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Rapid Quality Assessment of Bakery Products Using Machine Vision

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Hanieh Amani

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The PhD School

Name: Doctoral School of Food Scienc

Discipline: Food Science

Head: Simonné Dr. Livia Sarkadi

University professor, DSc in chemistry

Hungarian University of Agriculture and Life Sciences, Department of Food Chemistry and Nutrition

Supervisor(s):

László Baranyai

Head of Department of Measurements and Process Control, Ph.D. in food science

Hungarian University of Agriculture and Life Sciences

Katalin Badakné Kerti

Head of Department of Grains and Industrial Plants Processing, Ph.D. in food science

Hungarian University of Agriculture and Life Sciences

The applicant met the requirement of the Ph.D. regulations of the Hungarian University of Agriculture and Life Sciences and the thesis is accepted for the defense process.

Head of the Doctoral School

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Supervisor Supervisor

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List of Abbreviations

AD	**A**bsolute **D**ensity
CVS	**C**omputer **V**ision **S**ystem
CT	**C**omputed **T**omography
CMOS	**C**omplementary **M**etal-Oxide **S**emiconductor
CRD	**C**ompletely **R**andomized **D**esign
DLP	**D**igital **L**ight **P**rocessing
CCD	**C**harged-**C**oupled **D**evice
DMD	**D**igital **M**icromirror **D**evice
ET	**E**lectrical **T**omography
Eq	**E**quation
Fig	**F**igure
FTIR	**F**ourier **T**ransform **I**nfrared **S**pectroscopy
FGLS	**F**irst-order **G**ray-level **S**tatistics
GLCM	**G**ray **L**evel **C**o-occurrence **M**atrix
H	**H**ue
HIS	**H**yperspectral **I**maging
ISO	**I**nternational **S**tandards **O**rganization
IOS	**M**obile **O**perating **S**ystem **C**reated by **A**pple
JAR	**J**ust **A**bout **R**ight
L*	**L**ightness
MC	**M**oisture **C**ontent

Min	**M**inute
MRI	**M**agnetic **R**esonance **I**maging
NIR	**N**ear-**I**nfrared
NIRs	**N**ear-**I**nfrared **s**pectroscopy
OL	**O**verall **L**iking
Px	**P**ixel
PVI	**P**ore **V**olumetric **I**ndex
RLM	**R**un-**L**ength **M**atrix
ROI	**R**egion of **I**nterest
RGB	**R**ed, **G**reen and **B**lue colours
SEM	**S**canning **E**lectron **M**icroscopy
Sec	**S**econd
SVM	**S**upport **V**ector **M**achine
TPA	**T**exture **P**rofile **A**nalysis
X-MCT	**X**-ray **C**omputerized **M**icrotomography
X-ray	**X**-radiation

List of Symbols

cm	Centimeter
g	Gram
mm	Millimeter
M_0	Initial Mass
P	Pressure
V	Volume
V_{bs}	Bulk Solid Volume
V_{cp}	Closed Pores Volume
V_{ts}	True Solid Volume
γ	Gama
θ	Angle
δ	Delta
°C	Degree Centigrade
%	Percent

CHAPTER 1: INTRODUCTION

The leavened bakery products are known as stapled food products in families' food baskets over the past century. These products such as bread, cakes, and buns can be manufactured using various formulations and processes; however, the primary ingredients used in their recipes are flour, water, and yeast. Depending on the final product, other ingredients including sugar, shortening, and egg may or may not be added. (Rathnayake, Navaratne and Navaratne 2018).

Pogácsa, a popular salty cake, is a traditional leavened product made of wheat flour, cheese, margarine, yeast, and salt. Hungarian *pogácsa* cake has a specific texture, tender on the inside and crispy on the outside, which endows a unique and desired sensorial perception. Although this product is widely produced at the domestic and industrial levels, the number of research attempts to improve its physical and sensorial quality parameters are scarce. Therefore, there is a very good scope for processors to further work on quality improvement of this traditional product (Amani et al. 2021).

Quality parameters of *pogácsa* are highly related to the mechanical and sensory characteristics of the crumb, ingredients, and baking conditions that may influence consumer purchase. Various quality parameters of *pogácsa* products are correlated to the appearance criteria such as size, colour, shape, and crumb texture (Lassoued et al. 2007; Puerta et al. 2021). The availability of accurate, robust, and efficient analytical techniques is one of the big concerns in monitoring the quality of bakery products. The routine quality assessment methods have limitations of low capacity, using instrumentation, high expenses, and needs of skilled personnel (Ye, Guo, and Sun 2019).

Image processing is the core of computer vision system, which allows analysing various appearance parameters (e.g., size, colour, shape, and texture) from a digitalized image (Amani et al. 2020). This method has numerous advantages in speed, cost-effectiveness, and flexibility over conventional analytical methods. This superiority has made this method a useful non-invasive technique for grading, quality evaluation of morphological and textural features, as well as identification in bakery products (Abdollahi Moghaddam, Rafe, and Taghizadeh 2015; Ghasemi-Varnamkhasti and Lozano 2016; Gunasekaran 1996). Although considerable studies have been focused on employing image-based texture analysis in leavened bakery products, to our knowledge, no study has focused on pores structure and porosity measurement of *pogácsa* using image processing. Currently, the only analytical prediction for porosity measurement is available for bread, but no reliable method is available for porosity measurement of other bakery products like *pogácsa* cake. This hypothesis indicates a potential application of digital image processing as a simple technique for pore characteristic evaluation of *pogácsa*.

In view of the aforementioned points, this study has been designed with the following objectives:

1. To develop robust methods to evaluate the internal structure of the *pogácsa* cake.
2. To evaluate the effect of baking conditions (different time and temperature) and formulations (using cheeses with different moisture content (MC)) on the pores structure and sensory properties of *pogácsa*, with the help of image analysis.
3. Relationship between selected image texture features and physicochemical parameters of volume, colour, moisture, porosity, and mechanical texture parameters in *pogácsa*.

CHAPTER 2: LITERATURE OVERVIEW

2.1. Structure of bakery products

Leavened bakery products, often referred to as staples, have consistently found their place within the family's food basket. These products can be manufactured using various formulations and processes; however, the primary ingredients used in their formulation are flour, water, leavening agent (biological or chemical leavening agent such as yeast and $NaHCO_3$, respectively), and other ingredients (e.g., egg, fat, and sugar), which may or may not be used depending on the type of the end product (Rathnayake, Navaratne and Navaratne 2018). Flour and water are the most important ingredients, which have the significant effect on the crumb properties and texture (Mondal and Datta 2008).

Dehydrated granules and moist pressed cakes are two types of yeast being used as the leavening agent in bakery products. Both of the aforementioned yeasts are consist of numerous living cells of *Saccharomyces cerevisiae* (Ali et al. 2012). The yeast starts to ferment after adding water to the flour, resulting CO_2 production as a by-product. Baking powder (chemical leavening agents) may be used by adding a wheat flour with a low ability of gluten development such as cake flour. The gas evolution rate increases when a biological leavening agent is added, and the leavened gas will substantially escape from the batter. Therefore, the gas cells might expand excessively and eventually collapse, which lead to a coarse-grained structure with a reduced volume (Rathnayake, Navaratne and Navaratne 2018). Different methods have been using to produce a well-developed porous structure batter. However, the primary processing steps of kneading, fermentation, proofing, and baking are existing in almost all the different processes.

The process of kneading contributes to homogenous mixing of the ingredients, formation of gluten protein, absorption of water by hydrophilic groups of starch and wheat protein molecules, building a viscoelastic structure, and incorporation of air in to the dough mixture (Romano et al.

2007; Scanlon and Zghal 2001; Ali et al. 2012). Several research studies have proved that the gas cell nuclei can diffuse during the mixing stage of dough development through the aqueous phase (Nwanekezi 2013; Scanlon and Zghal 2001).

Proofing dough is classified as an anaerobic process. During the fermentation process, yeast cells consume the carbohydrates in the lack of oxygen to produce ethanol, energy, and CO_2 as the final products during various stages, with the help of many enzymes. The fermentation process is also beneficial for flavour compound development. (Petersen 1930; Romano et al. 2007; Ali et al. 2012; Stear 1990).

The final bread crumb structure is a result of simultaneous heat and mass transfer processes, which can lead to a wide range of physical, chemical, and structural changes such as moisture loss, volume expansion, starch gelatinization, and protein denaturation. The temperature range of the starch gelatinization and protein denaturation is usually 60–85°C, which is contributed to the conversion of the dough to the crumb (Mondal and Datta 2008; Scanlon and Zghal 2001). The saturation pressure of the water in the dough increases as a result of the thermal expansion of steam, by increasing the oven temperature. Hoseney and He explained that during the first 6 to 8 minutes of baking, the product's volume increased, causing a strong strain within the dough that might compress the product's heat-set cellular structure (Hoseney and He 1992a; Mondal and Datta 2008; Scanlon and Zghal 2001). The long axes of the outer cells can therefore be extended parallel to the crustal axes. Once the bubble walls begin to crack under pressure during proofing and baking, CO_2 releases from the dough, causing the porous structure to become more constant and open to the exterior of the final baked bread (Mondal and Datta 2008).

2.2. *Pogácsa* cake

Pogácsa is a traditional leavened product generally made of wheat flour, yeast, margarine, and salt (It can be filled or stuffed with cheese, potato, or sprinkled herbs and grains like dried dill, sesame, and black nigella seed on top). *Pogácsa* has been consumed in Hungary, Macedonia, Bosnia and Herzegovina, Bulgaria, Austria, Croatia, Serbia, Kosovo, Montenegro, Romania, Slovenia, Greek, Albania, and Turkey with variations such as *kumru* and *karaköy*. There are different versions of *pogácsa* in different places. Therefore, the texture and flavour of each variety is different. They can also be in very small (2.5 cm around and 2.5 cm high) or big size (8.5 cm around and 5.5 cm high). Some *pogácsa* products have a crumbly texture and some others have crispy texture (*Codex Alimentarius Hungaricus* 2012). Although *pogácsa* is widely manufactured at both domestic and industrial levels, the number of studies on its quality assessment is meager. Since *pogácsa* has a unique internal structure, understanding its internal texture characteristics and the impact of process variables during its production are necessary for manufactures (Amani et al. 2021).

2.3. Quality evaluation of *pogácsa* cake

With the increasing demand for high-quality bakery products, the need for accurate and rapid quality assessment is growing. Therefore, food quality and safety assurance has become a big concern for industries and authorities in the field of food production (King et al. 2017). Food quality corresponds to attributes of texture, appearance, smell, taste, and nutritional value, which must fulfil consumers' acceptability of nutritional quality. Food quality assurance has also an important role in consumer protection of contamination, spoilage, and adulteration. The life of modern civilization is concerned about the existence of hazardous components in food products due to changing consumer preferences of food consumption, environmental challenges, and rising complexity of food supply chains. Moreover, food is subjected to a wide range of chemical environmental materials, which are mostly dangerous for people (King et al. 2017; Malik et al. 2010).

Although it is impossible to completely eliminate food contaminants and implement the perfect analytical techniques for food quality evaluation, appropriate procedures for food quality evaluation are necessary. Thus far, substantial numbers of research studies have been carried out to introduce different approaches for assessing the quality of leavened products. However, each method has its own advantages and disadvantages. For instance, human sensory evaluation, as the most traditional method, solely provides information regarding quality parameters, grading, and defection in products (Ghasemi-Varnamkhasti and Lozano 2016; Jatinder Singh and Kaur 2012). Besides, this procedure is time-consuming and depends on trained personnel; hence, it may not be useful for in-line quality inspection during the processing. The conventional instrumental methods such as texture analysis also have their own drawbacks, which include being expensive, destructive, and needing expert trainers with regular maintenance (Grillo et al. 2014; Jatinder Singh and Kaur 2012). Therefore, a rapid, reliable, and efficient method would be useful as an alternative approach to non-destructively examine the quality of *pogácsa* at different stages of its production.

2.4. Quality parameters of *pogácsa* cake

Quality assessment is always a severe concern in the bakery industry as the consumer's demand for high-quality bakery products is constantly increasing. Therefore, maintaining the quality of products is the manufacture's ultimate goal (Haralick and Shapiro 1992). The major quality parameters of *pogácsa* are typically considered as shape, colour, size, and texture. These features are highly affected by the ingredients as well as processing conditions, in particular the time and temperature of baking (Amani et al. 2021). These two parameters are significantly linked to the texture quality of baked *pogácsa*.

2.5. Crumb structure

Among the aforementioned quality parameters, crumb texture is accounted as the most influential parameter in quality assessment of leavened bakery products, particularly in quality evaluation of *pogácsa* (Lassoued et al. 2007; Rathnayake, Navaratne and Navaratne 2018). Texture is generally defined in literature as "the structural and rheological properties, which can be detected using tactile, mechanical, visual and auditory recipients" (Pieniazek and Messina 2017). Texture has a key role in the overall liking of leavened bakery products. Hence, studying its pore structure in the crumb may enhance the acceptability and help the industry sector optimize the production of bakery products.

By slicing a leavened baked product, the exposed cell structure of crumb can be recognizing. This structure is characterized as a two-phase soft cellular solid including a fluid phase formed by air and a solid phase apparent in the cell wall composition (Sapirstein, Roller, and Bushuk 1994). Open and closed-cell foam are the two primary types of solid cellular materials. Pores are attached together in an open-cell structured porous form. Open-cell form structures are softer than closed-cell ones, which have high compressive strength because of high density of their structure (Wang, Austin, and Bell 2011).

The subsequent discussion provides an exposition on the existing porosity evaluation methodologies for bakery products, classifying them into two categories of destructive and non-destructive with detailed explication to ensue. It is important to note that there is currently no accepted or established method specifically designed to assess the porosity of *pogácsa*. The methods used for assessing porosity in bread may not be appropriate for accurately characterizing the internal structure of *pogácsa* or similar baked goods. Each type of baked product has unique characteristics and internal structures, and a one-size-fits-all approach is not suitable for assessing porosity in different baked goods. Therefore, it is essential to develop or adapt specialized method for porosity assessment of *pogácsa*.

2.6. Available techniques for porosity evaluation using conventional laboratory methods

Nowadays, several methods are available to evaluate the porosity of bakery products. Each of them has its own advantages and disadvantages. Organoleptic evaluation is one of the simplest approaches for determining porosity. Conventional laboratory quality assessment methods have the advantage of being efficient, but also have drawbacks in terms of the subjectivity of definitions, being destructive, and time-consuming. Following are some laboratory methods for evaluating the internal structure and porosity of bakery products:

2.6.1. Pycnometry

The pycnometer uses helium gas to flood voids present within the sample and measures changes in pressure by displacement. A typical gas pycnometer consists of a sample chamber and a reference chamber of known. Very careful calibration of these volumes of the sample chamber and reference chamber must be performed to ensure accurate measurements. The ideal gas law is used in helium gas pycnometry to identify the real volume of the solid. However, the gas does not reach the closed pores (only the blind and flow-through pores do), thus the solid true volume contains the volume of the closed pores, as well. When a porous solid is added to the sample chamber during the process, the change of the chamber pressure starts to be measured. According to the ideal gas law, if p and V are the initial pressure and the sample chamber volume, respectively, by introducing V_{ts} as the true solid volume, pressure raises to p_1:

$$pV = p_1(V - V_{ts} - V_{cp}) \quad \text{Eq. (1)}$$

From which closed pores volume and true solid volume (V_{cp} + V_{ts}), can be calculated as following (Datta et al. 2007; Sun 2016):

$$V_{cp} + V_{ts} = \left(1 - \frac{p}{p_1}\right) V \qquad \text{Eq. (2)}$$

The procedure has advantages of suitability for both large ground and intact samples and being non-destructive (i.e., the sample can be reused for other analysis), but it requires a gas pycnometer, which can be relatively expensive (Amoozegar, Heitman, and Kranz 2023). Moreover, removal of the solvent or off-gassing might occurred and indicate the gas permeability or porous network of the sample (Dawan et al. 2022).

2.6.2. Zhuravlev method

The Zhuravlev method is the Ukrainian standardized method for evaluating the porosity of bakery products. This technique involves the preparation of the sample, collecting a notch from the bread crumb, followed by weighing and carrying out the necessary calculations. It should be noted that such calculations use a standard notch volume equal to 27 cm^3. Moreover, the actual volume of the metal cylinder, with the help of which the notch is obtained, may deviate from such a clearly established value. The advantage of this method is the high accuracy of the total porosity calculation, and the disadvantage is the complexity of manufacturing device. Moreover, due to the inability to obtain a notch from buns, this procedure is not applicable for small-baked bakery products. (Petrusha, Daschynska and Shulika 2018).

2.6.3. Liquid extrusion porosimetry (LEP)

The Liquid Extrusion Porosimetry is a variation of the gas-liquid displacement porosimetry technique based on the contact between the sample to be analysed and a membrane having pores much smaller than the sample, known as a capillary barrier membrane. The sample and capillary barrier membranes are completely immersed in the wetting fluid, and the wetting fluid is extruded from the sample under gas pressure (Tanis-Kanbur et al. 2021). The amount of wetting fluid moving out of a membrane is estimated by introducing the gas pressure. Required gas pressure to move the wetting fluid from the porous is measured by dividing the work done by the gas to expand the surface energy, followed by:

$$P = \frac{4\gamma\cos\theta}{D} \qquad \text{Eq. (3)}$$

where P is the pressure difference across the length of the pore, D is the diameter of pore, γ is the wetting liquid surface tension, and θ is the contact angle of the liquid with the sample. The largest of the pores will have the most liquid driven out, while the smaller pores will become relatively empty as pressure increases. The membrane is selected assuming that it has the smallest pores among all pores in the sample. Therefore, the amount of gas pressures required to remove the pores of the sample is not able to empty liquid from the membrane pores, while the liquid driven out of the sample can pass the membrane. The distribution of pore volume as a function of diameter is determined from the related volume of liquid and measured pressure, which corresponds to diameter, as provided in Eq. (1) (Datta et al. 2007).

2.6.4. Calculation from bulk density

The rapeseed displacement method can be used to measure the bulk volume (V_{bs}) of bakery products (AACC, 1995). Then the difference between the bulk solid volume (V_{bs}) and volume of the true solid (V_{ts}) can be determined to calculate the total porosity of the sample using the following formula (Shittu, Raji and Sanni 2007) :

$$\text{Total porosity } = \frac{V_{bs} - V_{ts}}{V_{bs}} \qquad \text{Eq. (4)}$$

2.7. Available techniques for porosity evaluation using non-destructive methods

2.7.1. Hyperspectral imaging (HIS)

Hyperspectral imaging (HSI) is a technology integrating optical sensing technologies of imaging, spectroscopy, and chemometrics. There are three crucial components in every hyperspectral imaging device: a light source, a wavelength dispersive element, and an area-array detector. A broadband quartz-tungsten-halogen (QTH) arc lamp, light-emitting diodes (LEDs), or lasers can be used as the source of light (Lu et al. 2020). Hyperspectral imaging can give both spatial and spectral information at the same time by combining conventional imaging sensing technologies and spectroscopy. Technically, HIS is able to generate numerous images of the same object in various spectral bands. It has the potential to evaluate physical and morphological aspects as well as intrinsic molecular and chemical food characteristics in a non-invasive approach. However, it has the disadvantages of being expensive, complicated, and needs large data capabilities. In addition, it is not available for the industry (Lorente et al. 2012).

2.7.2. Fourier transform infrared spectroscopy (FTIR)

Fourier transform infrared spectroscopy is a vibrational spectroscopic method used to analyse the molecular structure and chemical components of food products in a non-destructive manner. The Michelson interferometer is the most significant part of FTIR spectroscopy and where it derives its distinction from typical infrared spectroscopy. FTIR spectroscopy uses an interferometer and post-processing of the transmitted light to simultaneously irradiate the sample with various IR light frequencies. A beam splitter divides beam source of various IR wavelength light into two parts, with one reaching a fixed mirror and the other one reaching a mirror that moves at a steady velocity. To create an interference pattern that reflects the constructive and destructive interference of the recombination, two split beams are then reflected and recombined. The interferogram (interference pattern) is then sent to the sample, and the interferogram's transmitted portion is sent to a detector. After comparison with a reference sample beam spectrum in the detector, a Fourier transform is performed to obtain the full spectrum as a function of wavenumber. This technology has been successfully applied for food applications. It is applicable for both dry and wet samples. Moreover, FTIR can continuously collect the light wavenumbers and increase the ratio of signal-to-noise and beam intensity, with high-resolution wavelength. These superiorities make FTIR a fast and economic method. However, its resolution needs to improve, and also if the Fourier transform isn't performed to generate the spectrum first, there will be a problem with interpretation of the interferogram (Hussain, Sun, and Pu 2019).

2.7.3. Near-infrared spectroscopy (NIRS)

Spectroscopy is a strong tool for identifying and describing the physical characteristics by analysing sample absorption of different light wavelengths. Near-infrared spectroscopy is an evaluation technique that involves transmitting electromagnetic radiation into the sample and measures light absorption at wavelengths between 780 to 2500 nm. NIRS allows the inference of the scanned sample's interior chemical composition, and hence can be utilized to classify or identify objects. This technique can penetrate the surface of the object and retrieve the composition information from the inner part of the sample. This information appear in the form of spectrum, which is the fingerprint of each sample. Therefore, it can be utilized as a high accuracy sensing technique. There are some challenges for utilizing NIRS technologies like the complexity of the sample analysis process and also results variation by changing the users (Klakegg et al. 2017). In addition, there are various issues in implementing NIR spectrometers for portable and high-volume usage. The NIRscan Nano is a spectrometer inspection module that uses DLP technology (use a digital micromirror device (DMD) instead of a linear array detector to select wavelengths), which results in a small, cheap, and high-performance spectrometer system. The sampling procedures and also possibility of programing the spectral filters in NIR spectrometers have been provided through the utilizing the DLP digital micromirror device in combination with a single point detector (Gelabert et al. 2016).

Although considerable researchers report the potential application of the aforementioned methods, their weakness is not negligible. One of these limitations is the costs of those methods, which are mostly expensive. Illumination conditions during image acquisition are also another potential uniformity challenge, which must be duly addressed (Contreras-Naranjo, Wei and Ozcan 2015). For instance, light scattering from an unknown source may create an unpleasant noise. In this respect, different studies have been highlighted the concern of uniformity issues as a challenge during their analyses (Masawat, Harfield and Namwong 2015).

Moreover, the porous size in baked goods is large enough to be detected using less pricey and lower magnifying techniques. Therefore, these expensive tools are not necessarily required for investigation the porosity properties of bakery products.

2.8. Computer vision system (CVS)

Various quality parameters of food products can be monitored/inspected using visual assessment and/or image processing. Computer vision system (CVS) is a powerful tool, which allows analysing various appearance parameters (e.g., size, colour, shape, and texture) from a digitalized image (Kandpal et al. 2019). This method has numerous advantages in terms of speed, cost-effectiveness, and flexibility over conventional destructive methods (Sonka, Hlavac and Boyle 2014; Sun et al. 2008). This superiority has made this method an effective non-invasive method for numerous food analyses such as risk assessment of µ-hemolysin, paralytic shellfish poisoning toxins, saxitoxins, mycotoxins, and cholera toxin, classification, shelf-life studies, as well as adulterations assessments The CVS has thus far been introduced for quality assessment of a wide range of food categories, including fish and meat, fruits, and vegetables, bakery and confectionery, and dairy products (Amani, Badak-Kerti and Mousavi 2020). Image processing is the core of CVS, which is mainly composed of an image acquisition part (including a camera, light source, software, and hardware components), pre-processing, image segmentation, object measurement, and classification (Du and Sun 2004; Hosseininia, Kamani and Rani 2017; Sun 2012).

2.8.1. Digital image acquisition

The first step in all the image processing systems is image acquisition. The capturing device can be in the form of a digital camera and webcam or scanner, which is externally connected to a computer, where image information is processed (Amani et al. 2015). A considerable number of studies have been recently carried out to develop techniques for image acquisition. In addition, different sensors configurations have been widely developed for the conversion of images into the digital form. Various sensors have been used to capture images of food products, including charge-coupled devices (CCD), computed tomography (CT), magnetic resonance imaging (MRI), electrical tomography (ET), and light microscopy (Rathnayake, Navaratne and Navaratne 2018). In addition, conventional photography had been widely utilized for image acquisition of two-dimensional (2D) images of pores crumb. It also has been considered as an economically feasible, convenient, fast, and powerful method of image acquisition (Lassoued et al. 2007). The most common image acquisitions systems are listed below:

2.8.1.1. Digital camera

Digital cameras record images electronically with their built-in computer. First, light reflects an object passing through a mirror in the camera and pair of lenses. The light then bounces when it enters the pentaprism and passes through the eyepiece and into the eyes. It has several lenses to focus light onto a semiconductor device that electronically records light, to generate an image. The electronic data is subsequently converted to digital data using a computer. The key part of a digital image is a string of Os and Is that represents all the coloured pixels or dots, which form up an image.

