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Article

Mechanobiological factors in fermentation: Understanding the impact on food texture and nutrient release

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Abstract: Evaluating people's food intake is crucial for establishing the link between diet and disease. Deprivation of vital nutrients causes the body to deteriorate organs and increases the risk of severe diseases that manifest in maturity. Making healthy food choices is one of the best ways to avoid developing chronic diseases, such as diabetes, heart disease, stroke, and even certain types of cancer. Hence, this paper proposes a deep learning-based automated nutrition classification system (DL-ANCS) for predicting food ingredients and nutrition. The DL-ANCS with Internet of Things (IoT) sensors to quantify food nutrition and a smartphone app to compile ingredient nutritional information. It is possible to take pictures of food eaten using the camera that comes with most mobile phones. It is possible to automatically identify the food items for record keeping using image processing. The effectiveness of the proposed DL-ANCS relies on its ability to accurately classify food items in these photos utilizing meal prediction algorithms and DL-ANCS. This research introduces a novel approach to extracting texture information from food photos to show how these features improve the accuracy of a nutritional assessment system that runs on mobile phones. The proposed method improvesthe food texture ratio of 98.7%, effectiveness ratio of 99.2%, accuracy ratio of 95.89%, food ingredient predictionsand their nutritional compatibility ratio of 96.8%, and food component classifications ratio of 97.29%.

Keywords: mechanobiological factors in fermentation; understanding the impact on food texture and nutrient release

1. Introduction

The intricate biochemical process of fermentation is essential to creating many meals; it changes many foods' texture, taste, and nutritional content. The fermentation environment's mechanical and biological interactions, known as mechanobiological variables, play a crucial role in determining the fermented foods' properties. The mechanical forces acting on microbial cells, the cellular reactions to these forces, and the following biochemical changes are all components of this equation. Improving food texture and nutrient release requires understanding fermentation's mechanobiological aspects. Mechanical pressures may impact the features of the completed meal on microbial cell development, metabolism, and the creation of fermentation byproducts. For example, shear stress and pressure may affect microbial cell membrane permeability, affecting the release of nutrients and enzymes. An increased availability of processed meals characterizes the modern nutritional environment, which may be linked to various health concerns [1]. A thorough understanding of the impact of diet on health is crucial for developing strategies to lower the risk of developing chronic diseases such as diabetes, heart disease, and some types of cancer [2]. Food fermentation is one of the things that can heavily affect the health benefits it carries [3]. Such food's nutritional composition and texture may be modified [4]. Fermentation is governed by mechanobiological variables responsible for quality determination and nutrient release, impacting calorie intake and general health [5]. An important factor in food quality, the introduction notes that food structure is complicated and multi-faceted. To get a better understanding, however, researchers must clarify how these features, especially texture and nutrition release, are intricately shaped by mechanobiological variables. Mechanobiology is an important part of controlling the fermentation microenvironment inside food matrices, which studies the effects of physical forces on biological processes. Mechanical signals such as hydrostatic pressure and shear stresses significantly impact microbial activity, cellular integrity, and substrate accessibility. Due to this, they have a major effect on the rate of nutrient release and the texture of fermented goods. Researchers desire to learn more about how fermented foods get their textures and nutrients by explaining how mechanobiology and fermentation work together. Not only does this deeper insight broaden our grasp of food science, but it also has ramifications for making production methods more efficient and improving product quality.

Mechanobiology is a branch of biology that mainly looks into biological processes influenced by changes in the mechanical properties of cells and tissues and external physical forces upon them [6]. During the fermentation process, mechanical manipulation such as grinding, mixing and compressing constitute some examples of mechanobiological factors affecting microbial activity during the fermentation process [7]. It might turn its taste into something delicious and more digestible [8]. For this reason, it may have better nutrient release and absorption [9]. Milk proteins also break down mechanically during fermentation, increasing the bioavailability of yoghurt products with thick, creamy texture [10]. However, if children do not get these vital nutrients, they become prone to organ damage and other severe ailments in old age [11]. People can delay chronic diseases by making healthy choices about food [12]. However, given the complex nature of food structure, it is hard to precisely evaluate the amounts consumed or their nutritive values or content [13]. Their understanding involves much deeper learning, while IoT could potentially provide new solutions to these issues since they are modern technologies [14]. In recent years, exciting new developments in fermentation science and mechanobiology have opened up new lines of inquiry into the role of mechanical forces in shaping the texture and release of nutrients in fermented foods. Despite their apparent differences, mechanobiology, the study of the effects of physical pressures on biological systems and fermentation, the metabolic process by which microbes transform substrates into products, shares a deep connection. By clarifying this connection, this study wants to use deep learning to understand how mechanobiological variables affect food texture and nutrient availability during fermentation. By outlining the rationale for conducting an extensive study into the complementary impacts of mechanobiology and fermentation on food quality, this study provides the framework for future research into this emerging field of study. Deep learning is very good at handling and learning from complicated and extensive datasets. The large amount of data produced by different fermentation parameters and biological interactions makes this capability vital when considering mechanobiological aspects of fermentation. While traditional ML methods have difficulty handling high-dimensional data, deep learning models, especially neural networks, can easily handle and extract useful patterns from massive datasets.

The DL-ANCS could rapidly calculate meal nutrition using IoT sensors and a mobile app [15]. Users take pictures of their meals through their phones' cameras, after which image processing algorithms assist them in automatically identifying different food components for future reference purposes.

1.1. Use of DL-ANCS

The nutritional value of fermented food can be better evaluated with DL-ANCS. As a result, the system offers a more accurate assessment as it understands fermentation and other mechanobiological factors that determine food texture and nutrient release. DL-ANCS represents a significant breakthrough in nutritional measurement through technology. The system combines deep learning with the Internet of Things to solve an imperative requirement for accurate real-time dietary information, which helps to curb chronic illnesses associated with poor eating habits.

1.2. Contribution of the paper

- DL-ANCS integrates IoT sensors and a mobile app for immediate nutrition analysis. Advanced image processing allows for capturing and classifying meals by phone camera shots.
- An innovative approach to extracting textural characteristics significantly improves classification accuracy.
- The system achieves improvement in texture recognition, effectiveness, and overall accuracy. It also boasts accuracy in food ingredient predictions and component classifications. This innovation aids in chronic disease prevention by promoting healthier food choices through precise nutritional evaluation.

The suggested DL-ANCS system employs deep learning and image processing to accurately assess food's nutritional value using IoT sensors and smartphone apps. Dietary monitoring and avoiding chronic illnesses benefit from this method's real-time delivery of correct nutritional information. Section 2 explains the related works, section 3 shows the proposed method, section 4 describes the result and discussion, and finally, section 5 denotes the paper's conclusion.

2. Related work

The analysis delves into gastrointestinal mechanosensation, highlighting the role of mechanical forces in the gut's functioning. In this paper, CB-SAH, HC-FS, CM-ES, PIN-FR, and TMF techniques are being explored to improve food quality, nutritional content, and safety.

