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# The prediction of cake texture during conventional baking based on AdaBoost algorithm

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**ABSTRACT**

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

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

## INTRODUCTION

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

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

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

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

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

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

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

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

## MATERIALS AND METHODS

### a. Experimental Data

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

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

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

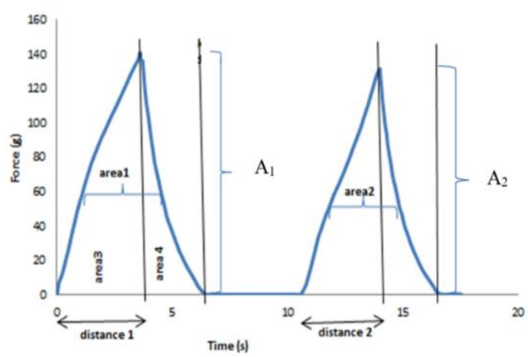



**Figure 1.** The textural parameters of the TPA curve.

As shown in Fig. 1, the force peak height on the first compression cycle is defined as hardness (N). The ratio of the positive force areas under the first and second compressions ($A_2/A_1$) was used to measure cohesiveness (N/N). This ratio indicates the extent to which a sample can be deformed before it ruptures. Springiness (s/s) is defined as the time index it takes for the sample to return to its original shape or size after being partially compressed. The parameter was calculated as distance$_2$/distance$_1$. Moreover, resilience (N.s/N.s), i.e., the degree to which the sample returns to its original shape and elasticity, was calculated as $A_4/A_3$. Two additional parameters were derived from the measured parameters. Here, gumminess (N) was defined by multiplying hardness by cohesiveness, while chewiness (N) was calculated by multiplying gumminess by springiness (Bourne, 2002; Zareifard et al., 2009). All experiments were performed in five replications.

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

**b- AdaBoost Modeling**

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

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

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

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

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

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

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

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

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

where $\boldsymbol{\mu_t}$ is the score of a class $\boldsymbol{\omega_t}$. Moreover, T, . N, and $\boldsymbol{\epsilon_t}$ are the total number of iterations, the total number of samples in the training set, and the minimum error, respectively.

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

### c Validation Criteria

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 mean square error as $RMSE = \sqrt{\frac{\sum_{i=1}^N (x_{i\_exp} - x_{i\_pre})^2}{N}}$, and quality coefficient as $QC = \frac{R^2_{train} + R^2_{test}}{RMSE^2_{train} + RMSE^2_{test}}$ (Batista et al., 2021b; Niu et al., 2020).

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

## RESULTS

### a. Experimental Analysis

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

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

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

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

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

By increasing the temperature from 140 to 220℃, the cake hardness negatively correlated with the cake's springiness, where higher hardness led to lower springiness. As the temperature increases, the cake absorbs more heat during baking. Consequently, it increases water evaporation inside the cake batter and the pressure gradient between the dough surface and core, resulting in crumb softening (Shahapuzi et al., 2015). This outcome is probably the reason for the decrease in springiness. Moreover, As the processing time increases at a constant temperature, porosity exhibits an upward trend. Consequently, as porosity increases and the sample swells, the formation of additional air pore during baking enhances the return to the initial state. Therefore, the observed increase in springiness appears reasonable, despite the rise in hardness. In this respect, similar results have been reported in a study on pizza (Clarke & Farrell, 2000) and Chhana Podo (Kumari et al., 2015).

