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# A Deep Learning-Based Decision Support System for Sensory Evaluation: A Predictive Framework for Functional Product Taste Assessment in Neuromarketing

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**Abstract**

This study aims to investigate the relationship between consumer neuroscience and neuromarketing using a multivariate methodology. Tools such as Principal Component Analysis (PCA) and deep learning neural networks were employed to interpret consumer responses to functional products. To this end, EEG signals were collected, recorded, and analyzed from 83 participants aged 20 to 29 to identify significant neural markers related to food consumption decisions. Key factors influencing decision making were identified, including low beta and gamma frequency bands. Participants' levels of attention and reflection also played a role. The findings validate the effectiveness of the proposed method, demonstrating its applicability in various fields requiring accurate and reliable classification. Furthermore, some possible applications of this topic are mentioned in the food industry section, with the aim of enabling them to develop personalized nutritional strategies based on the results obtained from the brain activity of consumers.

**Keywords:** artificial neural networks and deep learning; factor analysis and principal components; computational issues in computer and robotic vision; consumer behavior; demand theory

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## 1. Introduction

In order to understand the factors that influence the process in consumer decision making, it has become a topic of primary interest, both for academics and for the industry. Therefore, marketing departments strive to understand what drives consumers to make a decision, with the aim of improving advertising efficiency and thus reducing costs. The Mexican food sector, which contributed 3.9% of GDP in 2020 [1], contributed significantly in social, cultural, and economic aspects. On the other hand, obesity and overweight rates in Latin America have experienced a significant increase of 58%, in Mexico, reaching 76.4% in adults and 35.6% in children aged 5 to 11 years [2]. One of the main causes of the increase in obesity and overweight in Mexico is due to the fact that sufficiently healthy diets have

not been developed [3]. In addition, the situations presented have a high correlation with diseases such as type 2 diabetes [4] and hypertension, which are the most prevalent today. Therefore, because consumers have become aware of this problem, it has led them to adopt a healthier way of consuming. Consequently, the food industry must begin to consider consumer demands, with the aim of developing strategies that promote both commercial success and consumer well-being. In 2023, Mexico moved from second to fifth in the global obesity ranking, according to ENSANUT 2020, thanks to efforts to improve public health. Global measures against obesity include labeling of calories and fat content [5], allowing consumers to evaluate nutritional value [6], and a tax on sugary drinks.

However, more research is needed to fully understand the impacts of policy on consumer behavior due to limited data. The prioritization of health has been driven by global events like the COVID-19 pandemic [7], which raised awareness of the consequences of poor nutrition [8]. The shift in consumer attitudes has opened the market for beneficial nutritional products, such as functional foods. Functional foods, Figure 1, can be defined as those that, in addition to having basic nutritional value, contain biologically active components that have been scientifically linked to beneficial effects on one or more physiological functions, contributing to improved health and well-being. These products may include foods naturally rich in functional compounds (such as vitamins, minerals, dietary fiber, antioxidants, and essential fatty acids). Regular consumption of these foods has been associated with a reduction in risk factors for chronic diseases, improvements in digestive and immune function, and support for metabolic and cardiovascular health. In this context, functional foods are not intended to replace a balanced diet, but rather to complement it, especially in populations exposed to nutritional imbalances associated with modern lifestyles [9].




**Figure 1.** Examples of functional food products and their main health-related characteristics.

These provide vital nutrients and benefits, such as reducing the risks of chronic diseases, helping digestion, and improving immunity. However, companies must improve marketing to attract customers and establish a presence. Successful promotion relies on effective strategies to influence consumers. Understanding consumer preferences is crucial, but challenging; many prioritize sales over sound marketing. Consumer behavior involves rational, emotional, and cognitive factors. Although functional foods are associated with high health benefits, consumers do not tend to accept them. So, you must recognize the emotional connection to figure out your own tastes and see if you actually like a product. Thus, this would allow companies manufacturing these foods to create long-term and effective initiatives based on concrete data that will allow the successful adoption of alternative proteins on the market. Companies have demonstrated how the use of neuromarketing techniques has helped to better understand consumer reactions to their products.

More specifically for companies that produce beneficial health foods, they have helped to create a greater acceptance and positive perception of the brand, increasing the accep-

tance of a healthy product and changing consumers' perception of a functional food. This is achieved through tools that help neuromarketing identify which product characteristics can positively influence the choice of healthy options. In order to have greater insight into the knowledge of decision making, there are studies that analyze the prefrontal cortex. Neuromarketing tools such as EEG and functional magnetic resonance imaging have been useful to understand purchase decisions. Studies show that PCA is the preferred method for analyzing organoleptic properties [10–13]. Consumers are influenced by various stimuli that evoke different motivations, emotions [14] and responses [15]. Companies must dive deeper into consumer behavior for effective and sustainable marketing tactics. Technological innovation in functional foods and marketing based on the use of electroencephalography is justified because it provides companies with precise and real-time information on how brains respond to their consumers [16]. This tool has allowed companies to understand how people respond to various stimuli without the person even issuing a response, or without having the real response in advance, since on many occasions in market research the responses are flawed by the environment or the person's indecision; however, with the use of EEG you can have precision in the responses. Unlike other neuroscience techniques, EEG can be considered an effective tool in the study of human food consumption, due to its high temporal resolution, non-invasive nature, cost–benefit ratio, portability, ability to detect subconscious processes and the obtaining of real-time data. Similarly, EEG is used to measure at the brain level what emotions or attention different advertising stimuli awaken in the target population, thus achieving more effective advertising campaigns, thus improving the effectiveness and return on investment of advertising campaigns [17].

In essence, the main contribution of this paper is to present a new predictive model called ***BRAIN***, which combines EEG signal analysis using PCA and a DCNN model. The main findings show that our framework can precisely classify consumer taste preferences of functional foods, with good levels of performance achieved when certain neural markers (low beta and low gamma bands) are combined.

The document is organized as follows: Section 2 outlines our EEG signal collection methodology and theoretical background, including PCA and its application in the analysis of brain wave patterns. Section 3 explores the main findings of brain activity in product evaluations that improve deep convolutional neural network training and compares with other models. Section 4 summarizes key insights, future research avenues, and study conclusions.

## 2. Method

### *2.1. General Methodology*

Consumer behavior considers the psychological and physical aspects of factors like hunger and health, motivation, and emotions. This information can assist companies in creating products and marketing strategies that work best. The choice of the sample took into account obesity, eating habits and media exposure. In the next phase of research, participants' biological responses to physiological activities including eating, sleep and stress will be tracked. ***BRAIN*** stands for Behavioral Responses and Artificial Intelligence Neural modeling and it is an acronym that directly highlights the objective of the study, which is to model behavioral responses through neural networks based on artificial intelligence. In addition, the use of this acronym reflects the focus on brain activity (EEG) and its application in consumer behavior analysis. Thus, ***BRAIN*** is a neural network trained with images of a corpus, and its output is weighted only by the most relevant EEG signals activated in the consumer's brain. Figure 2a depicts the general model of the proposed system, which can be generalized into three parts: (i) the inputs of the model, which are images and EEG time series, (ii) the outputs, which are the prediction of whether the

consumer likes the functional product or not, and (iii) the feedback, which will help us measure the system's efficiency through a confusion matrix and an ROC curve.

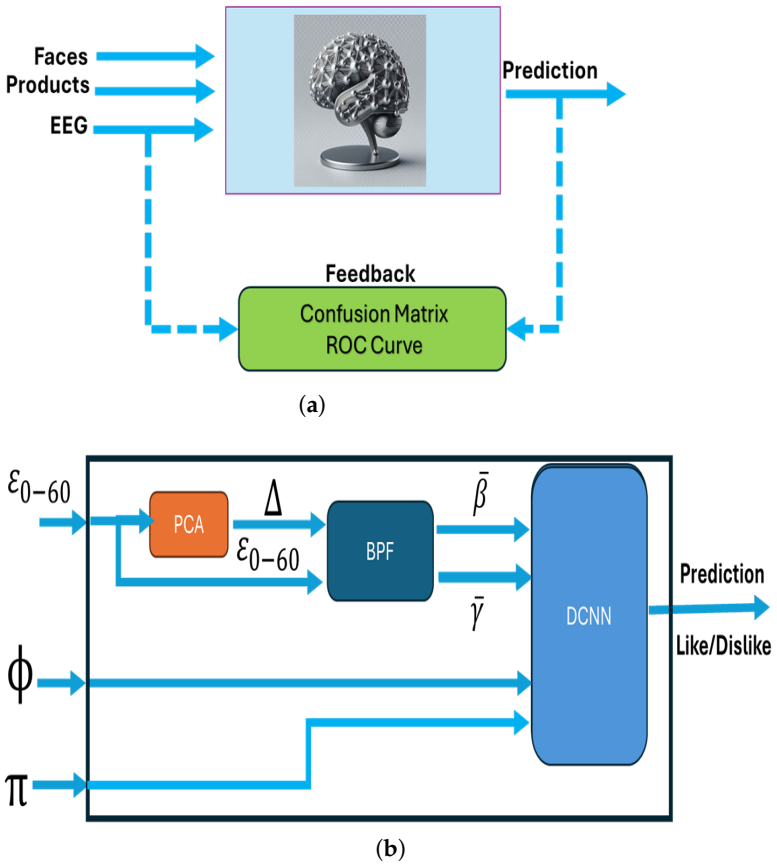



**Figure 2.** Schemes of the proposed model, (**a**) general model and (**b**) extended model.

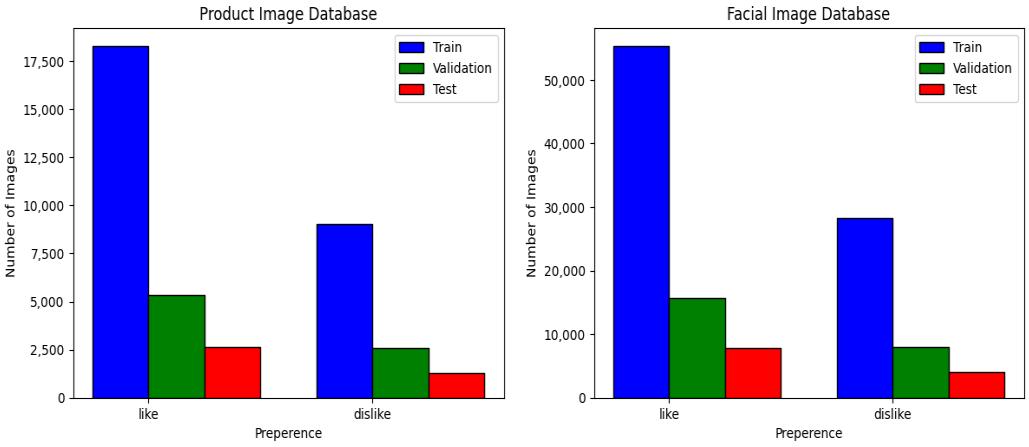
As shown in Figure 2, this study first recorded the brain activity of 83 participants who collected EEG samples. A total of 784 EEG tests were collected, recorded and analyzed to uncover patterns linked to specific stimuli. In addition, the panelists rated eight different functional products, with 39,143 photos of the samples analyzed for preferences. Facial expressions (119,216 in total) were also evaluated to determine reactions to taste samples. For training of the neural network model, the images and EEGs were processed independently. The EEG signals were processed using a recurrent neural network for temporal analysis, while the images were processed using a convolutional neural network. This separation was implemented to ensure the independence of each test subject, so that the samples corresponded to the same participant, as they were not distributed between the training and evaluation sets. This resulted in positive findings that could indicate a relationship between brain activity and perceptions of the functional products consumed.