2.8.1.2. X-ray computerized microtomography (X-MCT)

The X-ray computerized microtomography is a high spatial resolution tomography based on the computed tomography that has been applied in various researches of porous crumb structure investigation (Falcone et al. 2004; Wang, Austin and Bell 2011). The technique is able to obtain information of the internal structure of the sample in a three-dimensional format. Some examples of aforementioned information are including of fractal dimension, total pore volume, pores average size, and open pore volume (permeability). High price and insufficient intrinsic contrast of the pores crumb structure or low-density materials are the major drawbacks of X-MCT (Falcone et al. 2004; Sozer, Dogan and Kokini 2011; Wang, Austin and Bell 2011).

2.8.1.3. Magnetic resonance imaging (MRI)

MRI is a non-invasive and non-ionizing technology in which atomic particles interact with an external magnetic field and emit energy at specific frequencies. Therefore, the emitted signal intensity is representative of the imaged tissue structure (Bushong and Clarke 2003.). It is capable of analysing both microstructure properties of high MC grains and in-line tracking in the variation of grain MC (Horigane, Suzuki, and Yoshida 2013). This method has the advantages of high accuracy for MC measurement, non-invasiveness, and high spatial resolution. However, MRI is generally an expensive method and requires expert personnel to handle it (Bajd and Serša 2011; Wagner et al. 2008).

2.8.1.4. Scanning electron microscopy (SEM)

Scanning electron microscopy can evaluate crystalline structure, surface topography chemical component, and electrical behaviour in various objects. To evaluate the performance of this method in different conditions, several specific steps such as cold, hot, or allowance of real-time mechanical characterization can be included. SEM has a high depth of field, which allows for constant focus on majority of the specimen surface regardless of surface roughness. Since optical microscopes with high magnification have a relatively narrow depth of field, the smoothness of the surface has a significant impact on image quality. Additionally, extremely large magnifications (up to 1,000,000x) are achievable, with a total resolution of 1 nm. A major disadvantage of this technique is its high cost (Borel et al. 2014; Vernon-Parry 2000; Pathan, Bond and Gaskin 2008).

2.8.1.5. Smartphone imaging

The smartphone camera can portably capture an image with high resolution, whereas its programmability enables users to accurately analyse the captured image via developing an app(s) (Jeanmonod, and Suzuki 2018). In this context, the food researchers have taken these advantages as a reference point and recently introduced the "Smartphone-based Image Processing" as a novel technique for imaging-based quality control of foods (Bueno, Munoz and Marty 2016; Capitán-Vallvey et al. 2015; Roda et al. 2016; Ye, Guo and Sun 2019). This method enables users to implement a wide range of app software for different operating systems, including IOS, mobile, Windows, and Android, without requiring other analyser factors (Lane et al. 2010). They can also design and develop their personalized app(s) based on intended data processing (Kwon and Park

2017). Moreover, in smartphones with built-in cameras, there is an option to set the camera settings easily (Li et al. 2016; Zhu et al. 2013). Furthermore, this method may not require an external computer, which is beneficial in terms of cost-effectiveness. However, the optical components in the smartphone's built-in camera are not designed to use images for analytical purposes (Mavandadi et al. 2012). An entirely reliable method requires the images to be taken in the same fixed photographic conditions in terms of position, light, distance, pixels, and magnification to prevent non-standardized conditions and unwanted errors (Maarouf et al. 2018; Cavalla et al. 2019; Zeinhom et al. 2018).

2.8.2. Illumination

Illumination is a critical component of image acquisition. High-quality images would result to decrease the complexity and time of further image processing steps. Each image processing step results in decreasing the quality of the image and losing the information of the images. Therefore, higher image quality reduces the pre-processing steps of the image processing and increase the accuracy of the process, consequently, minimize the expenses of the image processing system. In addition, the lighting setting has a significant effect on the quality of the obtained image, which may results to the effective image analysis. The illumination method used for image acquisition may depend on the desired purpose of the image processing (Wasnik 2015). The most common light sources that is used in the food research is C(6774K), A(2856K), D(7500K), and D65(6500K) (Yam and Papadakis 2004).

2.8.3. Software

Till now, many software programs have been introduced for image processing in order to analyse images in real-time and provide accurate and precise measurements of shape, size, texture, and colour of the objects (López-García et al. 2010). Software like MATLAB, Octave, Scilab, LUCIA, Image-pro, and ImageJ, are commonly utilized by researchers. Images can be automatically transformed from original RGB images to implement those conversion using toolboxes of image processing in aforementioned software. The selected software and the setting of parameters are two crucial aspects in obtaining desired data (Pastorella and Paletto 2013).

2.8.4. Image pre-processing

Images acquired with any image acquisition device probably contain a variety of noises. These noises and artefacts can affect the image's quality, preventing it from providing accurate information for subsequent image processing. These noises should be eliminated by applying some operations to the image in order to improve the quality of the image. There are two types of pre-processing operations for food quality assessment: (a) Local pre-processing and (b) Pixel pre-processing, which are depended on the pixel size of the neighbourhood used for new pixel estimation. Pixel pre-processing is similar to “pixel by pixel” copying, with the exception that the contents are adjusted based on the determined transformation function. Local pre-processing approaches compute the average brightness value of numerous neighbouring points with similar characteristics to the processed point (Du and Sun 2004).

2.8.5. Image segmentation

Image segmentation is a crucial process that involves partitioning an image into constituent objects, referred to as image segments. This task can be particularly challenging due to the vast amount of visual information present in the image. Each partitioned region is expected to be homogeneous in terms of image properties, such as colour, intensity, and texture (Zheng and Sun 2007; Bong and Rajeswari 2011). Theoretical approaches to image segmentation can be broadly categorized into four types: thresholding-based, region-based, classification-based, and gradient-based segmentation. Of these, thresholding-based and region-based methods are the most commonly used for segmentation (Du and Sun 2004). Region-based segmentation techniques are generally less sensitive to noise, and various methods exist for this approach, including histogram thresholding, region growing, random field, split and merge, clustering, and watershed. Among these, histogram thresholding is the most widely used method due to its simplicity, high accuracy, and reliability (Shaaban and Omar 2009). In this technique, the image is divided into two-pixel groups based on a selected threshold, with pixel groups having values greater than or equal to the threshold and those with values lower than the threshold. Different thresholding methods exist, such as dynamic, local, grey-level histogram, and local-based global methods. Thresholding can also be classified into non-parametric and parametric processes. The grey-level distribution of an image is assumed to follow a specific statistical model in the parametric approach, and the best parameters for the model are estimated using a specific histogram. With the non-parametric approach, the best threshold is typically discovered by maximizing a function like entropy (Li et al. 2011).

2.8.6. Texture measurement of the object

Textural assessment of food products using image processing is a recent technique, which has been successfully applied in various food products. This technique can be used for segmentation, classification, and prediction of the textural properties in a non-destructive manner and provides a measure of features such as coarseness, regularity, and smoothness. The image texture analysis method can be classified into four groups, including statistical texture, transform-based texture, model-based texture, and physical-based texture. All these assessment methods have shown a high potential to evaluate the cellular structural properties without cell segmentation or thresholding 2D images. Among of, statistical texture techniques are the most commonly used approaches (Sun 2016). The main examples of these techniques are run-length matrix (RLM), gray-level co-occurrence matrix (GLCM), first-order gray-level statistics (FGLS), and Haar transform technique

(Sun 2016; Sun 2012). The GLCM is an efficient method, which is based on the use of second-order statistics of the grayscale image histograms (Gonzales-Barron and Butler 2008; Srinivasan and Shobha 2008). The GLCM, which is a well-known statistical method for texture characterization, provides information on the distribution of grey-level intensity differences in sample images (Sun 2012; Mohanaiah, Sathyanarayana, and GuruKumar 2013). Recently, different GLCM-based analysis methods have been introduced for the extraction of textural features from the digital images of food samples (Perez Alvarado, Hussein, and Becker 2016). Nouri et al. (2018) proposed a texture-based image analysis method to successfully evaluate the staling rate of baguette bread during five days of storage (Nouri et al. 2018). In another attempt, the effects of processing parameters (proofing time) on the quality parameters and texture features of bread were investigated with the help of an image-based textural technique. Their results indicated that the correlation between GLCM features and TPA-based hardness was splendid (Karimi et al. 2012). Rahimi et al. (2020) developed an imaging method, which could efficiently describe the microstructure of five groups of leavened bakery products based on their flour sources (Rahimi, Baur, and Singh 2020). In view of the above, it can be assumed that GLCM-based analysis method is a promising approach for assessing the texture quality of bakery products.

2.8.7. Classification

Image classification is a complex process that may be affected by many factors. A successful classification requires a sufficient number of training samples and a suitable classification system. Many potential variables may be used in image classification, including textural or contextual information, spectral signatures, transformed images, vegetation indices, multi-sensor images, multi-temporal images, and ancillary data. In general, image classification approaches can be grouped as supervised and unsupervised, or parametric and non-parametric, or hard and soft (fuzzy) classification, or per-pixel, subpixel, and per-field. Maximum likelihood, artificial neural network, minimum distance, decision tree classifier are some examples of supervised classification approaches and ISODATA, K-means clustering algorithm are categories as unsupervised classification. Linear discriminant analysis and maximum likelihood are classified as parametric and decision tree classifier, artificial neural network, support vector machine, evidential reasoning, and expert system are non-parametric classifiers. Most of the classifiers, such as artificial neural network, maximum likelihood, decision tree, minimum distance, and support vector machine are pre-pixel classifiers. Fuzzy-set classifiers, subpixel classifier, spectral mixture analysis are some examples of subpixel classification approaches. GIS-based classification can be classified as the pre-field classification. Regarding the hard classification, most of the classifiers, such as minimum distance, maximum likelihood, decision tree, artificial neural network, and support vector machine can be classified in this category. Fuzzy-set classifiers, subpixel classifier, spectral mixture analysis are also some examples of the soft (fuzzy) classification (Lu and Weng 2007).

2.8.8. Image resolution (mm/px)

Image resolution is a fundamental parameter that characterizes the level of detail illustrated in an image. The resolution is determined by the number of pixels used to describe a scene, as well as the quantity of grey levels utilized to represent the image's brightness. The checkerboard effect is produced by reducing the number of pixels and maintaining a consistent amount of grey levels. Conversely, when the number of pixels remains constant, but the amount of grey levels is decreased, false contouring can occur, resulting in an image with unnatural and exaggerated edges. According to the literatures, higher resolution images generally require less improvement with an increase in the number of grey levels, as the number of pixels in the image already provides sufficient detail. Therefore, the quantity of grey levels is not a major concern for detailed images (Petrou and Petrou 2010).

2.9. Application of computer vision systems in bakery products

Computer vision systems have been introduced for quality assessment of food and agriculture. This system is considered as a robust, non-invasive, accurate, rapid, and reliable tool for various inspection proposes in the food industry (Wang and Sun 2001). Several studies have been carried out to investigate the characteristics and defects of bakery products of bread, muffins, and cakes using computer vision systems. Aforementioned studies were mostly focused on height and slope of the baked loaves as well as their crumb structure, and surface colour (Grillo et al. 2014). In a recent study, images of 160 bread slice of four different types of bread were evaluated to develop the overall sequence of the digital image processing algorithm. The presented algorithm automatically found the whole crumb area in the bread slice image and made measurements of various crumb morphological and colour features. The results showed that the developed algorithm was efficient in consistently inspecting the crumb features of industrial bread (Peri and Romaniello 2006). In another study, Scott proposed a system that analyse the slope and height of the baked loaves of bread to evaluate their defects (Scott 1994).

To assess the quality of crumb grain of bread and cake, the crumb structure was also evaluated using machine vision. Different features influencing the crumb grain were investigated (Sapirstein 1995). A more recent study applied images of chocolate chip cookies to determine physical characteristics such as shape, size, and colour of the baked product, and the percentage of the top surface area consisted of chocolate chips (Davidson, Ryks, and Chu 2001). Afterwards, according to the three evaluated criteria, four fuzzy models were developed to estimate consumer ratings. A vision system has also been developed by Abdullah, Aziz, and Dos-Mohamed to automate the colour inspection of 200 muffins. They used a classification algorithm to separate light from dark samples utilising ungraded and pre-graded muffins. Accurate classification of 79% of ungraded and 96% of pre-graded muffins was obtained when compared with visual inspection (Abdullah et al. 2000).

CHAPTER 3: MATERIALS & METHODS

3.1. Materials

Wheat flour type BL55 (GoodMills Magyarország Malomipari Kft., Budapest, Hungary), vegetable oil margarine (Upfield Co., Katowice, Poland), lumpy cottage cheese (Alföldi tej Co., Budapest, Hungary; Real Nature Co., Budapest, Hungary), salt, yeast (Lesaffre Yeast Co., Budapest, Hungary), and additive (a mixture of spices acquired by Pr1mer Ltd.) were purchased from a local market. Different ingredients are listed in Table 1.

Table 1. Recipe used in *pogácsa* formulation

Material	Amount (g)	Composition (%)		
		Fat	Protein	moisture
Flour (g)	700	1	11.7	14
Margarine (g)	630	70	0.9	16
Cottage cheese A/B(g)	700	7	16.2	58/65
Fresh yeast	42	0.8	14	68
Salt	42	-	-	-
Additive (Schopback)	7	-	-	-

3.2. Methods

3.2.1. Dough preparation for the experiment 1 and 2

In order to prepare the dough for the experiment 1, different ingredients at room temperature were mixed as following: First, cottage cheese was mixed with margarine, yeast, salt, and additive using a pilot-scale blender (C.P Co., Brescia, Italy). Afterward, wheat flour was added to the blender chamber and mixed for 3 min to obtain a homogenous dough (Amani et al. 2021).

Three different groups of dough were prepared for the experiment 2 of the study. In the first and second groups, the dough preparation was the same as the experiment 1, with modification in cottage cheese. Two cottage cheese with two different MC of 58% and 65 % were used in dough formulations. MC of aforementioned groups were measured using oven drying method (AACC 1995). Third group of *pogácsa* dough was prepared without cottage cheese. For this purpose, first margarine, yeast, salt, and additive were mixed using the pilot-scale blender (C.P Co., Brescia, Italy), wheat flour was then added and mixed for 3 min using the blender.

All the groups of the prepared dough were then rested in cold storage (4°C ± 2°C) overnight. After cold storage the dough was rolled out, folded, and again rolled out. This step was repeated triple times and carefully to avoid softening of margarine and maintain the appropriate layering texture in *pogácsa*. Rolled dough plated uniformly into a smooth flat shape with 6 mm thickness and cut into small pieces by a 4 cm diameter cutter (Fig. 1). The dough preparation was done at room temperature in the laboratory. A total of 354 *pogácsa* samples were selected for further analysis in experiment 1, consisting of 59 pieces from each of the six groups with distinct baking conditions. Similarly, in experiment 2, a total of 420 *pogácsa* samples were chosen for analysis, with 70 pieces from each of the six groups, each having different baking conditions.

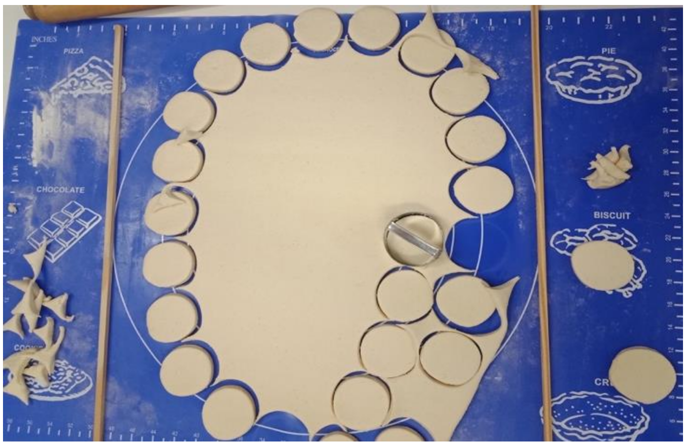

Fig. 1. Moulding step of *pogácsa* preparation

3.2.2. Proofing process

The moulded dough was placed on baking trays and transferred to a proofing chamber (S-200, SvebaDahlen AB, Fristad, Sweden). All samples were subjected to a similar proofing setting of 40°C and 20 min.

3.2.3. Baking settings

3.2.3.1. Experiment 1

The main important aim of the current research study was investigating the correlation between the results of image analysis and internal structure. For this purpose, the effect of different processing conditions was evaluated, by means of changing baking time and temperature, on the quality of *pogácsa,* with the help of image analysis. Therefore, a preliminary trial was conducted to find the desired ranges for the temperature and time of baking. Based on the preliminary observations, different temperatures (200, 215, and 230°C) and times (5 and 7 min) were selected for further study of internal structures in *pogácsa*. As shown in Table 2, six different groups of *pogácsa* samples were prepared under different baking conditions. The baking setting of the group D was regarded as the industrial recipe.

Table 2. Sample groups according to baking time and temperature

Samples	Baking	
	Temperature (°C)	Time (min)
A	200	5
B	200	7
C	215	5
D	215	7
E	230	5
F	230	7

3.2.3.2. Experiment 2

In the next step, the effect of formulations (using cheeses with different levels of moisture content (MC)) and baking temperature (200 and 215°C) on the porous structure and sensory properties of *pogácsa* was also evaluated. The aforementioned baking temperatures were selected based on the results of the previous part of the internal structure inspiration. Based on the porous structures, the best two groups of the previous study were selected for further study of porosity. The baking temperature of 200 and 215°C demonstrated the highest effect on changing the porous structure of the *pogácsa.* While the impact of baking time on the internal structure was meager. Therefore, for this part of the study, all samples were baked for 7 min, which is the baking time of the standard industrial recipe. Six different *pogácsa* groups (A1- 3 and B1-3) were prepared as introduced in Table 3.

Table 3. *Pogácsa* groups according to the formulation and baking temperature

Sample	Baking temperature (°C)	Cheese (% of dough)	Cheese MC* (%)
A1	200	33	58
A2	200	33	65
A3	200	-	-
B1	215	33	58
B2	215	33	65
B3	215	-	-

* MC: moisture content

3.2.4. Baking processes

After proofing, the baking process was performed using an oven (S-200, SvebaDahlen AB, Fristad, Sweden). Fig. 2 shows the both proofing and baking chambers. The baked samples were cooled down to room temperature and packed in air-tight plastic containers and labelled with threedigit codes for further analyses. Fig. 3 illustrated the moulded, proofed, and baked sample. Each group of *pogácsa* was prepared separately in three separate batches, and pieces were randomly selected from each batch. Evaluation of the PVI, TPA, GLCM, MC, volume, porosity, colour, and sensory analysis were conducted with 10,12, 22, 10, 10, 10, 3,15 replication for each sample group, respectively. Table 4 shows an overview of measured parameters and corresponding samples number in each experiment.

Table 4. Summary of measured variables and sample sizes across experiments

	Experiments	
	Experiment 1	Experiment 2
Treatments	6 (A, B, C, D, E, F)	6 (A1, A2, A3, B1, B2, B3)
PVI (%)	6*10 = 60	6*10 = 60
TPA	6*12 = 72	6*12 = 72
GLCM	6*22 = 132	-
Sensory	6*15 = 90	6*15 = 90
Porosity (%)	6*10 = 60	6*10 = 60
Moisture content (%)	6*10 = 60	6*10 = 60
Volume (mm^3)	6*10 = 60	6*10 = 60
Colour	-	6*3 = 18

Fig. 2. Left to right: proofing and baking chambers

Fig. 3. Left to right: moulded, proofed, and baked sample of the *pogácsa*

3.3. Image analysis

3.3.1. Image acquisition

For image capturing of samples, first, the *pogácsa* samples were vertically cut into two halves by a sharp knife. After that, images of the cross-sectioned samples were captured using a DFK 33UX273 USB colour industrial camera (The Imaging Source Co., Germany) equipped with a CMOS sensor and F:1.8 lens (type VS-2518VM). The setting of the camera was as following: shutter speed: 1/800 s, gain: 25 dB, gamma correction: 1.0, and white balance: 6000 K. Samples were illuminated using two white D65-lamps on both sides of a white fabric background with an angle of 45° with the sample to give a uniform light intensity over the sample. Moreover, this geometry found to be the best for emphasizing the pores' structure. The digital camera was vertically mounted on a stand at a distance of 350 mm from the sample in such a way that the angle between the lens axis and lamps was 45°. The images were taken using IC Capture software (version 2.4, The Imaging Source Co., Germany). Images were saved in 24 bit/pixel bitmap format for further analyses. The size of each image was 1280 × 960 pixel. A schematic of image processing setup is illustrated in Fig. 4.

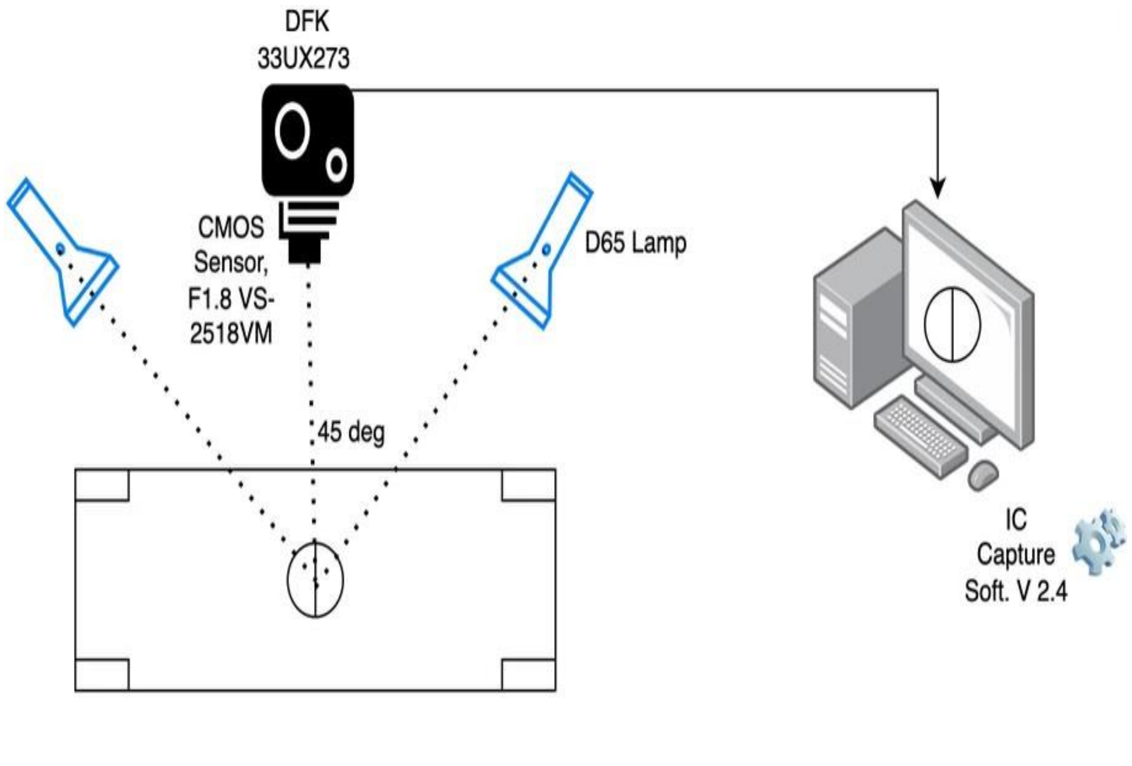

Fig. 4. Schematic of the digital image processing setup

3.3.2. Image processing

Imaging technique is the most appropriate means of texture evaluation because it is the only analytical method that generates results in the form of the image rather than numbers. All the features of porosity, coarseness, shape, colour, pore distribution, and size are important for texture analysis. Almost all these features can be analysed by digital image processing. In the current research work, the evaluation of the internal structure, and pores characteristics was studied by image processing of the baked *pogácsa* using two different software: MATLAB software (version R2018a, MathWorks Inc. Natick, MA, USA), and Fiji Image J software (National Institutes of Health, USA).

3.3.2.1. GLCM features extraction for the experiment 1

Gray level co-occurrence matrix (GLCM) is one of the most common and widely used statistical texture analysis methods, which specifies the texture of an image by counting the number of occurrences of pixel pairs of a particular gray level at a given displacement. In this study, MATLAB software was used to develop algorithms for extracting gray level parameters from a total of 132 image of the *pogácsa* samples, with 22 replicates for each specified group (version R2018a, MathWorks Inc. Natick, MA, USA). The overall sequence of digital image processing algorithm used for evaluating the crumb features of the *pogácsa* image is presented in Fig. 5.

