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Non-Destructive Prediction of Bread Staling Using Artificial Intelligence Methods

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Abstract
In foods with limited shelf life and in new product development studies, it is important for producers and consumers to estimate the degree of staling with easy methods. Staling of bread, which has an essential role in human nutrition, is an important physicochemical phenomenon that affects consumer preference. Costly technologies, such as rheological, thermal, and spectroscopic approaches, are used to determine the degree of staling. This research suggests that an artificial intelligence-based method is more practical and less expensive than these methods. Using machine learning and deep learning algorithms, it was attempted to predict how many days old breads are, which provides information on the freshness status and degree of staling, from photos of whole bread and pieces of bread. Among the machine learning algorithms, the highest accuracy rate for slices of bread was calculated as 62.84% with Random Forest, while the prediction accuracy was lower for all bread images. The training accuracy rate for both slices and whole bread was determined to be 99% when using the convolutional neural network (CNN) architecture. While the test results for whole breads were around 56.6%, those for sliced breads were 92.3%. The results of deep learning algorithms were superior to those of machine learning algorithms. The results indicate that crumb images reflect staling more accurately than whole bread images.

1.Introduction

Bread staling is characterized by an increase in crumb firmness and a loss of loaf freshness, in which the bread flavor has degraded, and the aroma has disappeared [1]. It contains the interplay of two major events: the migration of water from the crumb to the crust and the retrogradation of starch molecules, both of which cause economic losses in the baking industry and also negatively affect consumers' preferences [2]. Starch retrogradation, the gradual transition of starch components from amorphous to crystalline form, plays an important role in the bread staling process by causing gluten dehydration and the redistribution of water molecules throughout the bread [3, 4]. A growing number of studies have concentrated on reducing the retrogradation of starch in bread and improving its shelf life by adjusting the manufacturing formulation, packaging technique, and storage conditions. Accordingly, timely monitoring of bread staleness is necessary to improve control of the staleness process, limit the bread's quality deterioration, and advance the industrialization process. Traditional methods for determining bread staling, such as texture profile analysis, water content/activity, and differential scanning calorimetry, may be reliable,but their sample preparation and analysis procedures are time-consuming, destructive and laborious requiring highly skilled operators [5]. For the food industry, it is important to establish techniques and methods for quickly and accurately identifying and analyzing food quality and safety. To predict bread quality characteristics, there is a significant need for efficient and automated techniques. Several spectroscopic approaches, such as near-infrared (NIR)

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spectroscopy, Raman spectroscopy, and fluorescence spectroscopy, have been investigated and developed for the qualitative and quantitative study of food matrices as a result of recent technological advancements in photonics and optics [6].

NIR, MIR, and Raman spectroscopy were also employed to determine the staling region of wheat bread as well as its retrogradation behavior [7]. To observe and clarify the process of bread staling in the presence of maltogenic amylases over time, machine learning techniques using near infrared hyperspectral imaging were employed by Amigo, et al. [8].

Digital imaging systems have been used to evaluate the quality features of various foods, such as the size and shape, surface color, appearance, and surface defects, using computer vision and machine learning-based methodologies that are non-invasive, non-destructive, and objective with reduced human errors [9]. Deep learning uses artificial neural networks to create the visual neural network of the human brain to analyze and process enormous amount of data and automatically extract hierarchical data representations. The convolutional neural network (CNN), the most widely used deep learning architecture, has recently emerged as an effective and viable method for extracting features for detecting and analyzing complex food matrices, such as meat and aquatic products, cereals and cereal products and fruits and fruit products [10]. The browning degree of bread crust during seven different baking periods was identified by the CNN model with computer vision systems with the accuracy of 98.8% [11]. Image-processing techniques facilitate the extraction of quantitative features based on the shape, size, color, and texture of food products. These features can be utilized for training classifiers, as well as to provide objective data for decision-making or characterization of food products, such as the distribution of cell sizes in a slice of bread. Researchers have employed various statistical, machine, and deep learning methods to assess the diverse quality characteristics of baked products [9]. Artificial neural networks (ANN) and convolutional neural networks (CNN), in addition to efficient fuzzy-based classifiers, such as Random Forest (RF), Decision Tree (DT), and Support Vector Machine (SVM) methods, are examples of general techniques that simulate human decision-making processes and produce uniform outcomes [12]. The convolutional neural network (CNN) is an effective tool for extracting features with more accurate and stable and is considered to be the most popular architecture in deep learning. It has been increasingly used for detecting and analyzing complex food matrices [10]. CNN have recently demonstrated satisfactory results in evaluating the freshness of fish and meat products [13]. The purpose of this research was to establish a CNN architecture for the estimation of the bread's freshness over a period of four days under ordinary consumption conditions.

