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Recommendation system based on user emotions in e-markerting

Sistema de recomendación basado en las emociones de los usuarios en e-markerting

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Abstract

This work proposes a strategy for integrating an emotion recognition system into an e-marketing recommendation system. The system uses the mobile device's camera (with the user's authorization) to capture facial images and, via the Mini-Xception neural network, identifies emotions. The hybrid recommendation system combines a content-based approach, which uses TF-IDF and cosine similarity, with one based on popularity. A temporal decay scheme is applied to weight more recent emotional detections, and the emotional level is normalized to facilitate comparison across users. The results show 92% accuracy in emotion recognition. The recommendation system outputs a list of products tailored to the emotion levels computed during the session.

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Keywords: recommendation systems, deep neural networks, emotion identification systems, e-marketing, machine learning

Resumen
El presente trabajo propone una estrategia para integrar un sistema de identificación de emociones en un sistema de recomendación para e-marketing. El sistema emplea la cámara del dispositivo móvil (con autorización del usuario) para capturar imágenes faciales y, mediante la red neuronal Mini-Xception, identifica las emociones. El sistema de recomendación, de tipo híbrido, combina un enfoque basado en contenido, que utiliza TF-IDF y la similitud del coseno, con otro basado en popularidad. Se aplica un esquema de decaimiento temporal para ponderar las detecciones emocionales más recientes y se normaliza el nivel emocional para facilitar la comparación entre usuarios. Los resultados muestran una precisión del 92% en la identificación de emociones. El sistema de recomendación arroja una lista de productos ajustados a los niveles de emociones calculados durante la sesión.

Palabras clave: sistema de recomendación, redes neuronales profundas, sistema de identificación de emociones, e-marketing, aprendizaje automático

1. INTRODUCTION

The rapid growth of e-commerce in recent years demonstrates a shift in purchasing habits. Likewise, the widespread use of smartphones with apps that allow consumers to buy products at any time without having to travel to a shopping mall has fueled the expansion of this type of commerce (Bandyopadhyay et al., 2021). In this context, to be competitive in the digital age, increase productivity, and improve efficiency, companies need to incorporate online sales systems that help users find products that match their tastes and preferences. Integrating these solutions into their marketing strategies contributes to increased productivity and improved organizational efficiency (Fernandez and Ygnacio, 2023).

These systems need to capture users' interest; therefore, they must offer a service tailored to their needs. Since people can express their emotions through facial expressions, these applications, like a good salesperson, should identify which items are preferred by each user. As is known, emotions, being a complex psychological state, influence how people think, act, interact, and make decisions. Consequently, an e-commerce application can capture the emotion reflected in the consumer's face to predict their preferences and suggest products that meet their expectations or needs. This prediction uses the emotions of a set of previously registered users (customers)..

With recent advances in deep learning algorithms, various methods for real-time facial emotion recognition have been developed. As a result, the automatic recognition of human emotions has gained relevance and is applied in multiple fields: from the development of human-computer interfaces to personalized education, healthcare systems, organizational climate monitoring, and recommendation systems.

The detection of human emotions is assessed quantitatively. There are two basic approaches used to study the nature of emotions: the discrete approach and the two-dimensional valence-arousal approach. The former identifies six fundamental emotions: joy, sadness, anger, fear, disgust, and surprise (Ekman, 1992), while the latter operates on the dual axes of valence (the positivity or negativity of the emotion) and arousal (the intensity of the emotional experience) (Bagherzadeh et al., 2024).

Recommendation systems have incorporated emotion recognition modules to understand the customer's emotional state in relation to products. The inclusion of emotions has paved the way for leveraging them as descriptors that explain a greater proportion of the variation in user preferences than descriptors such as gender and age, traditionally used. For example, a user might want to consume different types of content when happy than when sad. Therefore, the list of recommended items must adapt to the user's mood; the system must be able to detect this state and use it in the algorithm as contextual information (Tkalcic et al., 2011).