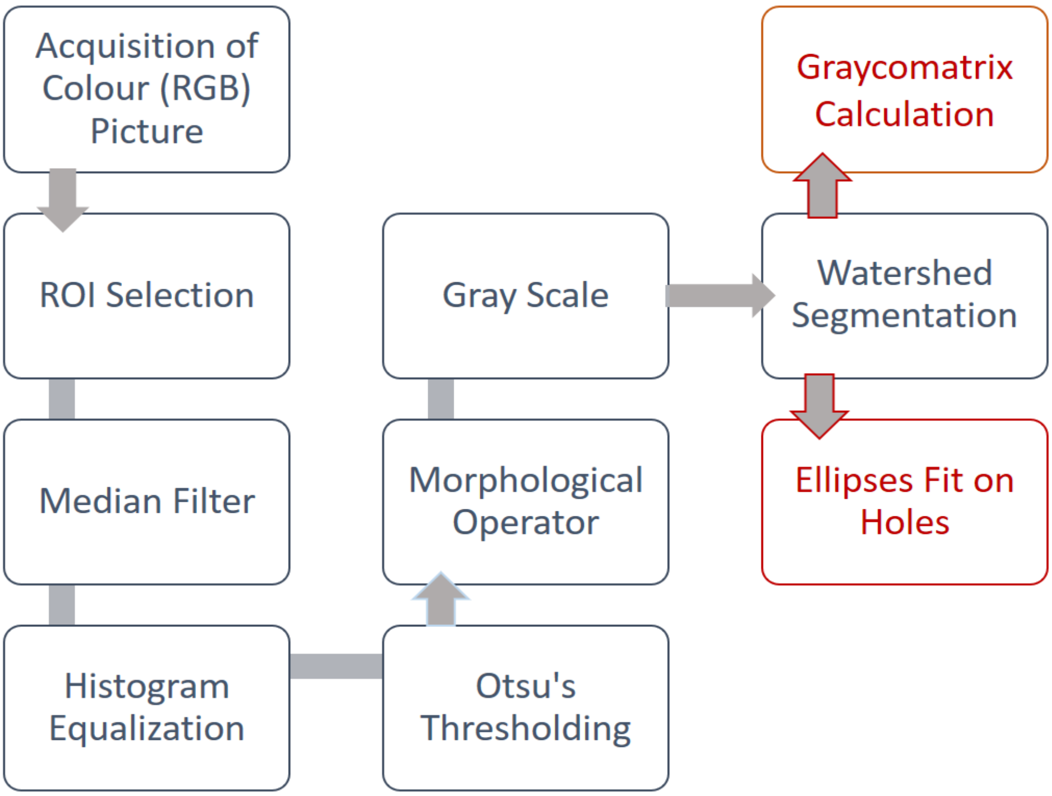

Fig. 5. The overall sequence of digital image processing algorithms used for GLCM parameters extraction of *pogácsa*

After acquisition the *pogácsa* images, the region of interest, i.e. the crumb region, was selected as the bounding box of the *pogácsa* samples. Selection of the region of interest in *pogácsa* images is shown in Fig. 6.

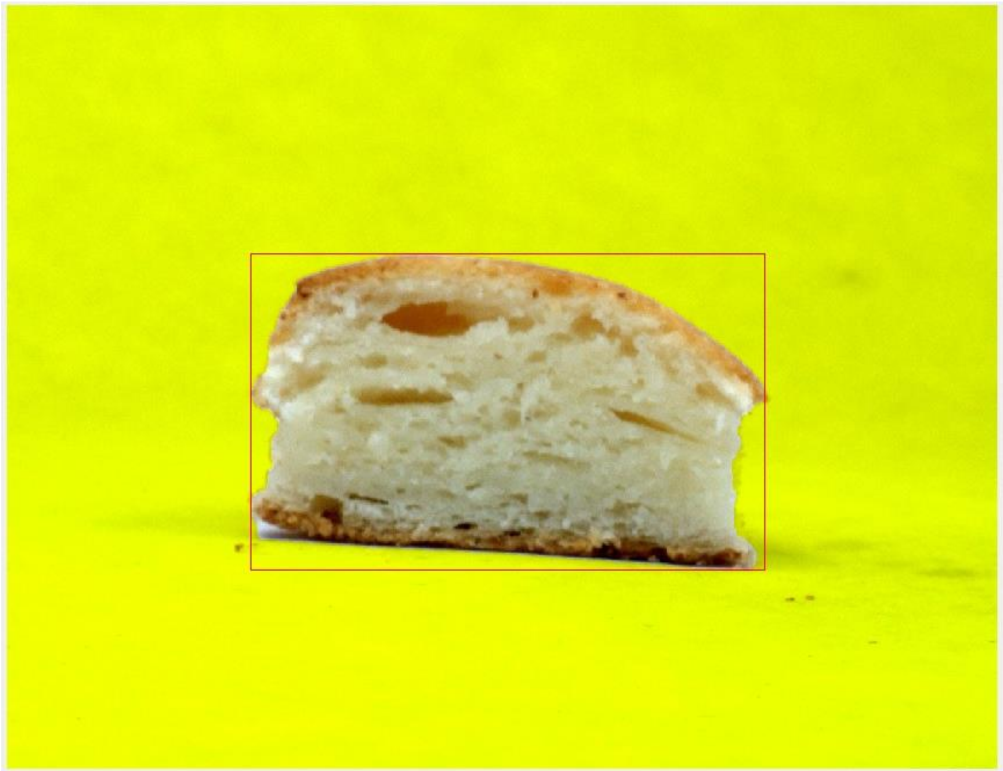

Fig. 6. The region of interest obtained in *pogácsa* images

There is a significant interaction (positive correlation) between the relative fineness of cellular structure and its overall reflectance that can adversely affect the accuracy of image segmentation (Sapirstein 1999). If the effects of this correlation, i.e. the brightness variations in the crumb image, are not controlled before image segmentation, then inaccurate crumb data are computed leading to wrong conclusions in the analysis of bread crumb features (Peri et al. 2003; Gonzalez and Woods 1993). Also, coloured ingredients poorly distributed in the *pogácsa* dough such as cheese, cause brightness variations in the *pogácsa* crumb image. To eliminate the pixel errors in the region of interest a processing algorithm was developed, which includes performing median filter to remove salt and pepper noises. Histogram-based equalization (adaptive histogram equalization) was also performed to increase the contrast. This step could significantly improve the efficiency and accuracy of finding pores in *pogácsa* images as the lightening inside of the samples and pores was non-homogenous. Fig. 7 shown the modified image of the internal structure of the *pogácsa* based on the aforementioned algorithms.

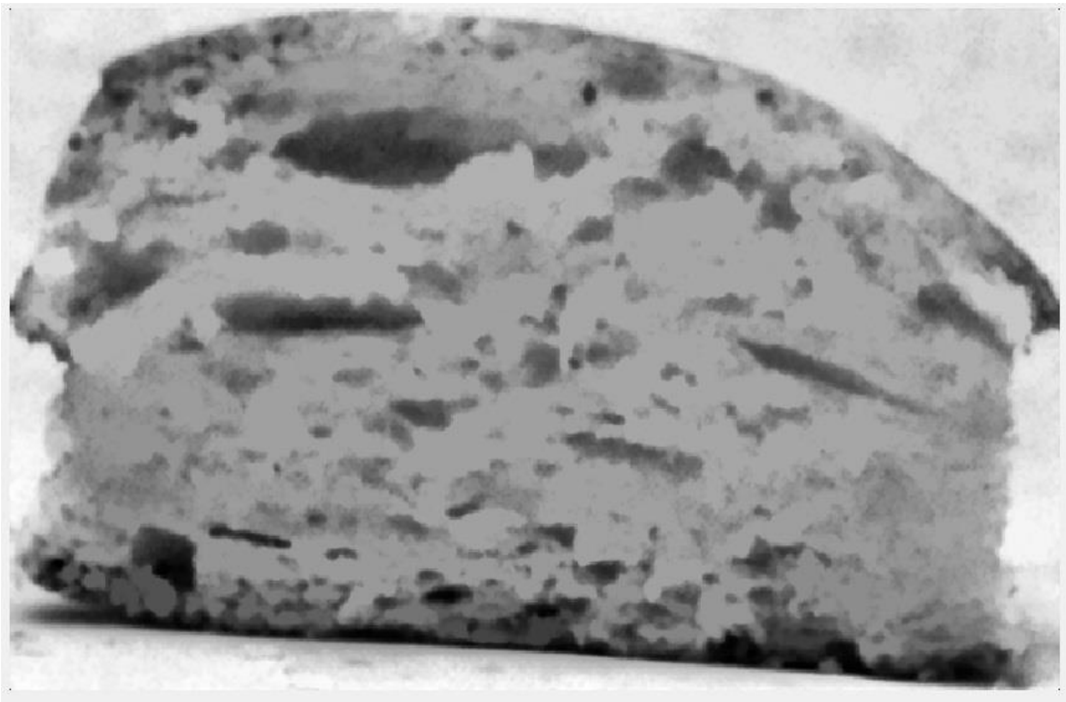

Fig. 7. Modified image of *pogácsa* sample, using developed image processing algorithms

Otsu's thresholding algorithm was used to remove background pixels. In the next step, a morphological operator of opening and closing (3*3 pixel size) was applied to correct the segmentation errors and remove irrelevant light artefacts in pores. All small areas, which were not connected to the image border, were also removed using the morphological operation algorithm. Colour image was then transformed to gray scale.

Afterwards, extraction algorithm was applied to compute the hills (pores) in the images. So far, several extraction techniques have been developed. Maximal inscribed sphere, skeletonizing and thinning, and watershed segmentation methods are some examples of these extraction methods. Most algorithms segment pores in the thresholding method, which is sensitive to illumination. Therefore, to separate and identify individual pores in the images we developed algorithms based on the watershed method as illustrated in Fig. 8. This segmentation method has many advantages as compared to other methods. For instance, applicable for surface texture analysis, high applicability for most segmentation problems, the possibility of closed contours production, which can be helpful for follow-on processing operations, such as pattern recognition (Lou et al. 2020). This algorithm simulates flooding from the markers. By setting watershed ridge lines where the simulated flood areas from different markers meet, regional maxima of the Euclidean distance map can be identified.

The gray-level co-occurrence matrix (GLCM) was calculated and analysed through the graycomatrix function in MATLAB by computing the second-order joint conditional probability functions of pixel intensity. Two pixels with gray-levels i and j co-occur in the image can be separated by a distance δ in a given direction θ. If the intensity of an image is flat (i.e., included no texture), the GLCM result would be entirely diagonal. With increasing the image texture (i.e., increasing the variations of local pixel intensity), the off-diagonal values in GLCM will also increase. Different values of δ and θ can be calculated using GLCM through counting the number of co-occurrences of pixels with gray values i and j at a given distance of 10 pixels and orientation angles of 0°, 45°, 90°, and 135° (Haralick, Shanmugam, and Dinstein 1973).

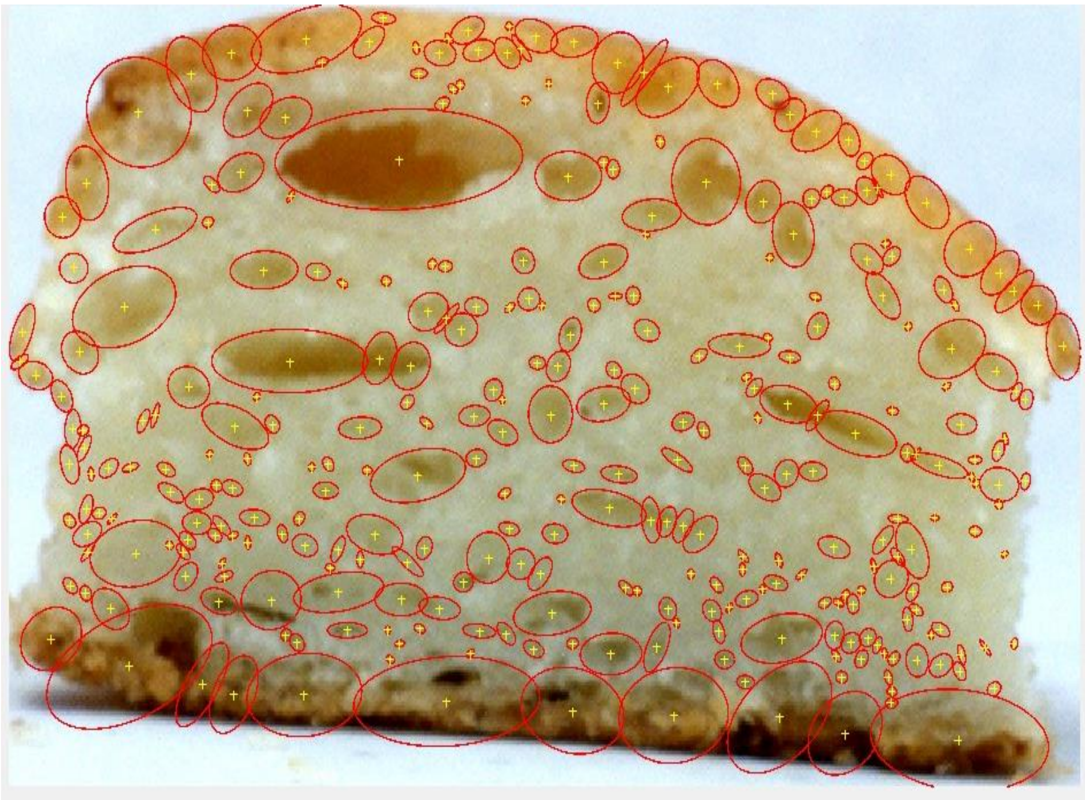

Fig. 8. Pore segmentation in *pogácsa* images, using developed algorithm

Ellipses were fit on holes and the following descriptors were finally calculated and used for subsequent analyses (Fig. 9): object size (px), number of pores, mean size of pores (px), standard deviation of pore size (px), and estimated pore ratio, which shows the frequency of pores with different sizes in the sample. Extracted advanced pattern features of GLCM were also included of the entropy (a measure of randomness which can characterize an image texture), contrast (a local grey level variation in the GLCM), correlation (explain how a pixel is correlated to its neighbour of the image), energy (estimate the orderliness or texture uniformity of the image), and homogeneity (the uniformity of the non-zero entries in the grey level co-occurrence matrix).

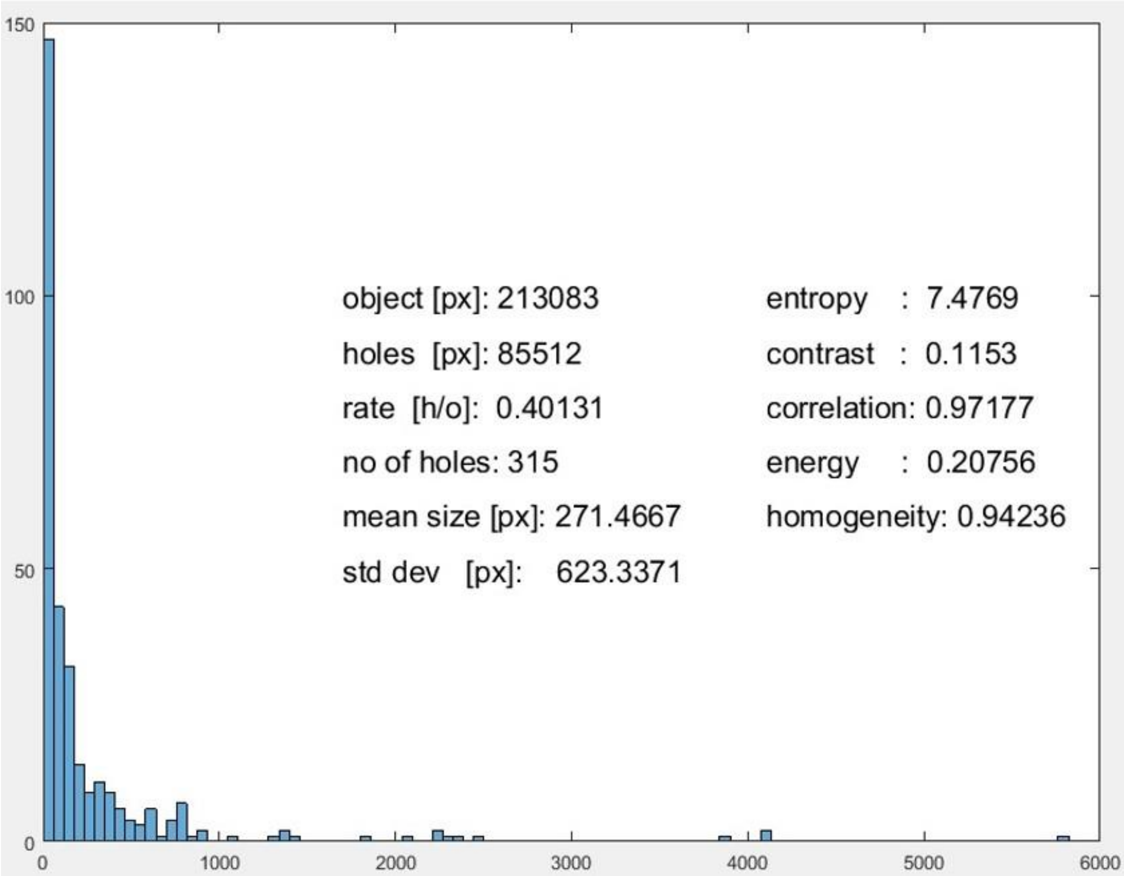

Fig. 9. Generated results of the image processing algorithms

3.3.2.2. Pores characteristics evaluation for the experiment 1 & 2

The analysis of the internal structure and pore characteristics of the *pogácsa* samples involved the examination of 60 samples in each experiment, with 10 replicates for each designated group, resulting in a total of 120 samples for both experiments. This analysis was performed using Fiji ImageJ software (National Institutes of Health, USA), as illustrated in Fig. 10.

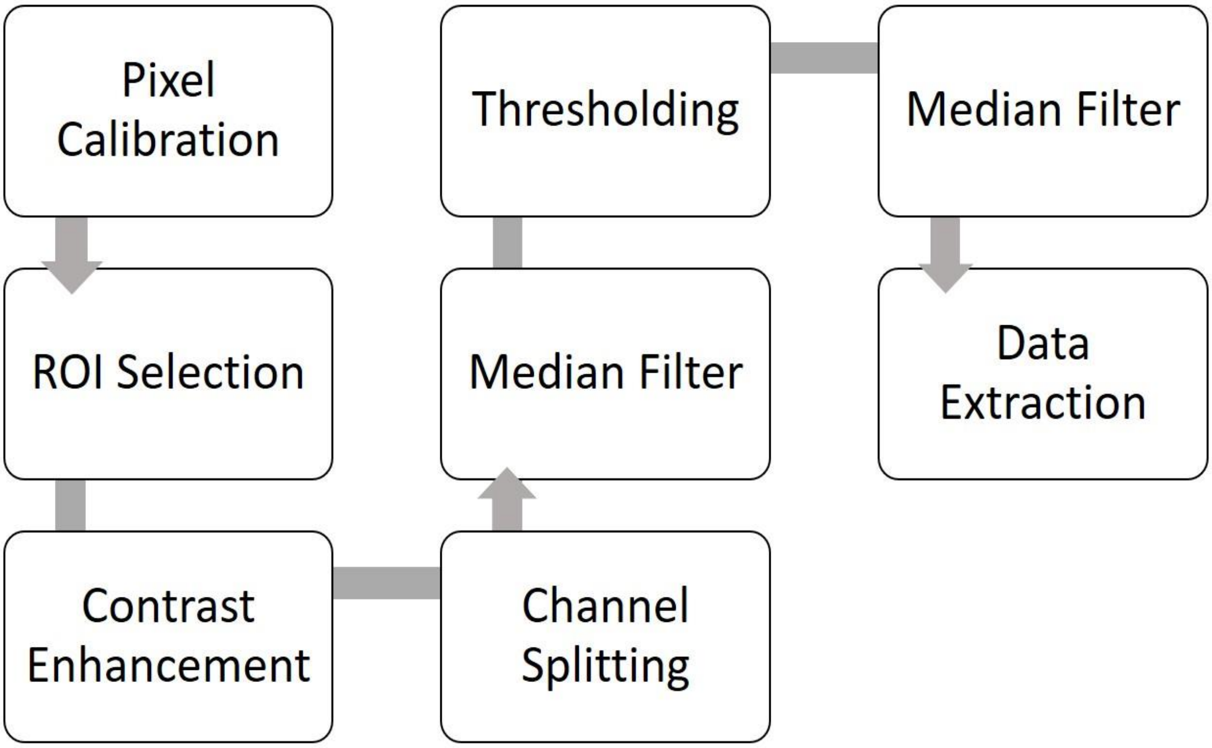

Fig. 10. The overall sequence of Fiji ImageJ algorithms used for pore characteristics evaluation of *pogácsa*.

First, in order to scale a picture to the metric units, the calibration of pixels was performed using a known dimension slide as a reference material. Image calibration gives a pixel-to-real-distance conversion factor (i.e., pixels/cm, calibration factor). This data can be utilized to convert pixel measurements of the image to their equivalent values in the real world. The calibration data can be modified or defined during the analysis. Calibration of pixels was carried out in ImageJ software, as shown in Fig. 11.

A line, which correspond to a known distance was selected using straight line selection tool. Then the scale was set though the “Set Scale” dialog in “Analyze” tool. The known distance and unit of measurement were entered in the “Set Scale” dialog. Based on the length of the selected line, ImageJ could automatically filled in the “Distance in Pixels” field.

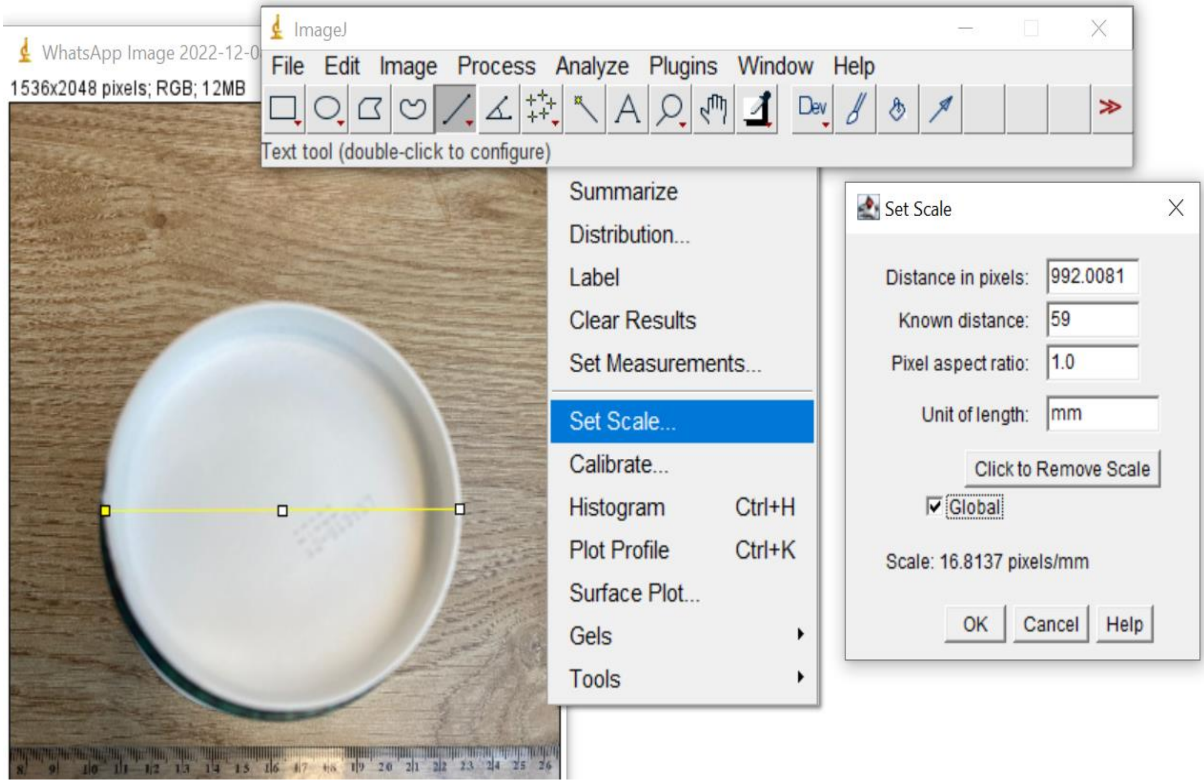

Fig. 11. Calibration of pixels in ImageJ software, using a known dimension slide

Next, the region of interest (ROI) was selected and cropped from the background. There are three different types of area selections including rectangular, polygon, and Composite. In this study ROIs were selected using the rectangular tool in the toolbar.

Image contrast was enhanced to improve the cropped image quality. There are several options to enhance the contrast through the ImageJ software such as using the "Enhance Contrast" command from the "Process" toolbar. In this study, contrast of the image was improved using the "Adjust" comment from the "Image" menu. The adjusting process was done manually as shown in Fig. 12.