2. Material and Methods

2.1. Material

For image analysis, whole bread and slices of bread were employed. Five different breads were purchased from a local bakery. A loaf of bread was sliced from the same oven. The thickness of the slices was about 2 cm. Five randomly selected slices were used for image analysis. The samples were stored at room temperature in sealed bags. Top, side, and bottom images of fresh and stale breads were taken on each day of storage (1st, 2nd, 3rd, and 4th days). Only the top and bottom images of the slices were taken.

2.2. Methods

2.2.1. Recommended architectural structure and workflow

In the proposed architectural structure (Figure 1), the images were first pre-processed. At this stage, the same procedures were carried out for whole bread and sliced bread. First, after the image pre-processing stage, machine learning and deep learning algorithms were applied separately. As a result of both methods, the number of days the breads were stored was estimated with a multiple classifier.

2.2.2. Image pre-processing

Photographs of whole and sliced bread were taken with an iPhone 7 mobile phone from a height of 45 cm. A total of 468 images were preprocessed for five classes. Firstly, unnecessary areas were removed, and resizing operations were performed on the images. As a result of this process, all images were reduced to 224*224 size. Later, Contrast, Sharpness, Brightness, and Color improvements were made using Python PILLOW library commands. Image preprocessing results for whole and sliced breads are shown in Figure 2. Images of the same five slices of bread were captured and analyzed each day.

2.2.3. GLCM future extraction

The feature extraction method consists of data acquisition steps to find a subset of useful image-based variables. In this study, seven textural features based on gray level co-occurrence matrix (GLCM) were obtained from each image. GLCM has been calculated for four directions: 0º, 45º, 90º, and 135º [14, 15].

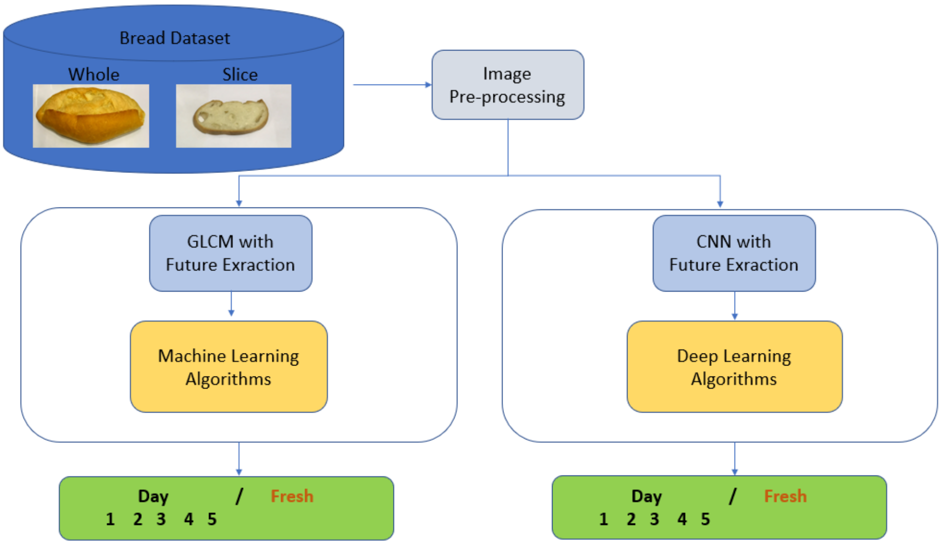

Figure 1. Recommended workflow model

With this method, the properties calculated for each of the four angles are as follows;

Energy

Energy is another name for "uniformity" or "angular second moments". It is the sum of the values of the square elements in the GLCM matrix. It is the transition from homogeneous regions to non-homogeneous regions.

