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Using self-organizing map for quality classification on fish processed product

Yusraini Muharni[a,*], H.M Hartono[b], Maria Ulfah[a], Lely Herlina[a], Anita Cempakasari[a]

[a]*Department of Industrial Engineering, Universitas Sultan Ageng Tirtayasa, Banten, Indonesia*
[b]*Department of Electrical Engineering, Universitas Sultan Ageng Tirtayasa, Banten, Indonesia*

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ABSTRACT

Assessing the quality of processed fish products stands as a critical factor in ensuring consumer satisfaction, upholding industry standards, and reducing wastage. Traditional methods for quality classification typically involve manual inspection, which is both time-consuming and subjective. In recent years, the utilization of advanced data analysis techniques, such as Self-Organizing Maps (SOMs), has emerged as a promising approach to enhance the accuracy and efficiency of quality assessment in the fish processing industry. SOMs provide a multi-dimensional map capable of representing various quality attributes of processed fish products. This study aims to classify the quality of processed fish products based on four attributes that impact their time to spoilage. The SOMs effectively segmented the dataset into two clusters, with one cluster being more prone to spoilage, while the other demonstrated a longer shelf life.

1. Introduction

Fish play a vital role as significant reservoirs of nutritious and superior protein within developing nations. The preservation and longevity of fish, especially in tropical climates, are significantly influenced by temperature. Elevated temperatures and relative humidity accelerate spoilage and diminish the freshness of fish. Fish freshness is critical to human well-being and consumer acceptance of the food, as it directly impacts the quality and safety of fish products. Fish that is not fresh may be of low quality and pose a health risk due to the presence of pathogenic bacteria and toxins [1]. Dehydration of fish serves to eliminate moisture, thereby prolonging the storage duration of dried fish. The process of drying entails the extraction of moisture from fish via controlled conditions, leveraging heat and mass transfer. This investigation extensively examines diverse drying methodologies and the kinetics governing the drying process of fish [2].

The presence of residential bacteria is linked to the quality and safety of processed fish products. The freshness of fish holds a significant role in human well-being, and consumers' acceptance of food is closely tied to safety concerns on a global scale. Items with inherently varying initial quality, like fresh fish, necessitate the use of sensors to monitor compounds aligned with quality Notably, attributes such as appearance, texture, juiciness, water content, firmness, tenderness, aroma, and taste are pivotal perceptible characteristics of meat. These attributes collectively impact consumers' pre-purchase and post-purchase judgments on the initial and eventual quality of a meat product.

Packaging is one factor to maintain the quality of different food items in terms of controlling microbial growth and gas concentration, and for providing convenience and easiness to its users in the form of time temperature indication [3] Increasing in temperature could impact the growth of in Salmonella foodborne [4]. Maintaining temperature is a crucial activity in supply chain or logistic of food product. Temperature data collected through environmental monitoring of food transportation can indicate if shelf life is being impacted. This data should be utilized to adjust transportation methods and supply chain processes, on the condition that there is a chance to make changes before food quality deteriorates past an unacceptable

*Corresponding author:
Email: bundamia1974@gmail.com

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level. The goal would be to use the temperature readings to identify and proactively mitigate any risks of shelf-life reduction before it reaches the point where quality standards fall below the established minimum thresholds. This allows intervention to prevent complete spoilage or waste of food products in transit due to temperature factors [5].

Drying, one of the earliest recognized techniques for preserving food, has been utilized for fish preservation across various regions where fish are sourced. Fish drying methods encompass a broad spectrum ranging from conventional sun-drying to technologically advanced, computer-controlled industrial procedures. It is essential to consider the impact of the drying technique on the nutritional value of the resultant product. Evaluating the cost-effectiveness of adopting new technology is a complex task. The potential benefits of introducing an innovative fish-drying method that yields a more stable and nutritious product while simultaneously generating employment in related industries could outweigh the supplementary costs involved. Among the array of fish drying methods, exposure to natural sunlight is overwhelmingly the most prevalent. The approach to sun drying varies from fishery to fishery, where larger fish species might undergo splitting, and fish could be subjected to brining or salting before being laid out for the drying process [6].

