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Prediction of convective heat transfer coefficient during deep-fat frying of *pantoa* using neurocomputing approaches

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ABSTRACT

Deep-fat frying (DFF) is the major processing step in preparation of *pantoa*, a popular Indian dairy sweetmeat. In this study, the dough for *pantoa* was rolled into balls of 15 g, and fried in sunflower oil at 125, 135 and 145 °C for 8 min. Convective heat transfer coefficient, which defines the heat transfer characteristics of the product during DFF, was determined using one-dimensional transient heat conduction equation as 92.71–332.92 $W \cdot m^{-2} \cdot K^{-1}$. Neurocomputing techniques such as connectionist models and adaptive neurofuzzy inference system (ANFIS) were compared vis-à-vis multiple linear regression (MLR) models for prediction of heat transfer coefficient. A back-propagation algorithm with Bayesian regularization optimization technique was employed to develop connectionist models while the ANFIS model was based on Sugeno-type fuzzy inference system. Both connectionist and ANFIS models exhibited superior prediction abilities than the classical MLR model. Amongst the three approaches, the hybrid ANFIS model with triangular membership function and frying time and temperature as input factors gave the best fit of convective heat transfer coefficient with R^2 as high as 0.9984 (99.84% accuracy) and %RMS value of 0.1649.

Industrial relevance: Convective heat transfer coefficient defines the heat transfer characteristics of a product during frying. Accurate prediction of heat transfer coefficient is important for design of process equipment and saving energy during commercial production. Developing models to predict heat transfer and the coefficients have been a challenge. Neurocomputing is one of the emerging intelligent technologies with analogies to biological neural systems. Therefore, it has the capability to predict complex relationships in food systems. Neurocomputing approaches such as connectionist and ANFIS models are now widely used in the food industry to predict various engineering properties of food, optimization of various transport processes, unit operations and formulating new products and product characteristics. No attempt has been made to predict the heat transfer coefficient during frying of *pantoa*. In this study, the convective heat transfer coefficient of *pantoa* was predicted using connectionist models and ANFIS techniques. These neurocomputing techniques are expected to alleviate the difficulties in conventional heat transfer modeling.

1. Introduction

Pantoa is a *chhana*-based popular milk sweet of India. It is prepared by blending heat-acid coagulated milk solids (*chhana*) and heat-desiccated milk solids (*khoa*), refined wheat flour (*maida*), arrowroot powder, semolina and baking powder to smooth homogenous dough. The dough is rolled into spherical balls and deep-fried in refined vegetable oil or clarified butter. The fried balls are soaked and served in sugar syrup of 50–60 °Brix (Nath, 1992). *Pantoa* is characterized by a light to deep brown crust and creamish spongy core. Also, it has a sweet caramelized flavor with a firm body and slightly chewy texture after soaking in sugar syrup.

Deep-fat frying (DFF) is the major process step in preparation of *pantoa*. The quality changes are due to heat-induced physicochemical reactions such as gelatinization of starch, denaturation of proteins, development of flavors, Maillard browning, caramelization, inactivation of enzymes, fat uptake, etc. The product quality during frying is found to be affected by the process conditions (Neethu, 2012). A better understanding of these quality changes during DFF is essential for better consumer acceptance of a product.

Heat transfer during DFF is a complex phenomenon. In *pantoa*, heat is transferred from the frying medium to the food surface by convection and from the surface to the interior by conduction (Yıldız, Palazoğlu, & Erdoğdu, 2007). An understanding of the mechanism of heat transport can lead to techniques to circumvent the limitations of heat transfer during frying, which in turn helps to identify the areas of high energy use and target these areas for energy conservation. The heat transfer coefficient is also significant for designing frying process and equipment,

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as it determines the size of the equipment in relation to the residence time of the product in the medium (Alvis, Vélez, Rada-Mendoza, Villamiel, & Villada, 2009).

Soft computing techniques such as connectionist and neurofuzzy models are now widely used for predictive modeling in food engineering applications (Sharma & Sawhney, 2015; Todorov, Nacheva, Metodieva, Doneva, & Tsvetkov, 2013). Connectionist models, also known as artificial neural networks (ANN), are computational techniques which imitate the structure and function of human brain to certain extent (Mehrotra, Mohan, & Raka, 1996). Similarly, Jang (1993) proposed that the adaptive neurofuzzy inference system (ANFIS) can construct an input–output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input–output data pairs using a hybrid learning procedure. The network learns by example and training, much similar to the human brain that learns by adjustments to the synaptic connections that exist between the neurons. Due to their adaptive learning abilities, they are expected to accurately describe relationships between independent and dependent variables, especially when the explicit form of mapping is unknown.

Connectionist models were also used to predict the thermal conductivity of bakery products such as bread, French bread, yellow cake, tortilla chips, whole wheat dough, baked chapatti and cup cake as a function of product moisture content, temperature and apparent density (Sablani, Baik, & Marcotte, 2002). Lertworasirikul (2008) performed a comparative study on the drying kinetics of semi-finished cassava crackers using mathematical, multilayer feed-forward neural network (MFNN) and ANFIS models, and estimated the dynamic drying parameters. Rahman, Rashid, and Hussain (2012) employed ANFIS technique to predict the effective thermal conductivity of various fruits and vegetables, and found that it was comparable to classical regression and connectionist models. Sharma and Sawhney (2015); Sharma, Lal, and Sawhney (2014a) and Sharma, Sawhney, and Lal (2014b) have developed connectionist and ANFIS hybrid models to understand sorption isotherms of dried acid casein and fortified weaning food.