- Cellulose-based Superabsorbent Hydrogel (CB-SAH)

Dietary and behavioural changes for obesity therapy are difficult to sustain. A CB-SAH platform was created as a mechanobiological treatment inspired by raw vegetable composition and mechanical capabilities. Vegetable intake is essential to dietary interventions and daily nutritional needs [16]. A simulation of the gut environment and an ex vivo organ culture (EVOC) model examined CB-SAHs' effects on gut tissue. References included fresh veggies and functional fibres. CB-SAHs had orders of magnitude more elasticity than functional fibres and performed similarly to raw veggies. The EVOC model indicated that biomimetic CB-SAHs with elasticity akin to raw vegetables preserved and regulated gastrointestinal tissue. Clinical trials progressed to non-systemic oral mechanotherapeutics based on this technology.

- Hybrid Cell-based Food Systems (HC-FS)

Given hybrid cell-based meat composed of animal cells cultured in vitro inside non-animal protein matrices, it is challenging to attain sensory equivalence between these and conventional meats [17]. To create the ideal hybrid cell-based meats, it is crucial to consider the connection between the structure and functioning of the food matrix. A thorough familiarity with the various food matrices and their interplay is crucial for attaining the desired organoleptic properties in HC-FS. Animal and plant-based meats' multiscale food matrix topologies are being studied in this paper, critically assessing the methods employed thus far. The paper also delves into the topic of using these methods to make meat food matrices that are based on hybrid cells. In contrast, research on the interactions between plant-protein cells and animal-derived cells seen in hybrid cell-based meats is lacking, even though these interactions are crucial for developing novel whole-food matrices. By integrating cultured cells with plant-based or synthetic matrices, HC-FS offers a sustainable approach to food production, promising enhanced nutritional profiles and reduced environmental impact.

- Culturing Meat Using Edible Scaffolds (CM-ES)

Sustainable and appealing substitute animal protein alternatives are gaining popularity. In response to concerns about the health impacts of mass-produced beef on individuals and the earth. Cultured beef may provide tasty, environmentally friendly protein. However, it will be important to discover technologies for making cultured meats in consumer-friendly sizes [18]. This review discusses the pros and cons of using edible scaffolds to increase cultured meat output. A comprehensive description of the several types of edible scaffolds, the processes used to fabricate scaffolds, and the materials often used for scaffolding is presented here. CM-ES improve cultured meat production. These advantages include accelerating cell growth and differentiation, providing structure for complicated three-dimensional tissues, and improving cultured meat's nutritional and sensory attributes. These scaffolds, derived from natural or synthetic sources, provide structural support and mimic the extracellular matrix found in animal tissues. CM-ES aims to produce cultured meat products that resemble conventional meat in taste, texture, and nutritional content by optimizing scaffold composition and architecture.

- Personalized Intelligent Nutrition using Fuzzy Reasoning (PIN-FR)

Making healthy choices is an increasingly important part of people's lives worldwide. When planning a healthy diet, it's important to consider more than the total quantity of food eaten. To balance calories and nutrients, one must also live an active lifestyle with enough physical exercise [19]. This leads people to seek the help of dietary experts for health evaluations, which is costly, time-consuming, and hard to acquire. While many e-nutrition solutions are available, most focus on meal planning rather than evaluating and assessing health status,which human healthcare providers have traditionally carried out. Meal planning requires nutrition health assessment, recommendation, and progress evaluation, which no automated system can achieve. Personalized intelligent nutrition recommendations (PIN) provide a ground-breaking framework. PIN employs fuzzy reasoning to simulate human health assessment specialists' abilities. Among these features is the ability to assess progress and make changes to recommendations; ideas about weight, calorie consumption, and activity are also available.

- Texture-modified meals (TMF)

This paper treats people with trouble chewing or swallowing, such as the elderly, the world's fastest-growing group. These meals must be soft, safe, simple to swallow, nutritious, and attractive to help overcome physiological dysfunctions and satisfy nutritional demands. This research covers common and novel components and methods for creating TMF with the right textural properties. This evaluation also includes nutritional and sensory enhancements. The structure and properties of TMF's food matrix and substance affect digestion and nutrient bioavailability [20]. Designing products with textural, nutritional, and sensory features for seniors must consider the compositional and structural components of the product during formulation and the alteration of food structure during oral processing and on the digestive tract. Increasing awareness about these issues might help build more useful products for seniors [21].

Carranza et al. [22] suggested the Texture-modified soy protein foods: 3D printing design and red cabbage effect. The first step in using an extrusion 3D printer to get the desired form was to make a variety of doughs with varying amounts of soy protein isolate (SPI) (20, 25, and 30 w/v %). In this instance, the dough with 25% SPI (25-SPI) was the most suited. After that, rheological and physicochemical analyses were conducted before printing the 25-SPI doughs containing 10, 20, and 30 wt % red cabbage (RC). Since the viscosity dropped with an increase in shear rate, all doughs exhibited shear thinning behavior, an appropriate rheological behavior for 3D printing. Concerning the impact of RC on food formation, the viscosity and storage (G') and loss (G'') moduli rose with increasing RC content, with $G' > G''$ for all doughs. This indicates a solid-like behavior, which is useful for printing food samples to keep their shape and size. Superficial imaging microscopy (SEM) verified that the 3D printed samples were uniform and that the holes in the doughs diminished with increased RC content.

Miehle et al. [23] examined the impact of processing on the in vitro glucose release of fiber-rich, high-glycemic foods. Doughs that were either untreated, baked at 180 °C, or extruded at 150 °C and 180 °C with partial enrichment of high-methylester pectin were used to assess the effects of composition and microstructure on in vitro glucose release and starch digestibility. Products baked at 180 °C and extruded at 150 °C had their glucose release reduced because pectin enrichment lowered starch digestibility, changed the food matrix, and doubled in vitro chyme-viscosity. Baking and extrusion cooking make the starch more digestible, meaning it quickly turns into starch and free glucose. There was an additional increase of up to fivefold in resistant starch levels. The intricate relationship between starch digestibility, food matrix, and viscosity is the source of the glucose release fluctuations.

Based on the survey, there are several issues with existing models in attaining a high food texture ratio, effectiveness ratio, accuracy ratio, food ingredient predictions, nutritional compatibility ratio and food component classification ratio. Hence, this paper proposes a deep learning-based automated nutrition classification system (DL-ANCS) for predicting food ingredients and nutrition.

3. Proposed method

A healthy diet is an important tool in the fight against and maintenance of chronic illnesses, diabetes, cardiovascular disease, stroke, and even some forms of cancer. Prevention is crucial when trying to prove a connection between diet and illness. Using traditional methods to evaluate a person's diet might be tedious and misleading. In response to these issues, the authors of this work suggest DL-ANCS, an Automated Nutrition Categorization System that makes use of deep learning, together with IoT sensors and an accompanying mobile app. To help people make better dietary decisions, this system employs visual processing and meal forecasting algorithms to categorize food products and evaluate their nutritional content correctly.