Entropy

Calculates the randomness of the image. As a result, a homogeneous image will result in lower entropy values.

Contrast

It measures the intensity that connects the contrast between a pixel and its neighbor across the entire image.

Correlation

It is a measure of grayscale linear dependencies in an image. Specifies how a pixel is associated with its neighbor.

Homogeneity

Explains the similarity of pixels. The GLCM matrix of the homogeneous image gives the value 1. Image texture is very low if it requires minimal changes [16].

2.2.4. Machine learning algorithms

Decision Tree

Decision Trees (DT) are trees that classify samples by ordering them according to their feature values. Classification is carried out on the samples in the data set, and each sample is classified according to its properties starting from the root node [16, 17]. Decision tree learning, used in data mining and machine learning, uses a decision tree as a predictive model that matches observations about an item with the item's results [18].

Support Vector Machine (SVM)

SVM is a type of supervised learning algorithm used for classification and regression [18-20]. The goal of SVM is to get the highest margin individual hyperplane that can divide classes linearly. SVM is most commonly used when identifying datasets where the number of training data is limited and the optimal solution cannot be obtained with the normal use of many statistics [21-24].

K-nearest neighbors (KNN)

In KNN, the main idea is to determine the category of a given query not only by the document closest to it in the document area but also by the categories of the k documents closest to it. With this in mind, the Vector method can be viewed as an example of the KNN method where k = 1. It can be predicted that as the K value increases, it will increase in the samples [25].

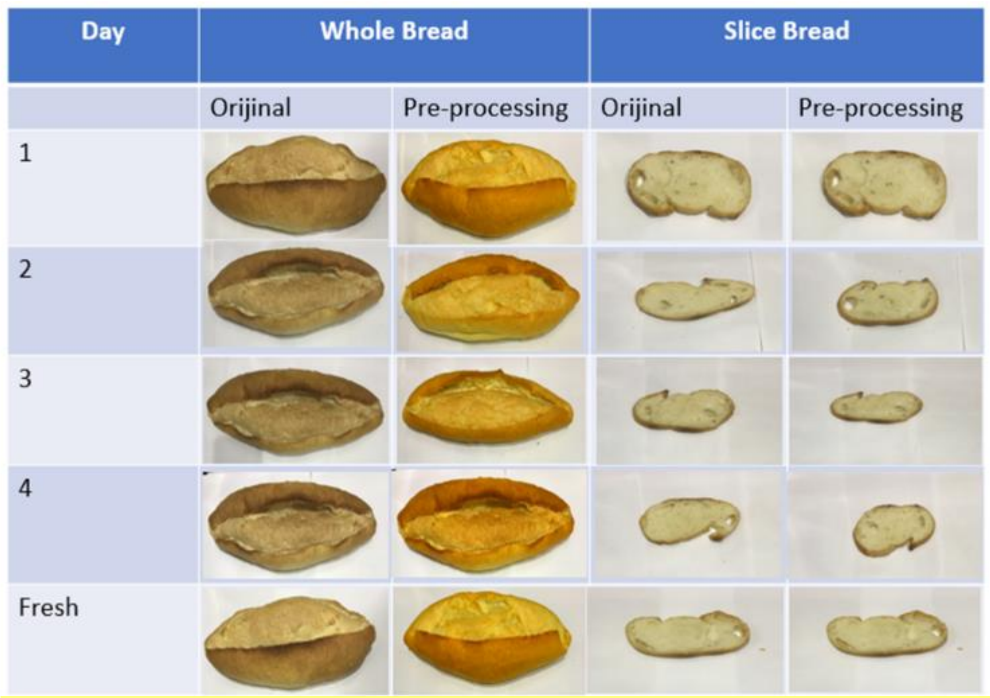

Figure 2. Pre-processed whole and sliced breads

Random Forest

Random Forest (RF) is a regression method that combines the performance of multiple Decision Trees algorithms to classify or predict the value of a variable [26, 27]. In other words, it is the process of constructing an input vector (x) obtained from the values of different features analyzed for a training domain, with a set of K regression trees, and averaging the results [28].