In order to disambiguate the relationship between participants and data samples used for training models, this dataset was organized in a way that explicitly separates by participant. The 83 contributors for this dataset added the following data: 9–10 EEG recordings per participant (784 files) of tasting sessions of various flavor samples. For each single EEG, there are multiple facial expression captures (on average 1435 images per participant) and product image (on average 4.7 images per participant). In particular, in the context of training and evaluation, the split at the subject level was adhered to: all data related to a specific participant (EEG, facial images and product images) were part of only one of the three sections—training (69.5%), validation (20.0%) or test set (10.5%). Alternatively, such partitioning (as described in the dataset structure report) ensures that

the model is tested on unseen individuals instead of memorizing data from individual participants and helps prevent any leakage of information between the training/validation and test sets.

Figure 2b depicts the extended model of the proposal, which is divided into three main parts: (i) Principal Component Analysis (PCA) of EEG signals ($\varepsilon_{0-60}$) from 0.5 to 60 Hz, (ii) Band-pass Filtering (BPF) of the main rhythms present in consumer decision making ($\Delta$), and (iii) Training of a Deep Learning Convolutional Neural Network with the image corpus of faces ($\Phi$) along with products ($\pi$) weighted with low beta ($\overline{\beta}$) and low gamma ($\overline{\gamma}$) signals. Thus, the output of the system is whether a functional product is liked or not, as in the general model. Finally, the efficiency of ***BRAIN*** is measured using the confusion matrix (CM) and the receiver operating characteristic curve (ROC curve).

The structure of the facial emotion image database $\Phi$ is shown in Figure 3a and it is organized into three separate subsets to facilitate model training. The training set (in blue) consists of 83,661 images. The validation and test sets (green, red) number 23,742 and 11,813 images, respectively. Both visually and in terms of numbers, we notice a strong imbalance in class distribution for all the subsets. The number of images with like is much higher than dislike annotations. These data are highly unbalanced and the imbalance can be observed in the training corpus where you have ≈56k like instances compared to only ≈28k for dislike, which is a very important feature that we will need to carefully take into account while building and evaluating our systems to avoid any bias. The representative sample of images in $\Phi$ database is shown in Figure 4, where various facial expressions and appearances are observable for like and dislike expressions.




(**a**) Like (**b**) Dislike

**Figure 3.** Distribution of facial emotion $\Phi$ (**a**) and product $\pi$ (**b**) image databases.



**Figure 4.** Sample images from the $\Phi$ facial emotion database showing examples of like and dislike expressions.

On the other hand, Figure 3a gives an overview of the contents of the product image database $\pi$ split into train, validation, and test datasets for model training and evaluation. The training set (27,325 images and shown in blue) is the largest dataset; both the validation set (7919 images and shown in green) and the test set (3899 images and shown in red) are relatively smaller. The following data distribution feature, which is noteworthy for the purpose of classification analysis, is an imbalanced one: i.e., like tends to outnumber dislike, throughout all subsets. This discrepancy is clearly visible in the training set, namely 18,000

vs. ≈9000 like and dislike images, respectively, inducing thus a 2:1 ratio, which carries over to the validation and test subsets as well. This intrinsic imbalance is an important concern when designing the training and evaluation procedures of the subsequent models.

### 2.2. Research Methodology

This section describes how this study used a methodology to obtain the electrical brain signals of the participants, while they tasted eight types of functional food samples, in which it was possible to perceive taste sensations, for example, sweet, bitter, sour or salty. Data analysis was conducted using a Machenike T58 laptop computer in conjunction with code executed on the Google Colab Pro platform. Colab runs on the Google Compute Engine backend in Python 3, using 167.1 GB system RAM, an A100 GPU with RAM of 80.0 GB and 235.7 GB disk space. For this purpose, a neuroscientific technique called electroencephalogram (EEG) was used, to understand consumer behavior and thus provide a useful tool for neuromarketing. This phase commenced with the preparation and training of the panelists for the initial data collection, aimed at identifying and characterizing consumer preferences for functional products, where various working conditions were considered such as environmental factors, schedule, and time intervals, according to the Manual of Sensory Evaluation by Emma Wittig de Penna. This manual focuses on the methods and techniques used for the sensory evaluation of foods [18]. This manual details how to carry out sensory evaluations, what must be done to select and train panels of judges, how to organize sensory tests, and how to interpret the results obtained. It explains the methodology of sensory food evaluation, which was originally created to investigate the reasons behind soldiers' refusal to serve rations during World War II. These panels of trained judges use their senses to evaluate foods. Although instrumental methods exist to measure quality, sensory evaluation is often more accurate due to the sensitivity of human senses.

The tasting conditions were intended to reduce extraneous sources of variance. Participants were asked to fast two or more hours prior to the session. The participants each received eight functional food samples in the controlled sensory laboratory. Each sample was a 15 mL standardized portion of a drink. The participants sampled only one sample at a time, separated by 2 min. During these 3 days, the participants cleaned their mouths with unsalted crackers and mineral water to remove the remaining taste according to established sensory analysis protocols. The EEG recording was time-locked to each tasting event and started after participants placed the functional product in their mouths and ended about 20–30 s later.

The eight functional food samples were chosen by sensory science professionals from commercially available products. The products to be selected should be products that have been broadly perceived as healthy/functional in their category as well as having one of four basic taste profiles, namely sourness (tart), bitterness, sweetness, and saltiness. Against each basic taste, two contrasting commercially available products were selected to reflect differences in strength. This strategy enabled the study to employ authentic market-available products as test samples and simultaneously control the relevant experimental variable under scrutiny: basic taste perception. By choosing two products for each taste, this study could also control for some of the variability within a taste category and validate generalizability of the neural signatures associated with each basic taste.

This article focuses on the results obtained in Phase 1, on the basis of which the feasibility of continuing the research will be evaluated. Phase 1 was subdivided into four sub-phases related to the sense of taste: (i) collection of panelists' preference beliefs, (ii) recording of brain activity by electroencephalography (EEG), (iii) verification and validation of the collected information, and (iv) identification of the EEG waves that exhibit

an association with the reported preferences. These data will support the replication and scaling up of the procedure in subsequent stages of this research. Upon completion of Phase 1, Phase 2 will be started, focusing on the combination of basic taste modalities related to the combination of basic senses of taste, where, to avoid bias in responses, it is intended, before the combination of flavors, to repeat Phase 1 where working conditions are monitored for a period of at least five consecutive days. In this phase, to mitigate response bias, Phase 1 will be replicated prior to flavor combination, under controlled working conditions monitored for a minimum period of five consecutive days. A total of 83 individuals were recruited through a sensory panel service. They reported their taste preferences and aversions via a digital response application while tasting a functional food product for the first time.

Regarding the ethics of the tests carried out in the experiment, an exhaustive review of the study process was carried out, which ranges from the beginning of planning the test to be carried out to the explicit explanation of the analysis of the results, ensuring that at no time were the safety or well-being of participants put at risk. The study was reviewed and approved by an Institutional Review Board (IRB), consisting of individuals from the institution in which the test was conducted—students, teachers, and administrators—who determined that participants were sufficiently compliance ensured for the highest ethical standards. This work was approved by the Ethics Committee of the National Polytechnic Institute of Mexico (Instituto Politécnico Nacional, IPN) with protocol reference D/1477/2020. The research subjects had complete freedom to decide whether or not they wanted to participate in the test and were informed in a clear and detailed manner about each of the aspects that their participation involved. Participants were fully aware that images of their face, their responses and EEG shots of their brain were and will be used, understanding the purpose and use of these data in the research. Express written consent was obtained from each participant, in a clear and very detailed manner explaining the objectives and fines, where they were informed of the risks and benefits of the experiment and, above all, how the provided data would be used and continued. Using a consent form, the voluntary nature of their participation was highlighted. The authorization of the use of their information was obtained, showing that they were in total agreement to participate in the experiment. They also indicated that they were fully aware of and understood the process to be carried out and that they had the right to withdraw at any time without adverse consequences. It is worth mentioning that only one person on the team was in charge of being in contact with these data during the execution of the experiment and that same person was in charge of encrypting the personal data of the participants. This person was previously trained and indicated on each sheet filled out by the participant that they were committed to making correct use of the information they observed. For future continuity of research, it has been considered not to obtain name data, but only physiological data such as age and gender.