Application of soft computing models to predict heat transfer coefficients during DFF of dairy products is still limited. Mittal and Zhang (2000) developed a connectionist model to predict heat and mass transfer during DFF of infinite slab shaped foods. Frying time, slab thickness, initial temperature, oil temperature, moisture diffusivity of food, heat transfer coefficient, initial moisture content, etc., were inputs. Similarly, Mittal and Zhang (2001) proposed a connectionist model to predict heat and mass transfer during DFF of meat balls. In the model, frying time, radius, heat transfer coefficient, thermal diffusivity, moisture content, temperatures, etc., were used as inputs. Sablani, Kacimov, Perret, Mujumdar, and Campo (2005) used connectionist approach to estimate heat transfer coefficients in several foods. However, there is no work reported on the application of such neurocomputing techniques on heat transfer analysis of *pantoa*. Therefore, the objectives of this work were to evaluate and compare the performance of two soft computing techniques vis-à-vis multiple linear regression (MLR) model in predicting the convective heat transfer coefficient of *pantoa* during DFF.

2. Materials and methods

The dough for *pantoa* was prepared by blending *khoa* and *chhana* in the ratio of 4:5. For preparation of *khoa*, cow milk from the livestock farm of ICAR-National Dairy Research Institute, Bengaluru, India was standardized to 4% fat and 8.5% solids-not-fat (SNF). The milk was taken in a steam-jacketed kettle and allowed to boil vigorously with continuous stirring to a semisolid consistency of 24–28% moisture content on wet basis (w.b.). For preparation of *chhana*, fresh milk was standardized to 4% fat and 8.5% SNF and heated to 90 °C with continuous stirring for 15 min. After cooling to 85 °C, 2% citric acid solution was slowly added to milk until all the milk solids coagulated. The coagulated mass was strained through a cheese-cloth, tied and hung for 30 min to drain the whey. The moisture contents of *khoa* and *chhana* were adjusted to 40 and 58% (w.b.), respectively. Refined wheat flour, semolina and arrowroot powder were added to the *khoa-chhana* dough each at 3% on w/w basis. Baking powder and ground sugar were added to the dough at 0.3 and 0.7% (w/w), respectively. The dough was kneaded in a dough blender (Lalith Industries, Bengaluru, India) for 5 min. The moisture content of the kneaded dough was adjusted to 40% (w.b.) before frying.

2.1. Deep-fat frying

The dough was rolled into balls of 15 g weight (29.11 mm dia.), and fried in refined sunflower oil at temperatures of 125, 135 and 145 °C. Exactly 4.5 L of oil was taken in an electric fryer (model CMF-6/I/E, Continental Equipments India Pvt. Ltd., Bengaluru, India) of 2 kW heating power and 6 L bowl volume. The dough was fried at 125, 135 and 145 °C for 8 min. The product to oil ratio in the fryer was maintained as 1:25 on w/w basis. The first batch of balls was fried for 30 s and the oil was drained from the product. The next batch was then fried for 60 s, and so on, till 8 min of frying, maintaining the product to oil ratio fairly constant. The core temperature of *pantoa* was measured using a K-type thermocouple connected to a data logger (Model: Center 309, Ankom International, Bengaluru, India). As frying progressed, samples were withdrawn at 30 s interval for measurement of apparent density, geometric and thermal properties and analysis of moisture content. Three replications with three sub-sampling were carried out at each frying temperature.

2.2. Measurement of thermal properties

The thermal conductivity, thermal diffusivity and volumetric specific heat of *pantoa* at different stages of frying (from 0 to 480 s at 30 s interval) were measured at ambient temperature using the thermal properties analyzer (Model: KD2 Pro, Decagon Devices, Pullman, Washington DC) with the 30 mm long SH-1 dual needle probe. The probe, working on line-heat source method, was inserted into the center of the product, and kept undisturbed during measurement.

2.3. Determination of moisture content

Fried *pantoa* was ground in a pestle and mortar. From the ground mass, about 5 g of the sample was taken and weighed to 0.1 mg precision into a Petri dish and kept at 100 ± 2 °C for 5 h in a hot air oven for determination of moisture content by AOAC method 927.05 (AOAC, 2012).

2.4. Determination of geometric properties

The dimensional changes of *pantoa* at 30 s intervals of frying were measured in ‘x’, ‘y’ and ‘z’ directions of the geometry. From the ‘a’, ‘b’ and ‘c’ values obtained (dimensions in the three axes), sphericity (ϕ) was calculated using Eq. (1) (Mohsenin, 1980).

$$\phi = \frac{Geometric\ \ mean\ \ diameter}{a} = \frac{(a \cdot b \cdot c)^{\frac{1}{3}}}{a} \tag{1}$$

where ‘a’, ‘b’ and ‘c’ were the dimensions of *pantoa*.

From the geometric dimensions, the volumetric change during frying was calculated. The apparent density (ρ_{app}) of fried *pantoa* at different frying times was then calculated using Eq. (2).

$$\rho_{\text{app}} = \frac{weight\ \ of\ \ pantoaball}{volume\ \ of\ \ pantoaball} = \frac{w}{\frac{4}{3}\pi r_0^3} \tag{2}$$

where ‘w’ was the weight and ‘r_0’ was the radius.