This paper proposes a recommendation system for e-commerce using facial emotion recognition

1.1. Previous work

The literature offers several studies that have incorporated emotion detection into product recommendation systems. Among them is the work of Won et al. (2023), which presents a personalized image recommendation system based on environmental information and facial expressions. The system uses a deep learning algorithm to classify facial expressions, while environmental data is collected using smartphone sensors. Furthermore, to make recommendations, it employs a hybrid approach that combines content-based filtering and collaborative filtering.

Based on the premise that users typically search for music that matches their emotional state, Singh and Dembla (2023) propose a recommendation system that integrates emotion recognition through facial analysis. For detection, they employ transfer learning with models such as CNN, ResNet50V2, VGG16, and EfficientNet-B0, trained on FER2013 and reinforced with additional images obtained from Google. The recommendation system relies on a Spotify dataset and uses K-means to group tracks by emotion, thus personalizing suggestions according to the detected emotional state.

Manimaran et al. (2025) also present a music recommendation system. In this work, a CNN is used for emotion detection, and a dataset correlating emotions with musical attributes such as genre, tempo, and lyrical content is analyzed to recommend songs consistent with that emotion. The system continuously learns from user responses to suggestions, adjusting its recommendations over time. Furthermore, it incorporates a hybrid recommendation approach to improve accuracy and user satisfaction.

Intelligent recommendations based solely on emotions detected on the fly, without relying on historical data or previous purchase records, can improve response times, as demonstrated by the work proposed by Bandyopadhyay et al. (2021). This approach divides captured customer images into frames, converts them to grayscale, scans the region of interest, and processes each frame using an emotion classifier to identify its corresponding emotion. The system calculates positive responses (the sum of emotions of happiness and surprise) and negative responses (the sum of expressions of sadness and anger) to ultimately calculate the satisfaction level (the absolute difference between positive and negative responses). The satisfaction level is then categorized into four different levels to select the products associated with each level of satisfaction.

Recurrent Neural Networks, specifically LSTM networks, have also been used for emotion identification. For example, Ruan et al. (2025) extract emotional characteristics from user comments (content-based sentiment analysis) and combine them with historical behavioral data (collaborative filtering) to make personalized recommendations. The system uses an ATT-LSTM model for sentiment analysis, which improves the accuracy of emotion recognition in text comments. It then integrates these emotional characteristics with the user's historical behavior to predict which content the user is most likely to be interested in. In this work, for cold-start users who lack sufficient interaction data, the model employs a content-based recommendation strategy, using semantic similarity between articles and general user preference patterns derived from aggregated sentiment trends.

2. THEORETICAL FRAMEWORK

2.1. Recommendation systems

A recommendation system is an algorithm that shows users items of interest, whether movies to watch, books to read, products to buy, or any other item depending on the company or organization. If there is a database containing information on these items, the recommendation system will show the maximum number of items from this database that can be recommended to the user (Rivero A, 2023)..

Formally, a recommendation problem can be formulated as follows: Let C be the set of all users and S the set of all possible items that can be recommended, such as books, movies, or shoes, etc. Let U be a function that stores the utility (ratings) of the items S for the user $c \in C$, that is:

$$U: C \times S \rightarrow R$$

where R is a totally ordered set of ratings (non-negative integers or real numbers within a certain range). The recommendation system must select for user c the set of elements $s \in S$ that maximizes the utility function U. Based on the algorithm used, there are different families of recommendation systems: popularity-based, content-based, or collaborative.

2.1.1 Popularity-based systems

This system adapts to current trends. Essentially, it uses the most popular items (products). The most popular item among the general public is more likely to be recommended to new customers (Sreekala, 2020). It doesn't recommend based on user preferences, but rather on recommendations within the general category of the item. This system is based on sales volume, product ratings, and promotions (Fernandez and Ygnacio, 2023).

2.1.2 Content-based systems

These systems use the user's preference history (such as brand, color, price, and ratings) to predict which products might be of interest to both the user and the company, and consequently display suggestions similar to the user's interests (Afoudi et al., 2021). The method originates from information retrieval and information filtering systems and requires product information; that is, the product attributes that characterize it and allow for the identification of user preferences must be identified. This data is called labels(t). In this method, the utility function u(c,s) of element s for user c is calculated from the ratings that user c assigns to the s′ elements that are "similar" to elements (Rivero A, 2023).