The DL-ANCS architecture, shown in **Figure 1**, combines human input, mobile devices, deep learning, and IoT sensors to accurately classify foods and assess their nutritional value. At the heart of the system is the user interface and user experience, allowing users to input their dietary limitations and preferences while taking pictures of food with their smartphones. This data is sent to the smartphone application (iOS/Android) as the central processing hub.

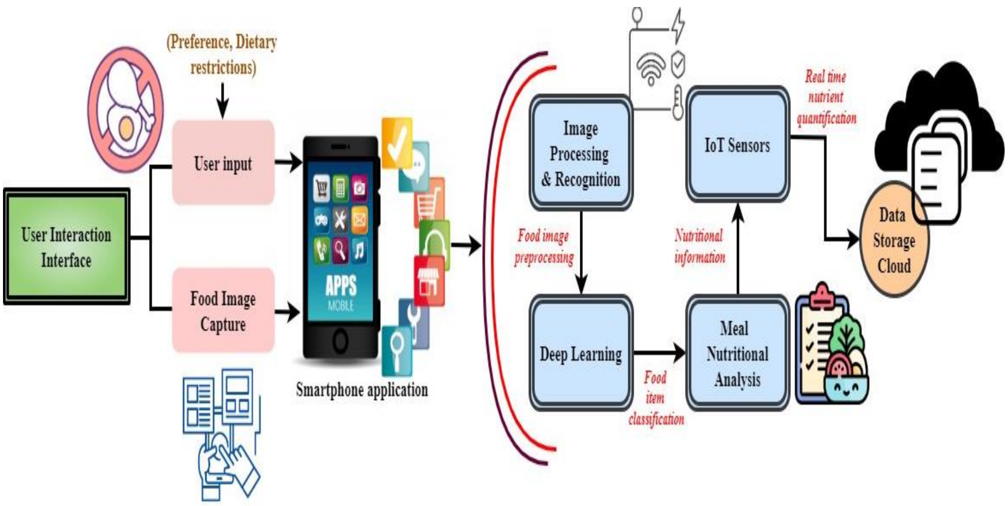


Figure 1. Deep learning-based automated nutrition classification system.

Before analyzing the photographed food, the app does Image Processing & Identification to prepare the photographs. The procedure entails using sophisticated image processing algorithms to discern food items in the photographs. The Machine Learning Module takes these cleaned-up photos and uses a neural network model it learned to categorize the foods. With proper training, this model can identify many different types of food and their characteristics. Convolutional neural networks (CNNs) algorithm has been chosen for this study because of their proficiency in automatically learning significant characteristics from complicated, high-dimensional data and their competence in processing such data. These skills shine when applied to the context of fermentation's mechanobiological components. Convolutional neural networks (CNNs) are a powerful tool for accurately predicting and optimizing fermentation processes because they capture the complex patterns and spatial hierarchies seen in biological and fermentation data.

After the food components are categorized, the system checks their nutritional value using an app called Meal Structure & Nutritional Analysis. This study comprehensively summarises the nutritional components, including calories, macronutrients, and micronutrients. The app communicates with IoT sensors, spectrometers, and weight scales to measure nutrients in real-time. The sensors precisely assess the food's chemical and chemical qualities, improving the nutrient content's accuracy. A Cloud Data Store safely stores all the acquired data, including sensor readings and user inputs. By keeping all of the most recent dietary patterns and nutritional information in one place, this centralized storage makes it possible to learn and improve the model continuously.

$$K(A) = \frac{1}{\sqrt{ב}} \int_{-\infty}^{\infty} \frac{א^{-\omega^2} df}{t - \mu\pi} = \sigma \int_{0}^{\infty} f^{-er-k/8} cv \quad (1)$$

The suggested DL-ANCS approach can solve the provided Equation (1). In this context, $K(A)$ represents the kernel function that is used in the classification system. It takes into account different aspects of food texture and ingredients, such as $\frac{1}{\sqrt{ב}}$, to accurately predict the nutritional content $\frac{א^{-\omega^2} df}{t-\mu\pi}$. As a result, it achieves a high level of reliability and accuracy when doing tasks related to food and nutrition classification $f^{-er-k/8}cv$.

$$\int_{-\infty}^{\infty} qw^{-esf^2} nm = \left[\int_{-\infty}^{\infty} qad^{-epl^2} nm \int_{-\infty}^{\infty} zxb^{-rpu^2} nk \right]^{1/2} \quad (2)$$

By seeing it as a representation of the multi-pronged strategy for extraction of features and analysis in DL-ANCS, Equation (2) may be linked to the suggested technique $qw^{-esf^2}nm$. Various food qualities, including texture and ingredients $qad^{-epl^2}nm$, can be represented by $zxb^{-rpu^2}nk$ in DL-ANCS when examined across certain ranges.

$$\left[\int_{0}^{4ב} \int_{0}^{\infty} hj^{-rf^2} pg \, de \, d\tau \right]^{1/2} = \left[\mu\pi \int_{0}^{\infty} zf^{-ub} wq \right]^{1/2} = \sqrt{\pi\varphi} \quad (3)$$

By seeing the Equation (3) as a representation of the interconnected web of characteristics in the system $hj^{-rf^2}pgde\,d\tau$, it may draw connections to the suggested DL-ANCS technique. Different food qualities and processing parameters can be represented by $\mu\pi$, $zf^{-ub}wq$, and $\pi\varphi$ in DL-ANCS.

3.1. Factors affecting the fermentation process and metabolic processes in microbes

For instance, what happens to the digestibility of legume protein during fermentation depends heavily on the fermentation settings and the plant material type, according to the reviewed literature. Nonetheless, fermentation usually leads to a rise in IVPD, albeit the extent to which this occurs varies somewhat. Products made from legumes may have more free amino acids after fermentation; however, this varies by cultivar and type of bean. Fermentation is a common method for lowering raw materials' phytic acid concentration. Fermentation typically reduces the quantity of condensed tannins; however, effects on different tannin molecules vary. Furthermore, there is typically (not necessarily) a decrease in inhibitory activity towards trypsin. Therefore, protein digestibility and mineral absorption are improved due to decreasedphytic acid concentration, tannin compounds, and perhaps other ANFs. **Figure 2** shows a high-level view of how the fermentation process affected the ANFs and nutrient availability. A review of nutritional quality characteristics of plant-based meal matrices and how they are impacted by fermenting process conditions and microbial physiological events. While fermentation generally improves protein availability and rocks solubility, and certain compounds derived from proteins and phenols can have beneficial biological activities (green dashed lines), it can reduce activities that could be good for people's health (blue dashed lines) due to phytic acid, protease blockers, and tannin compounds.