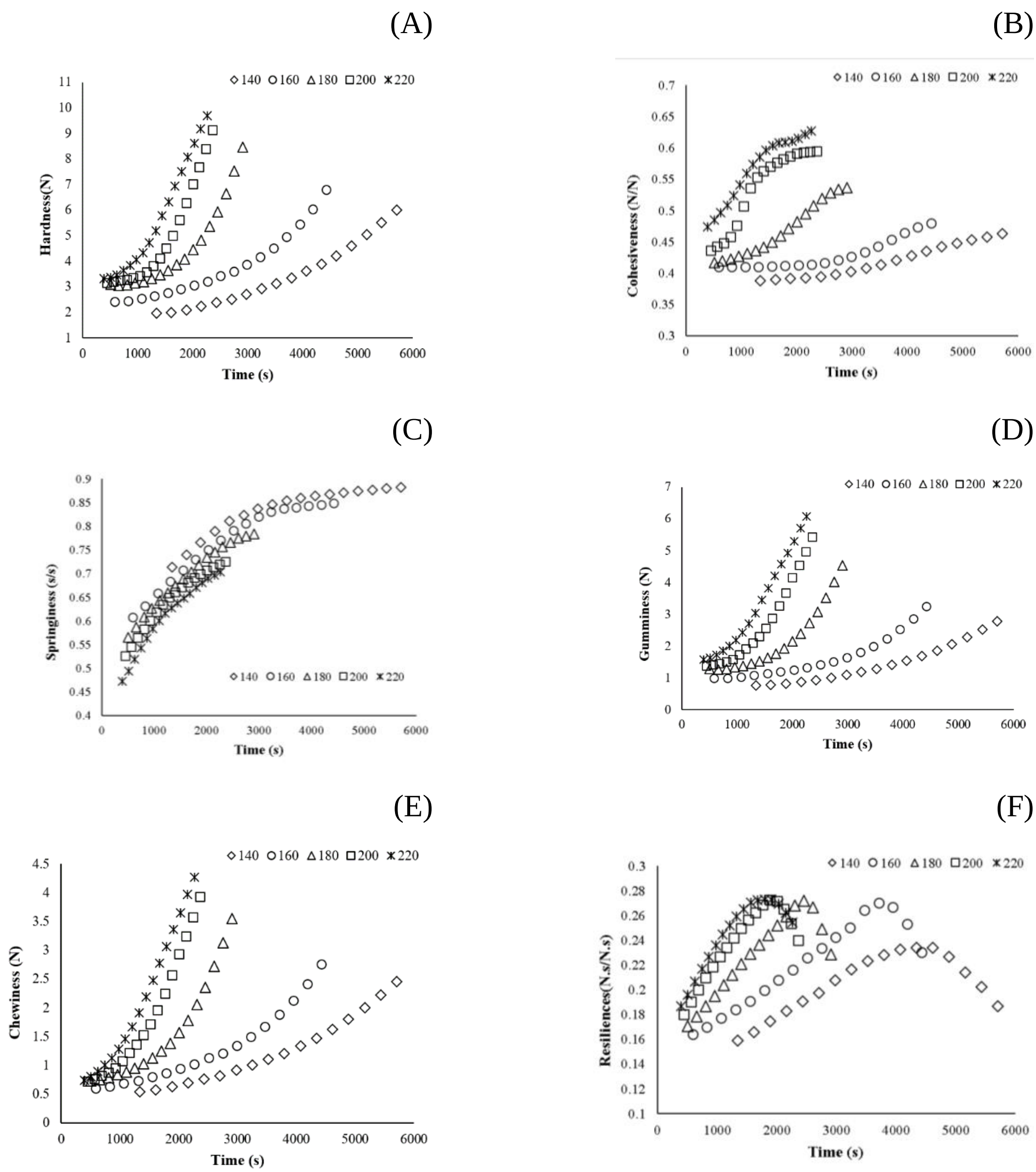



**Figure 2.** The effect of temperature and time on hardness (A), cohesiveness (B), springiness (C), chewiness (D), gumminess (E), resilience (F).