2.1.3 Collaborative systems

It is one of the most widely used systems; its recommendation mechanism is based on filtering only user tastes and preferences. It also evaluates product ratings and predicts which products the customer might like (Tewari, 2020). This method is based on the assumption that users tend to select items similar to those previously selected by similar users. To do this, it calculates the usefulness of an item (s) for a particular user (c) using ratings previously given by other users. This type of system presents the problem of a cold start.

These systems (methods) present some problems, such as:

- Cold start is a difficulty that recommendation systems, especially collaborative ones, face in generating good recommendations when there is a lack of interaction history, either because there is no history of the user or the item, or because it is a new system.
- • Lack of diversity and novelty; all approaches can fall into filter bubbles
- Fairness and bias: can disadvantage minority groups/creators.

- Misaligned metrics: optimizing clicks doesn't always maximize long-term satisfaction
- Explainability: difficult to justify why something was recommended.
- Context and multi-space: preferences change by time, place, device; it is not always modeled.

One possible solution to these problems is to use a hybrid method. This method proposes combining two or more existing systems, either in parallel, by incorporating features from one system into another, or by creating a unified method (Rivero A, 2023).

2.2. E-marketing

E-marketing, also called digital marketing or electronic marketing, refers to the use of the internet, telecommunications networks, and related digital technologies to achieve an organization's marketing objectives (Luque-Ortiz, 2021). In other words, it is the use of a set of digital tools and strategies, such as recommendation systems, to improve or promote the sale of products or services. Therefore, digital marketing is the strategy that organizations use to reach their customers through the implementation of information technologies (Fernandez and Ygnacio, 2023).

3. METHODOLOGY

This work proposes a strategy that integrates an intelligent system, which identifies emotions from customers' faces, with a recommendation system. It was carried out in two phases. The first phase involved developing the emotion detection model, and the second phase involved building the recommendation system by integrating the emotion detection model.

3.1. Emotion identification system

The system uses the mobile device's camera to capture facial images, a process performed only with the user's prior authorization. To identify emotions from these images, the Mini-Xception neural network (Arriaga et al., 2017), a simplified and computationally less complex version of the Xception architecture, was trained. This variant is characterized by a reduced number of parameters and lower resource requirements, without compromising performance in the classification task. Finally, each emotion is detected within a specific time interval and sent to the recommendation module, where it is integrated as an input signal for content personalization.

The workflow begins with the camera activating and capturing a facial image. This image is then processed to extract the facial features required by the pre-trained model, which is loaded and responsible for detecting emotions from the captured image. Finally, the identified emotion is sent to the recommendation system. As mentioned earlier, the deep neural network model employed is based on the Mini-Xception architecture, trained on the FER2013 database, which contains 35,887 48x48 pixel grayscale images collected from the internet. The images show human faces labeled with seven types of emotions: anger, disgust, fear, happiness, sadness, surprise, and neutrality. Development was carried out in Python, using several libraries: OpenCV for image processing, TensorFlow and Keras to build, train, and validate the deep neural network model, and Dlib to locate key facial points, allowing for precise alignment of faces before emotional analysis.

3.1.1. Neural network model for identifying emotions

To develop the emotion recognition model, classic machine learning steps were followed. A discrete approach was used to train the classification model, using face images labeled for the seven categories defined in the FER2013 database. The main steps of the process are described below:

Image capture and processing

The system has a presence sensor, so when it detects the proximity of a person, it activates the USB camera connected to the Raspberry Pi 5 and captures facial images of the teacher in JPG format with three channels (RGB).