Each participant received two samples of each healthy food with its respective taste flavor and, as a way to compare the responses with the study, they were asked to indicate whether each sample of the food consumed was to their liking or not. It should be noted that one of the reasons why the sample was limited to 83 participants is derived from the provisions of the Sensory Evaluation Manual [18], where the panel size is considered a minimum of 8 people. Results are generally better with a small, well-trained team than with a large, untrained team. Therefore, when considering two aspects to analyze, (i) taste or dislike and (ii) flavors, the sample was doubled. A comparison of the data obtained from the participants with the data obtained in the EEG part was made. It should be noted that there was a brief interval between the test of each food sample, in order to eliminate any flavor that the participant had previously tasted. For this purpose, each person received a

taste of an unsalted cracker and a small taste of water. In a study with 83 panelists aged 20 to 29 (median = 25), comprising 39 women and 44 men, brain activity and facial expressions were recorded using electroencephalography (EEG) during sample tasting. The study, which was conducted with prior informed consent, included 46.9% women and 53.01% men. The analysis of these recordings aimed to evaluate the correlation between panelists' responses and brain activity measurements, thereby providing information on consumer preferences for these products. This information was intended to be relevant to the food industry for the development of products based on these preferences.

### *2.3. Electroencephalographic Signals*

#### 2.3.1. Acquisition

To obtain the EEG signal, a series of electrodes were used, which were placed on the surface of the brain, positioned according to the International Positioning System (IPS) 10–20 [19,20]. These electrodes manage to detect the electrical currents between the neurons activated in the cerebral cortex, achieving a system that functions as a brain–computer interface (BCI).

The ThinkGear TGAM1 device is a non-invasive BCI, whose objective, depicted in Figure 5, is to record and analyze neural signals, with an accuracy of 98% [21]. This is achieved since the value of the data is taken into account; for this, those data where the indicator, whose name is Poor Quality Indicator, is equal to or less than zero are eliminated. These attributes of brain signals, obtained through the use of electrodes, are classified by flag indicators, whose values are: Reliable Signal (25), Overpassed Signal (26), Power Similarity (27), and, finally, when the signal is detected Outside the Head area (29). These placed indicators fulfill a fundamental function because it is possible to optimally measure the compliance of the signal; for example, when there is an indicator value of 51, it means that the signal is somewhat optimal, since it indicates a criterion of non-compliance in the flatness of the signal. These indicators have been meticulously selected in order to guarantee the effectiveness of each possible combination. In addition, the RAW signal of the same time series is obtained, this through a sampling frequency of 512 Hz; this frequency allows sampling up to 256 Hz, which makes it possible to separate signals into brain wave bands; furthermore, this sampling allows eliminating frequencies whose value corresponds to 60 Hz; this is done due to electromagnetic interference; this action is carried out through the use of a Notch filter of 60 Hz ±0.1% or, in other words, a Band Stop-Filter is performed.

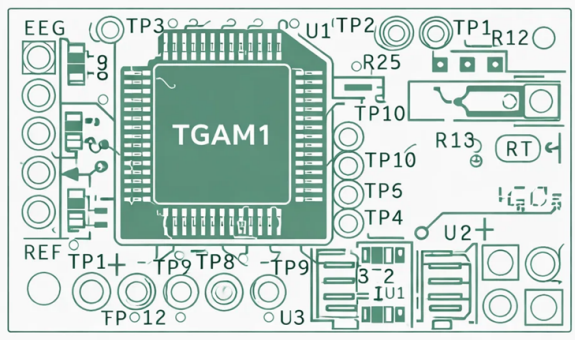
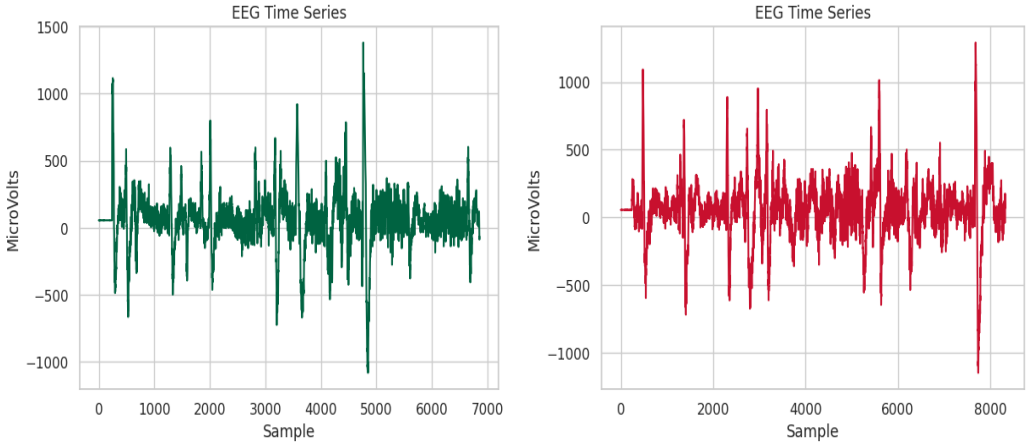



**Figure 5.** ThinkGear TGAM1: non-invasive brain–computer interface.

BCIs, as described in studies such as [10,22–24], can predict user intention through EEG signals using different BCI techniques. Research has been carried out in neuromarketing since it aims to analyze brain responses during certain marketing stimuli. It has also compared various feature selection methods to achieve accuracy in detection of consumer preferences and reported that the performance of classifiers would have better results with the use of feature selection.

### 2.3.2. Time Series Corpus

The dataset $\varepsilon_{0-60}$, with 124 samples that vary in time, each containing 9000 to 15,000 data points, is analyzed using the TGAM1 EEG sensor at a rate of 512 samples per second for the RAW time series and other brain rhythms at one sample per second. This study focuses on raw EEG signals to extract information from various frequency bands and assess attention and reflection levels during PCA tasks. Figure 6a,b illustrate brain responses to a product both positively and negatively.




(**a**) Like (**b**) Dislike

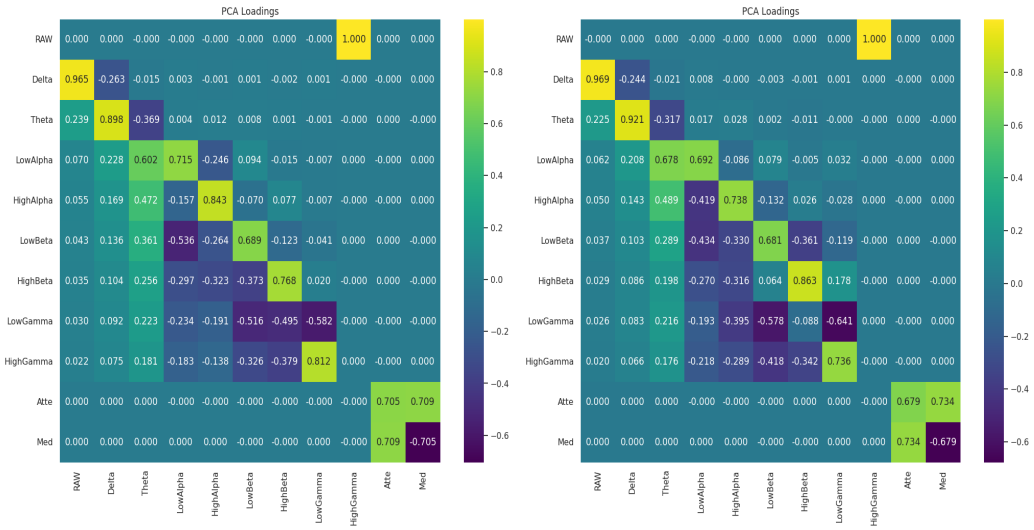
**Figure 6.** EEG samples of panelists showing their response to something sweet.

### 2.3.3. Principal Component Analysis

A PCA was then conducted to determine the common predominantly active neural patterns for taste ratings across participants. PCA was performed on the combined and standardized data of all 83 subjects. This will guarantee that the extracted components represent common sources of variability in the EEG signals and not person-specific artifacts.

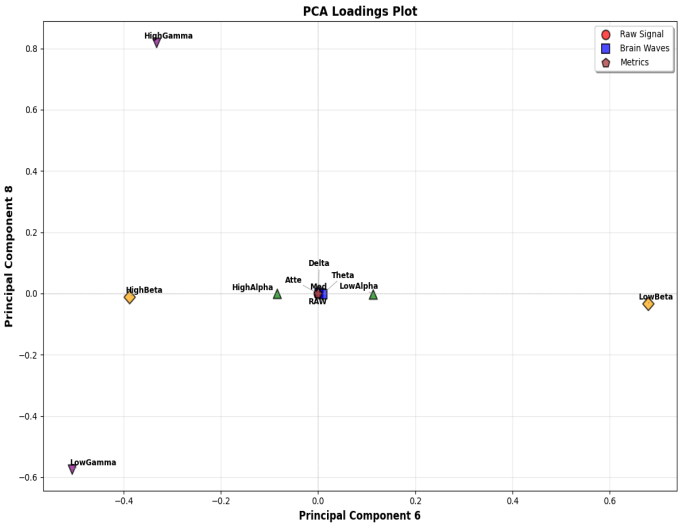
On the one hand, in Figures 7a and 8a, we noticed interesting rhythms and interactions in communication patterns within the brain; this is because there are some complex interactions of brain waves during food tests. Some frequency bands march in tight synchrony, for example, $\delta$ waves oscillate with nearly perfect correlation (0.97) to the raw EEG, but others do not, highlighting their driving dominance in brain activity during taste stimulation. The $\theta$ waves were close behind, strongly connected with the $\delta$ (0.92), and it seems possible that these slower rhythms might be involved in the first way the panelist processes flavors. In contrast, the $\alpha$ band exhibited internal consistency (0.75 between the Low and High $\alpha$), potentially reflecting how relaxation and mild cognitive engagement co-occur during the consumption of food that tastes good.

But some brain waves traveled in the opposite direction, which is a reflection of neural contrast. $\gamma$ waves (both Low [−0.6] and High [−0.44] frequencies) followed the opposite pattern to other bands, suggesting that high-frequency brain activity may reflect a qualitatively distinct mode of operation, possibly related to sharper cognitive processing or finer sensory detail extraction. The conflict between attention and reflection (−0.69) was especially revealing, indicating that the panelist cannot meditate while simultaneously attending when eating, the brains either keenly focus in or optimally space out, but not a bit of both together.