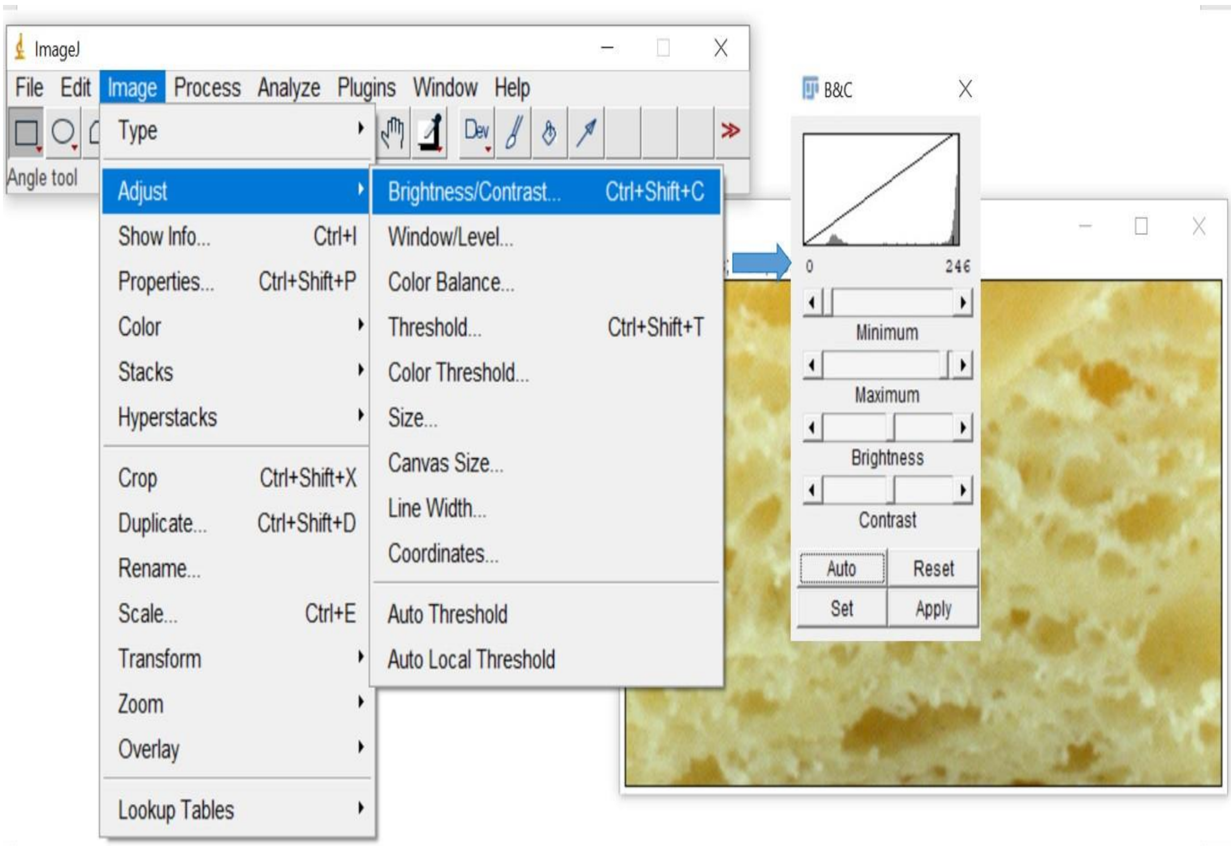

Fig. 12. Steps of image contrast enhancement process in ImageJ software

Afterwards, the images were split to three channels of red, green, and blue through the "Image", "Colour", and "Split Channels" menu entry (This was a prerequisite stage of the thresholding since the auto threshold plugin processes the full greyscale space). For further processes, blue channel of 8-bit images were selected as this channel emphasized more on pores structure. Due to the presence of numerous noises in the images captured by digital cameras, a median filter was applied in neighbourhood pixels of 1.5 to remove salt and pepper noises. This filter helps to decrease noises in the image through replacing the values of each pixel with the median of the neighbouring pixel. The steps of applying the median filter is illustrated in Fig. 13.

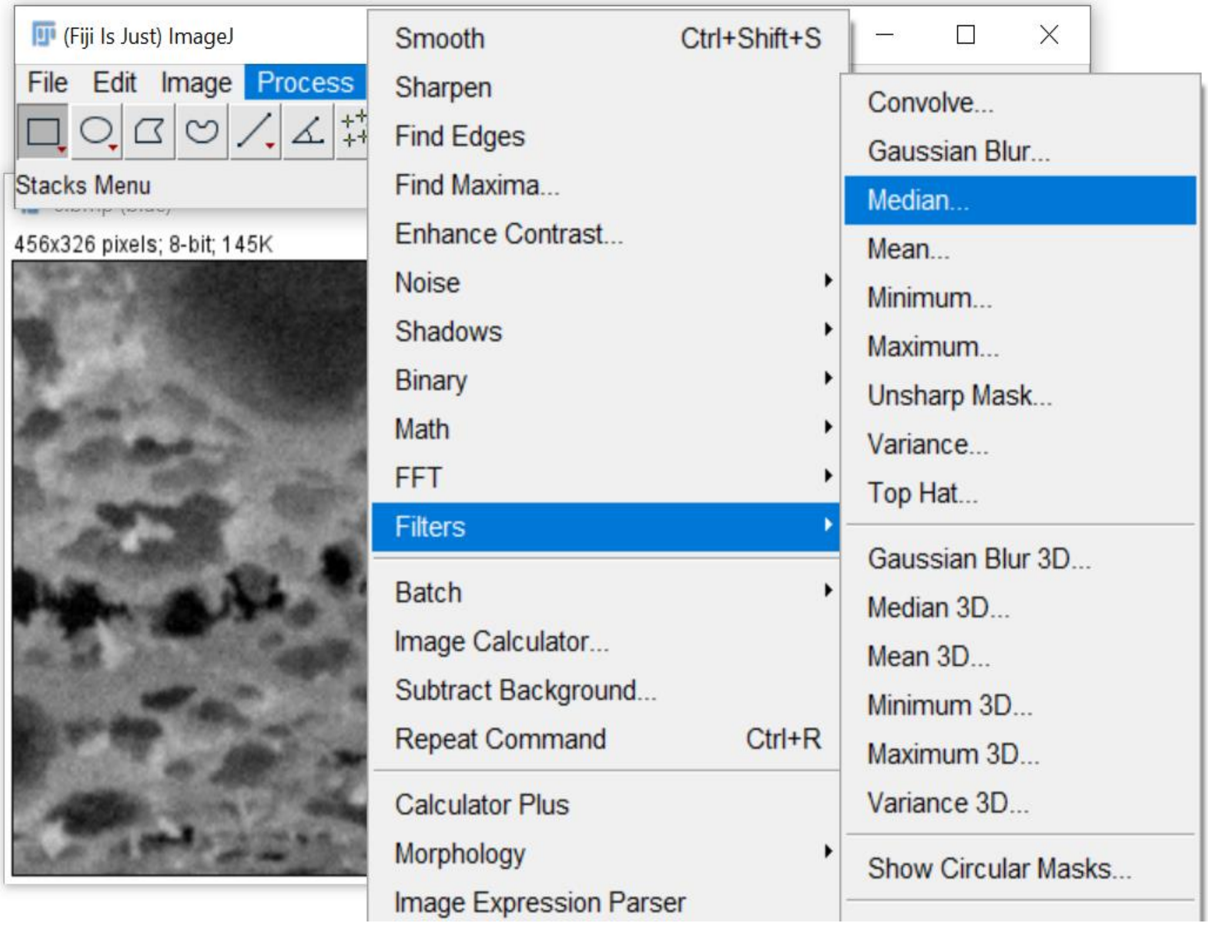

Fig. 13. The steps of applying the "median" filter

Next, threshold process of images was conducted to make the feature of interest evident. To select the best segment method, first "Try all" option was selected in one image through the following path way: Image > Adjust > Auto Threshold > Try all. This produces a montage with results from all the methods allows to explore how the different algorithms perform on a particular image or stack. All methods were including Default, Huang, Huang2, Intermodes, IsoData, Li, MaxEntropy, Mean, MeanError(I), Minimum, Moments, Otsu, Percentile, RenyiEntropy, Shanbhag, Triangle, and Yen (Fig. 14). Besides the montage of the all threshold algorithms, it's also possible to evaluate the threshold values of the all predefined algorithms by selecting the "show threshold values in log window" in the same dialog box. The processing steps of computing all thresholds are shown in Fig. 15.

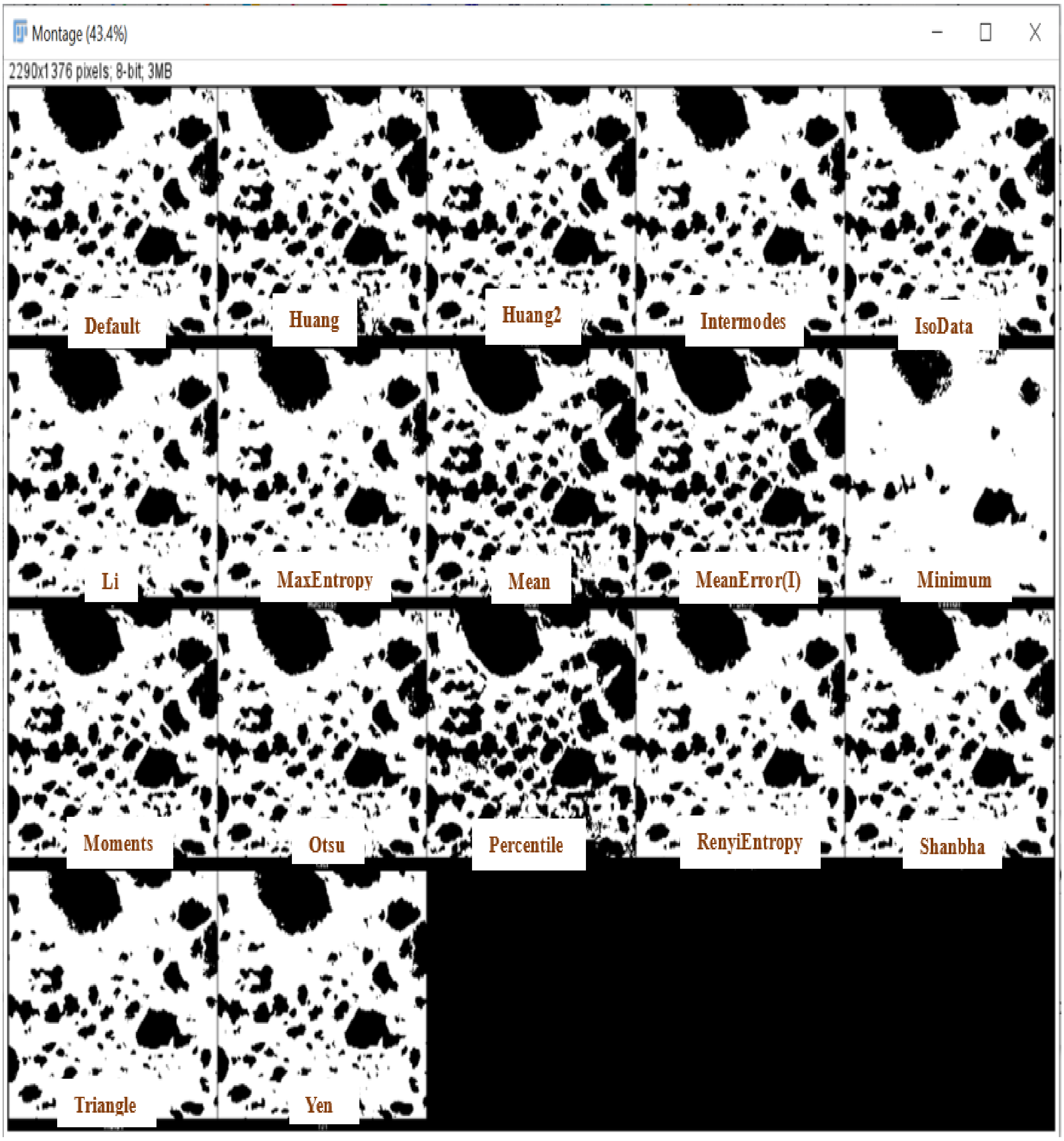

Fig. 14. Montage of all the threshold algorithms

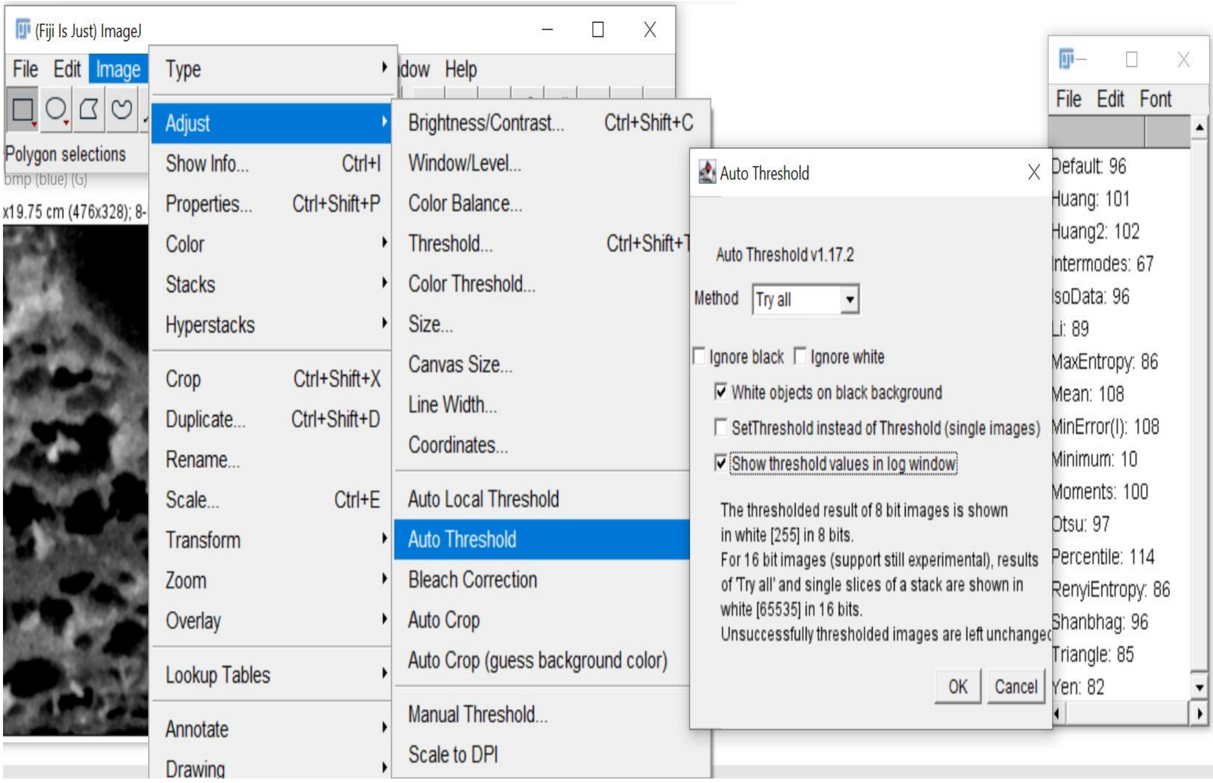

Fig. 15. Pass way of thresholding process in ImageJ software

After evaluating the results of the all threshold methods, a predefined algorithm "Otsu" was selected due to the minimum intra-class variance between the foreground and background pixels of this algorithm. Otsu is a threshold clustering algorithm, which define as a weighted sum of variances of the two classes (Otsu 1979). Aforementioned algorithm was applied on de-noised images using following pass way: Image> Adjust> Auto Threshold> Method> Otsu. The "Median" filter was again applied the same way as it explained before, to remove possible noises raised during the colour conversion step. Image processing steps to evaluate the pore structure in *pogácsa* are shown in Fig. 16.

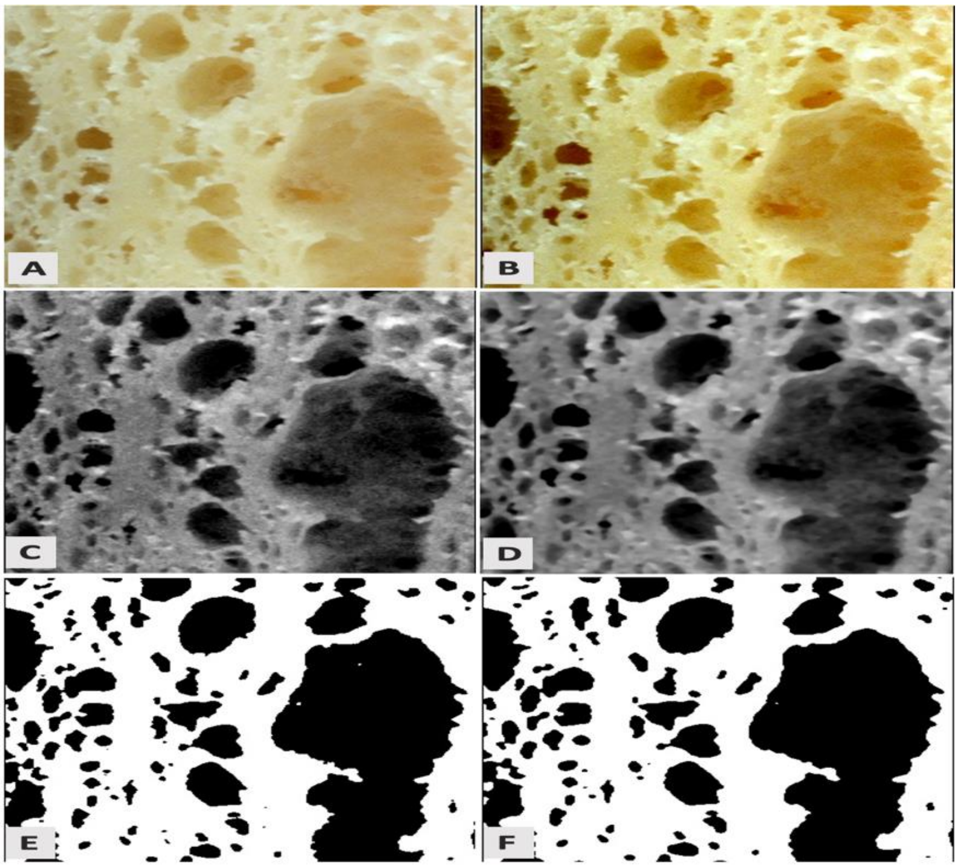

Fig. 16. Set of the processed images for measuring pores characteristics: (A) Original; (B) Contrast enhanced; (C) Channel split; (D) Noise removed; (E) Thresholded; (F) Noise removed

Parameters of area of pores (mm^2) and pore size (mm) were first selected through the "set measurement" in "Analyze" menu. Aforementioned parameters were then extracted using "Measure" comment from the "Analyze" menu.

The pore volumetric index (PVI) (%) was determined using a methodology that involved the application of equations. For spherical pores, the pore volume calculates using equation (5), which calculates the volume of a sphere based on its radius:

$$\text{Estimated pore volume} = area^{\frac{3}{2}} \qquad \text{Eq. (5)}$$

However, as the *pogácsa* pores are non-spherical, the volume of the sample was estimated by calculating the volume based on the surface area of the sphere pores. For this purpose the height and diameter of the all the baked *pogácsa* samples were measured using a digital calliper (General Tools & Instruments, New York, N.Y., U.S.A.). *Pogácsa* volume were then calculated using equation (6):

$$Sample \text{ volume } (mm^3) = \frac{1}{4}\,\pi h d^2 \qquad \text{Eq. (6)}$$

In which h and d are the height and diameter of the sample, respectively.

The PVI was then obtained by dividing the pore volume by the volume of the sample, as shown in equation (7):

$$\text{PVI } (\%) = \left(\frac{pore\ volume}{sample\ volume}\right) X\ 100 \qquad \text{Eq. (7)}$$

3.4. Evaluation of physical and textural properties

Pogácsa mass was recorded by a digital balance (0.001 g accuracy). The volume of 120 samples (10 replicates for each designated group in each experiment) was determined following the method explained in the previous section.

A chromameter (Minolta CR-310, Apeldoorn, Netherlands) was used to measure L* a* b* colorimetric parameters of the crust surface colour and crumb colour of 18 *pogácsa* samples (3 replicates for each *pogácsa* group). For this purpose, the colorimeter was first calibrated by a white tile. The crumb and crust of the samples were seperated, and the CIE L*, a*, b* values of each part were measured using the device (Bolin and Huxsoll 1991). Measurements were performed at room temperature.

The MC of 120 *pogácsa* samples (10 replicates for each designated group in each experiment) was estimated in both experiment by a proportion of the weight loss after drying in oven (WEC310, Whirlpool, USA). The primary weights of *pogácsa* were measured with pre-weighed aluminium pans, and samples were dried in an oven at 105°C until constant weight. The weight of dried samples was measured with the aluminium pans, and the percentage loss in MC was measured with the following equation (AACC 1995) (Eq. 9):

$$MC\ (\%) = \frac{W_2 - W_3}{W_2 - W_1} \times 100 \qquad \text{Eq. (9)}$$

W_1, W_2, and W_3 were referred to the weight of the dry aluminium pan, wet sample and the dry aluminium pan, and the weight of the dry sample and the dry aluminium pan, respectively.

The porosity in 120 samples of *pogácsa* was examined, comprising 10 replicates for each sample group in both experiments. Porosity assessment utilized a well-established method originally designed for bread analysis, as detailed in the work of Lásztity and Törley, serving as the reference standard (Lásztity and Törley 1980). The primary objective was to develop a predictive model for determining the absolute density (AD) of *pogácsa* at varying MC levels. This goal was achieved through the construction of a regression model, utilizing a dataset associating MC and AD values specifically tailored to bread. Among the candidate equations, following empirical equation (Eq. 10) was selected due to its notably high determination coefficient (R^2 = 0.990) obtained from the regression model. Subsequently, the application of this chosen equation demonstrated its effectiveness in accurately estimating the AD of *pogácsa* samples under diverse MC conditions.

$$AD\ (\frac{gr}{cm^3}) = (7.937 \times 10^{-5} \times xMC^2) - 0.012 \times MC + 1.637 \qquad \text{Eq. (10)}$$

Subsequently, the porosity of the samples was estimated by utilizing Equation 11, which incorporated the initial weight of the product (W_0), the predicted AD, and the sample volume (V).

$$Porosity\ (\%) = (1 - \frac{W_0}{AD \times V}) \times 100 \qquad \text{Eq. (11)}$$

3.5. Mechanical texture analysis

Texture measurements are based on rheological properties or stress-strain relationships. Texture instruments have been categorized as measuring force, time, energy, and distance. They may also estimate ratios of these variables or measure in multiple units (Trinh and Glasgow 2012). In the current study, a texture analyser (model TA-XT2i, Stable Microsystems, Surrey, UK) was used to determine the mechanical properties of *pogácsa* samples. The texture analyser machine was equipped with a 25 mm diameter cylindrical probe. The crust of the *pogácsa* sample was removed and the remained part (4 cm diameter × 2 cm height) was axially placed on the platform. A two-cycle compression test was performed up to 40% compression at a speed of 0.5 mm/s. The instrument settings were defined as: test speed: 0.5 mm/s; pre-test speed: 10.0 mm/s; post-test speed: 0. 5 mm/s; trigger type: auto; trigger force: 2.0 g. Force-time curves were plotted, and the following parameters were calculated using the Exponent software (version 6.1.16.0, Stable Microsystems, London, UK): hardness (maximum force of the first compression), cohesiveness (divided force ratio of the second and the first compression), gumminess (multiplication of hardness by cohesiveness), resilience (divided the first compression upstroke area by its down stroke area), springiness (the ratio between the distances of maximum force during the second and first compression), and chewiness (multiplication of gumminess by springiness). The mechanical texture test was conducted 12 times for each assigned group, resulting in 72 samples for each experiment and a total of 144 samples across both experiments.

3.6. Sensory evaluation

The sensory evaluation was performed on 90 *pogácsa* samples in each experiment (15 replicates for each designated group and 180 samples in both experiments). 15 trained panellists (7 female, 8 male; aged between 22 and 45 years) in the Hungarian University of Agriculture and Life Sciences (Budapest, Hungary). Assessors were well-familiar with the sensorial attributes of the *pogácsa* product. The evaluation was done under similar illumination conditions at room temperature according to ISO 8589 (ISO 8589:2007). *Pogácsa* samples were freshly prepared for panellists, and they were asked to complete questionnaires by scoring on taste, colour, aroma/odour, oiliness, chewiness, hardness, elasticity, pores structure, and overall crumb structure of more or less crumbliness. Samples were evaluated using a 5-point scale, "Just About Right" (JAR), where categories 1, 2 belong to "not enough" levels, 3 = JAR, and 4, 5 expresses "too much" levels. Assessors were also asked to evaluate the product's **overall liking (OL)** on a 9-point hedonic scale, where one presents "extremely dislike" and nine expresses "extremely like" of the *pogácsa*. This sensorial evaluation allows to demonstrate all the possible ways to increase the OL of the product. Penalty analysis, which shows the main reasons of the products rejections, was used to statically analyse the JAR data. Mean drops (penalties) were calculated as the differences between means of the JAR and the mean of two categories of non-JAR, and consequently, to determine which sensory attributes differentiate the *pogácsa* (Bagdi et al. 2016; Iserliyska, Dzhivoderova, and Nikovska 2017).