2.2.5. Deep learning algorithms

In classification problems, Convolutional Neural Network (CNN) networks are most commonly used among deep learning algorithms [29]. CNNs can achieve the highest results based on performance results. In the early stages of CNNs, they extract local features from images or numerical data. In subsequent layers, features are combined to detect objects or feature symbols. These processes repeat until the input image is created. CNN architecture is a structure that continues with the Convolution layer, the pooling layers, the activation functions used, and the fully connected layer. Finally, according to the classification problem, the output is tried to be estimated with the binary or multiple softmax function. The model proposed for this study is shown in Figure 3. After the input image was set to 224*224*3, convolutional layers were created with filters with a size of 32, 64, 128, 256, 512 respectively. Following each convolutional layer, the max pooling layer and dropout layers were added. The maximum pooling layer and 3*3 filters ensured that the features with the greatest value were taken into account. The dropout layer was preferred at a rate of 0.2 and the last two layers at a rate of 0.1 to simplify the intermediate layers. ReLU was chosen as the activation function. With the Flatten layer, the matrix values were converted to one dimension. Then the architectural structure is followed by 256, 512, and 5-element dense layers. Finally, with the softmax function, the output is set to 5 classes.

2.2.6. Performance evaluation criteria

Accuracy indicates the proportion of correct predictions;

$$Accuracy = (TN + TP)/(TP + FP + TN + FN) \quad (1)$$

(True Positive (TP); Cases where both the predicted and actual values are positive; True Negative (TN);

cases where the predicted and actual values are negative; False Positive (FP); cases where the predicted value is positive but the true value is negative; False Negative (FN); cases where the predicted value is negative but the true value is positive.)
Precision shows how many of the positively predicted values are actually relevant;

$$Precision = TP / (TP + FP) \quad (2)$$

Sensitivity is a true positive rate that expresses the probability of a positive test if it actually happens;

$$Sensitivity = TP/(TP + FN) \quad (3)$$

The F1-Score takes into account both precision and precision as the harmonic mean [30];

$$F1 - Score = 2 * (Recall * Precision) / (Recall + Precision) \quad (4)$$

For machine learning and deep learning, images are divided into 80% training and 20% testing. The training and testing phases were fixed at 100 steps and were run with Tensorflow-GPU version 2.2 with a GTX 1050 Ti graphics card.