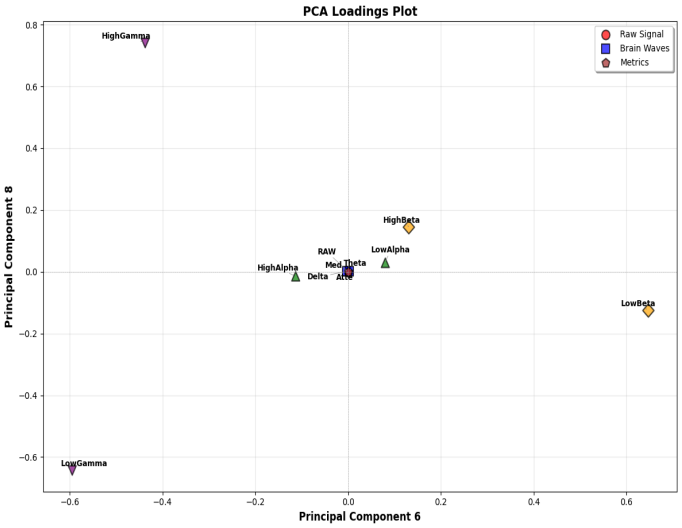



(**a**) $\Delta_{Like}$ (**b**) $\Delta_{Dislike}$

**Figure 7.** Principal Component Analysis (Δ) when the panelists taste a functional product.



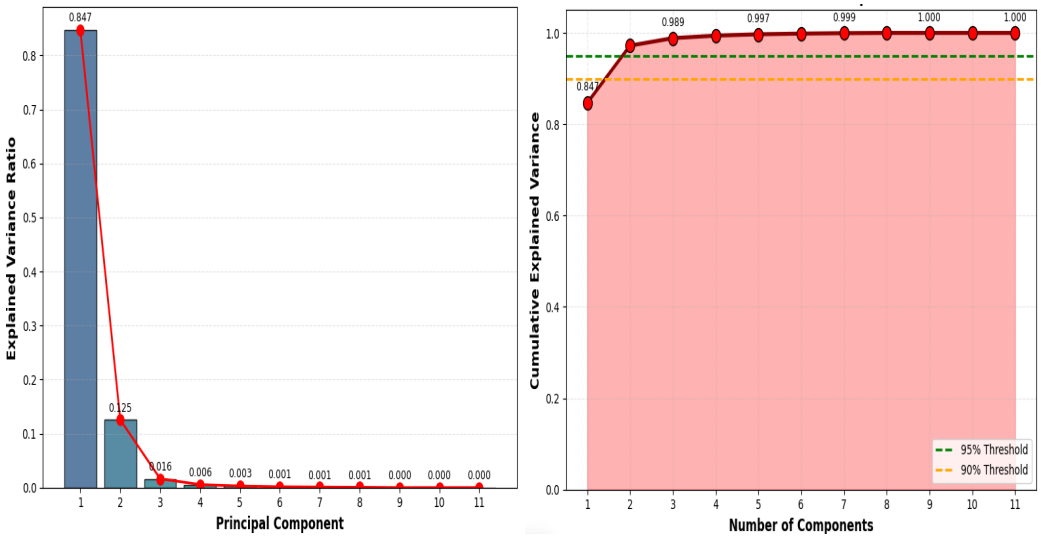

(**a**) Like




(**b**) Dislike

**Figure 8.** Principal Component Analysis 6 and 8 with the electrical signal (Δ), when the participant tests a functional product.

The correlation matrix of the EEG bands was submitted to Principal Component Analysis. In accordance with the Kaiser criterion (eigenvalue $> 1$) and aiming to explain more than 95% of the total variance, we kept for further analysis the first round of principal components (PC1 and PC2). PC1 explained 84.7% of the variance, PC2 added 12.5% and in total 97.2% of the variance was explained. These two features, that represent the basic shape of the neural data, served as input for band-pass filtering and designed model learning, Figure 9.




(**a**) Individual Variance Explained (**b**) Cumulative Variance Explained

**Figure 9.** (**a**) Scree plot and cumulative variance of the PCA. PC1 explains 84.7% of the variance and PC2 adds 12.5%, exceeding the 95% threshold with two components; (**b**) the cumulative curve surpasses 99% by the third component. Dashed lines mark the 90% and 95% variance thresholds.

Even more significantly, they observed correlations between states of attention and activity in the high–frequency bands of the brain. The high link between attention and High $\gamma$ (0.69) is expressive: when panelists like a food, their brains engage in both attentional focus and higher frequency processing, as though every sensory detail counts. However, surprisingly, reflection and attention also showed beneficial alignment (0.72), suggesting a unique state of the brain where relaxation and focus overlap.

On the other hand, Figures 7b and 8b, PCA in EEG-based functional food haters also produces a separate neural map, characterized by deep synchronous processing and higher emotional arousal. When adding the $\delta$ and $\theta$ wave (0.89), we are led to believe that deep cognitive processing was taking place along with memory recall: panelists may have been drawing on past taste experiences or negative expectations. At the same time, a higher wave activity $\beta$ (0.77 between Low and High $\beta$) indicates active critical evaluation, suggesting a conscious judgment of the unpleasantness of taste or texture. In addition, in a novel finding, the close link with High $\gamma$ (0.82) is interpreted to indicate increased emotional arousal and sensory processing, as previously suggested to be related to aversion or negative sensory integration by neuroscience. This shared neural response suggests that dislike does not result solely in a somatosensory rejection but rather an evaluation/processing state of disliking.

The relationship between attention and reflection measures helps to illuminate the nature of what is disliked. A negative relationship between attention and reflection ($-0.7$) indicated that the more a woman paid attention to sensory aspects of food, the more she lost relaxation and acceptance in experiencing it. This suggests that the aversion response creates a state of tension and awareness, rather than receptivity or pleasure. Attention and reflection were also associated with high $\gamma$ activity, helping to support the idea that cognitive processing during dislike is related to increased emotional and sensory arousal.

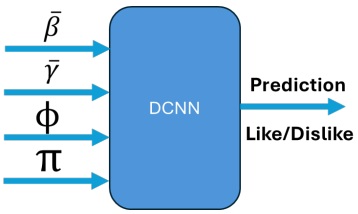
From a neuromarketing point of view, these results are interesting because they suggest that disliked food experiences are more complex neuroscience events: they require memory recall, critical comparison, and emotional intensity. For the food industry, it demonstrates the potential of EEG not only as a tool for detecting rejection but also to understand its multi-layered brain reactions that underpin it and therefore provide an avenue to improve product by reducing or eliminating the individual cognitive and sensory triggers that lead to dislike. These important implications for both neuromarketing and food science emerge from the EEG analysis performed by panelists who tasted the food. The prevalence of $\delta$ and $\theta$ waves indicates a strong relationship between food liking and sensory memory, indicating that what panelists like to eat may be strongly embedded in emotional memory or past sensory experiences. However, increased $\beta$ and $\gamma$ activity shows that cognitive processing is an equilibrium between emotional resonance and cognitive evaluation that provides a strategic implication: functional food marketing will trigger consumers emotionally, say through storytelling or the senses, but it should also give people something to think about. Collectively, this brain activity in response to liked foods reflects a balanced interaction between sensory integration, emotional engagement, and practical evaluation—showing that EEG-informed tools can not only decode but also shape more effective product development and communication in the food industry.

#### 2.3.4. Pass-Band Filtering

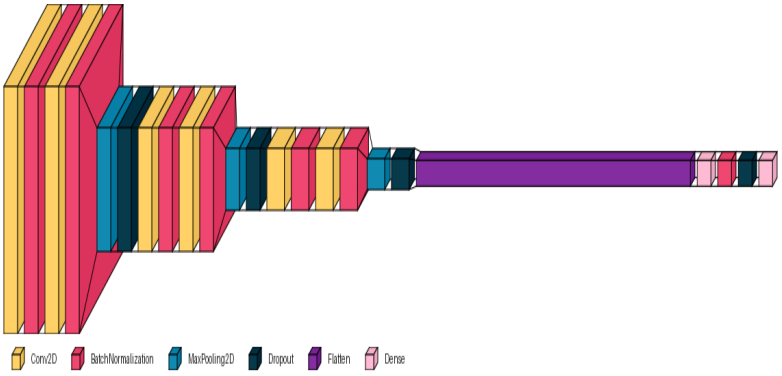
In terms of performance, filters can be classified as high-pass, low-pass, band-pass, all-pass, and reject-all filters. The frequency range that they allow to pass is known as the Pass-Band, and the frequency range that they do not allow to pass is known as the Stop-Band. An ideal filter is one that completely rejects signals whose frequencies are not in the interval for which it was designed; unfortunately, such types of filter do not exist because of the physical limitations of the components with which they are manufactured. The response of an ideal filter can be approximated by mathematical functions, including Butterworth [25], Chebyshev [26], and elliptic filters [27]. In this manner, it can be stated that a band-pass filter is a melding of a low-pass filter and a high-pass filter. Therefore, we apply a band-pass filtering processes, that is, from a RAW time series in $\varepsilon_{0-60}$, we generate two time series for the two bands whose behavior was observed to be the most relevant in $\Delta$. In other words, we created a filtered time series that contained only the band $\overline{\beta}$ or frequencies ranging from 12 to 21 Hz, and another filtered time series containing only the band $\overline{\gamma}$ or the frequency range between 30 and 45 Hz.

#### 2.3.5. Deep Convolutional Neural Network Architecture

Figure 10a depicts the generated model in which a deep convolutional neural network (DCNN) is trained with four input signals: the image corpus $\Phi$ and $\pi$, along with brain rhythms $\overline{\beta}$ and $\overline{\gamma}$. The objective is to obtain two classes at the output, namely, to predict whether a person likes or dislikes the functional product they consume.




(**a**) System Model




(**b**) DCNN Architecture

**Figure 10.** Deep convolutional neural network architecture.

Figure 10b shows the architecture of the DCNN model proposed here consists of multiple convolutional layers followed by batch normalization, max-pooling, and dropout layers to prevent overfitting. The first convolutional layer applies a filter of 64 units with a kernel size of $5 \times 5$, using the ELU activation function and He normal kernel initialization. Batch normalization is applied after each convolutional layer to normalize the activations and speed up the training process. Max-pooling layers with a pool size of $2 \times 2$ are added after every two convolutional layers to reduce the spatial dimensions of the feature maps. Dropout layers with dropout rates of 0.4 and 0.5 are introduced to randomly deactivate neurons during training, further preventing overfitting. The final layers include fully connected dense layers with ELU activation and batch normalization, followed by a softmax activation function in the output layer to classify the input images into different classes. The model is compiled using the Adam optimizer with a learning rate of 0.001 and a categorical cross-entropy loss function, to optimize accuracy during training.

$$\text{Inputs:} \quad \Phi, \pi, \overline{\beta}, \overline{\gamma} \tag{1}$$

Figure 10a along with Equation (1) depict the generated model in which a deep convolutional neural network (DCNN) is trained with four input signals: the image corpus $\Phi$ and $\pi$, along with the brain rhythms $\overline{\beta}$ and $\overline{\gamma}$. The objective is to obtain two classes at the output, namely, to predict whether a person likes or dislikes the functional product they consume. In addition, Figure 10b shows that the architecture of the DCNN model proposed here consists of multiple convolutional layers followed by batch normalization, max-pooling, and dropout layers to prevent overfitting.