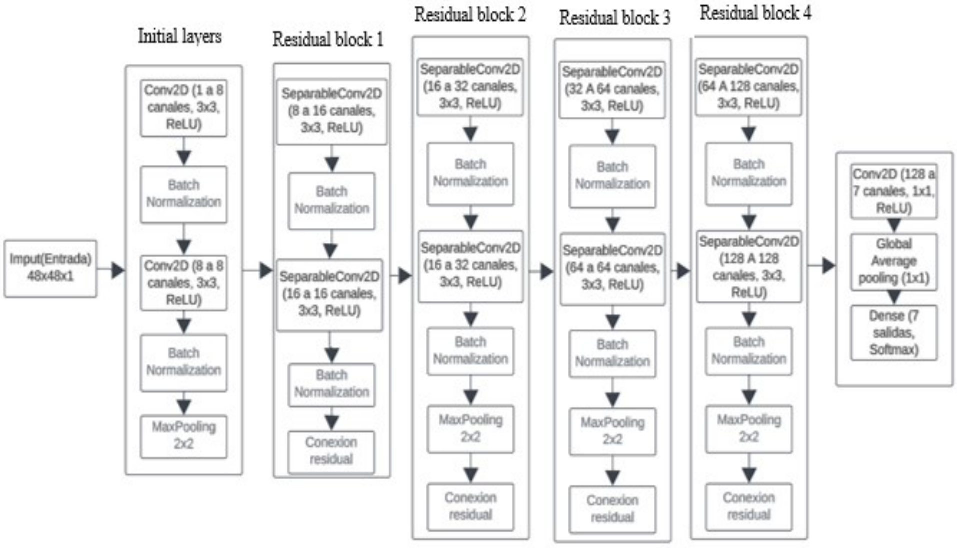
Image preprocessing

Each captured image is processed by converting it to grayscale (to reduce computational complexity and focus only on the relevant features of facial expressions); histogram equalization (to improve image contrast, facilitating the detection of facial features in uneven lighting conditions); facial detection – reference point (the Dlib library was used to identify 68 key points on the face, such as the eyes, nose, and mouth); facial alignment (to ensure all images were in a standard position); image normalization (images were adapted to the dimensions required by the 48x48 pixel model); and image filtering: blurry or poorly captured images were discarded using algorithms that assessed their quality and sharpness, ensuring the processed dataset was consistent.

Model construction

A deep neural network (DNN) architecture based on the mini-Xception model was employed. This architecture utilizes separable depth convolutions (SeparableConv2D), along with batch normalization mechanisms and ReLU activations to stabilize and accelerate training. The final block includes global average pooling followed by a dense layer with softmax activation for classification. Together, these design decisions favor the computational efficiency and generalizability of the model. Mini-Xception was selected due to its ability to balance accuracy and performance on resource-constrained devices and its excellent performance on the FER2013 dataset. The architecture of the Mini-Xception deep neural network is described below (Figure 1).

Figure 1. Detail of the Mini-Xception architecture used (source: own elaboration)



Initial layers: Their purpose is to prepare and compress the image information for the remaining Xception-type residual blocks. This layer is a combination of:

- First Conv2D (1-8 channels, Relu): Extracts basic features such as edges and simple textures. Increasing to 8 channels allows capturing different aspects of facial images. The Relu function introduces controlled nonlinearity.
- Second Conv2D (8→8 channels, Relu): delves deeper into feature detection, refining the patterns detected in the first layer.
- Batch Normalization: Stabilizes the learning process by normalizing activations, reducing problems such as covariate changes.
- MaxPooling (2x2): Reduces the resolution (dimension) by half so that subsequent layers work with more compact feature maps, improving computational efficiency.

Residual blocks (Mini-Xception blocks): Their purpose was to capture more complex features and abstract relevant emotional patterns. Each block includes separable convolutions, residual connections, and clustering techniques. Four residual blocks were considered.

- Residual Block 1 (8→16 channels): extracts more complex features while preserving input information through a residual connection.
- Residual Block 2 (16-32 channels): Detects facial patterns such as eye and mouth shapes. The higher number of channels allows for capturing more detail.

- Residual Block 3 (32→64 channels): Analyzes high-level features, such as complete expressions, using a greater number of filters to identify more subtle patterns.
- Residual Block 4 (64→128 channels): Generates abstract representations of facial expressions. This block uses the maximum number of filters, condensing the information for the final stages.

Final layer – Classification: performs aggregation and class decision, translating the high-level features learned by the residual blocks into efficient classification probabilities with good generalization capacity.