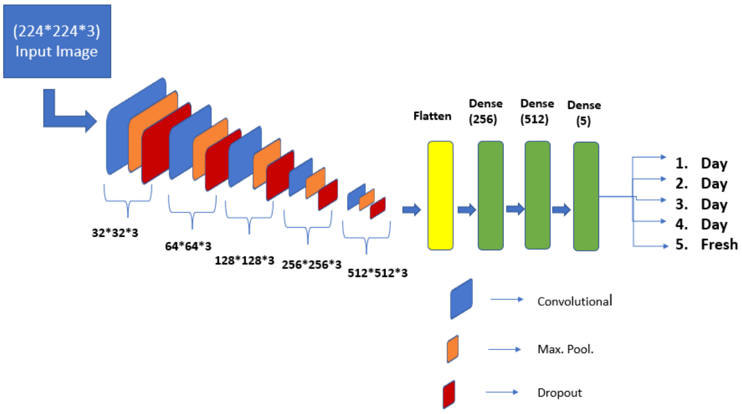

Figure 3. The designed CNN model architectural structure

3. Results and Discussion

Freshness is a key factor in determining the quality of a loaf of bread when it is consumed, and it is necessary to determine its freshness on a daily basis since consumers may mistake changes in freshness for a lack of quality. Thus, it is essential to monitor the bread's freshness during storage. Machine learning and deep learning results are shown in Table 1. The highest accuracy rate among machine learning algorithms was calculated with Random Forest for slice breads with a rate of 62.84%. In the images obtained from different combinations of whole breads, four machine learning algorithms could not perform very well with an accuracy of almost 50%. With an accuracy ranging from 86.75% to 87.25%, the SVM approach is used to categorize biscuits into eight unique groups [31]. The SVM algorithm has been used to accurately categorize biscuits moving on a conveyor belt at a high speed of 9 meters per minute [32]. Archandani, et al. [33] utilized a multilevel SVM classifier to classify bread samples into five fault categories. These categories comprise fractures, cuts, folds, non-uniformity, blackened or burnt areas during baking, deformity, color, and size. Despite the algorithm having a simple construction, the authors claimed that it achieved a 97% classification success rate. The authors concluded that the system's speed ensures its usability in a machine vision system.

Table 1. Machine learning and deep learning algorithms for accuracy results

Test Accuracy	Machine Learning			
	All Bread Images Included	No Side Shots Images	No Bottom Taken Images	Slice Bread Images
SVM	50.45%	52.33%	52.57%	60.87%
KNN	47.46%	43.12%	45.49%	54.64%
Decision Tree	50.12%	41.37%	49.83%	52.39%
Random Forest	52.17%	54.76%	53.46%	62.84%
	Deep Learning			
Train Accuracy	99%	99%	99%	99%
Test Accuracy	56.67%	59.04%	56.99%	92.37%

Using CNN with a limited training dataset is a highly active area of study that can be implemented in real-time manufacturing [34]. Considering the results obtained with CNN architecture in Table 2, the training accuracy rate was found to be 99% for both slice breads and whole breads. However, the test results remained around 56.67% for whole breads. This can be explained by the fact that the image samples are few and similar. In addition, with a more comprehensive data set, training and test results can be optimized to a closer value. However, the most remarkable result was seen in the test results for slice breads. The test results of 92.37% revealed the success of the architectural structure. This is a natural result of extracting more features from the dense layers of the CNN architecture that we have built inside each other.

