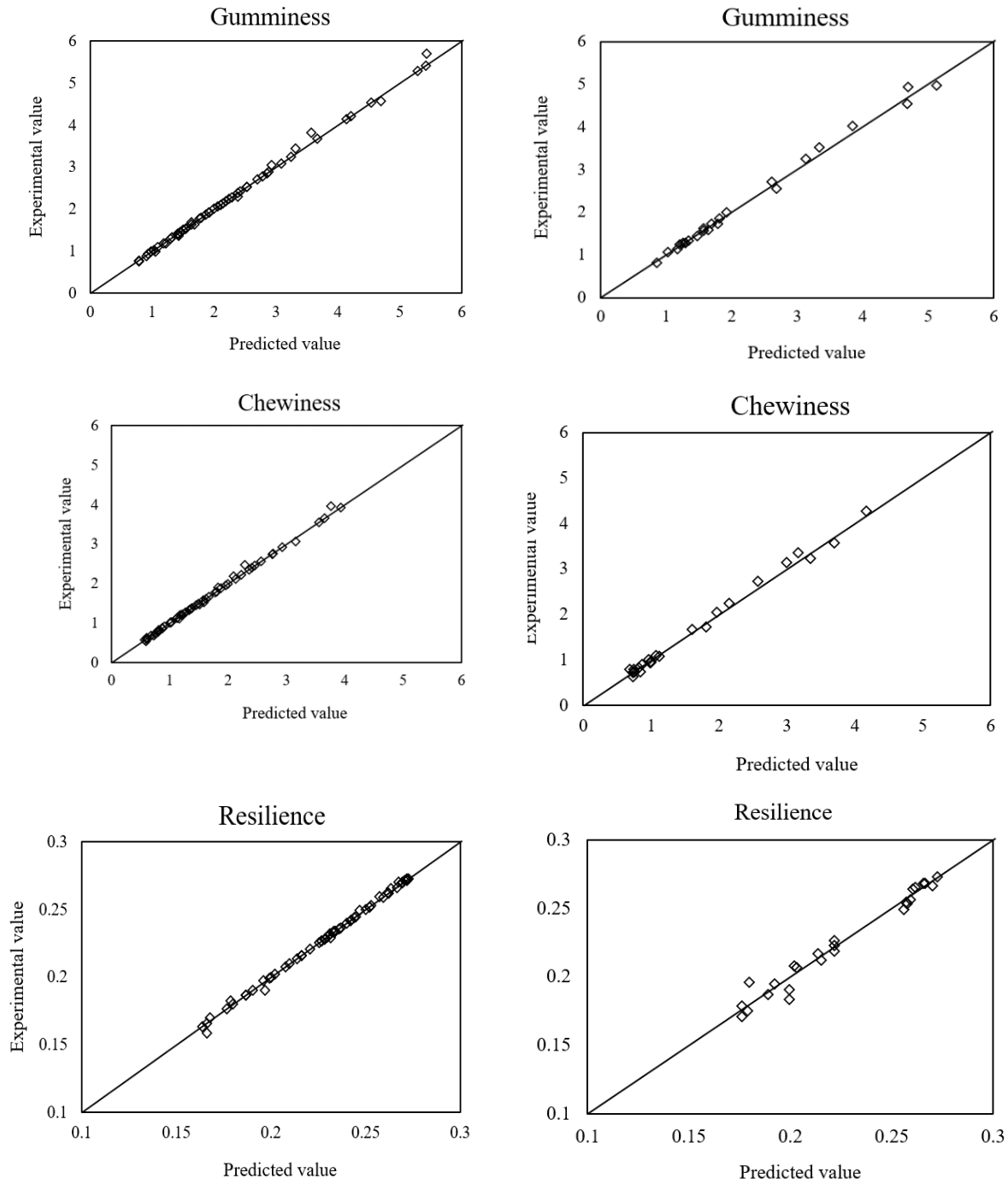


Figure 5. AdaBoost topology for Texture prediction.

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228
229
230 Table 2 demonstrates the effect of different cooking temperatures on the prediction of the
231 AdaBoost algorithm. In fact, we only included the average values of textural properties during
232 cooking at each temperature in this table to demonstrate that as the process temperature increased
233 from 140°C to 220°C, the total time and, consequently, the time intervals (at which samples were
234 taken) decreased, leading to potentially higher measurement errors. As a result, the differences
235 between predicted and experimental values would increase resulting in lower R^2 and higher RMSE.
236 This indicates a gradual decrease in the accuracy of predictions. Another reason for lower model
237 accuracy may be the increased chemical reactions at higher temperatures, which could affect the
238 textural properties. By all means, the least amount of R^2 was 0.989, and the maximum amount of
239 RMSE was 0.034, respectively, proving the ability of AdaBoost in predicting the textural properties
240 of food. Also, there are several studies on predicting food properties using the AdaBoost algorithm.
241 The following research examples demonstrate that AdaBoost is a powerful algorithm in this
242 context.