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

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

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

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

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

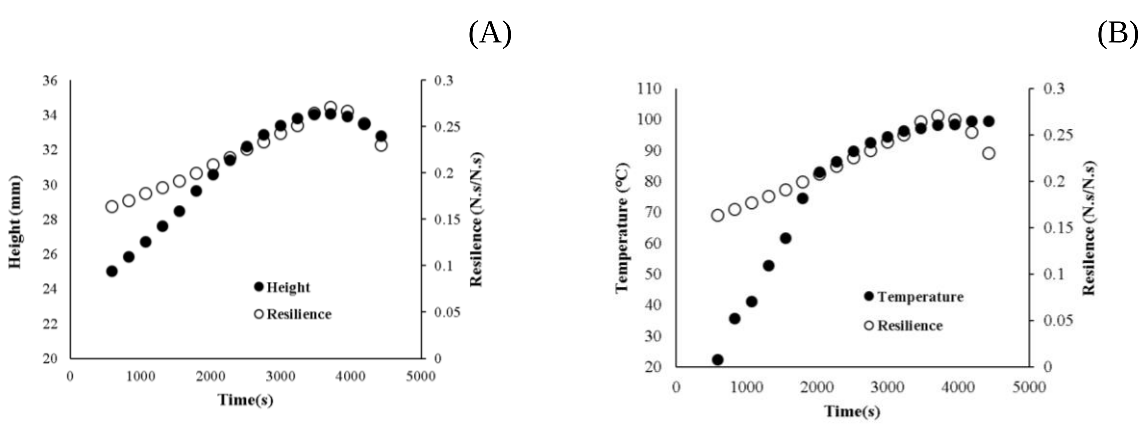



**Figure 3**. Relationship between height (A) and center temperature (B) with resilience of the cake at 180°C.

**b. Model Analysis**

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

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

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

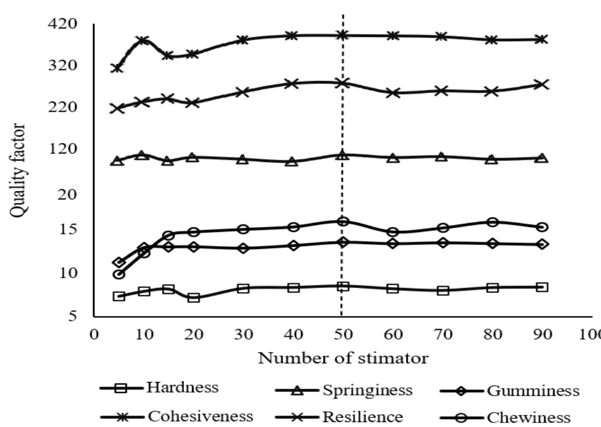



**Figure 4**. The effect of estimator number on AdaBoost algorithm performance in the training and testing phase.

**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 | 0.167 |
| 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 |