The architecture of the $i$th layer is defined as a repeated process with several convolutional layers, pooling and dropout layers. Equation (2) defines the general form of the first and subsequent convolutional layers, denoted as $\mathbf{H}_i$ where $i = 1 \ldots n = 3$. It can be written as:

$$\begin{aligned} \mathbf{H}_i &= \text{ELU}(\mathbf{W}_i * \mathbf{D}_{i-1} + \mathbf{b}_i) \quad & \mathbf{P}_i &= \text{MaxPool}(\mathbf{H}_i, \text{pool size} = 2 \times 2) \\ \mathbf{H}_i &= \text{BatchNorm}(\mathbf{H}_i) & \mathbf{D}_i &= \text{Dropout}(\mathbf{P}_i, \text{rate} = 0.5) \end{aligned} \tag{2}$$

where $\mathbf{W}_i$ represents the filter weights $\mathbf{X}$ is the input and $\mathbf{b}_i$ is the bias term. The filter size is $5 \times 5$ with 64 units; $\mathbf{P}_i$ and $\mathbf{D}_i$ define MaxPool and Dropout layers, respectively. The Exponential Linear Unit (ELU) activation function is applied, and He normal initialization is used for the kernel. The output layer $\mathbf{O}$ is defined by Equation (3), which is a group of fully connected dense layers $\mathbf{F}_i$ with batch normalization using the softmax activation function. This is defined as:

$$\begin{array}{ll} \mathbf{F}_i = \mathrm{ELU}(\mathbf{W}f \cdot \mathrm{Flatten}(\mathbf{D}n) + \mathbf{b}_f) & \mathbf{O} = \mathrm{Softmax}(\mathbf{W}_o \cdot \mathbf{F}_i + \mathbf{b}_o) \\ \mathbf{F}_i = \mathrm{BatchNorm}(\mathbf{F}_i) & \mathrm{Optimizer} = \mathrm{Adam}(\mathrm{learning\ rate} = 0.001) \end{array} \quad (3)$$

The model is compiled using the Adam optimizer with learning rate equal to 0.001 and the categorical cross-entropy loss function. Equations (2) and (3) explain how the architecture used is the structured approach, which was adopted in our DCNN model, to improve the accuracy in feature extraction and classification using PCA and DCNN methodologies. The proposed model, depicted in Figure 10b, uses a sequential architecture optimized for image classification tasks. It begins with two convolutional layers, each with 64 filters of size $5 \times 5$, using the ELU activation function, He-normal initialization, and batch normalization, followed by a max-pooling layer ($2 \times 2$) and a 40% dropout to prevent overfitting. This same configuration is repeated, adding greater complexity, compared to the later layers; these include two convolutional layers with 128 filters of size $3 \times 3$ and other blocks with 256 filters. Each convolutional block incorporates an ELU activation function, batch normalization, max-pooling layers, and progressively higher dropout rates. The model then flattens the feature maps and subsequently adds a dense layer with 128 neurons, using the ELU activation function and a 60% dropout rate before reaching the final softmax classification layer.

## 3. Results

### 3.1. Experiments

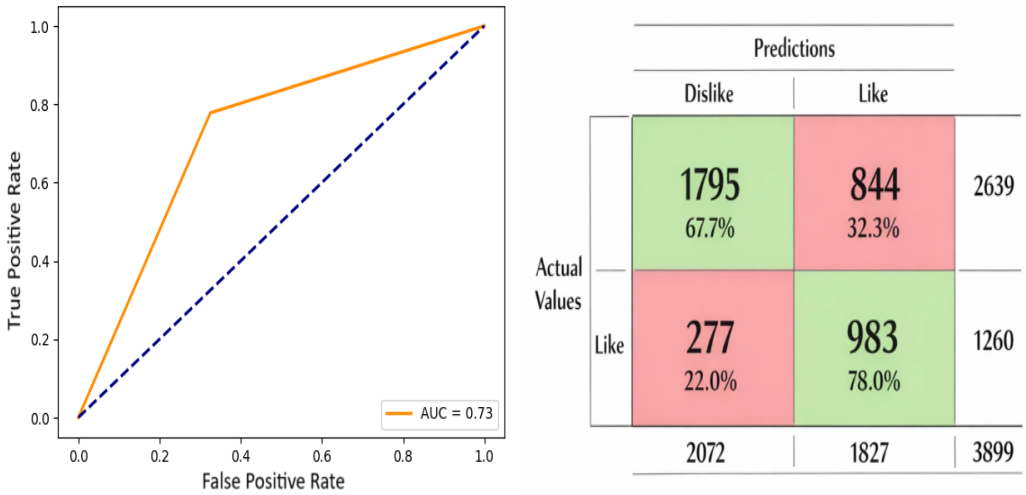
To begin with, the results are divided into two main scenarios, where the customer's preference is classified when consuming a functional product, that is, the like/dislike classes are analyzed, (i) excluding the $\overline{\beta}$ and $\overline{\gamma}$ signals, or (ii) including these signals, with the aim of improving the classification process, evaluating the effectiveness of a deep convolutional neural network model (DCNN) in categorizing customer preferences.

Something that should be highlighted is that the image dataset used was divided into three categories: 69.5% for training, 20% for validation, and, finally, 10.5% reserved for the testing phase. To avoid the possibility that the observed performance improvement resulted from data leakage, we partitioned the dataset at the subject level. This approach had the merit of ensuring that all EEG and facial/product signals of a participant appeared in only one subset (train/validation/test), also avoiding the model capturing subject-specific patterning, which may help inflate performance artificially [28,29]. In order to ensure reproducibility, the dataset used in this research is ready to be downloaded through the following link: Google Drive (https://drive.google.com/file/d/1yxmVkqSJVpHaPsmYHcla49UmsJrr5jQm/view?usp=drive_link (accessed on 24 February 2026)).

For this database, neuromarketing and multimodal sensory science research was conducted, examining the human response to functional products with different flavor profiles. To mitigate challenges, a novel approach in brain–computer interface (BCI) research was introduced: fusing multiple dynamic visual signals simultaneously obtained from this biologically controlled brain and facial expressions/product images to form a comprehensive representation of the sensory experience. With respect to four basic tastes—sour (S), bitter (B), sweet (S), and salty (T)—the goal was to explore human physiological and emotional reactions, classifying them as either "liked" or "disliked." To achieve this, the data was

structured in a hierarchical organization suitable for machine learning (ML) methods. The data was divided into three main groups: training (69.5%), validation (20.0%), and testing (10.5%). The sets were further divided into positive ("like") and negative ("dislike") responses. In all categories, EEG recordings are saved in the "eeg" folder and visual data files in the "faces" folder. This allows for direct use in model training, tuning, and evaluation without the need to reorganize the data. The dataset consists of 83 panelists (IDs from 01 to 83), which provides on average eight EEG recordings. Subjects were tested with various combinations of the four tastes, up to eight samples for each taste, allowing intra- and inter-subject comparisons. The sourness category exhibits a slight taste preference shift from dislike to like as the number and concentration of bitter members increases. By publicly releasing this dataset, other researchers will be able to reproduce the results obtained, as well as confirm the methodological process used and generate new paths of advancement for the field, a necessary component for transparency and collaboration in science.

On the other hand, the ROC (receiver operating characteristic) curve is analyzed, which represents the true positive rate versus the false positive rate, demonstrating the balance between sensitivity and specificity at different threshold levels. Unfortunately, the ROC curve of the first version of the proposed DCNN model did not show the expected pronounced increase toward the upper left corner, as the ROC is equal to 0.73, which suggests a less-than-optimal performance in distinguishing between the classes, Figure 11.




(**a**) ROC Curve (**b**) Confusion Matrix

**Figure 11.** Efficiency of the DCNN architecture excluding $\overline{\beta}$ and $\overline{\gamma}$ brain rhythms in training, validation and test phases.

Classification metrics excluding or including $\overline{\beta}$ and $\overline{\gamma}$ brain rhythms in the training, validation, and test phases are shown in Tables 1 and 2, respectively, when the customer's preference for a functional product is classified. In this way in Table 1, the F1 score is evaluated, the result of which is the combination of precision and recall presented by the proposed model, with the objective of obtaining a complete evaluation of the performance of the model. The F1 score ranges from 0 to 1, where higher values indicate better accuracy. As a result, the proposed model obtained an F1 score of 0.72, which is below the expected expectations, and also reveals challenges in achieving an accurate classification in different categories. In summary, the results obtained in this first testing stage, using the proposed model, without considering the signals $\overline{\beta}$ and $\overline{\gamma}$, show a series of limitations associated with effectiveness. The problems encountered manage to characterize the complexity of the classification task and underscore the need for further improvements and adjustments. Table 2

shows how there was a relevant improvement in the performance (25%) when adding brain activity rhythms $\overline{\beta}$ and $\overline{\gamma}$ to the system demonstrating that such frequency bands are important to encode cognitive processes as well as emotional mechanisms related with consumer decision making. $\beta$ frequency band (13–30 Hz) activity is associated with focused attention, analytic reflective thought and conscious assessment—important when people evaluate product attribute and preferences. Concurrently, $\gamma$ activity (30–100 Hz) is considered to index more temporally extended processes of information processing, such as bringing together sensory inputs with affective and other cognitive responses. By incorporating such signals, the DCNN can accurately take a more full neurophysiological account of the panelist mental state during product evaluation allowing for better distinction between like and dislike answers. This is demonstrated by the significant difference between the precision, recall and F1 score values (0.72–0.74) obtained without these bands and with those (0.97–0.98) while using them. In general, the results of this study demonstrate that discarding higher frequency EEG components results in a loss of relevant information and highlight the necessity for thorough frequency band coverage when decoding subtle cognitive/affective states during neuromarketing studies.