3.7. Statistical analyses

All statistical analyses were performed using IBM SPSS statistics software (version 29.01.0 Inc., Chicago, USA). The Analysis of variance (ANOVA) was applied to the obtained data and Duncan's multiple range test was performed to detect the differences among means at the significance level of $\alpha=0.05$. A completely randomized design (CRD) was applied for data collocation. Factorial design was also used to assess the main effect for each independent variable of time and temperature of proofing and baking. Two-way ANOVA was applied to evaluate the impact of two distinct independent variables on the structural attributes of *pogácsa* samples and overall liking. Specifically, in experiment one, the independent variables of baking time and baking temperature and combination were analysed, while in experiment two, the independent variables of baking temperature and formulation and combination were evaluated. The statistical test was performed at a 5% significance level. The correlation coefficients (R) between images data and mechanical parameters were obtained with the help of Pearson correlation test. In order to investigate the relationship between imaging parameters and porosity of the product, the regression equations also build using SPSS and the best selected based on the R^2 value. The penalty analysis of sensory data was carried out using XLSTAT software (version 2020.5, Addinsoft, New York, USA).

CHAPTER 4: RESULTS & DISCUSSION

4.1. Results of the experiment 1

4.1.1. Results of the PVI evaluation

The PVI, which is an expression that characterizes the volume of pores in the measured area, can influence the texture, flavour, and overall quality of the baked goods. In this context, the variation in PVI is depicted in Fig. 17. Sample C had the highest PVI value (24.26%), followed by samples B (21.34%), D (21.28%), E (20.35%), and A (19.73%). The lowest PVI was found for sample F (baked at 230°C for 7 min) with a value of 12.81. As it can be interpreted from the Fig. 17, temperature and duration of baking are crucial factors that affect the PVI of the *pogácsa*. The temperature of 215°C and shorter baking time (5 min) resulted in the highest PVI value (sample C), while the longer baking time (7 min) and higher temperature (230°C) resulted in lower PVI values (sample F).

The difference in the PVI values could be also ascribed to the increased yeast activity, which causes a larger production of CO_2 in the dough when exposed to the higher temperature. However, other factors might cause changes in the PVI of *pogácsa* samples such as fast water evaporation during the baking and low gas diffusion rate in the dough, which resulted in gas expansion during the baking (Chiotellis and Campbell 2003). Fig. 18 shows the pore structure of *pogácsa* samples under different baking conditions. It was observed that the crumb structure was noticeably varied by changing the time and temperature. In align with the result of the present study, Ćurić et al. (2008) reported that increase in the baking time (from 25 to 30 min) could significantly affect the porosity of the bread. In this context, they also commented that longer baking time might increasingly influence the crust hardness and specific volume (Ćurić et al. 2008). In another study Kumari et al. (2015) examined the impact of baking conditions on the crumb grain characteristics of an Indian baked good. They reported higher temperatures and shorter baking times tend to produce a softer and more porous texture, while lower temperatures and longer baking times result in a denser texture with fewer pores (Kumari et al. 2015). This information can be useful for manufacturers in optimizing the baking conditions for *pogácsa* production to achieve the desired texture and quality.

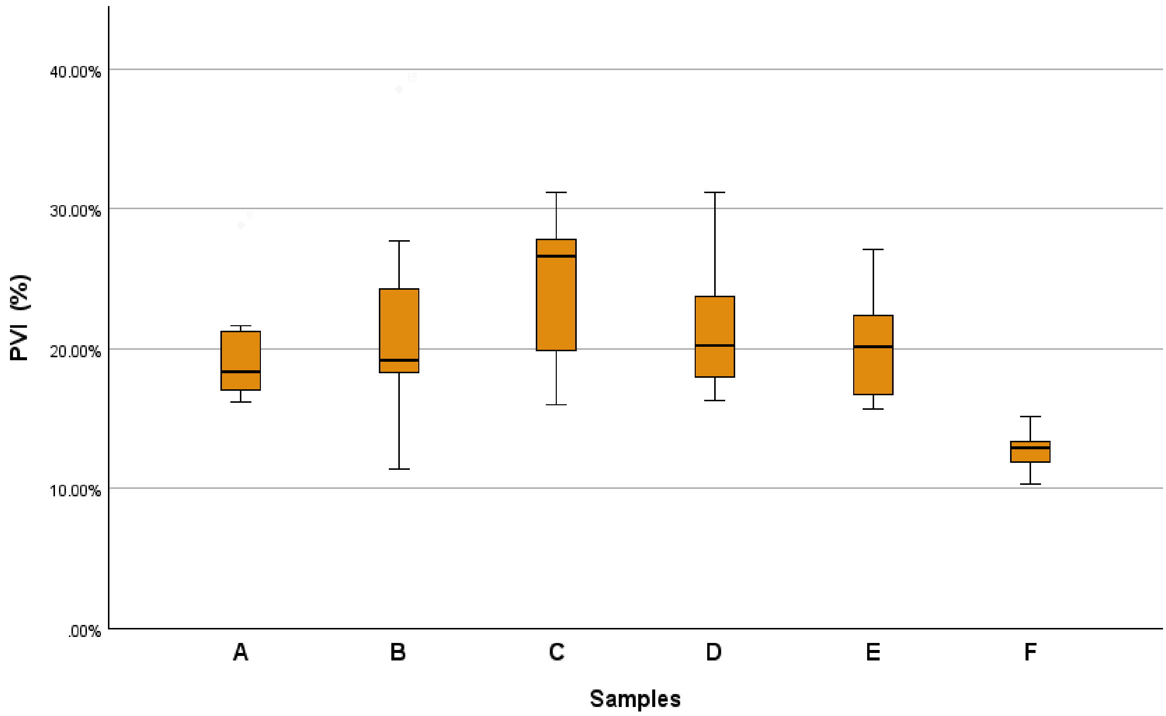

Fig. 17. Results of the calculated PVI of the *pogácsa* groups. A: 200°C, 5 min; B: 200°C, 7 min; C: 215°C, 5 min; D: 215°C, 7 min; E: 230°C, 5 min; F: 230°C, 7 min

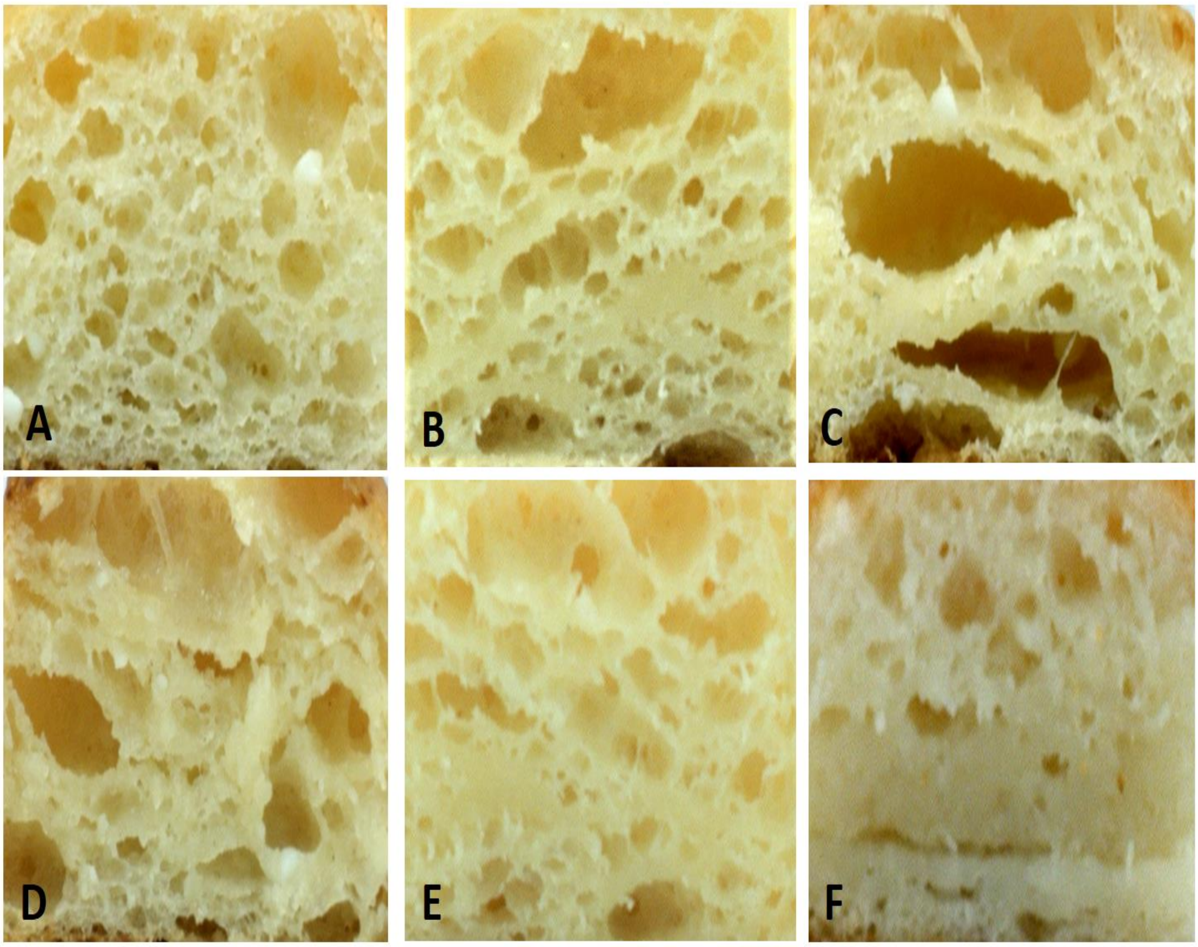

Fig. 18. *Pogácsa* crumb samples showing different pore structure characteristics. A: 200°C, 5 min; B: 200°C, 7 min; C: 215°C, 5 min; D: 215°C, 7 min; E: 230°C, 5 min; F: 230°C, 7 min

4.1.2. Results of changes in physical and textural properties of *pogácsa* due to variation in baking time and temperature

Textural parameters of baked *pogácsa* highly depend on processing variables, particularly temperature and time. The results of TPA analyses are detailed in Fig. 19. Changes in hardness, springiness, gumminess, cohesiveness, and chewiness in *pogácsa* were linked to time and temperature. With increasing these two baking variables, the hardness was drastically increased. While, in case of cohesiveness, gumminess, chewiness, and springiness, both increasing and decreasing trends were observed as the consequence of change in temperature and time treatments.

However, no noticeable change (except for sample F) was recorded in adhesiveness when different time and temperature settings were applied. This might imply that bakery products are not generally adhesive. Samples D (baking at 215°C for 7 min) and E (baking at 230°C for 5 min) showed the highest and lowest values of cohesiveness, respectively. By increasing temperature (at any baking time), gumminess was monotonically increased. Additionally, a monotonically increasing pattern in gumminess was observed as the baking time was extended from 5 to 7 minutes at any baking temperature. Therefore, sample F with the highest temperature and time demonstrated the maximum gumminess, whereas sample A, which was baked under the lowest temperature and time, had the minimum gumminess. Chewiness, which depends on springiness and gumminess, showed the same tendency as gumminess; monotonically increased by both increasing the temperature at any baking time and increasing the baking time at any baking temperature. Since *pogácsa* has a gas-filled cellular texture, it can be fractured by mechanical force. Therefore, the present result obtained for hardness might be useful to calculate the required force for breaking the structure. The results of the hardness test showed that maximum baking temperature had the maximum hardness value (sample F). On the other hand, with increasing the hardness of samples, springiness decreased. This implies that increasing baking parameters (time and temperature) may result in a firmer and harder texture. Similarly, Shittu (2007) reported that the crumb hardness of bread was noticeably affected by both baking time and temperature. In addition, they found the time of baking was a primary factor contributing to increase of hardness in bread crumb (Shittu, Raji, and Sanni 2007). Karimi et al. (2012) also found that baking conditions could considerably affect the hardness of the bread. These authors pointed out that increasing the proofing time (from 25 to 45 min) may lead to CO_2 production, which ultimately increases porosity and decrease the hardness (Karimi et al. 2012).

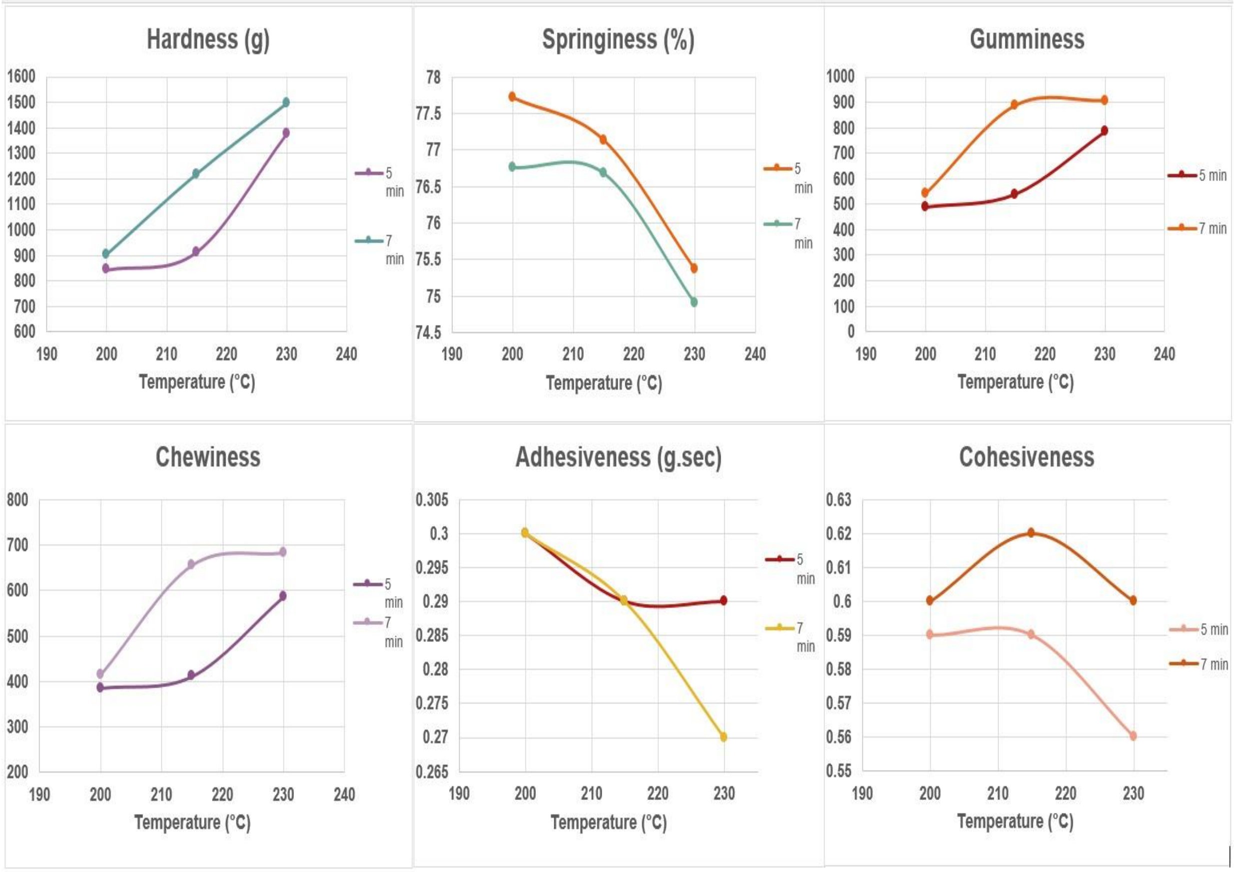

Fig. 19. Changes in textural parameters of hardness (g), springiness (%), gumminess, chewiness, adhesiveness (g.sec), and cohesiveness (%) in *pogácsa* groups.

Table 5 presents a comprehensive overview of the experimental results focusing on crumb MC, volume, and porosity across six distinct groups of *pogácsa* samples. According to the results, Sample A exhibited the highest crumb MC at 41.64%, significantly different from the other samples. As baking time and temperature increased (from A to F), the crumb MC decreased progressively. The lowest crumb MC was observed in sample F (20.4%), which was baked under highest baking time and temperature. The findings suggested that higher baking temperatures and longer baking times result in lower crumb MC, which may lead to a drier texture in the *pogácsa*.

The analysis of volume data displayed in Table 5. Considerable variability was observed among the volume value of different samples ($p < 0.05$). Sample D had the highest volume (29.02 cm^3), significantly greater than the other samples. Samples C, B, and E also had larger volumes compared to samples A and F. Moreover, sample F had the smallest volume (19.64 cm^3). These results indicated that baking at 215°C for 7 minutes (sample D) led to the highest expansion of the *pogácsa*, resulting in a larger volume. In addition, highest baking temperature along with the highest baking time resulted in decreasing the volume values. Decreasing trend in volume value was also observed when lowest time and temperature of baking was used.

Results of the porosity evaluation (Table 5) revealed that samples B, C, and D had almost similar porosity values, with sample B having the highest value (60.77%) among them. Sample F had the lowest porosity value of 51.28% and sample E had the highest porosity value of 61.96%. The porosity results showed that baking conditions significantly affect the pore structure of the *pogácsa*, with higher values indicating a more porous structure and higher porosity. Overall, the results demonstrated that variations in baking temperature and time have a substantial impact on the crumb MC, volume, and porosity of *pogácsa*. Sample F, baked at 230°C for 7 minutes, had the lowest crumb moisture content, volume, and porosity, resulting in a denser and drier product.

Table 5. The mean (± SD) of crumb moisture content (MC), volume, and porosity of the *pogácsa* in the experiment 1*

Sample	Crumb MC (%)	Volume (cm^3)	Porosity (%)
A	41.64 ± 5.85^{d}	21.15 ± 1.32^{b}	58.02 ± 2.98^{b}
B	36.78 ± 5.02^{c}	23.41 ± 0.83^{c}	60.77 ± 3.6^{bc}
C	36.96 ± 1.33^{c}	26.57 ± 1.98^{d}	60.5 ± 3.16^{bc}
D	31.66 ± 4.97^{b}	29.02 ± 1.32^{e}	59.34 ± 3.15^{bc}
E	28.07 ± 4.63^{b}	23.63 ± 1.05^{c}	61.96 ± 2.62^{c}
F	20.4 ± 2.34^{a}	19.64 ± 1.32^{a}	51.28 ± 2.48^{a}

*Means with different superscripts within the same column indicate significant differences ($p < 0.05$). Refer to Table 2 for *pogácsa* cake formulations.

4.1.3. Results of GLCM textural features

Fig. 20 shows the changes in the GLCM textural features in six different groups of *pogácsa.* There were significant variations ($p < 0.05$) among the entropy values of different groups. Sample D showed the highest value (7.74) for entropy, whereas the lowest belonged to group C with a value of 7.48. The difference recorded between the entropy of samples C and D indicated the importance of the baking time, as the same temperature (215°C) was used for both samples. Interestingly, no significant difference ($p > 0.05$) was found amongst other groups (A, B, E, and F) when the time of baking increased from 5 to 7 min. In case of contrast parameter, sample D had the highest value, followed by samples A, and C, while the value for sample F was the least. As indicated in Fig. 20, values for correlation and homogeneity were reported up to three decimals as the third decimal was critical to distinguish the presence of difference(s) among the groups for these particular parameters. This has likewise been reported by (Nouri et al. 2018). Sample F, which was baked with the highest temperature and time (230°C for 7 min), exhibited the maximum levels of correlation and homogeneity. However, due to the existence of slight differences visible, only the third decimal of standard deviations was significantly varied ($p < 0.05$). Nouri et al. made a relatively similar observation for the range of correlation value when they used GLCM features for the textural evaluation of freshly prepared baguette bread. As previously mentioned, the homogeneity of sample F was the highest, implicating that the grey levels of each pixel pair are quite similar in this group. Sample C exhibited the highest value for energy, which was noticeably reduced (from 0.2 to 0.16) when the baking time increased from 5 to 7 min. In contrast, the increasing baking time did not show any marked effect on the energy values of other *pogácsa* samples, which were prepared at 200 and 230°C.

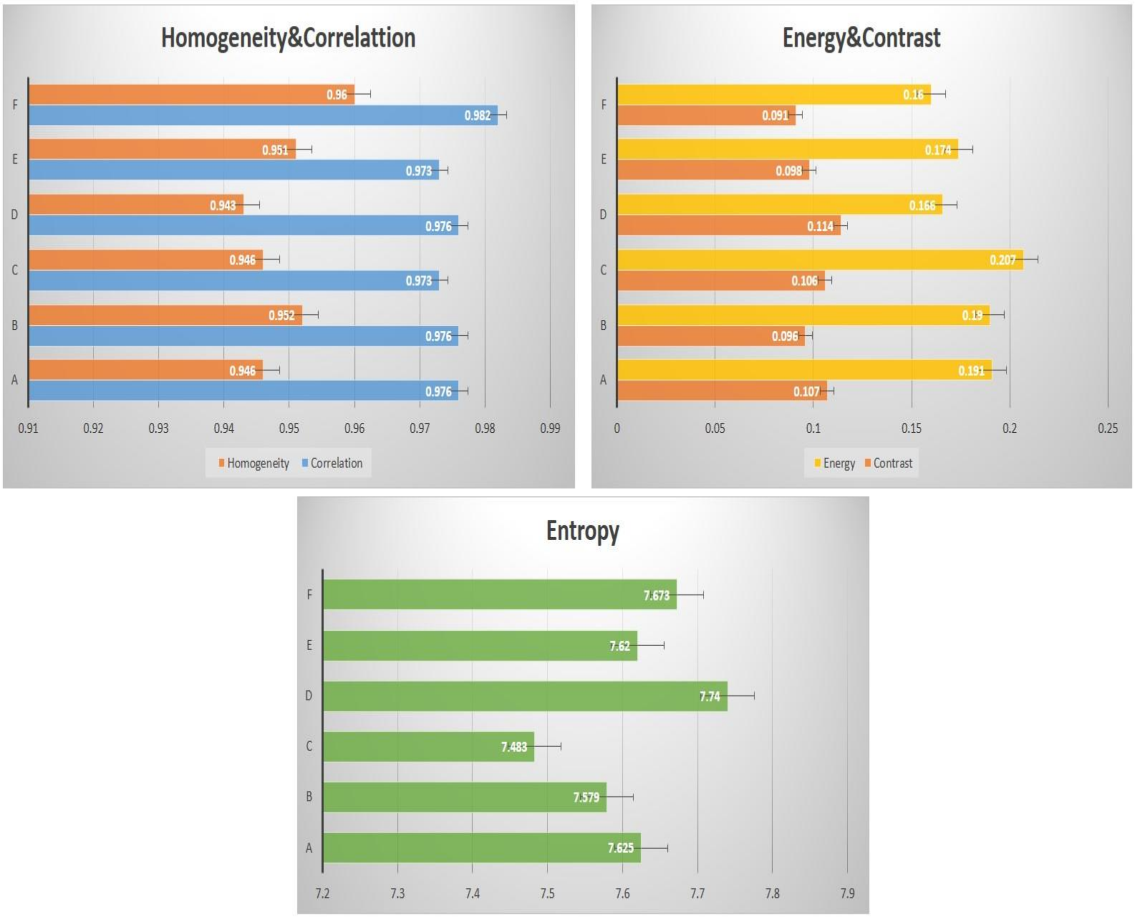

Fig. 20. GLCM features extracted from *pogácsa* images. A: 200°C, 5 min; B: 200°C, 7 min; C: 215°C, 5 min; D: 215°C, 7 min; E: 230°C, 5 min; F: 230°C, 7 min

4.1.4. Results of correlation coefficient among the different parameters

The results of the correlation test between GLCM textural features and instrumental textural parameters are presented in Table 6. The hardness showed strong positive correlation with contrast ($p < 0.01$) and strong negative correlations with both homogeneity and correlation ($p < 0.01$). This may imply that the softer texture of *pogácsa*, the lower contrast and vice versa. Hence, it can be interpreted that the increase in hardness might lead to changes in the visual appearance of *pogácsa* as well as its image textural features (Karimi et al. 2012). Springiness had positive and negative correlations with homogeneity and contrast, respectively. Among all parameters, gumminess exhibited the best correlation coefficients, in particular for contrast, correlation, and homogeneity, having suitable relationship with instrumentally measured texture parameters. While the entropy and energy could be ignored due to non-significant correlation with any parameters. Generally, there were significant correlation coefficients between the GLCM parameters and the TPA data. As can be seen in Table 6, the harder *pogácsa* crumb is associated with higher contrast and lower correlation and homogeneity. In addition, *pogácsa* with higher springy crumb had higher homogeneity but lesser contrast. Among the image textural features, contrast and homogeneity showed the best correlation coefficients with the sensory features. In agreement with our results, Nouri et al. (2018) reported high correlation coefficients between imaging and instrumental textural parameters in stored baguette bread. Their findings revealed that the stale baguette bread with firmer crumb had higher contrast and lower correlation and homogeneity compared to the fresh bread samples (Nouri et al. 2018). In another study, Pieniazek et al. (2017) found noticeable high correlations between textural features of the image and TPA parameters in freeze-dried potatoes. According to their results, cooked freeze-dried rehydrated potato had lower image linearity and higher smoothness values as compared to cooked potato (Pieniazek and Messina 2017).