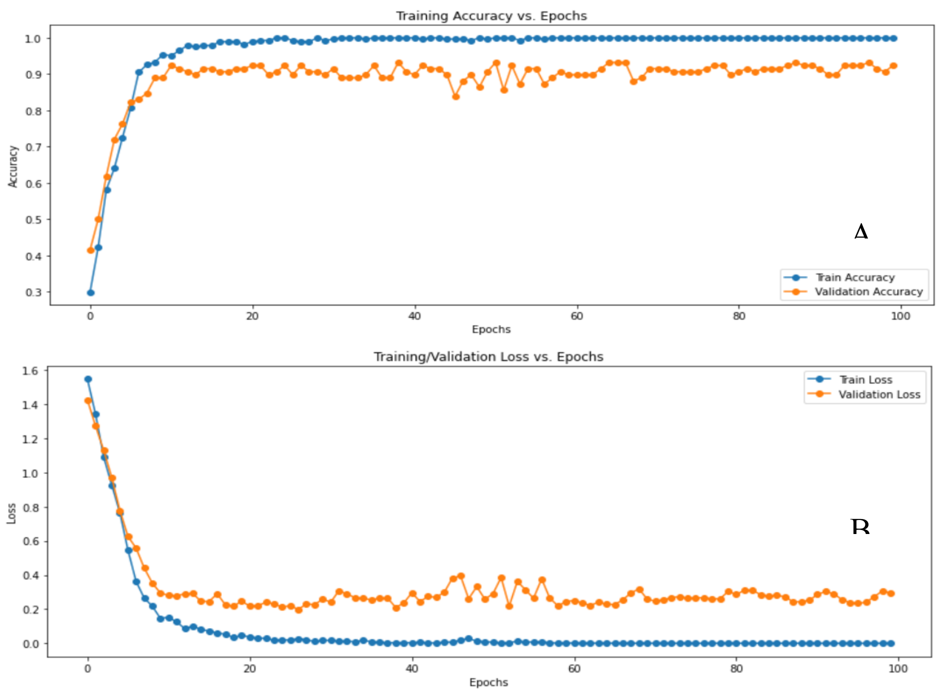

Figure 4. Accuracy (A) and loss (B) graphs for training and validation result

Figure 4 shows the accuracy and loss functions obtained as a result of the 100-step operation of the CNN architecture. When the graphs are examined, it is calculated that the accuracy and loss functions are at an acceptable level, even if they are not very close to the training results. Today, deep learning is recognized as an algorithm that can be applied to the surface of bread. A simple neural network was used to classify the surface color of baked bread with 93% accuracy [35]. In another study of changes in the color of cereal product, with an accuracy of 98.8%, short-CNN was able to predict the level of bread crust browning during baking, which was directly related to customer purchase decisions. This model was found to be superior to AlexNet and

VGGNet-16 models [36].

In their study, Zhang, et al. [37] investigate two techniques for identifying tea quality, utilizing deep convolutional neural networks and transfer learning. Building CNN models based on a small input size can result in a high-quality identification effect for tea and attain superior performance comparable to transfer learning models while consuming less computing power and memory.

Wang, et al. [38] proposed a portable computer vision system to assess the freshness of crayfish, based on a convolutional neural network (CNN), which captures microscopic images of crayfish with different degrees of freshness. The use of optimized networks resulted in freshness prediction accuracy reaching 86.5% and 83.3%.

Figure 5 shows the confusion matrix graph calculated as a result of the test process. When the class results are examined, while 23 data points are known correctly for the 1st day, for the other days, 22, 21, and 22 images respectively and 21 images for fresh bread, were correctly recognized. It was observed that incorrectly labeled data was often confused with the class closest to it. This kind of mislabeling is normal, as there is little variation between fresh bread and day 1, or between day 1 and day 2 or day 3.

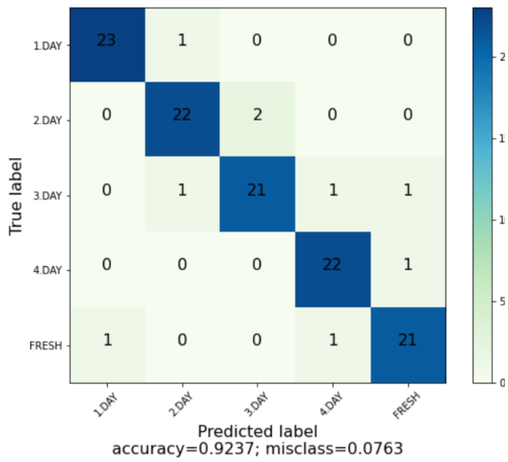

Figure 5. Confusion matrix graph obtained as a result of the test process

4. Conclusion

In this study, a method was proposed to predict the staling process of bread under storage conditions without damaging the bread. In this study, we have shown that the staling level of bread can be determined by utilizing these changes in the appearance of bread in the first few days of consumption. The images of the bread crumbs better reflect staling than the whole bread. In general, when the proposed artificial intelligence algorithms are evaluated, it is revealed that deep learning algorithms perform better than machine learning algorithms if sufficient data is available. The proposed methods and techniques have been encouraging in the food industry, especially in a critical phenomenon such as the detection of problems caused by staling of bread. In addition, it is thought that the current algorithms can be developed for other bread types in future studies and important results can be obtained. In the near future, CNN models are expected to be applied to mobile devices for real-time detection and analysis of food matrices and used to monitor the degree of staling of bread and also to develop effective food spoilage monitoring systems to maintain food quality requirements.

Contributions of the Authors

The authors confirm that the contribution is equally for this paper.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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