**Table 1.** Excluding $\overline{\beta}$ and $\overline{\gamma}$.

| | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Dislike | 0.82 | 0.68 | 0.74 | 2639 |
| Like | 0.62 | 0.78 | 0.69 | 1260 |
| Accuracy | | | 0.72 | 3899 |
| Macro avg | 0.72 | 0.73 | 0.71 | 3899 |
| Weighted avg | 0.74 | 0.72 | 0.72 | 3899 |

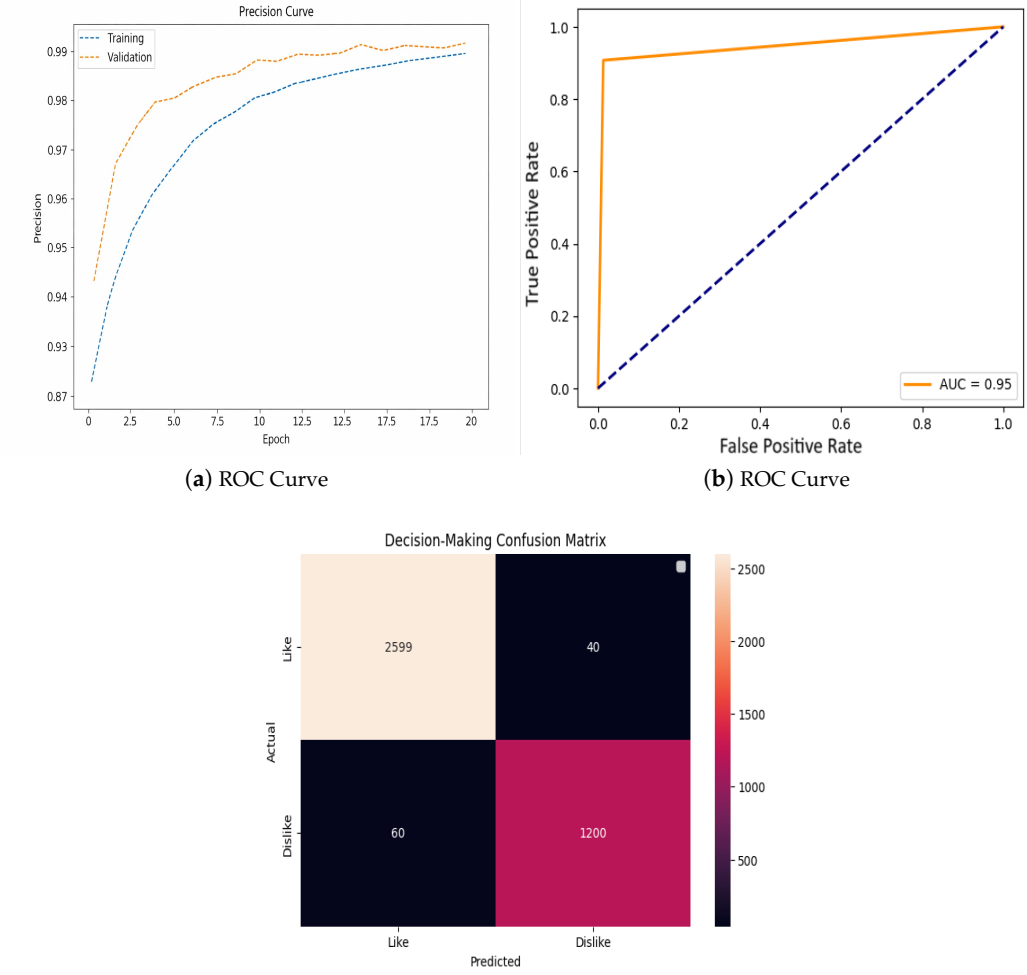
**Table 2.** Including $\overline{\beta}$ and $\overline{\gamma}$.

| | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Dislike | 0.98 | 0.98 | 0.98 | 2639 |
| Like | 0.97 | 0.95 | 0.96 | 1260 |
| Accuracy | | | 0.97 | 3899 |
| Macro avg | 0.97 | 0.97 | 0.97 | 3899 |
| Weighted avg | 0.97 | 0.97 | 0.97 | 3899 |

On the one hand, it is important to mention that the training step was closely inspected to avoid overfitting. The loss and accuracy curves over training and validation during the epochs for our final DCNN model are shown in Figure 12a, where $\overline{\beta}$ and $\overline{\gamma}$ are included. The curves demonstrate that there is no discrepancy gap between the training and validation curves, which means the model can generalize well on new images without overfitting too much. At the same time, Figure 12b serves well to validate this strong generalization: its ROC curve shows excellent discrimination (far from the random-response baseline) and is characterized by a large AUC of 0.95.

On the other hand, in Figure 12c the confusion matrix is analyzed. The objective of this matrix is to provide information about the effectiveness of the model, through the count of predictions of true positive, true negative, false positive and false negative values obtained respectively in the proposed model. The results obtained in the confusion matrix show a notable number of misclassifications in various categories, suggesting that there may be substantial inaccuracies in the classification. Therefore, three approaches were presented with the aim of demonstrating the efficiency of the results obtained in the ***BRAIN*** model; these approaches include only the $\overline{\beta}$ and $\overline{\gamma}$ signals obtained from the EEG time series. These approaches are: (i) customer preference, (ii) the flavor of a sample that the customer consumes, and (iii) the flavor of a sample along with the customer's preference.

The results obtained through these performance metrics demonstrate exceptional accuracy, showing effectiveness in classification, thus achieving the research objective.




(**a**) ROC Curve (**b**) ROC Curve

(**c**) Confusion Matrix

**Figure 12.** Matrix and curves to show the efficiency of the proposed model; these results include the brain signals of $\overline{\beta}$ and $\overline{\gamma}$, in the process of training, validation and testing.

In Table 2, it is shown that the model achieved an F1 score value of 0.97, which demonstrates a good level of precision in the model. The F1 score is a method that measures the precision of the model, providing a comprehensive evaluation of the effectiveness of the model's classification both in false positives and false negatives. If a high F1 score value is obtained, it means that the reliability of the model in data classification is quite accurate. Furthermore, in Figure 12b, the ROC curve is shown, which is an indicator that displays the classification performance of the model. The result obtained from this AUC curve is 0.95, which means that the model shows a remarkable discriminative capability, with a high proportion of true positive values and a low proportion of false positive values across a wide range of values. Additionally, the confusion matrix generated by the proposed model demonstrates outstanding classification performance in all categories, achieving values above 0.97 in each of them, as can be observed in Figure 12c. This matrix visually illustrates the model's classification accuracy by presenting the proportions of true positive, true negative, false positive, and false negative predictions. The consistently high metrics in the confusion matrix confirm the model's ability to accurately classify instances across all categories, while keeping classification errors to a minimum. In general, the results of this first test using the DCNN model, without considering $\overline{\beta}$ and $\overline{\gamma}$, bring attention to the

obstacles and constraints linked to its effectiveness in our particular scenario. The problems faced emphasize the complexity of the classification assignment and stress the need for additional enhancement or adjustment, Table 3.

**Table 3.** Efficiency of ***BRAIN*** architecture: classifying the flavor of a functional product.

| | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Acidic | 1.00 | 1.00 | 1.00 | 986 |
| Bitter | 1.00 | 1.00 | 1.00 | 868 |
| Salty | 1.00 | 1.00 | 1.00 | 975 |
| Sweet | 0.99 | 1.00 | 1.00 | 986 |
| Accuracy | | | 1.00 | 3815 |
| Macro avg | 1.00 | 1.00 | 1.00 | 3815 |
| Weighted avg | 1.00 | 1.00 | 1.00 | 3815 |

From Figure 13, when classified as the flavor of a functional product that a customer perceives, namely acidic, bitter, salty, or sweet, our DCNN model maintains outstanding performance in different evaluation metrics taking into account both $\overline{\beta}$ and $\overline{\gamma}$. This includes an F1 score of 0.96 and a confusion matrix with values greater than 0.91 for all components. These results signify the efficiency of our approach and its suitability for application in various domains that demand accurate and reliable classification, Figure 13.

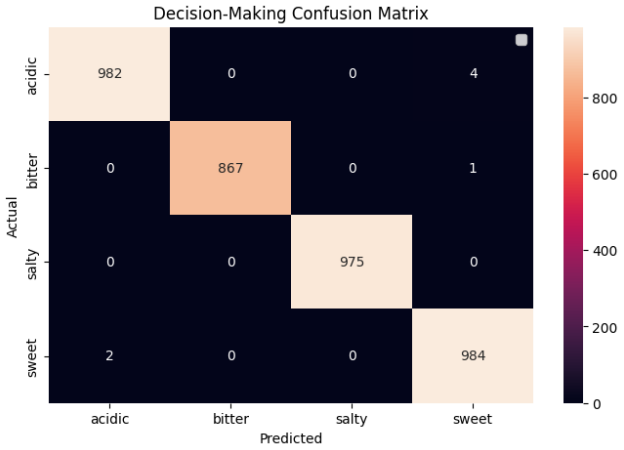



**Figure 13.** Confusion matrix of ***BRAIN*** architecture: classifying flavor.

Finally, from Table 4, when not only the flavor but also the customer's preference for a functional product is classified, namely whether the customer likes acidic, bitter, salty, or sweet flavors or not, this gives a result of the eighth instance. In this scenario, our DCNN model has demonstrated exceptional performance in various evaluation metrics, incorporating both $\overline{\beta}$ and $\overline{\gamma}$. These metrics include an F1 score average of 0.91, an AUC value of 0.95, and a confusion matrix with values greater than 0.78 for all components. These findings substantiate the robustness of our methodology and its suitability for deployment in multiple domains that require precise and reliable classification, Figure 14. Although the observed performance is remarkably high compared to the unweighted EEG band configuration, this behavior can be attributed to the improved representation of cognitive and sensory processing provided by the beta and gamma bands, which are associated with attention, decision making, and sensory integration. Furthermore, the classification task performance is enhanced by the accurate definition of the flavor categories, which may reduce ambiguity between classes. To mitigate overfitting, data separation at the subject level was implemented, ensuring that no data leakage occurred between the training and test sets.