Table 6. Pearson correlation coefficients between the GLCM texture features and instrumental texture parameters of *pogácsa*

Sensory features	GLCM features				
	Energy	Contrast	Correlation	Homogeneity	Entropy
Hardness	0.214^{ns}	0.495^{**}	-0.431^{**}	-0.494^{**}	0.117^{ns}
Springiness	-0.024^{ns}	-0.307^{*}	0.166^{ns}	0.309^{*}	0.055^{ns}
Gumminess	0.253^{ns}	0.523^{**}	-0.516^{**}	-0.528^{**}	-0.156^{ns}

** p <0.01, * p <0.05. ns: not significant.

4.1.5. Results of the effect of the temperature and time of baking on PVI and overall liking of *pogácsa* cake

A two-way ANOVA was performed to analyse the effect of the baking times and baking temperatures on two different variables of the PVI and overall liking (OL). Results are illustrated in Table 7 as the mean values ± SD. Regarding the PVI, the ANOVA showed that the individual effect of the baking time is statistically significant ($p < 0.05$), while in case of OL, the effect of the baking time is not statistically significant ($p > 0.05$). In particular, Table 7 showed differences in PVI values according to the different baking time (the highest value observed in groups baked for 5 minutes). A decreasing trend in PVI was highlighted in the case of higher baking time (Table 7). Furthermore, in case of baking temperature, the individual effect of the baking temperature was statistically significant for only OL ($p < 0.05$). However, in case of PVI, the effect of the baking temperature was not significant as the *p* value was higher than 0.05. Increasing the baking temperature to 230°C resulted in decreasing the values of both PVI and OL. Moreover, the interaction effect of the baking time and baking temperature was not significant for both of PVI and OL ($p > 0.05$).

Table 7. Comparison of the experimental condition on pore volumetric index (PVI) and overall liking (OL)

Parameter	Baking Time (min)		Baking Temp. (°C)			ANOVA *p* value		
	5	7	200	215	230	Time	Temp.	Time x Temp.
PVI (%)	21.44±0.68	18.48±0.86	20.54±1.06	22.77±1.06	16.58±1.06	0.01	0.24	0.14
OL	8.38±0.24	8.00±0.24	8.30±0.30	8.88±0.30	7.38±0.30	0.27	0.003	0.73

4.1.6. Results of the sensory evaluation

Fig. 21 (A, B, C, D, E, and F) illustrated the results from the sensory evaluation conducted in the first phase of the experiment. Significant differences observed in nine parameters of taste, colour, aroma/odour, oiliness, pore's structure, hardness, chewiness, elasticity, and overall crumb structure among different *pogácsa* groups. Samples C had noticeably higher pore structure whereas the lowest value for pore structure observed in sample A. The oiliness in all the samples, except F, was high. Among all *pogácsa* groups, A and C exhibited the highest value of hardness whereas the lowest belongs to sample B and F.

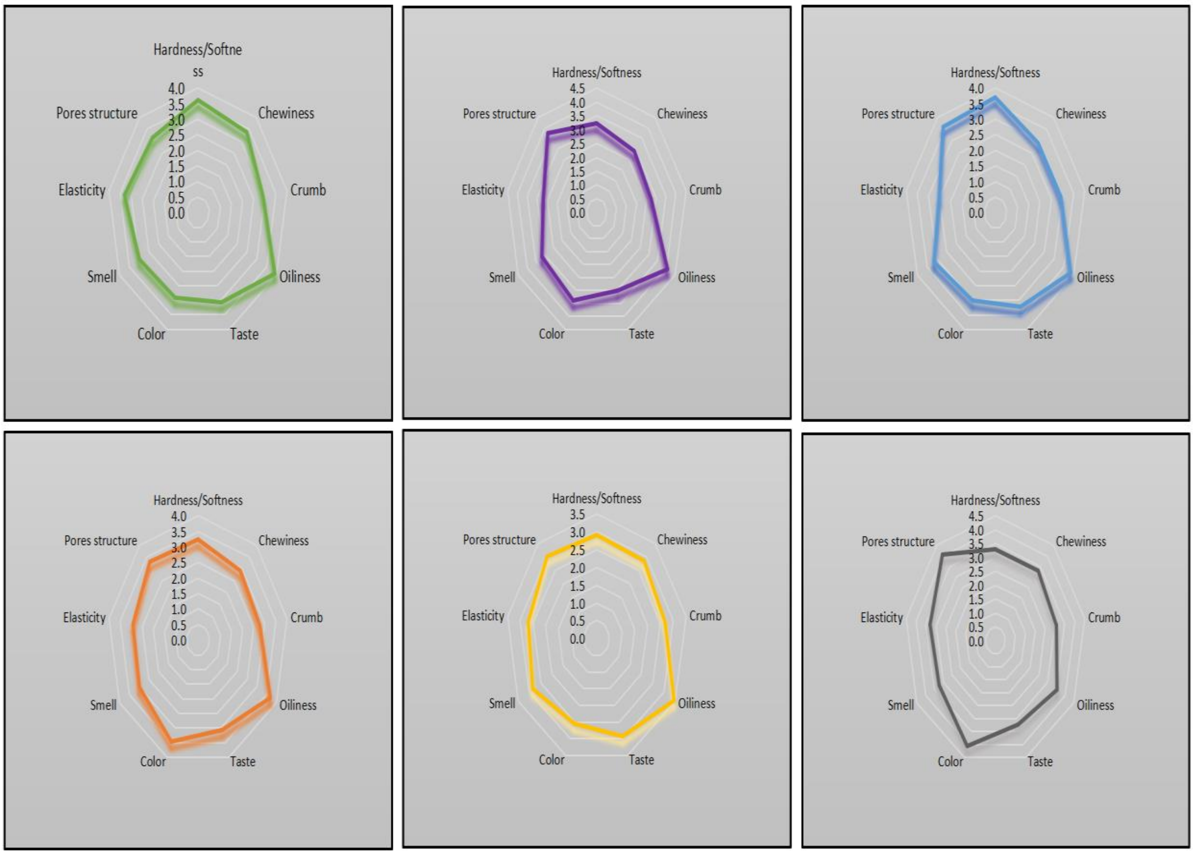

Fig. 21. Average sensory profiles of *pogácsa* cake samples: A: 200°C, 5 min; B: 200°C, 7 min; C: 215°C, 5 min; D: 215°C, 7 min; E: 230°C, 5 min; F: 230°C, 7 min

Penalty analysis is a graphical method to find the feasible penalty arisen by the product, which decreases OL by not being "Just About Right (JAR)" in an attribute ((Bagdi et al. 2016; Iserliyska, Dzhivoderova, and Nikovska 2017). This analysis has been performed in both academia and industry sectors, providing technologists a classified list of critical characteristics of the product, which are most penalizing (Xiong and Meullenet 2006). In the present study, penalty analysis was conducted to describe the non-optimal sensory parameters in different groups of *pogácsa* cakes.

Results of the penalty analysis of *pogácsa* samples are illustrated in Fig. 22, A-F (A: 200°C, 5 min; B: 200°C, 7 min; C: 215°C, 5 min; D: 215°C, 7 min; E: 230°C, 5 min; F: 230°C, 7 min). The plot demonstrates the percentage of consumers against the mean drops. Mean drops indicate the difference between the mean OL for the JAR levels and "too much" or "not enough" rates. Only attributes with the percentage of consumers more than 20% were deemed significant. The main important part of the plot is the upper right subspace, which possesses more than 20% of the panellist's ratings. In sample D, more than 60% of consumers felt that baked product was "too much" oily, and less than half of panellists expressed elasticity as "not enough". Also, the low percentage of panellists (~ 20-30%) found the hardness as "too much" in sample D. The oiliness was considered as "too much" by the most respondents in all six groups of the product. Around 40% of consumers rated colour and pore structure as "too much" in samples A, B, C, E, and F. The values of "percentage of consumers" in sample D were markedly lower than the other five samples (sample D: 80%; A, B, C, E, and F: 100%). This indicated that respondents considered sample D closer to non-optimal compared to the other five groups. Hence, modification in the baking process of the industrial recipe may lead to an increase in the acceptability of the product. In addition, panellists presented that the oiliness of *pogácsa* was "too much" in all six sample groups (sample D was less oily than other groups). Therefore, less oily products would probably have higher acceptability.

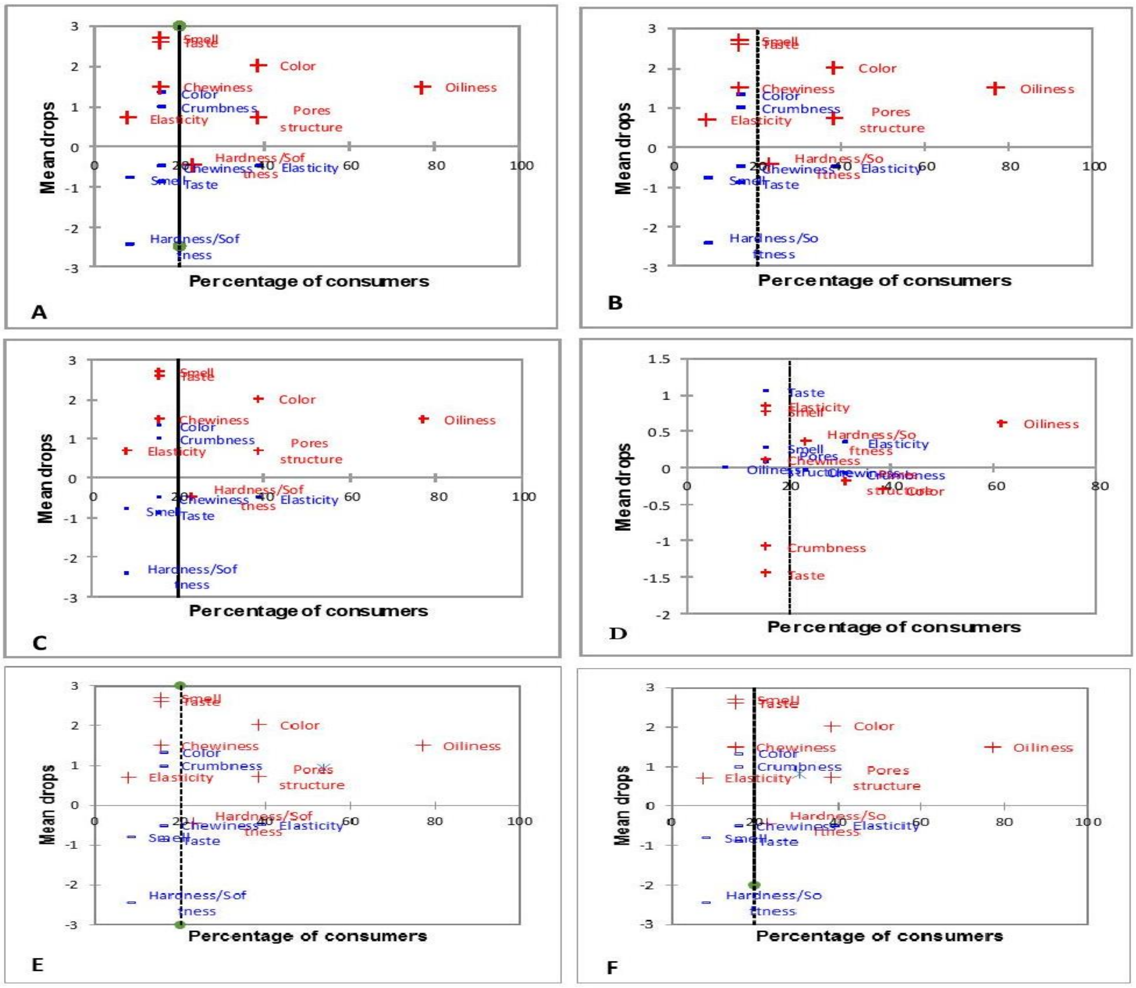

Fig. 22. Mean drop plot of *pogácsa* (capital letters on subplots indicate the sample group). Red colour corresponds to "too much", while the blue colour corresponds to "not enough" endpoints of JAR scale. The dashed line corresponds to 20% of the consumers. A: 200°C, 5 min; B: 200°C, 7 min; C: 215°C, 5 min; D: 215°C, 7 min; E: 230°C, 5 min; F: 230°C, 7 min

4.2. Results of the experiment 2

4.2.1. Results of the PVI evaluation

To study the effect of cottage cheese addition with different MC, and baking temperature on the internal structure of the *pogácsa*, pore characteristics of the PVI was analysed. As depicted in Fig. 23, sample A2 exhibited the highest PVI value (26.64%), followed by samples B2, A1, and B1 with PVI values of 18.52%, 18.43%, 17.33%. Samples A3 (1.57%), and B3 (1.12%) had the lowest PVI. Significant differences were found among the sample groups prepared with cheese (A1, A2, B1, and B2) and cheese-free samples (A3 and B3). Specifically, it was observed that as the MC increased, the PVI also exhibited a concurrent increase in *pogácsa*. Consequently, it can be inferred that the presence of cheese in the samples significantly impacted the PVI, suggesting the importance of the MC in affecting the textural properties of the final product. As evidenced by the highest value of this parameter found in *pogácsa* samples with high moist cheese (65% MC). Higher value of the PVI positively affects the acceptability of *pogácsa* cake. The above observations showed that the lowest values for pore characteristics were achieved with cheese-free samples (A3 and B3), which was accounted in the sensory test as undesirable. Fig. 24 shows the pore structure of *pogácsa* samples formulated with different cottage cheese and baked under different baking temperature.

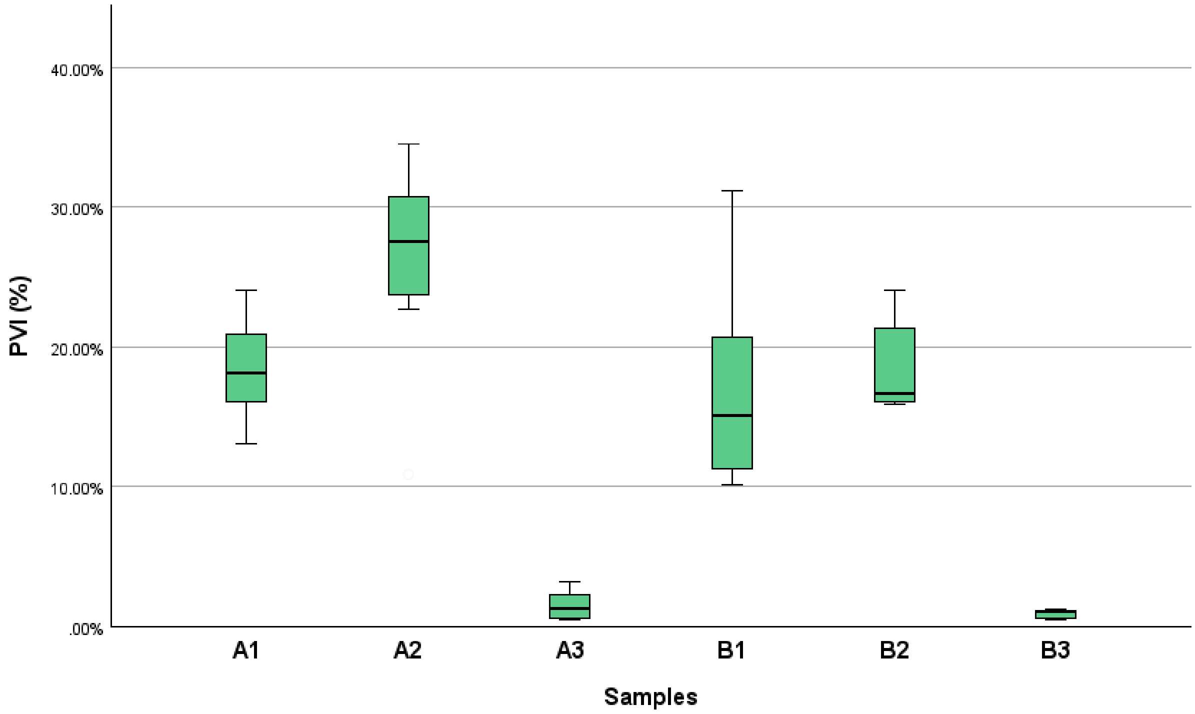

Fig. 23. Results of the calculated PVI of the *pogácsa* groups. (A1) baked at 200°C, cheese with less MC (58%) in formulations; (A2) baked at 200°C, cheese with high MC (65%) in formulations; (A3) baked at 200°C, no cheese in formulation; (B1) baked at 215°C, cheese with less MC (58%) in formulations; (B2) baked at 215°C, cheese with high MC (65%) in formulations; (B3) baked at 215°C, no cheese in formulation.

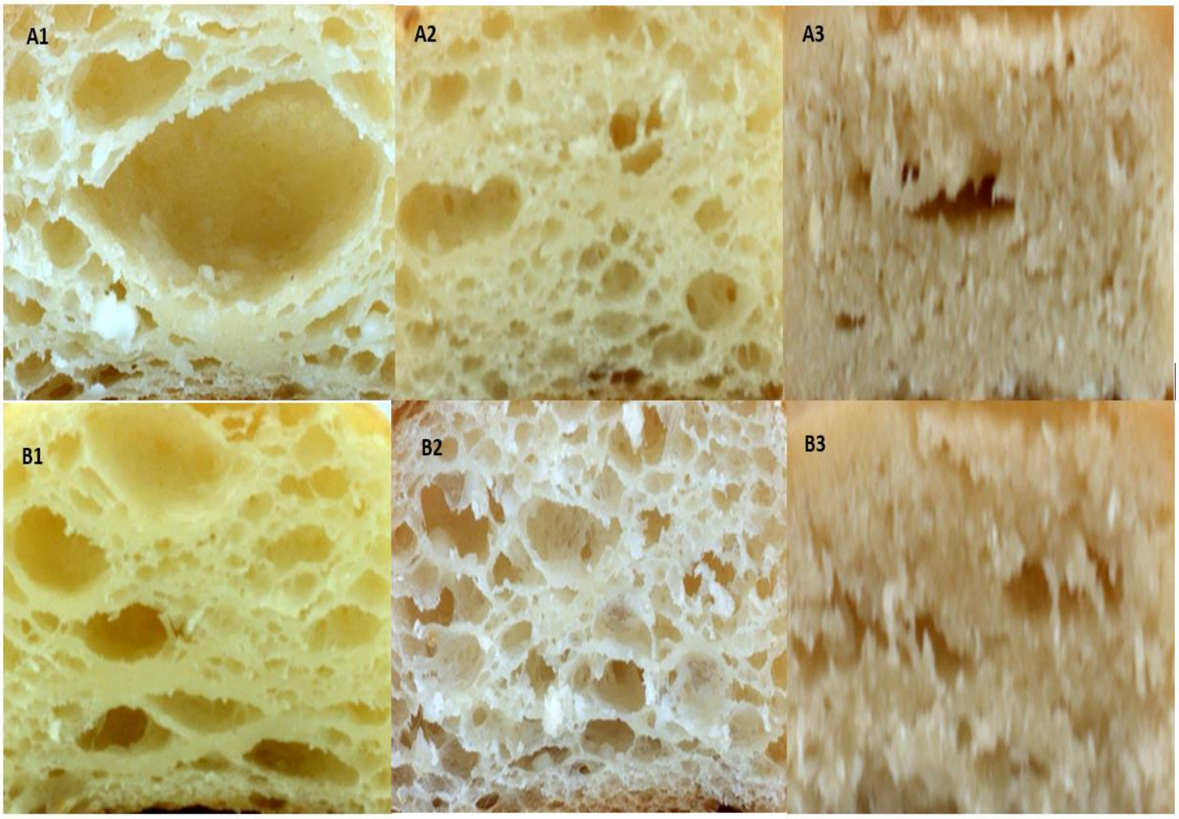

Fig. 24. Internal structure of *pogácsa* samples showing different pore structure characteristics. (A1) baked at 200°C, cheese with less MC (58%) in formulations; (A2) baked at 200°C, cheese with high MC (65%) in formulations; (A3) baked at 200°C, no cheese in formulation; (B1) baked at 215°C, cheese with less MC (58%) in formulations; (B2) baked at 215°C, cheese with high MC (65%) in formulations; (B3) baked at 215°C, no cheese in formulation.

4.2.2. Results of changes in physical and textural properties of *pogácsa* due to variation in baking temperature and addition of cheese

Fig. 25 shows the results of textural properties of baked *pogácsa* samples, which were formulated with different cottage cheeses and baked under two different baking temperatures. Significant variations ($p < 0.05$) in the hardness, chewiness, cohesiveness, gumminess, and springiness were observed among different groups. Hardness and chewiness values showed that higher baking temperature (215°C) along with less moist cottage cheese (58% MC) in the formulation led to harder crumb and higher chewiness compared to the samples baked at lower temperature (200°C). In case of *pogácsa* groups prepared with no cottage cheese (samples A3 and B3), sample B3, which was baked under higher baking temperature, had higher values for hardness and chewiness compared to sample A3 with lower baking temperature. This implies that the baking temperature could influence hardness and chewiness. Significant differences ($p < 0.05$) were also found among the cohesiveness values. Sample A1 exhibited the highest value for cohesiveness (0.61), whereas the lowest belonged to sample B3 with the value of 0.32. In case of gumminess, sample B1 showed a value of 694.81, which was noticeably higher than other groups, while the lowest was belonged to sample A3 (191.51). Changes in the springiness values could be related to the variation in hardness, in such a way that increasing the hardness could cause a reduction in springiness and vice versa. This signifies that the increasing in baking temperature (from 200 to 215°C) may result in a harder crumb texture.

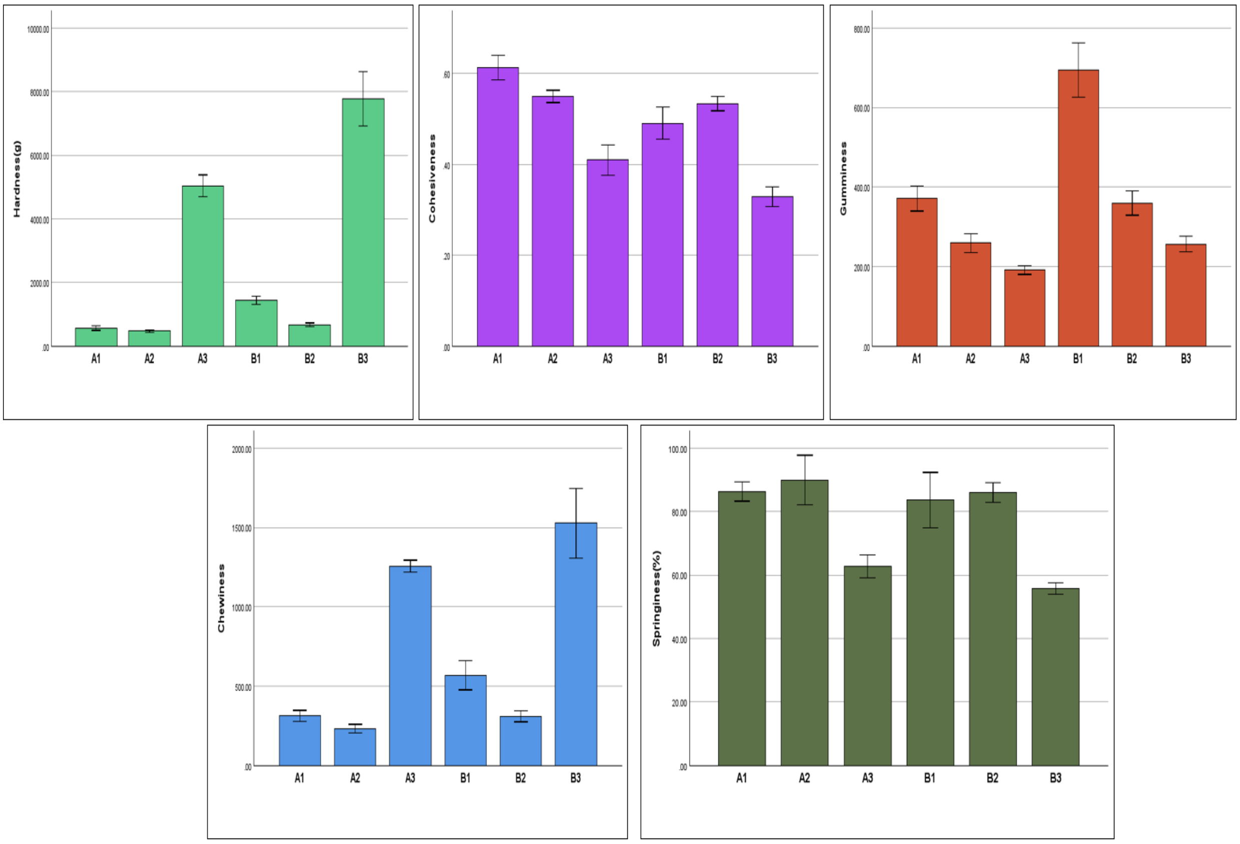

Fig. 25. Mean of mechanical texture properties of *pogácsa* samples. (A1) baked at 200°C, cheese with less MC (58%) in formulations; (A2) baked at 200°C, cheese with high MC (65%) in formulations; (A3) baked at 200°C, no cheese in formulation; (B1) baked at 215°C, cheese with less MC (58%) in formulations; (B2) baked at 215°C, cheese with high MC (65%) in formulations; (B3) baked at 215°C, no cheese in formulation.