- Conv2D (128→7 channels): Reduces the dimensionality to 7, corresponding to the emotions studied for classification.
- Global Average Pooling (GAP): Replaces traditional dense layers, eliminating unnecessary parameters and reducing the risk of overfitting. This step also improves the model's robustness to spatial distortions.
- Denso + Softmax (7 outputs): Performs the final ranking, assigning probabilities to each of the 7 possible emotions. Activating Softmax ensures that the results can be interpreted as probabilities, totaling 1.

Model training, optimization, and hyperparameter tuning: During training, the model parameters were tuned. Cross-validation was applied to ensure model robustness and minimize the risk of overfitting, thus ensuring that the system could generalize well under real-world conditions. The following data division was used: Training set: ~28,709 images, Validation set: ~3,589 images, and Test set: ~3,589 images. The parameters considered were:

- Batch size: 32 samples.
- Number of epochs: 100.
- Image dimensions: 48x48 pixels.
- Initial learning rate: 0.001.
    - Optimizer: Adam.
    - Loss function: Categorical cross-entropy.

Model validation: Metrics such as accuracy and sensitivity (sensitivity, recall) were used to ensure accurate and reliable emotion recognition. Some tests were conducted in real-world environments under varying environmental conditions, including different lighting levels, to determine the system's robustness and efficiency.

3.2. Recommendation system

The product recommendation system uses basic user data such as gender, age, and emotional state. The first two are obtained during registration, while emotional state is inferred using the emotion recognition system. The system assumes that users, when in a particular emotional state, tend to prefer products associated with that state.

To capture emotional dynamics and strengthen the estimation, a time decay scheme is applied, giving greater weight to more recent detections. Additionally, the emotional level is normalized relative to the total observed to facilitate comparison between users with different numbers of observations. Specifically, a normalized emotional index is defined as:

$$\hat{e}(t) = \frac{\#pos(t) - \#neg(t)}{N(t)}$$

Where #pos(t) and #neg(t) represent, respectively, the weighted detections of positive and negative emotions up to time t, and N(t) is the total weighted sum of detections. Under exponential decay with half-life $T_{1/2}$, the weights are defined as $w_k = \exp(-\lambda (t - t_k))$, with $\lambda = \ln(2)/T_{1/2}$

The operational interpretation of $\hat{e}(t)$ is established by relative thresholds:

- $|\hat{e}(t)| < \tau$: neutral state.
- $|\hat{e}(t)| \geq \tau$: predominance of positive emotions.
- $||\hat{e}(t)| \leq -\tau$: predominance of negative emotions,

where $\tau \in (0,1)$ is a calibratable parameter (e.g., $\tau=0.25$).

For testing the recognition system, one of the data tables (wdcproducts50cc50rnd000un_valid_large.json) provided by WDC Products: A Multi-Dimensional Entity Matching Benchmark (Peeters, Der & Bizer, 2023), containing 4500 records, was used. The first five columns were selected, renamed, and additional columns with random values were appended: number of visits, number of likes, and emotion level. Figure 2 shows the first 5 rows of the table.

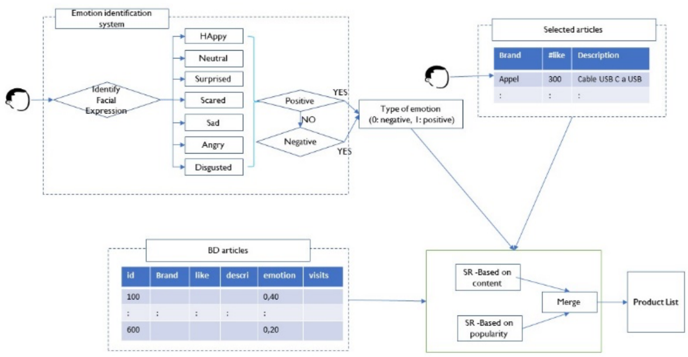
Finally, this emotional signal, along with the user's metadata and recent history of viewed products, is integrated into the recommendation module to personalize the content.

The recognition system is hybrid, combining a content-based recognition system that uses the tags description, price, and emotion_level to find similar products. The inverse frequency (TD-IDF) was used to assign a numerical value to the description attribute; cosine similarity was used to find similar products. A recommendation system based on product popularity was also used. To select items to recommend, the attributes likes, emotion_level, and number_of_visits were used, selecting those above a value μ relative to the total number of products of that brand. The value μ is adjusted according to the number of products of the brand (see Figure 3).