**Table 4.** Efficiency of ***BRAIN*** architecture: classifying flavor and preference.

| | Precision | Recall | F1 Score | Support |
|---|---|---|---|---|
| Acidic Dislike | 0.81 | 0.85 | 0.83 | 26 |
| Acidic Like | 0.94 | 0.92 | 0.93 | 66 |
| Bitter Dislike | 1.00 | 0.92 | 0.96 | 65 |
| Bitter Like | 0.86 | 1.00 | 0.92 | 30 |
| Salty Dislike | 0.79 | 0.93 | 0.85 | 44 |
| Salty Like | 0.92 | 0.75 | 0.83 | 48 |
| Sweet Dislike | 0.82 | 0.75 | 0.78 | 12 |
| Sweet Like | 0.95 | 0.98 | 0.96 | 83 |
| Accuracy | | | 0.91 | 374 |
| Macro avg | 0.89 | 0.89 | 0.88 | 374 |
| Weighted avg | 0.91 | 0.91 | 0.91 | 374 |

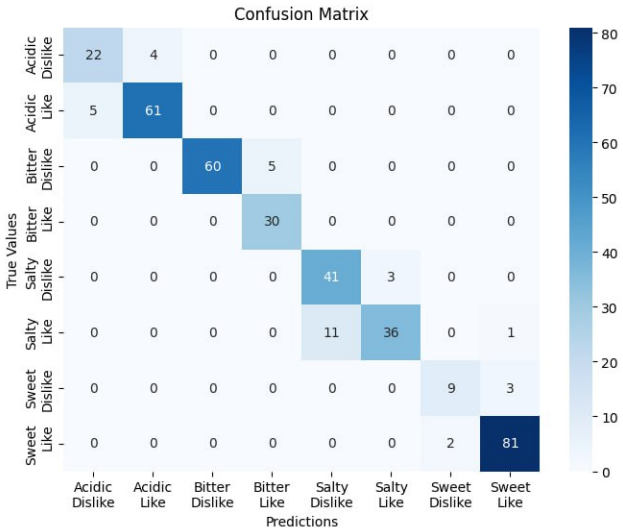


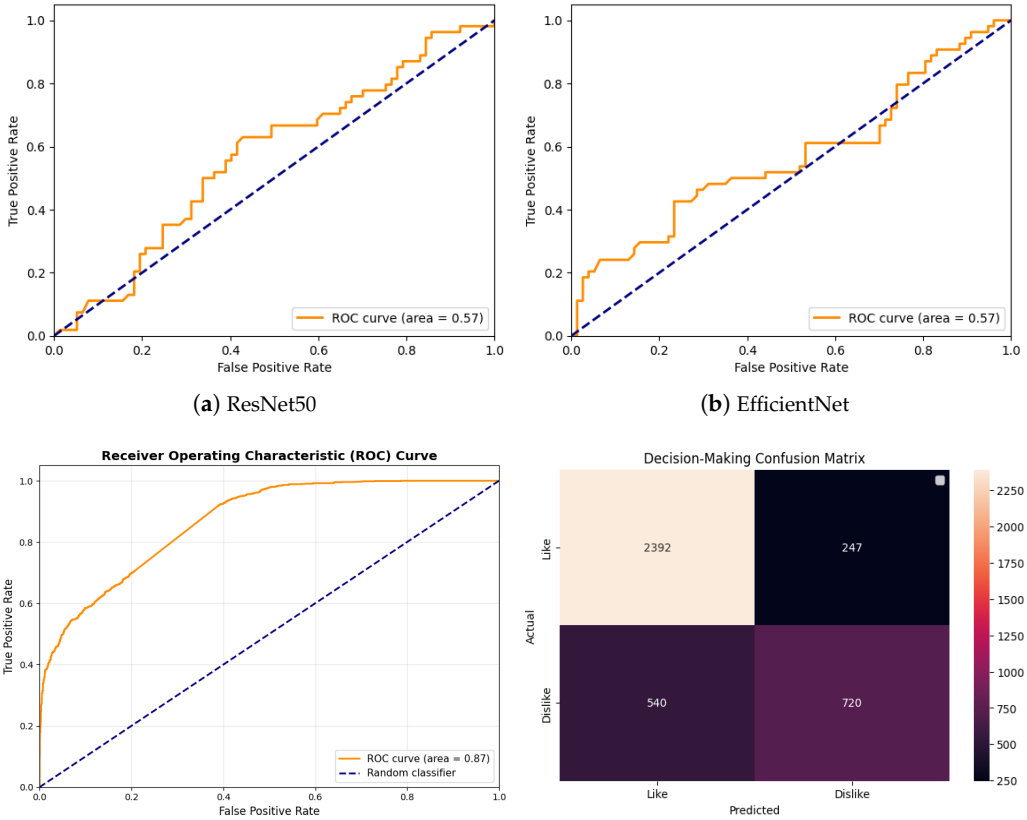

**Figure 14.** Confusion matrix of ***BRAIN*** architecture: classifying flavor and preference.

### *3.2. Comparison of Proposed Architecture vs. Well-Known Models*

The same dataset is used to test different architectures in terms of the image classification measure of the proposal, so VGG16, EfficientNetB0, and ResNet50 are tested with the same input and classification objective. All three CNN architectures follow the same approach by treating models pre-trained on ImageNet as feature extractors and freezing their layers to preset them with prior knowledge. All models are fine-tuned for a custom binary classification task (i.e., like and dislike) with RGB input images of size 224 × 224 pixels. The custom classification head added on top of all three architectures is a Flatten layer followed by Dense with 256 units and ReLU activation, Dropout with a 50% rate to avoid overfitting, and finally a Dense layer with softmax activation for classification. A learning rate of 0.0001, categorical cross-entropy loss, and accuracy evaluation metric are used to compile the three models, using the Adam optimizer. While these backbone architectures are similar in terms of core structure and fine-tuning methodology, they differ: VGG16 is simple and deep with its convolutional layers; EfficientNetB0 uses an efficient scaling method; and ResNet50 relies on residual connections to optimize learning and performance. These settings use a pre-trained feature extraction leading to task-specific minimal customization yielding accurate and efficient classification performance.

It is important to mention that, using an identical image database, the EfficientNetB0 and ResNet50 architectures produce an AUC-ROC of 0.57 and an F1 score of 0.59 as reported; the results are shown respectively in Figure 15b and 15a. Seventy-seven images are actually classified as Like and 54 of them are also incorrectly processed as Like (among 131 test

cases). In addition, the models never predict any of the cases as dislike. In comparison, a VGG16 architecture performs markedly better with AUC-ROC achieving 0.87 and F1 score 0.80. Since the VGG16 gives results above 80%, we need to dive deep into this architecture, Figure 15c. VGG16 gives a confusion matrix, Figure 15d, that shows how well the VGG16 model predicts whether someone Likes or dislikes something. The model got 2392 Like predictions and 720 dislike predictions correct. However, it made mistakes on occasions—mislabeling 540 dislikes as Likes and 247 Likes as dislikes.



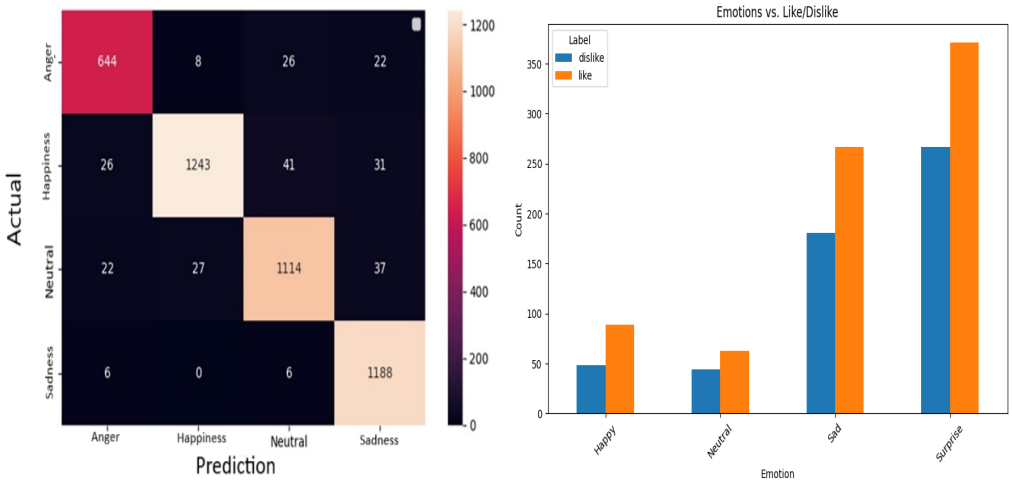

(**a**) ResNet50 (**b**) EfficientNet

(**c**) VGG16 (**d**) Confusion Matrix VGG16

**Figure 15.** AUC-ROC curve: analysis of (**a**) ResNet50, (**b**) EfficientNet, (**c**) VGG16 models and (**d**) confusion matrix of VGG16.

### *3.3. Emotional Reaction During the Experiment*

With functional products, we did not measure the emotion where associated with the during tasting experience. Thus, we trained the same architecture shown in Figure 10b with a corpus of images which can be downloaded via https://drive.google.com/file/d/1aLtLZmoUWukwKsXSKB6OxbzGVaIpbuhq/view?usp=sharing (accessed on 24 February 2026). The DCNN was trained with a corpus of 30,948 images for training, 8899 images for validation and 4441 images for testing in order to classify four feelings: happy, sad, angry and neutral. After the training and validation stages, this model obtains 94% in terms of F1 score, indicating that the model can make accurate and reliable predictions with previously unseen data, achieving the effective detection of the emotion of a human being. This model not only achieves good performance with overall accuracy but also has a confusion matrix shown in Figure 16a where it correctly classifies all emotions at a rate of 92% to 96%.




(**a**) Confusion Matrix (**b**) Emotion Estimation

**Figure 16.** Emotional reaction during the experiment: (**a**) confusion matrix, and (**b**) emotion estimation during the experiment.