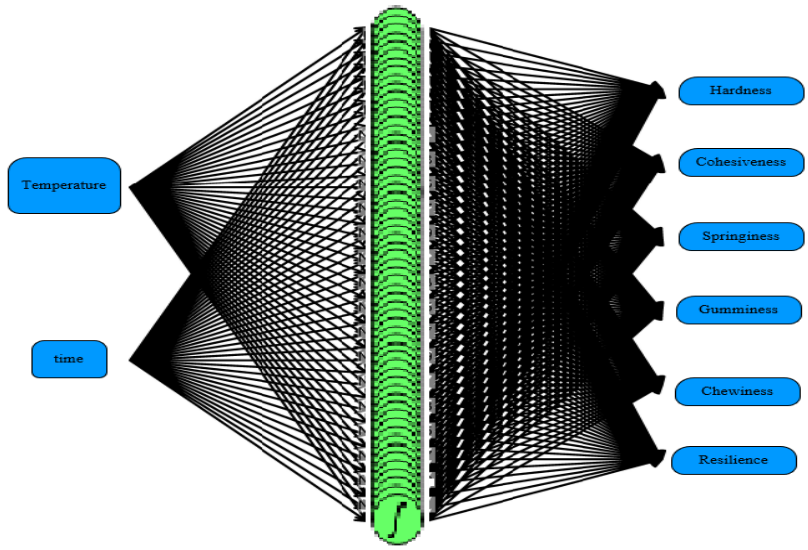
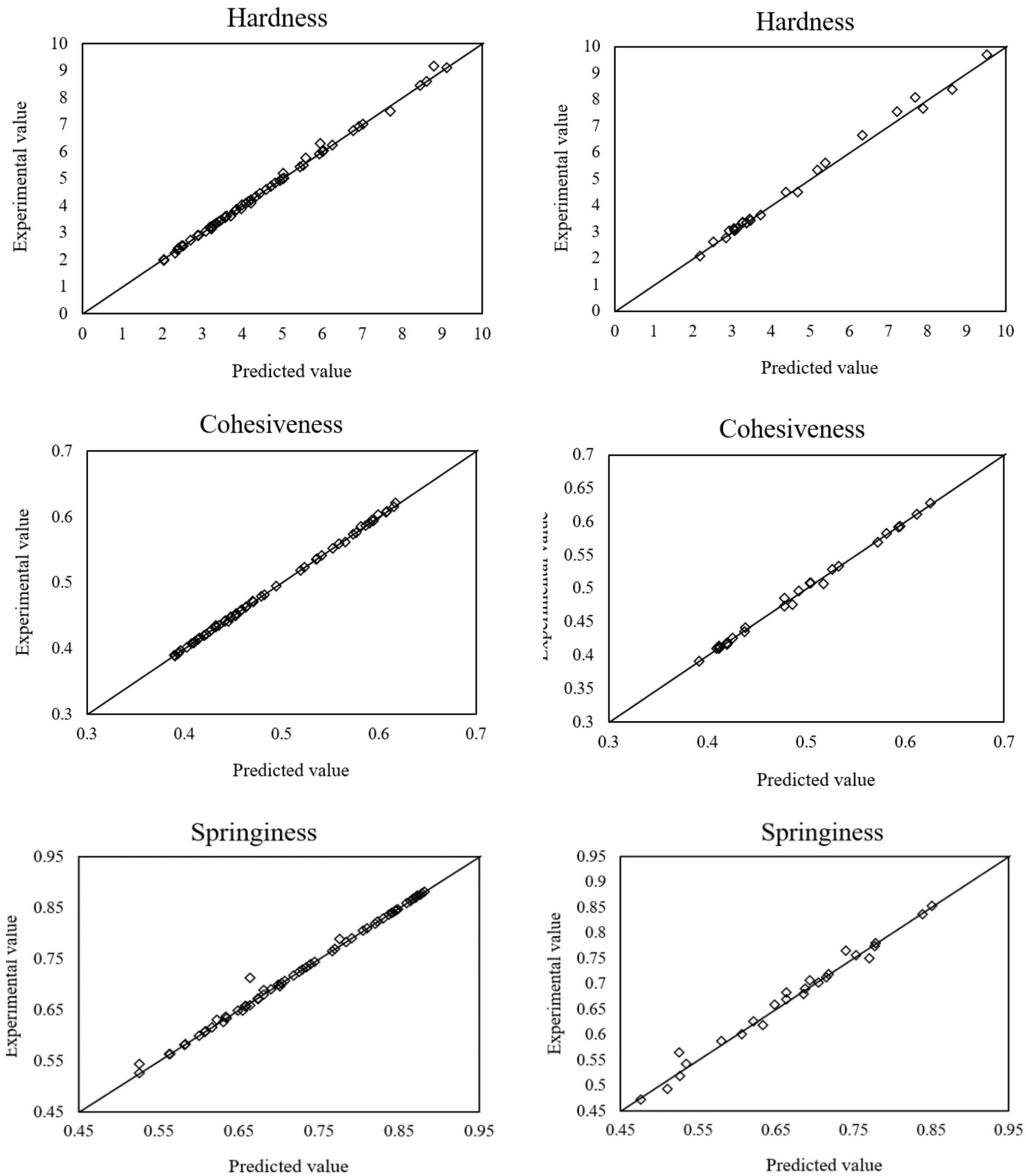