The application of principles of moisture removal, commonly coupled with the incorporation of chemicals. Emphasizing the role of water in processes like solubilization, dehydration, gelatinization, microbial management, packaging design, and other pertinent factors is pivotal for the effective development of product formulations. In considering the potential for novel salted products, an initial exploration of prevailing consumer preferences is essential [7].

Fish processing involves numerous stages, including cleaning, filleting, freezing, and packaging. The final quality of the processed fish products depends on factors such as freshness, texture, color, and odor. These quality attributes can be challenging to assess accurately through manual inspection alone. Incorporating SOMs into the quality assessment process offers a data-driven approach that can lead to more objective and consistent results. As information and communication technology has evolved, food computing has become one of the areas where multiple studies have been undertaken. To address food-related issue such as medicine, biology, gastronomy, quality, a series of computational approaches are applied in food-related issues [8]. Food image classification and recognition was applied in a previous study for the purpose of dietary assessment [9]. Some researchers develop methods, frameworks, and applications for tracking alterations in the duration a food product remains viable, characterized as the period before its quality falls below an established threshold [5]. To address the challenge of quality detection in the manufacturing and processing of filled food products, a small neighborhood clustering algorithm is proposed to segment frozen dumpling images on a conveyor belt. This approach proves effective in enhancing the overall acceptance rate of food quality. This approach proves effective in enhancing the overall acceptance rate of food quality [10].

There are a wide range of studies and reviews that focus on applying machine learning to cluster and assess food quality. The application of machine learning algorithms in analyzing data collected by electronic nose systems for food quality assessment [11], [12]. They delve into different aspects of food quality evaluation, including data analysis, neural network approaches, and the utilization of SOMs for clustering and pattern recognition [13], [14], [15], [16].

2. Material and method

2.1. Data source

The dataset for this study consists of 60 records that were measured over 60 days in a fish processed factory. The attributes are gross weight of fish, fish dried weight, temperature, humidity, and time to spoilage. Statistical descriptive of collected data are shown in Table 1.

2.2. Self-Organizing Maps (SOMs)

Self-Organizing Maps (SOMs), introduced by Kohonen in the 1980s, are a class of artificial neural networks that have gained significant attention due to their ability to uncover patterns and relationships within complex datasets. SOMs are particularly useful for data visualization, clustering, and dimensionality reduction [17], [18].

SOMs, also known as Kohonen maps, consist of a grid of neurons, each representing a prototype vector in the input space. SOMs employ unsupervised learning to transform high-dimensional input data into a lower-dimensional representation while preserving topological relationships [19]. The training process involves competition and cooperation among neurons, resulting in the adjustment of prototype vectors to match the input data distribution [20]. Fig. 1 shows the Matlab code for SOM.

Table 1.
Descriptive statistic of data measured for 60 days

	Gross weights (kgs)	Dried Weight (kgs)	Temp. (^{0}C)	Humidity (%)	Time to Spoilage (Hr)
Minimum	10	8.42	24.3	65	65
Maximum	10.1	9.49	29.3	91	86
Average	10.01	8.95	27.45	79.70	75.77
Std. Dev	0.02	0.30	1.11	5.83	5.19

```
% ===== SIMULATION ========
% Format Input Arguments
isCellX = iscell(X);
if ~isCellX, X = {X}; end;

% Dimensions
TS = size(X,2);
% timesteps
% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
    % no processing
    % Layer 1
    z1 = negdist_apply(IW1_1,X{1,ts});
    a1 = compet_apply(z1);

    % Output 1
    Y{1,ts} = a1;
end

% Final Delay States
Xf = cell(1,0);
Af = cell(1,0);

% Format Output Arguments
if ~isCellX, Y = cell2mat(Y); end
end
```

Figure 1. Matlab code

Self-Organizing Maps (SOMs), are a type of artificial neural network that enables unsupervised learning [21]. The fundamental idea behind SOMs is to transform complex, high-dimensional data into a simplified, lower-dimensional representation while preserving the underlying relationships between data points [22]. This characteristic makes SOMs well-suited for tasks like clustering, visualization, and quality classification.