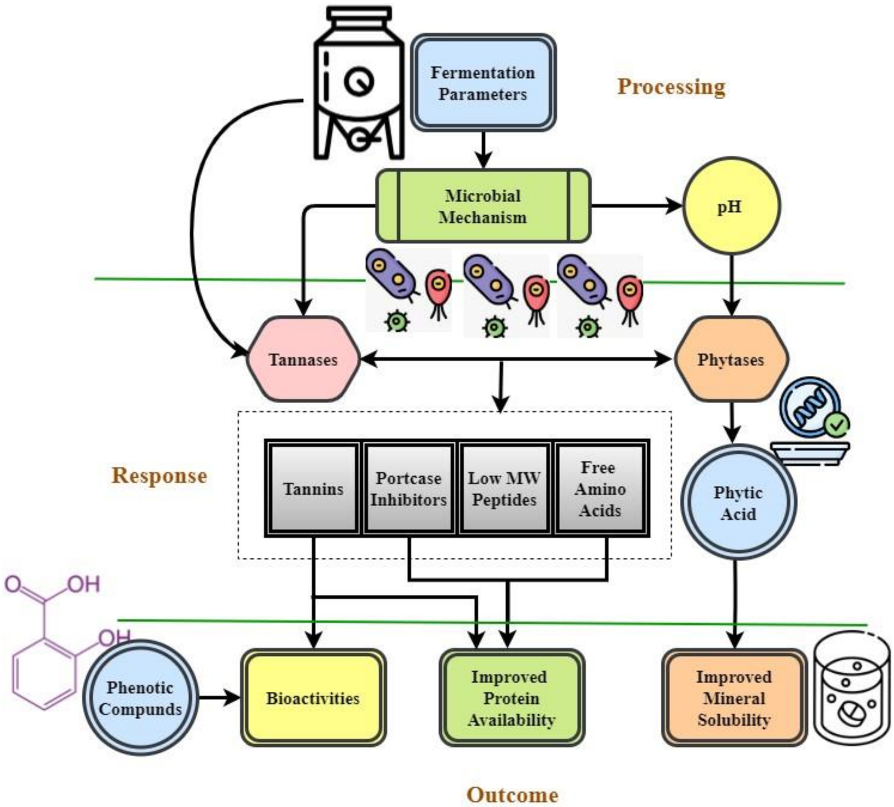


Figure 2. Factors affecting the fermentation process and metabolic processes in microbes.

$$(c_1 z + w_1) = \frac{e_{w1} q_{f2} x z^2 + (w_1 e_2 + p_2 q w_1) x y + e_1 b p_2}{\left(d_{f2} z + e d_2\right)} \tag{4}$$

The presence of a specific set of features or conditions inside the DL-ANCS is denoted by the Equation (4) $c_1 z + w_1$, whereby $e_{w1} q_{f2} x z^2$ and $w_1 e_2 + p_2 q w_1$ stand for particular food attributes or pieces of information. The existence of certain qualities $w_1 e_2 + p_2 q w_1$ leads to particular consequences $e_1 b p_2$ as shown by the implications $d_{f2} z + e d_2$.

$$\exists Qz \left(\mathrm{kmn}(Re) \wedge Zq\left(\mathrm{bpl}(zw) \rightarrow \mathrm{Eqp}(xc, wl)\right)\right) \tag{5}$$

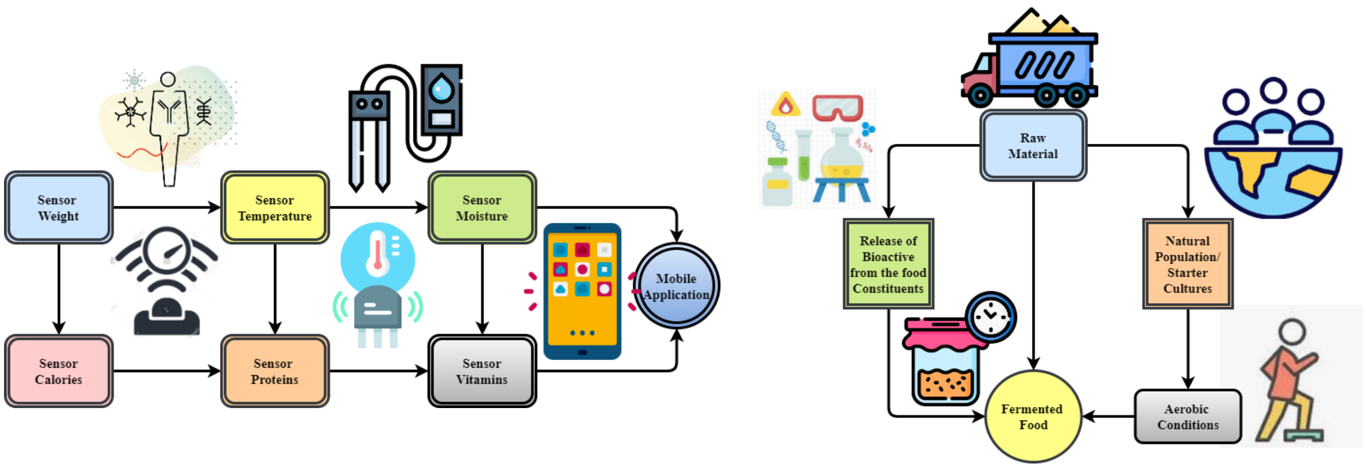
The specific procedures used to analyze food data, whereas Equation (5), $\exists Qz$ denotes the system's overall efficacy or output. The integral $\mathrm{kmn}(Re)$ represents the comprehensive and continuous feature extraction from the food photos $Zq\left(\mathrm{bpl}(zw)\right)$, similar to how DL-ANCS handles different properties, nutritional quantity and texture Eqp(xc, wl).

$$\mu(zg) = \int_0^{\infty} pt^{zr-1} fge^{-t} dpq = \frac{fw^{-wq}}{aw} \prod_{p=1}^{\infty} \left(1 + \frac{a}{pt}\right)^{-1} qf^{2z/kw} \tag{6}$$

In the DL-ANCS Equation (6), $\mu(zg)$ could stand for the expected nutritional score or classification outcome, and the terms $pt^{zr-1} fge^{-t} dpq$ represents different factors or characteristics retrieved from food pictures, ingredients, texture, and nutritional value. The deep learning model's function is shown reads $\frac{fw^{-wq}}{aw}$. Here, $\frac{fw^{-wq}}{aw}$ is the learning algorithm and $qf^{2z/kw}$ is the description of the relationship between various features, which is raised to a power of \(nt\) to indicate the model's extent and complexity.

3.2. IoT sensor network for food nutrition

Figure 3a displays an Internet of Things Sensor Network developed to conduct a thorough food nutrition analysis. Every one of the weight, temperature, moisture, calorie, protein, and vitamin sensors in this network is essential for evaluating some facet of nutrition. Important for controlling serving sizes is that the weight sensor determines how much food there is. Temperature sensors guarantee food safety by tracking the temperature throughout preparation and storage. The amount of water sensors impacts the freshness and texture of food. A calorie counter estimates the energy in food, whereas a protein counter measures the amount of protein the body needs. Vitamin sensors detect and measure individual vitamins to provide a comprehensive nutritional profile. Better dietary control and health outcomes are possible with the help of these sensors since they provide accurate nutritional analysis in real-time.



(a) (b)

Figure 3. Internet of Things sensor network. **(a)** IoT Sensor Network for Food Nutrition; **(b)** block diagram depicting the steps involved in fermentation.