243 **Figure 6.** Predicted and experimental values of TPA characteristics at the phases of training (left
244 column) and test (right column).
245

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247

248

249 **Table 2.** The effect of process temperature on models accuracy for different textural Properties.

Temperature	Hardness		Cohesiveness		Springiness		Resilience		Gumminess		Chewiness	
	R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE
140°C	0.999	0.002	0.999	9.3E-7	0.997	1.9E-5	0.996	5.3E-6	0.999	7.1E-4	0.998	0.001
160°C	0.999	0.003	0.999	1.2E-6	0.996	6.1E-5	0.995	2.2E-6	0.999	6.1E-4	0.998	0.002
180°C	0.998	0.016	0.999	3.8E-6	0.995	1.1E-4	0.993	1.4E-5	0.998	0.005	0.998	0.004
200°C	0.998	0.013	0.998	3.8E-5	0.995	3.9E-4	0.992	7.4E-5	0.998	0.005	0.997	0.003
220°C	0.997	0.034	0.998	1.0E-5	0.989	3.3E-4	0.991	1.8E-5	0.997	0.015	0.997	0.009

250
251 Khan et al. (2022) obtained food glycemic index by data extracted from pictures using five
252 machine learning (ML) algorithms, i.e., AdaBoost, random forest, decision tree, k-nearest-neighbor
253 classifier, and Naive Bayes classifier. They divided food into three categories: high, low, and
254 moderate sugar. The results demonstrated the better accuracy of the AdaBoost model in the
255 classification of the food glycemic index.

256 Bambil et al. (2020) collected 40 leaves of 30 varieties of trees and shrubs from 19 families
257 concerning the plant species detection from its morphology. The studied features from collected
258 pictures were color, shape, and texture. Also, the models employed for detecting the plant
259 morphology were three ML algorithms, namely AdaBoost, random forest, and support vector
260 machine (SVM), and a deep learning ANN model. The least correlation factor was 0.93,
261 representing the model's efficiency.

262 In another study, Kuang et al. (2022) used the AdaBoost algorithm to improve camellia oil fraud
263 detection. They employed this algorithm to optimize the backpropagation neural network model to
264 distinguish the fake and pure camellia oil by applying NI-Raman spectroscopy data. The results
265 showed a great accuracy with $R^2=0.999$ and $RMSE= 0.01$.

266 Lin & Zou (2018) used the AdaBoost algorithm to diagnose ripe fruit and their spatial positioning
267 for mechanized harvesting. The number of pictures used in this research was 120, of which 20 were
268 for the training part and the rest for the test step. Also, the lowest model accuracy was 0.867.

269 CONCLUSIONS

271 The effect of conventional baking on textural properties were investigated, followed by using
272 AdaBoost to predict textural properties during the conventional baking of cakes. The results
273 indicate that the hardness, cohesiveness, chewiness, gumminess, and resilience increased, while
274 springiness decreased when higher operating temperatures were applied. Model results confirmed

275 that both baking temperature and time significantly influence the texture properties. Also, $R^2 >$
276 0.989 and $RMSE < 0.0019$ for predicted texture characteristics reveal that the AdaBoost model
277 was an effective tool for predicting the textural properties of baking products during the process.

278

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405 پیش بینی بافت کیک طی پخت سنتی برپایه الگوریتم آدابوست

406 صدیقه سلیمانی فرد، نفیسه جهان بخشیان، و سمیه نیک نیا

407 چکیده

408 پژوهش حاضر به بررسی تأثیر دمای پخت (140، 160، 180، 200 و 220 درجه سانتی‌گراد) بر سینتیک
409 بافت می‌پردازد. همچنین یک متالگوریتم طبقه بندی آماری به‌نام آدابوست را برای پیش بینی تغییرات بافت در
410 طول پخت سنتی کیک بررسی می‌کند. نتایج تجربی نشان داد که خواص بافت به‌طور معنی‌داری تحت تأثیر دما
411 و زمان پخت قرار می‌گیرد. با افزایش زمان و دما، سفتی بافت، چسبندگی، صمغی بودن و قابلیت جویدن افزایش
412 و فنری بودن کاهش یافت. با این حال، تأثیر زمان و دما بر انعطاف‌پذیری متناقض بود و در یک چهارم انتهایی
413 فرآیند حداکثر بود. نتایج پیش‌بینی‌شده نشان داد که الگوریتم آدابوست ویژگی‌های بافت را با ضریب تعیین بالا
414 ($R^2 > 0.989$) و حداقل ریشه میانگین مربعات خطا ($RMSE < 0.0019$) در تمام ویژگی‌های بافتی به دقت
415 پیش‌بینی می‌کند. بنابراین، می‌تواند به عنوان یک ابزار کارآمد برای پیش بینی خواص بافت کیک در حین پخت
416 عمل کند. علاوه بر این، روش پیشنهادی را می‌توان برای پیش بینی خواص بافت سایر محصولات پخته شده
417 گسترش داد.