Table 8 demonstrated the results of the crumb MC, volume, and porosity in the six groups of *pogácsa* sample. According to the results, crumb MC was remarkably affected after using different recipes. High moisture cheese maximizes the crumb moisture in *pogácsa* samples, whereas its absence led to minimize crumb moisture. It must also be mentioned that baking temperature affects MC of the crumb. This phenomenon has been also validated by research conducted by other researchers (Eggleston, Omoaka, and Arowshegbe 1993).

The values of volume in the samples exhibited significant variation, with a statistical significance level of $p < 0.05$. The main reason for this alteration could be related to the type of formulation, and variation in the baking temperature. The presence or absence of cheese in the formulation played a significant role in determining the volume of the samples. It was observed that samples without cheese (A3 and B3) exhibited the lowest volume values. Conversely, when cheese was incorporated into the formulation, samples B1 and A1, which contained a lower MC (58%) in their formulation, displayed higher volume values compared to samples B2 and A2, which contained a higher MC (65%). Obviously, the low MC recorded for the aforementioned samples is due to the absence of cottage cheese in their recipe. Furthermore, a noteworthy impact on sample volume was observed when the baking temperature was altered. *Pogácsa* groups that were baked at a higher temperature of 215°C demonstrated higher volume values compared to those baked at a lower temperature of 200°C. Therefore, it can be interpreted that baking temperature has a significant effect on the final volume of the samples, with higher temperatures leading to increased volume.

The highest porosity value was found for sample B1 (72.75%), followed by samples A1 (69.63%), B2 (62.20%), A2 (53.36%), and B3 (38.83%). Whereas the lowest value (32.66%) for this parameter was observed in sample A3, which was cheese-free and baked at 200°C. Therefore, it can be interpreted that higher baking temperature had significant effect to increase the porosity in *pogácsa* cake. To our knowledge, only a few numbers of studies focused to assess the impact of moisture level on porosity value. Esteller et al. (2006) studied the effect of kefir addition on the porous quality of bread with the help of an image processing technique. They found out that by decreasing the MC of the product, the porosity would increase (Esteller et al. 2006). Given the above explanations, it can be assumed that higher porosity can be associated with the MC of the baked *pogácsa*.

Table 8. Crumb moisture content (MC), volume, and porosity of the *pogácsa**

Sample	Crumb MC (%)	Volume (cm^3)	Porosity (%)
A1	36.09 ± 3.40^b	24.13 ± 1.40^d	69.63 ± 1.58^e
A2	47.18 ± 4.96^c	19.54 ± 1.57^b	53.36 ± 5.15^c
A3	15.37 ± 0.61^a	17.77 ± 0.89^a	32.66 ± 3.34^a
B1	35.41 ± 0.97^b	27.95 ± 1.78^e	72.75 ± 1.48^f
B2	43.66 ± 5.28^c	21.51 ± 0.98^c	62.20 ± 1.49^d
B3	14.81 ± 0.37^a	18.05 ± 0.41^a	38.83 ± 6.32^b

* Different small letters in each row indicate significant differences ($p < 0.05$). Porosity was measured using the reference method. Refer to Table 3 for *pogácsa* cake formulations.

Colour also plays an important role in the overall consumers' acceptability of bakery products like *pogácsa* (Gebreil, Ali, and Mousa 2020). This parameter can be affected by formulation and processing conditions. Factors such as dough characteristics (e.g., pH and water content) and baking conditions (e.g., temperature and time) might alter the products colour. The LAB colour space, a 3-dimensional spherical system, is typically used to describe the surface colour of food materials. In this colour space system, L* represents lightness, which ranges from 0 to 100, whereas a* and b* are redness-greenness and yellowness-blueness, respectively, which can range from negative to positive (Kamani et al. 2015). The results of the colour measurements of *pogácsa* samples are presented in Fig. 26. According to these data, L* values of crumb and crust decreased with increasing MC of the product. This indicated the impact of MC on the colour surface. Cottage cheese contains protein which might contribute to a lower L* values in both crust and crumb. In addition, increasing the baking temperature could reduce crust L* values. This is expected because with increasing the baking temperature, the formation rate of brown pigment will also increase. The highest yellowness (b*) value was observed in sample A1 with values of 52.03 for crust and 29.38 for crumb, while the minimum value of b* was found for crust (40.90) and crumb (20.71) of the sample A3. Significant difference observed in a* values in crumb and crust of *pogácsa*. This implies that water migration from crumb to crust might increase a* values and thus change the visual appearance of the *pogácsa*. Hence, a* values of both crumb and crust were higher in groups B1, B2, and B3 compared to groups A1, A2, and A3. In agreement with our results, Shittu et al. (2007) reported that colour parameters such as L* of the bread crust significantly increased from 31 to 72, by increasing both baking time and temperature from 20 to 40 min and 190 to 240°C, respectively (Shittu, Raji, and Sanni 2007). Overall, the above L*a*b* results suggested that changes in baking temperature and formulation could cause variation in lightness, redness, and yellowness of *pogácsa*.

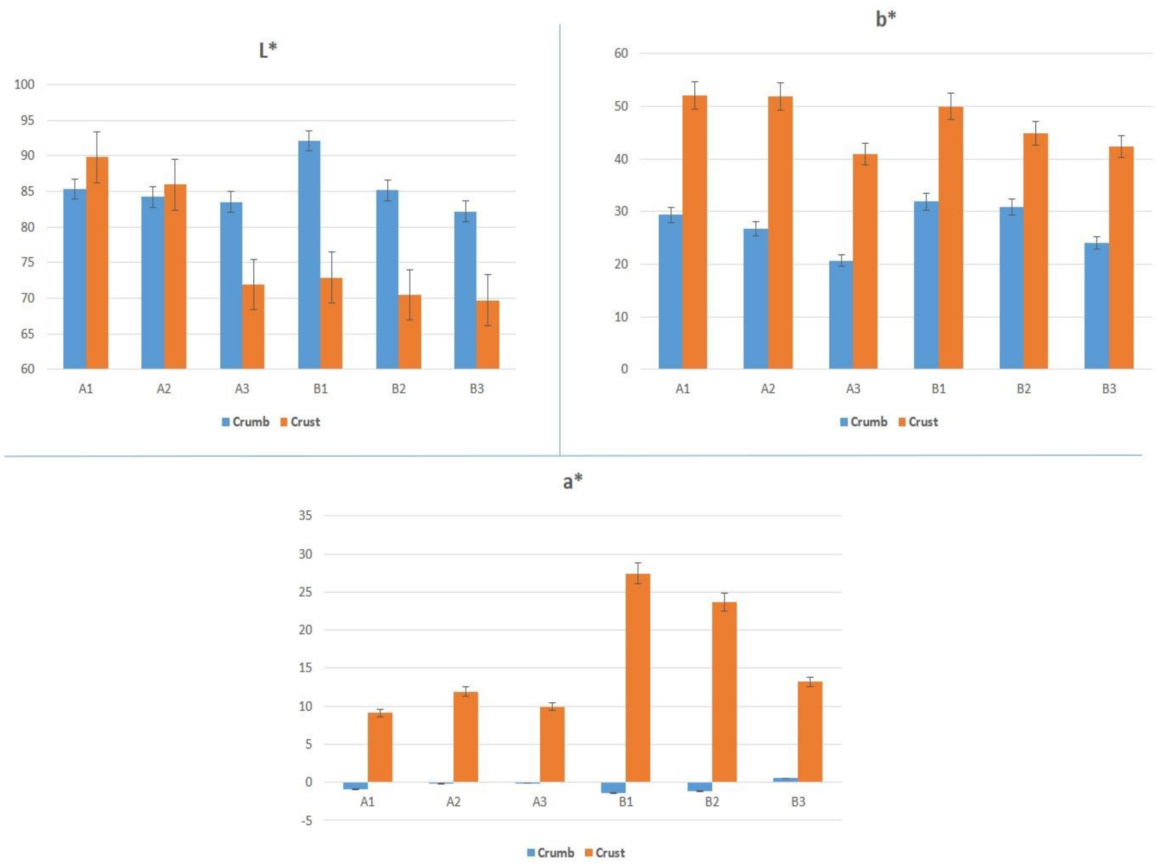

Fig. 26. Mean of colorimetric parameters of the *pogácsa* samples. (A1) baked at 200°C, cheese with less MC (58%) in formulations; (A2) baked at 200°C, cheese with high MC (65%) in formulations; (A3) baked at 200°C, no cheese in formulation; (B1) baked at 215°C, cheese with less MC (58%) in formulations; (B2) baked at 215°C, cheese with high MC (65%) in formulations; (B3) baked at 215°C, no cheese in formulation.

4.2.3. Results of correlation coefficient among the different parameters

As shown in Table 9, significant correlation coefficients were observed among the average values of PVI (image-based parameter), MC, and instrumental textural features. The PVI and MC showed a strong negative correlation ($p < 0.01$) with hardness, gumminess, and chewiness, strong positive correlation ($p < 0.01$) with resilience, cohesiveness, and springiness. In addition, strong positive correlation ($p < 0.01$) was observed between PVI and porosity results. It can be interpreted that changes in the image-based features, particularly PVI, is linked to the hardness variation of the *pogácsa* sample. In other word, the less firm *pogácsa* texture, the higher PVI, and vice versa. In addition, the harder *pogácsa* crumb is associated with lower MC. In line with the results of present study, Morreale et al. (2018) found high correlations coefficient between MC and instrumental texture parameters in gluten-free bread. Their findings showed a strong link between water content and crumb hardness (Morreale, Garzón, and Rosell 2018.). In another study, Esteller et al. (2006) examined the effect of the kefir concentration and proofing time on the quality of white bread porous. They reported high correlations between physical properties and microstructure observed by image processing. A strong correlation was observed between the microstructure of pores, brightness, and hardness of the white bread samples (Esteller et al. 2006).

Table 9. Pearson correlation coefficients among the pore volumetric index (PVI), moisture content (MC), instrumental texture (TPA) parameters, and porosity of the *pogácsa*

	Hardness (g)	Resilience (%)	Cohesiveness	Springiness (%)	Gumminess	Chewiness	Porosity
PVI	-0.833**	0.778**	0.760**	0.823**	-0.855**	-0.856**	0.719**
MC	-0.897**	0.832**	0.824**	0.900**	-0.924**	-0.929**	_

**. Correlation is significant at the 0.01 level. Porosity was measured using the reference method designed for bread.

4.2.4. Results of the effect of the baking temperature and formulation on the PVI and overall liking of *pogácsa* cake

The results of a two-way ANOVA performed on the parameters of PVI and overall liking (OL) for *pogácsa* samples are shown in Table 10. The two factors investigated were baking temperature and variation of cheese MC in the formulation. For PVI, the mean values for samples baked at 200°C and 215°C were 15.55% and 12.32%, respectively, while for high moisture cheese, the mean value was 22.58%. Samples without cheese had a mean PVI value of 1.34%. The results showed a significant effect of both baking temperature and changing the MC of cheese of the formulated *pogácsa* and the interaction between these two factors on PVI, with *p* values of 0.017, 0.002, and 0.019, respectively. For OL, the mean value for samples baked at 200°C and 215°C were 5.93 and 6.6, respectively. For changing the cheese moisture of high and low, the mean scores were 8.20 and 8.0, respectively. Samples without cheese in the formulation had a mean acceptability score of 2.6. The results showed a significant effect of baking temperature on OL, with a *p* value of 0.006. Moreover, there was a notable impact of fluctuation in cheese MC, as well as a significant interaction between the two factors of baking temperature and the utilization of cheeses with varying MC. This was evidenced by the corresponding *p* values of 0.00 and 0.001, respectively.

Table 10. Comparison of the experimental condition on pore volumetric index (PVI) and overall liking (OL)

Parameters	Baking Temp. (°C)		Cheese MC %			ANOVA *p* value		
	200	215	Low	High	No cheese	Temp.	Cheese MC%	Temp. x MC%
PVI (%)	15.55±0.83	12.32±0.83	17.88±1.02	22.58±1.02	1.34±1.02	0.017	0.002	0.019
OL	5.93±0.23	6.6±0.32	8±0.10	8.2±0.95	2.6±0.10	0.006	0.000	0.001

4.2.5. Results of the sensory evaluation

Results obtained from the sensory evaluation of *pogácsa* samples are illustrated in Fig. 27 (A1, A2, A3, B1, B2, and B3). Significant differences observed in nine parameters (taste, colour, aroma/odour, oiliness, chewiness, hardness, elasticity, pore's structure, and overall crumb structure) among different *pogácsa* groups. Samples prepared without cheese (A3 and B3) had noticeably higher hardness. The oiliness in samples A2 and B2, which were formulated with higher moist cheese, was higher than other groups. Among all *pogácsa* groups, B1 and B2 exhibited the highest value of pore structure. This might be due to the effect of increasing baking temperature (from 200 to 215°C) on its crumb structure. Using high temperature for baking might lead to increased yeast activity, thereby generating higher amount of CO_2 in the processed dough.

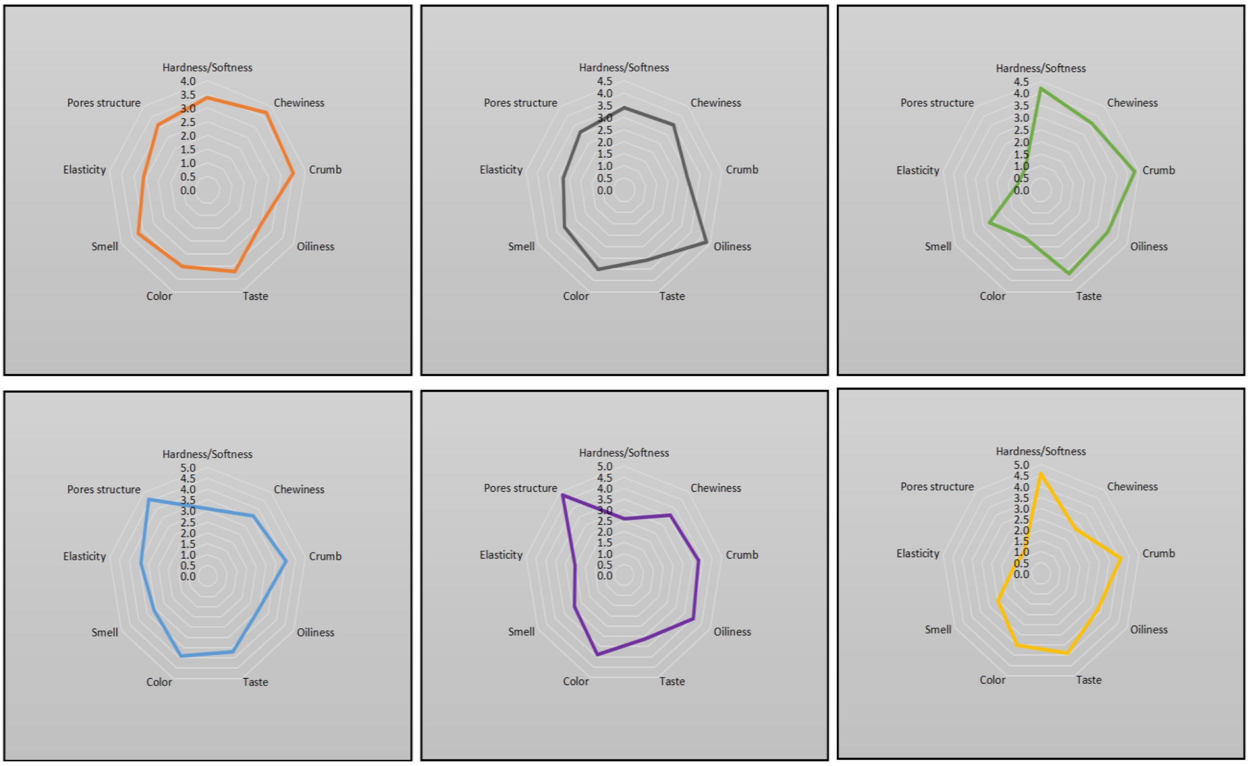

Fig. 27. Average sensory profiles of *pogácsa* cake samples: (A1) baked at 200°C, cheese with less MC (58%) in formulations; (A2) baked at 200°C, cheese with high MC (65%) in formulations; (A3) baked at 200°C, no cheese in formulation; (B1) baked at 215°C, cheese with less MC (58%) in formulations; (B2) baked at 215°C, cheese with high MC (65%) in formulations; (B3) baked at 215°C, no cheese in formulation.

Penalty analysis results of *pogácsa* groups of different formulations and baked under different baking temperatures are shown in Fig. 28. In sample A1, 40-50% of panellists expressed elasticity and oiliness attributes as "not enough" and chewiness and overall crumb structure as "too much". A high percentage of consumers (~ 80-100%) felt that the oiliness was "too much" in sample A2, which was prepared with higher moist cheese. In addition, 40% of respondents rated colour, chewiness, and hardness as "too much" and elasticity as "not enough". The hardness and taste were found to be "too much" by more than half of consumers in sample A3. The oiliness, taste, and colour were considered as "too much" by 40-60% of panellists in sample B1and the low percentage of those panellists (~ 20-30%) felt that the hardness was "not enough". In sample B2, more than half of the panellists found that the *pogácsa* sample was "not enough" hard and elastic. The values of "mean drops" in sample B3 were found to be negative (below zero). This indicated that sample B3 was considered by panellists as non-optimal compared to other *pogácsa* samples. Therefore, increasing the baking temperature from 200 to 215°C along with removing the cottage cheese from formulation might lead to a marked decrease in the overall acceptability of the baked product like *pogácsa*. In addition, the higher baking temperature would probably result in an undesirable colour score.

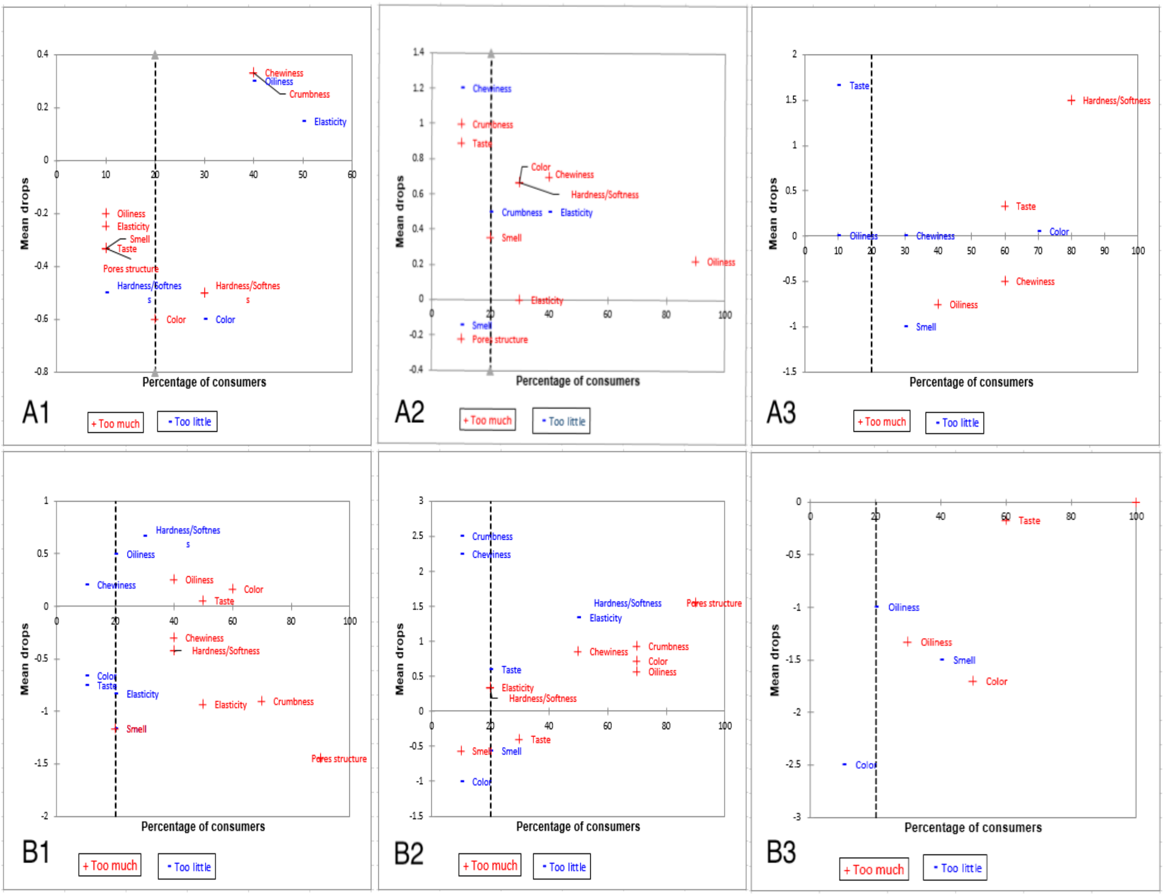

Fig. 28. Mean drop charts of *pogácsa* samples (capital letters indicate the sample group). Red colour corresponds to "too much", while blue corresponds to "not enough" endpoints of the JAR scale. The dashed line corresponds to 20% of the consumers: (A1) baked at 200°C, cheese with less MC (58%) in formulations; (A2) baked at 200°C, cheese with high MC (65%) in formulations; (A3) baked at 200°C, no cheese in formulation; (B1) baked at 215°C, cheese with less MC (58%) in formulations; (B2) baked at 215°C, cheese with high MC (65%) in formulations; (B3) baked at 215°C, no cheese in formulation.

4.3. Influence of baking conditions and cheese variations on *pogácsa's* overall liking

The influence of different baking conditions and cheese variations on the OL of the *pogácsa* cakes were studied. Table 11 presents the mean (± SD) of OL values for the *pogácsa* samples in two sets of experiments 1 and 2. In the experiment 1, sample E, baked at 230°C for 5 minutes, received the highest OL score of 9.15. This suggests that this specific baking condition was favoured by the panellists, possibly resulting in a desirable texture and flavour profile. Conversely, Sample F, baked at 230°C for 7 minutes, received the lowest OL score of 6.69. The prolonged baking time at high temperature may have negatively affected the sensory attributes of the *pogácsa*, leading to reduced liking. Samples A, B, C, and D, representing various combinations of temperature and time, exhibited intermediate OL scores, demonstrating the sensitivity of liking to baking conditions. In Experiment 2, the focus shifted to cheese content in the formulations, with variations in MC and the absence of cheese. Samples A1 and A2, baked at 200°C with cheese having different moisture content (58% and 65%, respectively), both received relatively high OL scores, with A2 (8.80) slightly outperforming A1 (8.70). This suggests that cheese with higher moisture content may contribute to enhanced liking. Sample A3, baked at 200°C without cheese in the formulation, received a significantly lower OL score of 3.30. This indicates that the absence of cheese negatively affected the overall sensory appeal of the *pogácsa*. Among the samples in Experiment 2, Sample B2 (7.60), baked at 215°C with cheese having high moisture content, garnered the highest OL score. This suggests that cheese with high moisture content can compensate for the higher baking temperature in terms of sensory preference. Sample B3 (3.60), baked at 215°C without cheese, received the lowest OL score, indicating that the absence of cheese in this condition led to reduced liking. Therefore, baking temperature and duration play a pivotal role in texture and liking. Moderate conditions seem to be more favourable, while extended baking times at high temperatures can lead to reduced liking. Cheese, especially when it has higher moisture content, contributes positively to OL, enhancing the sensory experience. While, the absence of cheese has a detrimental effect on OL, underscoring the importance of cheese in *pogácsa* formulation. These insights are valuable for optimizing the baking process and ingredient composition to achieve *pogácsa* cakes that align with consumer preferences.