3.3. Block diagram depicting the steps involved in fermentation

Anaerobic or partly anaerobic circumstances cause bacteria to slowly decompose organic molecules, which results in fermentation **Figure 3b**. Microorganisms are vital in fermentation because they help keep food fresh, improve its flavour, and increase its nutritional value. Fermentation is any procedure that uses the bulk cultivation of microbes to produce a product. The many products that come from fermentation can be achieved in two ways: either spontaneously or by adding starter culture. A diverse colony of microbes, including yeast, bacteria, and fungi, is necessary for natural fermentation.

$$ps = \frac{1}{2}sEw + kq_o pe + rzx_0 = \left(f = L\left(G + \frac{er}{po}\right)^{nt}\right) \tag{7}$$

The term ps could represent the expected nutritional score or classification outcome in Equation (7). The terms $sEw + kq_o pe + rzx_0$ represent traits or characteristics taken from food pictures, ingredients, texture, and nutritional value$f$. The deep learning model's function is shown as $\left(G + \frac{er}{po}\right)^{nt}$.

$$l(s,q) = \sum_{n=0}^{\infty} \frac{l^{(ns)}(ba)}{cn!}(zq - a)^n + (xq + yb)^{nz} = \sum_{k=0}^{n} \binom{nw}{ep} wp^{sp} ba^{en-pk}) \tag{8}$$

The general DL-ANCS function is given by the Equation (8) where $l(s,q)$, where the first sum $\frac{l^{(ns)}(ba)}{cn!}$ denotes the accumulation of diverse dietary features $(zq - a)^n$ and their transformations $(xq + yb)^{nz}$ through the model's layering process. Deep learning techniques normalize and scale the data using factoring and algebraic components $\binom{nw}{ep} wp^{sp} ba^{en-pk}$, while the iterative extraction and combination of food attributes are represented.

$$\text{dfp}\, pv + j\cos wl = (\sin\theta v + j\cos\partial)^{n+gh} = ef^{ipy} \tag{9}$$

The several input features that the DL-ANCS considers are reflected in Equation (9). The values dfp pv, which is a mix of dietary properties $\cos wl$and the weights or coefficients that are connected with them. Similar to the layers and activations of a deep learning model, the $(\sin\theta v + j\cos\partial)^{n+gh}$ encompasses the nonlinear changes and interactions among these features. The final version of the equation, ef^{ipy}, denotes the output or prediction of the system.

3.4. Image of the food recognition system

Figure 4 shows the image of the food recognition system. The goal is to develop a mobile-friendly automated tracking of nutrition and calorie estimate system based on the Internet of Things (IoT). The system's users possess the mobile portal for collecting physical measuring data and demographic information. The microcontroller module may be activated using the application and the MyMqtt broker. After placing it on the load sensor, the microcontroller estimates the food's weight and takes a picture using the USB camera. The snapshot is timestamped, and the Thingspeak cloud server stores all the gathered data. The acquired data is then used for the data analytics that follow. A Convolutional Neural Network model trained using deep learning and fed food item categorization data is first constructed. Next, the food type is predicted using the model that was built. The number of calories ingested is determined using the nutritional information collected from the USDA standardized data repository, which is based on the volume calculated by the load sensor and the forecast of the food item. There is an extended picture of all the actions in the system that follows the graphical representation of the food recognition system's design in **Figure 4**.

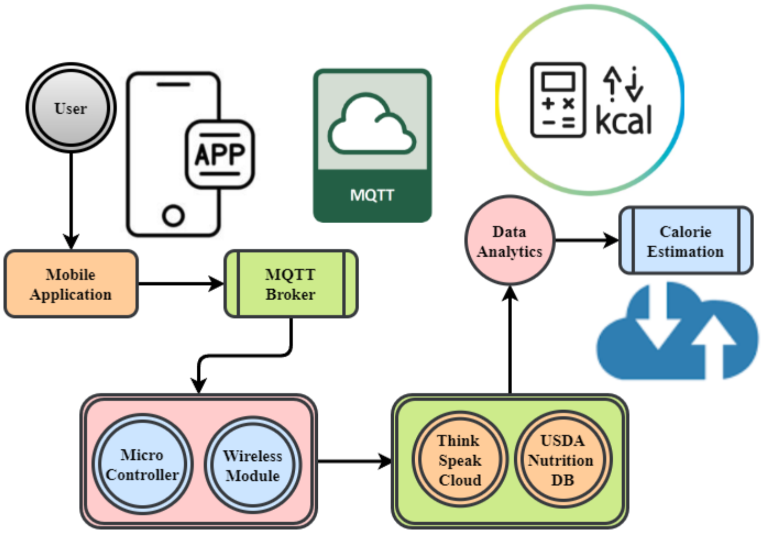


Figure 4. Image of the food recognition system.

$$\propto\cdot\, \rho\sigma\psi = \frac{p\sigma^2 A}{Py} + \frac{\partial^2 \forall}{\omega z^2} + \frac{\partial \pi^2 \vartheta}{\partial p z^2} = \frac{1}{k^2 \cos\theta}\left[\tan\theta \frac{gp}{cm}\right] \tag{10}$$

Similar to how features are weighted in the DL-ANCS, the Equation (10) $\propto\cdot\, \rho\sigma\psi$ represents the weights linked to various dietary properties $\frac{p\sigma^2 A}{Py}$. The following terms stand for different parts of data processing and analysis, the squared gradient of specific attributes $\frac{\partial^2 \forall}{\omega z^2} + \frac{\partial \pi^2 \vartheta}{\partial p z^2}$, the second derivative of a function concerning a variable $\frac{1}{k^2 \cos\theta}\left[\tan\theta \frac{gp}{cm}\right]$, and the association between multiple variables.

$$\frac{b2P}{\partial \omega y^2} = \left(r^2 \frac{\mu\psi}{\delta r\beta}\right) + \frac{\partial \omega}{\mu\tau\theta}\left(\cot\theta \frac{\omega\tau}{\theta\epsilon}\right) + \frac{1}{\tan\theta}\frac{\gamma^2 \beth}{\partial \aleph \varphi^2} \tag{11}$$

The system's sensitivity to changes in analysis of food textureis represented by the Equation (11), $\frac{b2P}{\partial \omega y^2}$. The following terms indicate various factors influencing texture analysis, such as the ratio of particular parameters $r^2 \frac{\mu\psi}{\delta r\beta}$, and the interaction between different variables $\frac{\partial \omega}{\mu\tau\theta}$, and the link between texture characteristics $\frac{1}{\tan\theta}\frac{\gamma^2 \beth}{\partial \aleph \varphi^2}$.

$$(1+j)^{snd} = gh + \frac{rs}{3!} + \frac{qm(w-sd)zxp^2}{4!} + \cdots \tag{12}$$

Different factors that contribute to the analysis of effectiveness are shown by Equation (12), which includes the initial performance gh, small enhancements $\frac{rs}{3!}$, and more complex enhancements and engineering features $\frac{qm(w-sd)zxp^2}{4!}$.