Self-Organizing Maps procedure for quality clustering consist of several step as follow:

a. Data Collection: Gather data on different quality attributes from a diverse set of processed fish products.
b. Data Preprocessing: Normalize and standardize the collected data to ensure that each attribute carries equal weight in the analysis.
c. Training the SOM: Train the SOM using the preprocessed data. The network will organize the data into clusters on the map, where similar products are grouped together. This SOMs Training was run in MATLAB software.
d. Visualization: One of the key advantages of SOMs is their ability to visualize complex data in a reduced dimensional space. Each node on the SOM corresponds to a cluster of products with similar quality attributes. This visual representation can aid in identifying patterns and outliers.

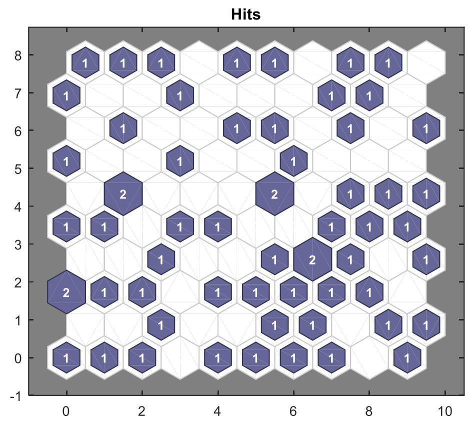

Figure 2. Cluster of sample hit

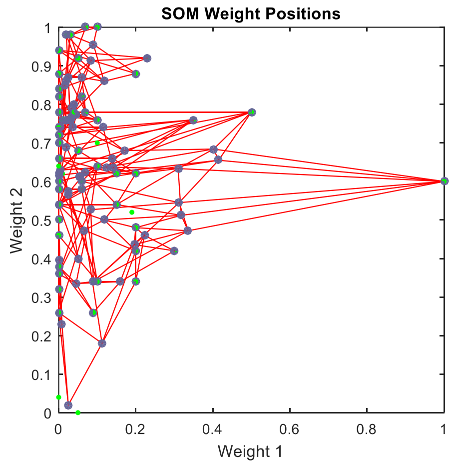

Figure 3. The plot of clustering weight

Table 2.
Cluster formed

Cluster	Member
1	1-8, 10-11, 13-14, 17-19, 22-36, 38 -60
2	20, 21, 34

3. Results and discussions

The SOM map visually represents clusters and relationships within the data. Each node on the map corresponds to a neuron that represents a cluster or group of data points. As shown in Fig. 2 and 3, there are two clusters formed on the map. Data points that are similar in terms of features were grouped together on the map. Mapping the SOMs result into original data set bring us to identify densely populated clusters with nodes that have many similar data points. The cluster member is summarized in Table 2.

Beside cluster, several data set are identified as outlier where nodes with very few data points compared to others. The outlier points are 9, 12, 15, 16 and 37 of data set. The clustering process was conducted to engage in quality classification. Specifically, the first cluster was identified as being more prone to spoilage, while the last cluster was found to have a longer shelf life.

The integration of Self-Organizing Maps into quality assessment processes for processed fish products offers several advantages. SOMs provide an objective framework for quality assessment, reducing the potential for human bias. In terms of efficiency, SOMs have the automated classification process that speeds up quality evaluation, allowing for quicker decision-making in the production chain.

4. Conclusions

As the fish processing industry continues to evolve, the integration of advanced data analysis techniques like Self-Organizing Maps offers a promising solution for enhancing quality classification. By providing an objective and data-driven approach, SOMs contribute to better decision-making, increased efficiency, and improved consumer satisfaction in the processed fish product market. Further research and practical implementations are likely to drive the adoption of this technology, benefiting both producers and consumers alike.

Declaration statement

Yuraini Muharni: **Conceptualization, Methodology, Writing-Original Draft, Algorithm and Coding**. Hartono: **Algorithm and Coding, Formal analysis**. Anita Cempakasari: **Data gathering Resources, Visualization**.

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article or its supplementary materials.

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