Table 11. The mean (± SD) of overall liking (OL) values of the *pogácsa* cakes in the experiments 1 (A-F) & 2 (A1-B3)*

Sample	Overall liking		Sample
A	8.00 ± 1.22^{ab}	8.70 ± 0.67^{c}	A1
B	7.84 ± 2.26^{ab}	8.80 ± 0.63^{c}	A2
C	7.92 ± 1.25^{ab}	3.30 ± 1.16^{a}	A3
D	8.61 ± 1.12^{b}	7.30 ± 0.94^{b}	B1
E	9.15 ± 0.98^{b}	7.60 ± 0.84^{b}	B2
F	6.69 ± 2.05^{a}	3.60 ± 1.35^{a}	B3

*Means with different superscripts within each column are significantly different ($p < 0.05$). Refer to Table 2 & 3 for *pogácsa* cake formulations.

4.4. Development of prediction models for porosity measurement of the *pogácsa* cake using image features and regression analysis

After examining the correlation coefficients between the variables presented in Tables 6 and 9, three parameters (GLCM, PVI, and porosity) were selected to avoid multicollinearity among the variables. Three parameters from each category of GLCM (contrast, correlation, and homogeneity) were selected. GLCM and PVI were considered as independent variables or predictors and porosity (using reference method, designed for breed) was the designated categorical dependent variable.

The selection of variables for model development was conducted using a novel and non-destructive approach, wherein exclusively image-based parameters were chosen as predictors. Lab-based data were intentionally excluded from consideration in order to focus solely on the objective of this study. Table 12 shows the list of developed models built by linear, quadratic and multivariate regression approaches. The models were built for all experimental batch as different baking condition was applied while baking. It is noteworthy to mention that only those models which (i) were statistically significant ($p < 0.05$); and (ii) had R^2 higher than 50 were included in this table. As can be seen, the best fit type of model for correlation, Homogeneity, and contrast parameters were linear type with appropriate R^2 (Table 12). Multivariate regression helps to assess the relationship between imaging parameters and porosity values measured by the standard laboratory method (method designed for bread). In this modelling approach, the most influential factor(s) in the equation could be found based on the output determination coefficient (R^2). According to R^2 value, by entering or extracting each variable in the model, the best selection of variables can be made (Hosseininia, Kamani, and Rani 2017). As can be seen in Table 12, the models built by three parameters (contrast + homogeneity + correlation) exhibited the highest R^2 which was 84.4 ($p < 0.05$). Using "homogeneity + correlation" as inputs showed a model with the same R^2 as the previous model (84.4), while a slightly lower determination coefficient ($R^2 = 81.1$)

achieved when "correlation" used as input. Therefore, using the combination of the GLCM parameters of contrast, homogeneity, and correlation as the input variables for predicting porosity, generated a model with highest R^2.

The same modelling technique also applied to those *pogácsa* samples which formulated with different cheese materials (having different MC ranging from 58 to 65% and samples without cottage cheese in the formulation). Following model with PVI variable was found to be statistically significant, indicating the robustness and accuracy of the PVI as a predictive tool for assessing the porosity parameter of *pogácsa* samples, even under conditions where the production recipe exhibits variations (R^2 = 75.5 and RMSE = 2.13):

$$\text{Porosity} = 3.48\text{PVI} - 0.086\text{PVI}^2 + 32.30$$

Predictive models are widely utilized as a popular method due to advantages such as non-destructive, rapid, non-hazardous and inexpensive in food sectors (Pahlavan et al. 2020). When image processing is combined with predictive multivariate analysis, it becomes a more powerful tool for quality assessment of food materials. Thus far, several studies have been demonstrated the potential of combined image processing and modelling technique (with suitable R^2) for prediction of quality parameters in a wide range of food products. The prime examples of these promising research efforts are predicting of lipid oxidation parameters (FFA, PV and TBARS) in fish (Kamani et al. 2017), estimation of spoilage parameter (TVB-N) in vacuum and non-vacuumed beef (Amani et al. 2015), predicting concentration of synthetic colorant (sunset yellow) in soft drink (Hosseininia, Kamani, and Rani 2017), prediction of non-volatile and volatile amines (TVN, TMA and histamine) in fillet (Kamani et al. 2015) and predicting various quality parameters (specific volume, hardness, elasticity) in breads (Pahlavan et al. 2020). In this context, Różyło and Laskowski (2011) stated that the multivariable regression is an effective method for predicting the baking qualities of different wheat cultivars. Their results also indicated that alveographic properties of flour and dough were considerably suitable variables in building prediction models. The application of canonical correlation also showed that alveographic qualities of the flour and dough could be used to predict specific volume and loaf volume of the bread (Różyło and Laskowski 2011). Konopka et al. (2004) developed a regression method to predict water absorption level and bread volume changes as a function of flour quality parameters and dough rheological properties (Konopka et al. 2004). The findings of present study are in line with these mentioned reports, indicating suitability of image processing and modelling techniques for prediction of porosity values in *pogácsa* cake. Despite an appropriate levels of determination coefficient obtained for all models; a considerable variation was also recorded in the R^2 of different groups. This indicates the impact of different baking conditions and formulation which used during *pogácsa* preparation, causing differences in GLCM, PVI and porosity values, and subsequently affects the R^2 of models developed by these parameters.

Table 12. Developed predictive models for estimating porosity in *pogácsa* *

Variables	Prediction Models	R^2 (%)	RMSE	RPD
Contrast + Homogeneity + Correlation	Y= – 65.9 Homo – 88.09 Corr – 0.58 Cont + 207.63	84.4	1.56	2.33
Homogeneity + Correlation	Y = - 65.84 Homo – 88.04 Corr + 207.46	84.4	1.56	2.33
Correlation	Y= 659.16 $Corr^2$ – 1443.89 Corr + 839.25	81.1	1.72	2.08
PVI	Y = 2.47 PVI^2 – 0.07 PVI + 41.44	80	2.1	1.94
Contrast	Y= – 6107 $Cont^2$ + 1312.84 Cont – 9.72	71.3	2.12	1.58
Homogeneity	Y = 180.99 $Homo^2$ – 504.89 Homo + 375.96	69	2.21	1.50

* The criteria for choosing the equations: 1. *p* value (< 0.05); 2. R^2 value (above 50); 3. In case of similar R^2, the linear was preferred than the quadratic model. All regression modelling analyses were carried out with 4 decimals.

CHAPTER 5: SUMMARY & CONCLUSION

Over the past centuries, leavened bakery products are essential to families' food baskets. This category encompasses products such as buns, cakes, and bread. According to the Bakery and Confectionery Global Market Report, the worldwide market of bakery products was around 887.82 billion dollars in 2020. *Pogácsa* is one leavened traditional Hungarian cake, typically made of wheat flour, margarine, yeast, salt, and other ingredients. *Pogácsa* is inelastic, slightly dense, with a particular texture, crispy surface, and tender core, giving characteristic and desired sensorial perception. Although this cake is regarded as a high-demand bakery product owing to its distinctive textural property, the studies focusing on the quality improvement and assessment of its physical and sensorial attributes are very limited.

As consumer awareness and expectation of high-quality bakery products increase, the importance of using accurate, non-destructive, and rapid quality assessment methods has become a big challenge for bakery manufactures. The ingredients and baking conditions, particularly time and temperature, are the principal processing parameters, which significantly influence the quality attributes of the end product. The most crucial quality attributes are colour, shape, size, and crumb texture. Among these, crumb texture is the critical parameter for their quality assessment. Thus far, the quality assessment parameters such as crumb porosity and pore size distribution have been examined to understand the internal structure of the bakery products using various analytical and sophisticated instrumental methods (e.g., human sensory evaluation, instrumental analysis). Each method, regardless of principle, has its own merits and demerits. For instance, the instrumental and sensorial approaches are usually time-consuming, expensive, and/or destructive, which may not suit in-line inspection.

With the need for more rapid and economical objective measurements of a quality, in recent times, image analysis is garnering prominence as a relevant tool for the qualitative and quantitative assessment of quality parameters in food processing. This recent approach has the advantage of being non-destructive, rapid, and cheaper compared to the analytical methods. This method has successfully been applied in various bakery products to evaluate the morphological and textural qualities, grading, and identification in bakery products.

In view of the aforementioned points, current research study was conducted with the following objectives:

1. To develop robust methods to evaluate the internal structure of the *pogácsa* cake.
2. To investigate the effect of formulations (using cheeses with different moisture content) and baking conditions (different time and temperature) on the porous structure and sensory properties of *pogácsa*, with the help of image analysis.
3. Relationship between selected image texture features and physicochemical parameters of *pogácsa*.

The experimental methodology for achieving the objectives envisaged for the study is summarized below:

- *Pogácsa* dough was prepared according to an industrial recipe. The prepared dough was rested in cold storage (4°C ± 2°C) for overnight. After cold storage, the dough was rolled out and cut into small pieces (4cm width, 6 mm tall) using a round mould. The moulded dough was placed on baking trays and transferred to a proofing chamber. All samples were subjected to a similar proofing setting (20 min and 40°C). After proofing, the baking process was conducted in the oven.
- The first part of the study was performed to evaluate the effect of time and temperature of baking as two fundamental factors on texture and sensory properties of *pogácsa*. Therefore, samples were baked under different temperatures (200, 215, and 230°C) and times (5 and 7 min). The second part was focused on the effect of formulations (using cheeses with

different MC) and baking temperature on the porous structure and sensory properties of *pogácsa*. Hence, for the second part of the study, the baking temperature was adjusted to 200 and 215°C and two kinds of cottage cheese with two different MC of 58% and 65% were used in dough formulations. One group of *pogácsa* was also prepared without cottage cheese.

- The images were analysed to determine its morphological characteristics namely, area of pores (mm^2), pore volume (mm^3), and PVI (%); advanced pattern features of GLCM including entropy, contrast, correlation, energy, and homogeneity.
- Physical, textural, and sensorial characteristics such as volume, moisture, L*, a*, and b* colorimetric parameters, porosity, TPA textural parameters, overall liking, and penalties were also evaluated for their performance in inspection of the *pogácsa* internal structure.
- Data were evaluated through analysis of variance (ANOVA) and Duncan's Multiple to detect significance difference at $p < 0.05$. Correlation coefficients between variables were estimated using the Pearson correlation test to assist in the selection of parameters for developing a prediction model for porosity measurement of *pogácsa* using image analysis. Tow-way ANOVA was also conducted to investigate the effect of the baking time and temperature, in combination, on PVI and OL, as well. Multiple regression analysis technique was used to develop the prediction model.

The general results obtained in this study are presented below:

- The TPA results revealed that the change in baking settings (time and temperature) could substantially influence the product texture and change hardness, cohesiveness, springiness, gumminess, and chewiness.
- *Pogácsa* samples prepared with high moist cheese (65% MC) showed the highest PVI. In addition, increase in baking temperature from 200 to 215˚C caused an increase in the PVI

value. However, increasing the baking time from 5 to 7 minutes along with increasing the baking temperature to 230°C led to a decrease in the PVI value. Using cheese in *pogácsa* formulation could generate bigger particle sizes occupied in the crumb of baked samples. While lowest values for pore characteristics were achieved with cheese-free samples.

- The GLCM textural features extracted from *pogácsa* images were found to be varied when different times and temperatures were applied. In addition, GLCM imaging analysis found to be suitable for porosity measurement and prediction the textural properties of *pogácsa*.
- The results of colour measurements revealed that L* values of crumb and crust decreased with increasing MC of the product. *Pogácsa* groups with high moist cheese in the formulation exhibited the lowest values of L* and vice versa. In groups, which were baked under higher temperature (215°C), water migration from crumb to crust increased a* values and thus changed the visual appearance of the *pogácsa*.
- Penalty analysis revealed that oiliness, pore structure, and colour of products were linked with baking time and temperature. High percentage of consumers felt that the oiliness was more than enough in the samples, which were prepared with higher moist cheese. Also, increasing the baking temperature resulted in an undesirable colour score.
- The results of OL revealed that baking temperature and time significantly impact OL, with moderate conditions receiving higher scores. Positive influence of cheese was observed on OL, particularly when it had a higher moisture content. Conversely, the absence of cheese had an adverse effect on liking. Therefore, delicate balance required in *pogácsa* preparation, where optimal baking parameters and the inclusion of cheese contribute to a more enjoyable sensory experience.

It is known that important parameters of temperature and time of the baking in addition to the heat flow inside the oven can affect the results of the internal structure of the baked product. In the scope of this thesis the first two parameters have been studied in detail. As an extension to this thesis for the future works it is recommended to perform the detail analysis on the effect of heat flow inside the oven. This effect has been previously studied for bread and some other bakery products but to the best of authors knowledge, this study has not been done for evaluating the internal structure of the *pogácsa* (Standing 1974; Litovchenko 2013). Furthermore, it is advisable to explore various metrics such as the ratio of pore area to segmented area, in order to gain additional insights in this context. It has the potential to reveal novel correlations and offer valuable supplementary information.

CHAPTER 6: NEW SCIENTIFIC RESULTS

1. The structural properties of bakery products can be affected by changes in baking conditions, and a reliable method for quantifying these changes is essential. The PVI (pore volumetric index) has been proposed as a promising approach for evaluating the structure of *pogácsa* samples, based on cross-sectional images. This method involves segmenting the pores using Otsu's thresholding technique and projecting the total pore area to volume, with the PVI expressed as the percentage of pores in the segmented sample. The PVI was observed to respond sensitively to changes in baking time ($p < 0.01$), baking temperature ($p < 0.01$), and recipe variation ($p < 0.002$) due to the use of cheese with different MC, demonstrating its potential as a useful tool for monitoring and characterizing the effects of baking conditions on the structural properties of *pogácsa* cake.

   [Amani, H., Baranyai, L., Badak-Kerti, K. Mousavi. K, A. (2022). Influence of baking temperature and formulation on physical, sensorial, and morphological properties of *pogácsa* cake: an image analysis study. Foods, 11, 321. https://doi.org/10.3390/foods11030321].

2. New model has been created to predict porosity of *pogácsa* of given recipe using digital image processing, utilizing pattern descriptors of homogeneity, correlation and contrast. The model fit well on experimental data with $R^2 = 0.844$, RMSE = 1.56, and RPD = 2.33:

$$\text{Porosity} = -65.9\ \text{Homogeneity} - 88.09\ \text{Correlation} - 0.58\ \text{Contrast} + 207.63$$

3. A singular visual parameter, PVI, and a statistical parameter representing the pattern of correlation were selected as potential predictors of porosity for an experimental investigation where varying time and temperature of baking was applied. When each of

these selected parameters was used separately, they resulted in good estimations of porosity, as evidenced by the appropriate R^2 value:

Porosity = 659.16 Correlation^2 – 1443.89 Correlation + 839.25 R^2: 0.81

Porosity = 2.47 PVI^2 – 0.07 PVI + 41.44 R^2: 0.80

4. The most influential parameter impacting the sensory attributes of a given *pogácsa*, particularly the critical factor affecting consumer overall liking, was the amount of cheese in the recipe (F=252.33, $p < 0.001$). Following this, baking temperature had a noticeably smaller effect (F=8.333, $p < 0.006$), and there was also a significant interaction effect (F=7.583, $p < 0.001$) between baking temperature and cheese content. It's worth noting that the interaction effect accounted for only 3% of the influence of cheese quantity on overall liking. This hierarchy of parameters underscores the scale of their respective impacts on the sensory attributes of the *pogácsa*.

   [Amani, H., Baranyai, L., Badak-Kerti, K. Mousavi. K, A. (2022). Influence of baking temperature and formulation on physical, sensorial, and morphological properties of *pogácsa* cake: an image analysis study. Foods, 11, 321. https://doi.org/10.3390/foods11030321].

5. The porosity prediction model for *pogácsa* remained unaffected by variations in MC. Remarkably, a single model exhibited a strong fit when applied to the entire dataset, in which comprised a range of formulated samples with distinct cheese moisture content levels (65% and 58%), as well as samples prepared without cheese in their formulation. This comprehensive model had a R^2 of 0.75 and a RMSE of 2.13, demonstrating its efficacy in accommodating diverse sample compositions and moisture conditions:

$$\text{Porosity} = 3.48\ \text{PVI} - 0.086\ \text{PVI}^2 + 32.30$$

CHAPTER 7: LIST OF PUBLICATIONS IN THE FIELD OF STUDY

7.1. Publications in journals with peer review process (Total Impact Factor: 20.71)

Amani, H., Baranyai, L., Badak-Kerti, K. Mousavi. K, A. (2022). Influence of baking temperature and formulation on physical, sensorial, and morphological properties of *pogácsa* cake: an image analysis study. *Foods*, 11, 321. https://doi.org/10.3390/foods11030321.
Q1 - IF 5.561.

Amani, H., Firtha, F., Jakab I, Baranyai, L., Badak-Kerti, K. (2021). Non-destructive evaluation of baking parameters on *pogácsa* texture. *Journal of Texture Studies*, 52: 510–519. https://doi.org/10.1111/jtxs.12619. **Q2 - IF 3.942.**

Amani, H., Badak-Kerti, K., Mousavi. K, A. (2020). Current progress in the utilization of Smartphone-based imaging for quality assessment of food products: A review. *Critical Reviews in Food Science and Nutrition*, 1-13. https://doi.org/10.1080/10408398.2020.1867820. **Q1 - IF 11.208.**

Pahlavan, A., Kamani, M. H., Elhamirad, A. H., Sheikholeslami, Z., Armin, M., **Amani, H**. (2020). Rapid quality assessment of bread using developed multivariate models: A simple predictive modeling approach. *Progress in Agricultural Engineering Sciences*, 16(1): 1-10. https://doi.org/10.1556/446.2020.00001. **Q4 - IF 0.43.**

7.2. Presentations in international conferences

Amani, H., Firtha, F., Baranyai, L., Badak-Kerti, K. Evaluation of the effect of internal structure on texture profile of *pogácsa* at International Conference of Food Physicists, Iasi, Romania, November 2020.

Amani, H., Firtha, F., Kovács, A., Baranyai, L., Badak-Kerti, K. Comparison of crumb structure in sponge cakes prepared with different sweeteners using computer vision system at BiosysFoodEng, Budapest, Hungary, December 2019.

Amani, H., Baranyai, L., Badak-Kerti, K. Computer vision system as rapid tool for volume inspection of *pogácsa* at 1st International Conference on Advanced Production and Processing, Novi Sad, Serbia, October 2019.

Amani, H., Baranyai, L., Badak-Kerti, K. Development of a computer vision technique for evaluating crumb structure in sponge cake at Spring Wind Conference. Debrecen, Hungary, May 2019.

Amani, H., Baranyai, L., Badak-Kerti, K. Evaluation of the relationship between protein content and colour of fish fillet using modeling method: A preliminary study at PhD conference on nutrition research, Budapest, Hungary, January 2019.

Amani, H., Baranyai, L., Badak-Kerti, K. Smart vision system for quality control of cocoa flavored swirl bun at Third International Conference on Food Science and Technology, Budapest. Hungary, November 2018.

CHAPTER 8: APPENDICES

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8.2. Appendix of the supplementary tables

Appendix Table 1. The mean (± SD) of textural properties of *pogácsa* samples in the experiment 1*

Sample	Adhesiveness (g.sec)	Cohesiveness (%)	Gumminess	Chewiness	Hardness (g)	Springiness (%)
A	0.30±0.02^{b}	0.59±0.01^{b}	486.35±49.38^{a}	385.86±32.85^{a}	843.04±79.13^{a}	77.71±1.91^{c}
B	0.30±0.02^{b}	0.60±0.01^{b}	540.86±33.10^{a}	415.21±28.27^{a}	900.65±56.25^{a}	76.76±2.23^{abc}
C	0.29±0.03^{b}	0.59±0.04^{b}	537.64±65.47^{a}	411.78±38.15^{a}	913.26±104.69^{a}	77.13±2.92^{bc}
D	0.29±0.02^{b}	0.62±0.02^{c}	887.28±105.36^{c}	656.11±92.7^{c}	1217.8±162.8^{b}	76.68±3.60^{abc}
E	0.29±0.01^{b}	0.56±0.01^{a}	783.61±63.44^{b}	586.41±47.91^{b}	1377.6±118.13^{c}	75.37±2.37^{ab}
F	0.27±0.04^{a}	0.60±0.01^{b}	906.09±123.98^{c}	683.19±80.4^{c}	1494.5±190.84^{d}	74.90±2.83^{a}

*Means with different superscripts within each column are significantly different (p <0.05). Refer to Table 2 for *pogácsa* cake formulations.

Appendix Table 2. Changes in GLCM texture features of *pogácsa* samples in the experiment 1*

Sample	Entropy	Contrast	Correlation	Energy	Homogeneity
A	7.625±0.08[bc]	0.107±0.01[c]	0.976±0.003[b]	0.191±0.02[b]	0.946±0.005[a]
B	7.579±0.01[b]	0.096±0.01[ab]	0.976±0.003[b]	0.190±0.02[b]	0.952±0.004[bc]
C	7.483±0.07[a]	0.106±0.00[c]	0.973±0.002[a]	0.207±0.02[c]	0.946±0.004[a]
D	7.740±0.05[d]	0.114±0.01[d]	0.976±0.004[b]	0.166±0.01[a]	0.943±0.005[a]
E	7.620±0.10[bc]	0.098±0.01[b]	0.973±0.002[a]	0.174±0.01[a]	0.951±0.005[b]
F	7.673±0.01[c]	0.091±0.002[a]	0.982±0.002[c]	0.160±0.01[a]	0.960±0.005[c]

*Means with different superscripts within each column are significantly different ($p < 0.05$). Refer to Table 2 for *pogácsa* cake formulations.

Appendix Table 3. The mean (± SD) of textural properties of the *pogácsa* in the experiment 2*

Sample	Hardness (g)	Cohesiveness (%)	Gumminess	Chewiness	Springiness (%)
A1	571.99±71.19[a]	0.61±0.02[e]	371.43±31.86[c]	309.71± 33.79[a]	86.30± 3.05[cd]
A2	471.67±43.24[a]	0.54±0.01[d]	259.29±23.70[b]	232.98±26.78[a]	89.94± 7.83[d]
A3	5042±338.91[c]	0.40±0.03[b]	191.51±11.11[a]	1256.08± 36.69[c]	62.74± 3.58[b]
B1	1441.1±131.65[b]	0.49±0.03[c]	694.81±68.20[d]	568.98± 91.78[b]	83.61± 8.75[c]
B2	674.46±57.84[a]	0.53 ±0.01[d]	359.69±30.10[c]	311.83±35.57[a]	85.97± 3.13[cd]
B3	7778.8±851.60[d]	0.32±0.02[a]	256.7±20.07[b]	1526.62± 220.53[d]	55.72± 1.83[a]

[*] Different small letters in each row indicate significant differences ($p < 0.05$). Refer to Table 3 for *pogácsa* cake formulations.

Appendix Table 4. The mean (± SD) of colorimetric parameters of the *pogácsa* in the experiment 2*

Sample	L*		a*		b*	
	Crumb	Crust	Crumb	Crust	Crumb	Crust
A1	85.36±1.94^{b}	89.80±3.29^{c}	-0.95±0.49^{b}	9.09±1.10^{a}	29.38±1.23^{d}	52.03±0.54^{c}
A2	84.23±0.60^{ab}	85.98±1.42^{b}	-0.16±0.01^{c}	11.92±0.42^{bc}	26.78±2.01^{c}	51.83±2.16^{c}
A3	83.54±0.49^{ab}	71.93±0.15^{a}	-0.15±0.04^{c}	9.94±0.27^{ab}	20.71±0.97^{a}	40.90±1.15^{a}
B1	92.10±1.63^{c}	72.92±0.66^{a}	-1.39±0.08^{a}	27.45±2.47^{e}	31.90±1.92^{d}	49.99±1.94^{c}
B2	85.16±1.34^{b}	70.47±2.54^{a}	-1.12±0.06^{ab}	23.61±0.64^{d}	30.83±1.09^{d}	44.87±1.66^{b}
B3	82.22±1.66^{a}	69.71±2.75^{a}	0.53±0.12^{d}	13.20±0.57^{c}	24.05±0.56^{b}	42.37±1.15^{ab}

*Columns with different letters are significantly different ($p < 0.05$). Refer to Table 3 for *pogácsa* cake formulations.

Appendix Table 5. PVI (%) values of the *pogácsa* cakes in the experiments 1 (A-F) & 2 (A1-B3)*

Sample	PVI (%)		Sample
A	19.73±0.03^{b}	18.43±0.03^{b}	A1
B	21.35±0.07^{b}	26.64±0.06^{c}	A2
C	24.26±0.05^{b}	1.57±0.00^{a}	A3
D	21.28±0.04^{b}	17.33±0.07^{b}	B1
E	20.35±0.03^{b}	18.52±0.03^{b}	B2
F	12.81±0.01^{a}	1.12±0.00^{a}	B3

*Means with different superscripts within each column are significantly different ($p < 0.05$). Refer to Table 2 & 3 for *pogácsa* cake formulations.

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