3.5. The structure of the suggested meal identification system

The food recognition-dietary assistance pipeline is illustrated in **Figure 5**. An interactive web browser and a recognition engine hosted on the server make up the system. A purpose-built API handles the communication between the two parts. The client communicates with the server in a two-part FormData object submitted via XMLHttpRequest. On the server side, it handles all of the API requests from the clients using WebSphere Liberty 5 and custom Javacode. Held on the server. The system's front-end client is built using basic HTML and JavaScript. It is a website built to perform flawlessly on mobile devices. In **Figure 5**, the desktop interface shows a space where the user may drag and drop images to submit; in **Figure 5**, the mobile interface goes straight to the user's camera roll or photo library on their phone. The following is how the returned JSON file containing the processed request is displayed: First, the top three broad categories and an image and name for each are displayed. The reference picture used by the K-NN classifier is the one that is physically nearest to the reference database. Since it was discovered that people had trouble understanding the absolute computations, they decided not to provide the classification score for each category.

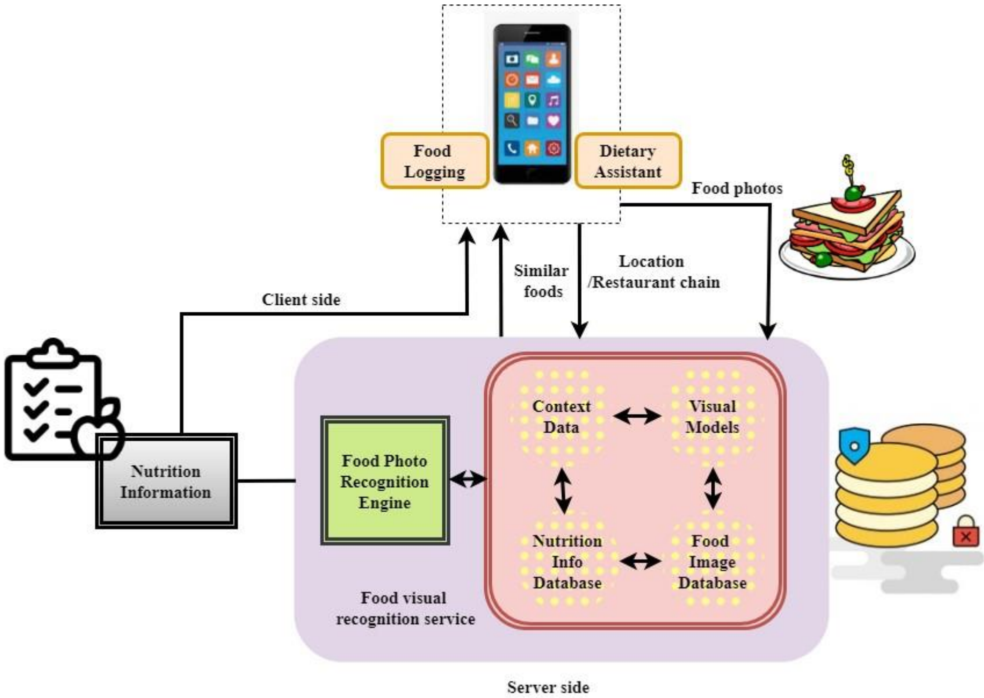


Figure 5. The structure of the suggested meal identification system.

$$\text{fgp}\,\pi \pm \text{zby}\,\sigma = 2\,\text{wsv}\frac{1}{2}(\sigma \pm \delta)\cos\frac{1}{2}(\alpha\beta \mp \Delta) \tag{13}$$

The suggested DL-ANCS approach incorporates improved accuracy analysis into Equation (13). In this case, the desired accuracy level in nutritional assessment is denoted by $\text{fgp}\,\pi \pm \text{zby}\,\sigma$, and the improved prediction mechanism in the DL-ANCS is represented by $2\,\text{wsv}\frac{1}{2}(\sigma \pm \delta)$. This equation shows how modifying parameters $\cos\frac{1}{2}(\alpha\beta \mp \Delta)$, as well as modulating the cosine operation, may improve the system's accuracy.

$$\int_S \nabla(1+\gamma\delta) \times \text{FSl} \cdot Ru = \oint_{CW} \text{DF} \cdot ef \tag{14}$$

This Equation(14), represents the Analysis of Food Ingredients Predictions and their Nutritional Compatibility in DL-ANCS and is expressed as $\nabla(1+\gamma\delta) \times \text{FSl} \cdot Ru$.

Contrarily, $\mathrm{DF} \cdot ef$ reflects the comprehensive evaluation method of DL-ANCS by including dietary components and their effects on nutritional compliance in a circular fashion.

$$m(b+c) = \frac{1}{2hj} \oint \frac{f(w)}{aw-p} Kp(w-jk) \tag{15}$$

The suggested DL-ANCS method's analysis of food component classifications is encapsulated in Equation (15). The classification conclusion for individual dietary components is represented by $m(b+c)$ here, which is similar to the system's result when recognizing different nutritional elements. The thorough evaluation of food characteristics, such as texture and composition, is represented by an integral value $\frac{f(w)}{aw-p}$, which reflects the feature extraction procedure in DL-ANCS and incorporates several data sources $Kp(w-jk)$.

Using advanced image processing and machine learning, it is expected that the proposed DL-ANCS Automated Nutrition Identification System can improve the precision and effectiveness of nutrition evaluations. The DL-ANCS platform employs IoT sensors and smartphone technologies for real-time dietary monitoring and nutrient assessment. Performance indicators, nutritional compatibility, ingredient prediction, and food texture analysis are some of them.

4. Result and discussion

The DL-ANCS system provides accurate nutritional information using deep learning and the internet. The crucial investigations include texture evaluation, system efficacy, accuracy improvement, ingredient prediction, and food categorization. Recognizing food textures may improve digestion and flavour. Testing the system ensures nutritional data accuracy. It needs additional database data and improved algorithms to be more exact. Predicting food nutrition helps consumers make smarter diet decisions. Correctly categorizing dietary components is essential for accurate nutritional evaluations. When combined, these assessments improve system usefulness and dependability.

4.1. Dataset description

Repeatedly eating high-energy, nutrient-poor meals may cause obesity [21]. Understanding the relationships between food flavour, individual taste preferences, food choices, and intake can help us understand why some choose and eat unhealthy foods. This review addresses important questions: nutrition-rich meals have different flavour profiles, whereas nutrition-low meals are sweet, salty, and greasy. People are born preferring sweet and hating bitter flavours; however, they vary in liking all essential taste attributes. These individual variances partially explain short-term food intakes of different taste profiles. It examines how taste, smell, and texture interact with individual traits, affecting nutrient-rich and deficient food intake. Various statistical approaches were used in the study to determine the significance of differences and correlations between variables. These methods included regression analysis, analysis of variance (ANOVA), and *t*-tests.

4.2. Analysis of food texture

An analysis of food texture is shown in **Figure 6** and is necessary for grasping how physical attributes impact customer satisfaction and nutritional release. The three fundamentals of a healthy diet are digestibility, nutrient absorption, and palatability, all impacted by texture. Food mechanical qualities, including cohesion, viscosity, and hardness, allow analysts to learn how different textures affect the sensory experience and overall food quality. Texture analysis is a great tool for fermented food producers looking to improve their processes while increasing their products' nutritional value and flavour. Increased health benefits and more customer acceptance are the results. Using this method, the analysis of food texture value is increased by the ratio by 98.7%.