Figure 2. First 5 records of the database used for the Recommendation System

```
print(df_sub.head())

         id           marca  \
0  15228268           Epson
1  62156844  Western Digital
2  56989328            None
3  49805702            Sony
4  66291779            None

                                           titulo  \
0  Genuine Epson C13T79034010 Magenta High Capaci...
1  WD Blue 250GB PC SSD - SATA 6 Gb/s 2.5 Inch So...
2                 Traveler's Notebook Refill - Grid
3   Sony 24mm F1.4 G-Master Full Frame E-Mount Lens
4                      Switch 8 puertos 10 100 1000

                                      descripcion  precio  likes  \
0                                            None   34.99    256
1  With superior performance and a leader in reli...   84.99    262
2  Midori grid white paper great for capturing sc...    7.00    263
3   Sony 24mm F1.4 G-Master Full Frame E-Mount Lens    2195    129
4        Switch 8 puertos 10 - 100 - 1000 tp - link  51,73€    283

   nivel_emocion  numero_visitas
0              0              82
1              1              59
2              1              94
3              1              20
4              0              77
```

Figure 3. Recommendation System Structure (source: own elaboration)



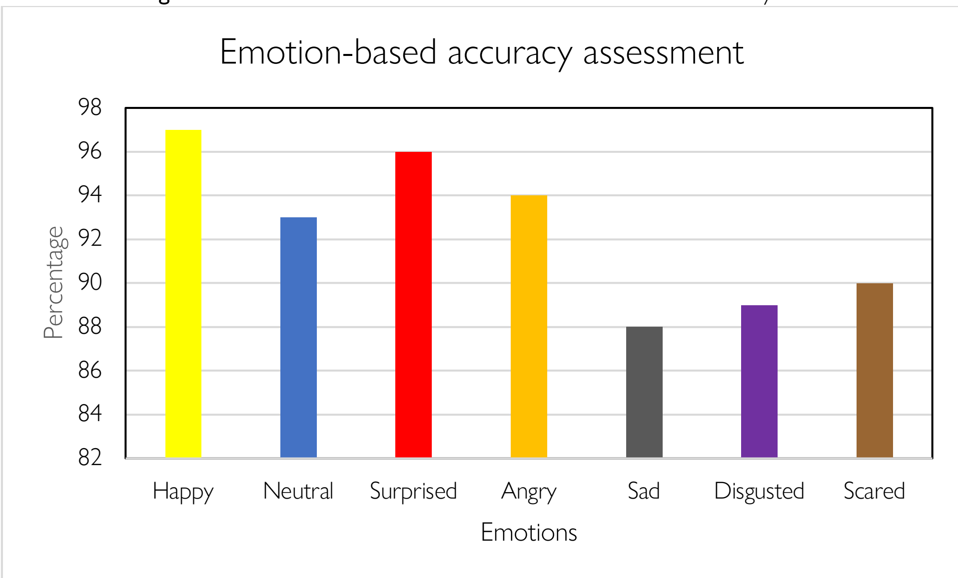
4. RESULTS

When evaluating the emotion identification model with the test data from the database, using the indicators of accuracy, recall, and F1-Score, it was determined that it met the required requirements (92% accuracy). Table 1 and Figure 4 show the performance of the Mini-Xception model in classifying each of the seven emotions in the FER2013 dataset, noting that the accuracy indicator exceeds 80% for every emotion studied.

Table 1. Evaluation of the emotion identification model

Emotion	Accuracy (%)	Recall (%)	F1-Score (%)
Happy	97	94	95
Neutral	93	90	91
Surprised	96	93	95.5
Angry	94	90	92
Sad	88	85	86
Disgusted	89	87	88
Scared	90	88	89

Figure 4. Bar chart of the evaluation of the emotion identification system



Additionally, to validate the model's performance, 24 sequential emotion detection tests were conducted, yielding an average processing time of 27.92 ms ± 3.94 ms. These values ensure that the model can maintain consistent and reliable performance during continuous operation, meeting and exceeding the established real-time response requirements.