**Figure 5**. AdaBoost topology for Texture prediction.

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


Hardness
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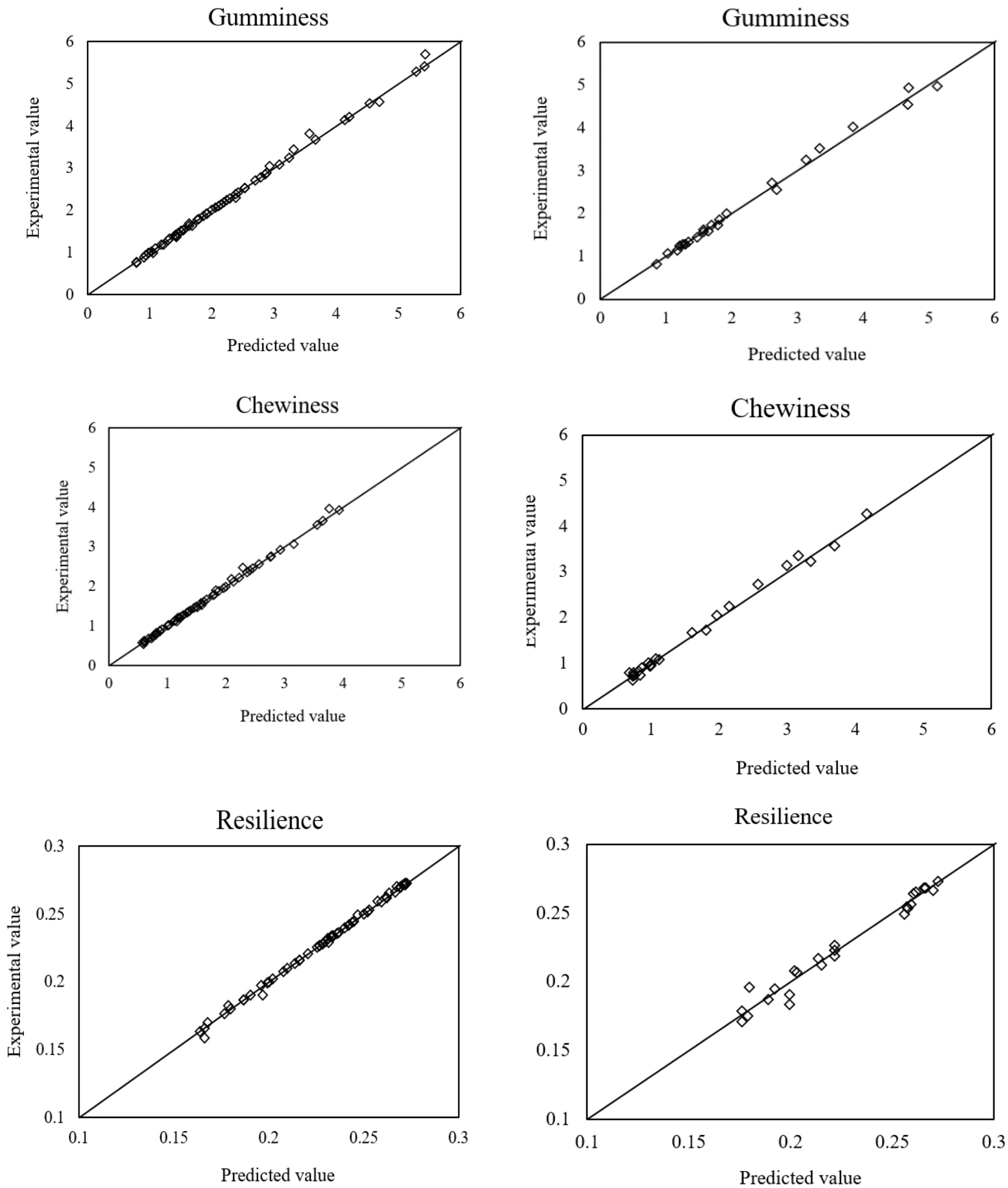


**Figure 6.** Predicted and experimental values of TPA characteristics at the phases of training (left column) and test (right column).

**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 |

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

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

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

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

## CONCLUSIONS

The effect of conventional baking on textural properties were investigated, followed by using AdaBoost to predict textural properties during the conventional baking of cakes. The results indicate that the hardness, cohesiveness, chewiness, gumminess, and resilience increased, while springiness decreased when higher operating temperatures were applied. Model results confirmed that both baking temperature and time significantly influence the texture properties. Also, $R^2 >$ 0.989 and RMSE < 0.0019 for predicted texture characteristics reveal that the AdaBoost model was an effective tool for predicting the textural properties of baking products during the process.

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# پیش بینی بافت کیک طی پخت سنتی برپایه الگوریتم آدابوست

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

**چکیده**

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