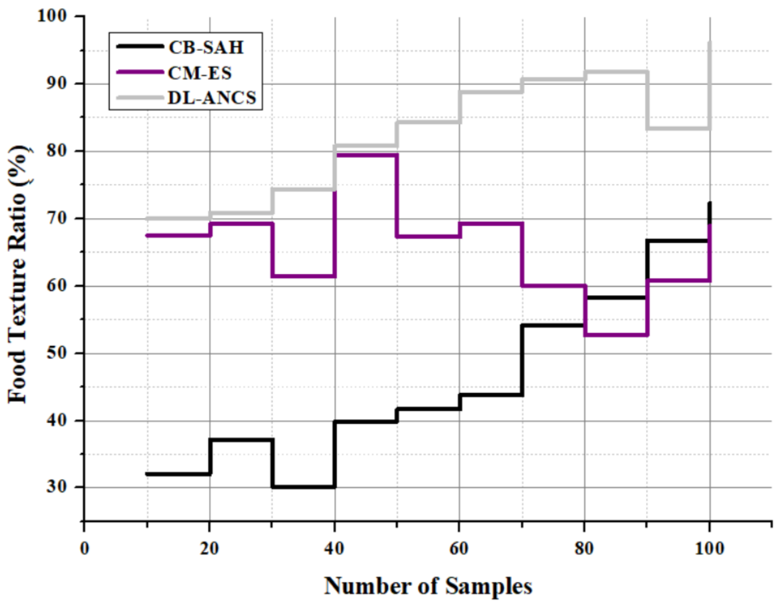


Figure 6. Analysis of food texture.

4.3. Effectiveness analysis

One metric that must be analyzed to determine how well the DL-ANCS system works is its ability to accurately quantify nutritional information and predict meal components, as described in **Figure 7**. Many metrics provide a precise assessment of efficacy, including accuracy, precision, recall, and user happiness. Analysts may assess the system's reliability by comparing the system's predictions with actual nutritional data gathered from verified sources. Furthermore, case studies and user comments may improve practical applications and usability. These results show that the DL-ANCS system meets all the criteria necessary for real-world use. It provides reliable nutritional assessments that can help people make healthier food choices. Compared to the existing method, the effectiveness analysis ratio of the proposed method is 99.2%.

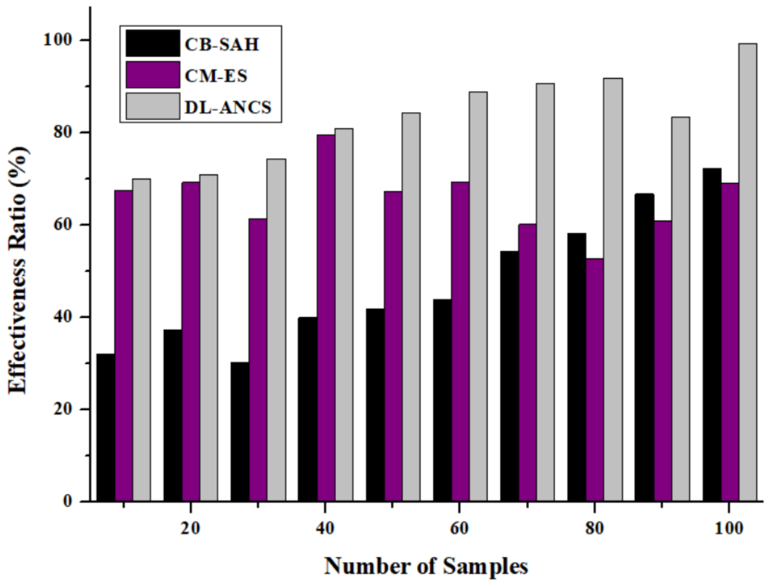


Figure 7. Analysis of effectiveness.

4.4. Accuracy ratio

Improving the DL-ANCS system's accuracy is crucial for making reliable nutritional assessments. **Figure 8** describes the accuracy improvement analysis, which can only be achieved by enhancing the food recognition and classification algorithms and deep learning models now in use. Training the algorithm on a dataset with a larger and more diverse selection of food photographs and nutritional information may improve its accuracy. Another component contributing to enhanced performance is using more intricate methods, such as texture analysis and contextual recognition. Constant improvement based on user feedback and real-world testing ensures that the system maintains high levels of accuracy. Because of this, the system is a trustworthy tool for analyzing nutrition. The improved accuracy analysis ratio is 95.89% in this proposed method.

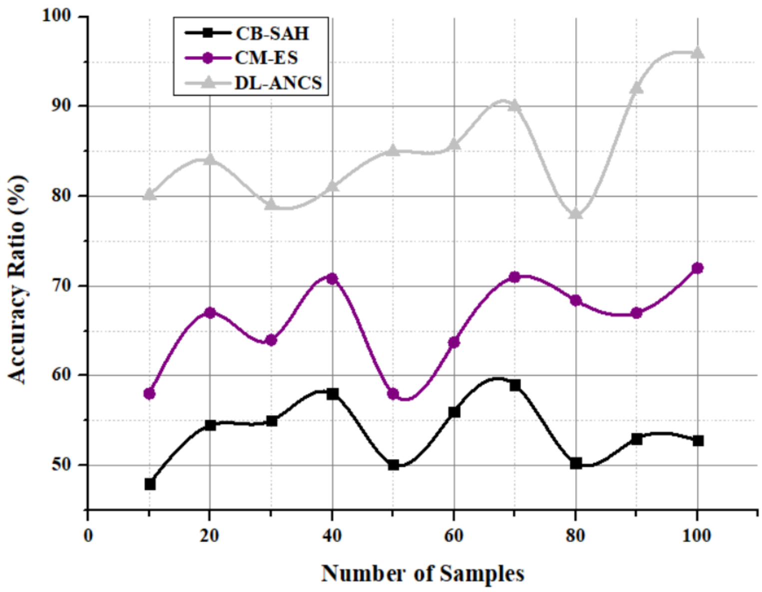


Figure 8. Analysis of improve the accuracy.

4.5. Food ingredients predictions and their nutritional compatibility

Accurately predicting dietary components and the nutrients they contain is one of the main tasks of the DL-ANCS system. The main objective of this analysis is to examine the system's ability to dissect complex meals into their components and calculate the total nutritional value of those pieces shown in **Figure 9**. The system can use deep learning algorithms trained on large datasets and massive amounts of data to identify foods and precisely predict their nutritional contents. People need to understand the nutrient composition in the food consumed to make informed decisions about what they eat. The study also suggests that adding more food items to expand food coverage in a database is one way of identifying areas for improvement. This method analyses food ingredient predictions and their nutritional compatibility ratio by 96.8%, higher than existing methods.