In this way, using transfer learning to this proposal; the emotional experiences recorded were quite different among categories when consuming functional products, Figure 16b. The happy, neutral, sad and surprise emotions were connected to the positive emotional expression like with 89,63,267, and 371 respectively. On the other hand, negative emotions connected to dislike were less common (sadness: 181; surprise: 267), and happiness and neutrality even rarer (48; 44). The emotional patterns correspond to different sensory experiences with functional products. Specifically, when the product exceeds expectations on attributes such as taste, texture or perceived health benefits they can elicit positive surprise and happiness. Another example is the emotion of sadness, which can indicate a link between products and customer-related factors. Thanks to this, the results obtained highlight a complex interplay between emotions and customer perception, underscoring the importance of addressing both sensory and psychological factors in food product development.

### *3.4. Discussion*

As the mathematical tool of Principal Component Analysis (PCA) is used as a prior method when performing the training of the proposed convolutional neural network, the following can be highlighted. PCA is a technique that reduces the dimensionality of the data while preserving its essential variance, which makes it crucial for its use in processing EEG signals that have high dimensionality [30]. Therefore, it allows the extraction of various significant neural metrics (low beta $\overline{\beta}$ and gamma $\overline{\gamma}$ frequency bands, as well as attention and reflection levels) within a dataset [31]. Using the PCA tool before training the proposed network helps reduce overfitting in the network and also improves training; this was achieved by eliminating noise and irrelevant features presented, thus achieving an improvement in its performance in the decoding part, in the analysis of consumer behavior [30]. In addition, by incorporating the PCA tool before the network, it has managed to simplify high-dimensional data, which has led to increased computational efficiency, as well as reduced resource usage, without compromising predictive power or accuracy in the network [32], thus, finally, improving the level of significance of the EEG signals, which is of great importance in the field of neuromarketing, which in turn seeks to uncover the neural mechanisms that are relevant in consumer decision making [33].

One of the main reasons why the PCA tool was used was due to its approach, since it is a widely used method in neuroscience studies, specifically when dealing with di-

mensionality reduction and feature extraction. PCA allows the identification of the most important components, which contain most of the variance in the data, which is considered significantly useful, due to the fact that EEG signals are highly complex. Although there are tools with a more advanced goal in machine learning, such as t-SNE or autoencoders, which could provide additional information, it is necessary to establish a solid foundation and obtain interpretable results. It is proposed that for future versions of this research more advanced algorithms could be integrated to explore the potential for better classification capability and deeper insights.

Brain insights obtained by EEG measurements in panelists tasting the food provide actionable paths for both product development and marketing strategies. Given that unique brainwave patterns are correlated with dislike, i.e., increased $\delta$ and $\theta$ activity, this activity can support sensory optimization in product development; it offers a potential scope to modify taste or texture to minimize affective aversion. Similarly, the expression of these neural profiles can inform marketing; if $\alpha$ waves indicate relaxation in a subset of consumers, advertisements might display soothing properties. In addition to formulation and messaging, these neural signatures can also be used for predictive modeling, allowing consumers to determine whether a new product is likely to be accepted long before it is put on the market, and segmentation by neurological responses rather than report [34]. And by integrating these EEG data with self-reported feedback, physiological metrics, and sales data, it delivers a complete picture of consumer experiences that spans from what the brain or mind is saying to what consumers actually purchase. This approach goes beyond conventional testing by targeting the subconscious drivers of preference, providing a scientifically grounded way to develop foods that are not just functionally valuable but also deeply satisfying on a sensory and emotional level [35].

In summary, the combined use of the mathematical tool PCA with the use of DCNN manages to leverage the benefit of both techniques, which ensures the creation of an effective classification model. With the results obtained, it is distinguished that ***BRAIN*** has the capability not only to categorize the various types of flavor that the functional food possesses, but also to classify consumers' personal preferences with remarkable precision, achieving a classification error of less than 10%. Furthermore, The PCA results demonstrated that the $\delta$, $\theta$, $\beta$ and $\gamma$ frequency bands are responsible for distinguishing taste preferences consistent with established neurocognitive theories. Increased $\delta$ and $\theta$ activity is associated with early sensory processing and internally directed attention, factors that could contribute to the sensation of taste qualities [36]. In addition, the significant $\beta$ and $\gamma$ contributions indicate an important role of higher cognitive processes. $\beta$ oscillations generally are known to be task- and stimulus-specific and related to sustained attention and cognitive control, whereas $\gamma$ activity represents the combination of sensory inputs leading to conscious perception. Their strong involvement in preference decisions in this study indicates that taste evaluation goes beyond mere sensory detection, to involve attentional and evaluative factors which could enable a conscious judgment of the product [34].

## 4. Conclusions

The present proposal can be considered as an early neuroscientific approach to taste evaluation that can potentially help the objective interpretation and classification of consumer food preferences by means of the analysis of neural patterns that are related to their cognitive and emotional response in tasting experience tasks. In addition, by using mathematical tools to perform the analysis of EEG signals, it has been demonstrated that using this technique allows the effective classification of taste preferences, through the analysis of EEG signal data, thus allowing the identification of whether the consumers who tasted the food liked it (or disliked it). The main EEG signals found in this decision-making

research were the frequency signals, corresponding to low beta and low gamma, in addition to these signals a relationship was found with the frequency signals corresponding to the levels of reflection and attention. These data can be of great importance to the food industry, as they provide relevant information for companies seeking to improve the acceptability of their functional foods. The results highlighted from the initial test using the proposed DCNN model, where the signals $\overline{\beta}$ and $\overline{\gamma}$ are excluded, present a series of challenges and limitations, which reflect the complexity in categorizing consumer preferences. By conducting a second test in the proposed DCNN model including the $\overline{\beta}$ and $\overline{\gamma}$ signals, effective performance is achieved, resulting in a ROC curve with an AUC of 0.95, an F1 score value of 0.95, and a confusion matrix with a classification value above 0.97. These results indicate the effectiveness and reliability of the proposed model to achieve precise and reliable classification in various fields.

Finally, it would be interesting to explore the potential application of these findings in the food industry through personalized nutrition approaches based on individual brain activation patterns. Its goal is to promote better eating habits in the Mexican population and therefore reduce obesity and overweight. Extending from these results, the next step is to proceed to construct a more advanced convolutional neural network to investigate the activity of the brain in decision-making processes.

Although this article provides some promising findings in consumer neuroscience/neuromarketing, several limitations should be acknowledged. First, the number of respondents is important, with a total sample of 83 participants within the age range of 20 to 29, so that the diversity of consumer preferences between different demographic groups might not be well captured. Furthermore, for the EEG data collected during the taste tests, the methodology approach used in Phase 1 does not incorporate enough elements to describe all the complexity of consumer decision making, including influence factors beyond taste. Furthermore, reliance on EEG signals as the main neuroscientific method can ignore certain relevant physiological and psychological processes of consumer behavior. Finally, the feasibility of progressing this research beyond Phase 1 and the issues related to extending the study to a larger number of subjects in more varied product categories are also unknown. Generally speaking, although the results of this study provide useful implications, these limitations should be carefully examined in order to interpret and apply the result in actual marketing venues. In the future, controlling such confounding factors will be critical to scaling up the robustness and generalizability of the research findings to more general consumer settings.

We will further refine this research by developing a second-level NN which tests brain waves whilst the subject is decision making. Although the research provides valuable information on consumer neuroscience and neuromarketing, some limitations need to be addressed. One of these reasons is that the knowledge derived might also be utilized by companies which will not ultimately manufacture or commercialize food for health purposes; therefore, global regulation becomes necessary to prevent this issue safely and ensure that it is used only in favor of people. The sample of 83 subjects, between 20 and 29 years old, might not reflect the varying consumer perceptions.

It recommends creating customized guided nutrition plans based on your brain activity and helping you change your diet. In future studies, a neural network that processes brain activity should be constructed. This research has interesting implications for consumer neuroscience and neuromarketing, but there are also certain limitations to this article.

The architecture of the proposed neural network had to be evaluated in order to measure its performance efficiency, due to the relatively small sample size that was used for its training. To achieve this, the performance of the proposed network was compared with the performance of other popular models, EfficientNet, ResNet, and VGG16. As

a result, the proposed architecture managed to outperform these models by at least 5% improvement in classification, allowing this research to identify how positive emotions (for example, happiness, neutrality, and surprise) are associated with a like result, while negative emotions (sadness, anxiety, anger) give a dislike result. These results highlight the complexity that exists in emotional factors and how they influence consumer perception, therefore leading to the conclusion that both sensory attributes and psychological factors should be considered in the design of food products.

The methodology, while thorough, may not capture the full complexity of consumer decision making influenced by various factors beyond taste. Using EEG signals as the primary technique can overlook other physiological and psychological factors. The viability of scaling up the study remains uncertain. Although this study provides valuable information, careful consideration of its limitations is essential. Addressing these limitations is crucial for improving the applicability of research findings to broader consumer contexts. There is clearly a bright future on the horizon for this research that may include more biosignals, particularly electrocardiogram. It is not possible to use the power of these advanced biosignals without a more complex programming structure that does multiprocessing like distributed or parallel computing. The proposed pivot will not just allow the integration of diverse and complex biosignals, but will also enable the inclusion of several types of imaging particularly the high-resolution qEEGs. This advancement is a major breakthrough that has the potential to open entirely new doors in biosignal processing and analysis.

Furthermore, it is proposed to expand the population sample in order to strengthen the validity of the results obtained. Specifically, the inclusion of broader age ranges is being considered to analyze potential differences in decision-making processes and neurophysiological responses to functional foods. Similarly, the incorporation of specific population groups, such as pregnant women and people with chronic diseases, is planned, as these groups have particular nutritional needs and may exhibit distinct patterns of perception, preference, and cognitive processing. This expansion of the database will allow the researchers to evaluate whether the findings in young adults are generalizable to other population segments and could contribute to a more comprehensive understanding of consumer behavior in the context of functional foods.

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**Data Availability Statement:** The image corpus used to train the DCNN for classifying feelings (happy, sad, angry, and neutral) can be downloaded via the following link: https://drive.google.com/file/d/1aLtLZmoUWukwKsXSKB6OxbzGVaIpbuhq/view?usp=sharing (accessed on 24 February 2026). This corpus contains 30,948 images for training, 8899 images for validation, and 4441 images for testing.

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