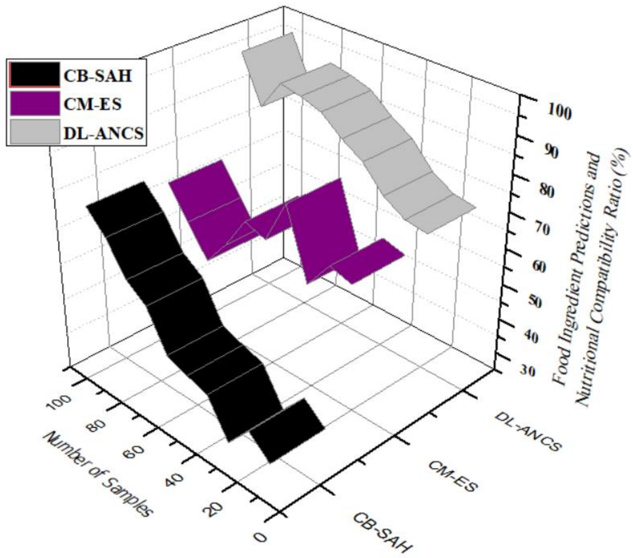


Figure 9. Analysis of food ingredients predictions and their nutritional compatibility.

4.6. Classifications of food components

DL-ANCS method is used to classify food components, paying attention to visual and nutritional features (**Figure 10**). The system's ability to identify particular food items using user pictures becomes this experiment's main performance evaluation criterion. Reliable nutritional information can only be provided if correct classification is done. On many occasions, sophisticated image processing techniques combined with machine learning ensure no mistakes when distinguishing between identical or different meals. Additionally, an assessment metric such as a confusion matrix or a classification report may also be deployed to determine the efficiency levels of this system, which could also include these factors. Classification algorithms are updated and modified regularly to ensure reliability and accuracy under different circumstances. The value exceeds 97.29% through analysis of food component classifications. **Table 1** shows the comparison results of the proposed methods with models.

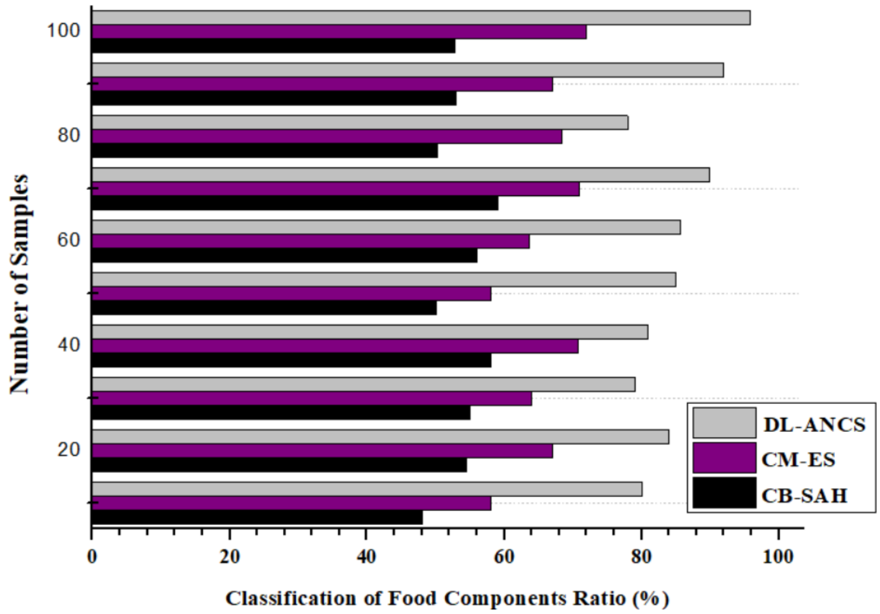


Figure 10. Analysis of classifications of food components.

Table 1. Comparison results of the proposed method with existing models.

Methods	Food texture ratio	Effectiveness ratio	Accuracy ratio	Food ingredient predictions	Nutritional compatibility ratio	Food component classifications ratio
CB-SAH	40.2	82.3	62.4	84.5	52.3	74.5
CM-ES	69.8	78.8	72.9	85.4	86.5	77.2
DL-ANCS	98.7	99.2	95.89	96.8	96.8	97.29

Using a multi-pronged approach to accurate nutrition assessment, DL-ANCS uses algorithmic models involving multiple input variables instead. One can enhance understanding of digestion and nutrient release by examining food texture properties. This meant testing its efficiency to apply the solution in real life. To improve the rheology of fermenting bread dough, we collaborated with a commercial bakery and used the mechanobiological framework. The mechanical characteristics of the dough might be adjusted to produce the desired volume and texture by methodically adjusting the mixing settings and dough composition. The optimization did wonders for the bakery's bottom line, increasing productivity, improving product homogeneity, decreasing manufacturing costs, and reducing ingredient waste.

Utilizing deep learning techniques, fermentation processes may be fine-tuned to meet specific dietary requirements. This customized approach to nutrition has the potential to enhance health results. Fermented foods with medicinal or preventative qualities, such as probiotics for digestive health or foods that reduce inflammation, may be developed with the help of this study. More research on the positive effects of fermented foods on health might propel public health initiatives that encourage better eating choices. Better nutritional literacy, more educated food choices, and better eating habits may be achieved by public awareness of the function of fermentation in food processing.

5. Conclusion

Mechanobiological parameters fermentation play parameters influence taste and nutrient diffusion from fermented foods. Understanding these factors is essential to improving food quality, especially regarding enhancing nutritional bioavailability and textural integrity,which are critical for human health. The nutritional content of a food can be reliably and instantaneously assessed using smartphones and IoT sensors based on the proposed DL-ANCS system. The deep learning models combined with image processing provide accurate identification and classification of food items by DL-ANCS. This would then inform better dietary choices. This research demonstrates that texture analysis provides much more precise nutritional assessments to lower diet-related chronic diseases when analyzing pictures of foods. Its potential as a powerful self-care tool and an advanced nutrition analyzer lies in its ability to automatically identify and catalogue various foods. The proposed method improves the food texture ratio of 98.7%, effectiveness ratio of 99.2%, accuracy ratio of 95.89%, food ingredient predictions and their nutritional compatibility ratio of 96.8%, and food component classifications ratio of 97.29%. Reliable and strong real-time data collecting and processing technologies are essential for implementing real-time CNN-based optimization and control of fermentation processes. Such a degree of integration is difficult to achieve and requires a lot of resources.

Future work

Several critical aspects of the DL-ANCS system will be the focus of future development efforts. The system's accuracy and reliability may be enhanced by expanding the database to include food images and nutritional information. A wider range of scenarios may be addressed by expanding the strategy to incorporate a wider variety of meals, particularly those from other cultures. In addition, enhancing the image processing techniques to handle multi-component difficult meals better could significantly increase food identification accuracy. Moreover, depending on how the system is used in the real world, integrated user feedback mechanisms may help with continuous system improvement. More analysis of the potential of AR to provide real-time dietary information and suggestions based on the discovered items would be beneficial. Furthermore, longitudinal studies analyzing the system's effect on nutrition and health outcomes for users are vital for validating the system's utility as a tool for promoting good eating patterns and preventing chronic diseases.

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