Latency times were within expected parameters, averaging 150 milliseconds from image capture to the display of the detected emotion. The interface responded correctly in 98% of the evaluated interactions. The system's response time averaged 300 ms.

User testing was conducted with the participation of several users, who interacted with the system in various usage scenarios, allowing for the collection of significant data on the system's performance under real-world conditions. Furthermore, additional tests were conducted using a specialized script, accumulating 178 records from 10 different participants under optimal lighting conditions, resulting in an overall model accuracy of 93.57%. This result significantly exceeded initial expectations and confirmed the system's robustness for application in educational settings. The confusion matrix generated during user testing reflected anger and surprise as the most difficult emotions to classify.

The recommendation system generated a list of products that matched the levels of emotion that were calculated during the consultation session.

Figure 5 shows the output of the recommendation system for a user who has performed the query: recs_q = **recommend_by_query**(**description_text** = "FeaturesPage yield25000 pagesBrand compatibilityXeroxCompatible productsPhaser 7760Colour of productBlackQuantity1Printing coloursYellowTypeTonerPackaging dataPackaging width95 mmPackaging height89 mmPackage weight680 gPackaging length368 mmPackaging typeBox**",** **price=**216.44**,** **tao=**0.35, **top_k**=8)

Where tao is the emotion level calculated in the time frame, and top_k is the number of products to recommend

Figure 5. Bar chart of the emotion identification system evaluation.

```
            id                                         titulo  precio  \
3382  45493711  Switch TP-LINK TL-SF1024 19'' Rackmount 24x10/...  217.30
1932  45493711  Switch TP-LINK TL-SF1024 19'' Rackmount 24x10/...  217.30
2734  66749842  Details aboutNEW 2020 Shimano Dura Ace 11 Spee...  218.88
1174  66749842  Details aboutNEW 2020 Shimano Dura Ace 11 Spee...  218.88
2087  66749842  Details aboutNEW 2020 Shimano Dura Ace 11 Spee...  218.88
1697  66749842  Details aboutNEW 2020 Shimano Dura Ace 11 Spee...  218.88
1380  56902092      Jabra BIZ 2400 II DQ Duo NC WB Corded Headset  209.00
661   47121877               Slušalke Audio-Technica ATH-PRO7x  208.95

      nivel_emocion  score_similitud
3382              1         0.992278
1932              1         0.992278
2734              1         0.992278
1174              1         0.992278
2087              1         0.992278
1697              1         0.992278
1380              1         0.992278
661               1         0.992278
```

5. DISCUSSION AND CONCLUSIONS

The system was evaluated through controlled tests, using both data from the FER2013 database and real-time interactions. The most relevant aspects are presented below.

Regarding the model's accuracy, it was observed that the emotions of happiness, neutrality, and surprise were detected with high levels of accuracy, while the emotions of disgust and fear presented additional challenges in terms of recognition. As for the response times of the emotion recognition system, it achieved the capacity to operate in real-world environments with minimal response times, which is essential for the proper functioning of e-commerce applications and interactive recommendation systems.

The integration of the emotional recognition module into the recommendation system allowed for the personalization of product offerings based on the user's emotional state. This was achieved using a hybrid algorithm that combines content-based and popularity-based techniques. This method allowed:

- Adjusting recommendations based on the emotional index: The suggested products corresponded to the levels of emotion detected during the session, offering a dynamic and contextualized experience.
- Improving the relevance of recommended products: By using real-time information, the system was able to quickly adapt its suggestions, increasing user satisfaction and interaction.

In summary, the experimental data support the technical feasibility of the system for emotion detection and its integration into recommendation algorithms. The results obtained demonstrate both high accuracy and real-time operational capability, confirming its applicability to e-marketing environments. Furthermore, this work demonstrates that applying deep learning techniques for emotion recognition, combined with hybrid recommendation methods, is a promising strategy for transforming e-marketing. The ability to dynamically adapt product offerings based on the user's emotional state can translate into more relevant recommendations and, consequently, improved customer satisfaction.

6. AUTHORSHIP STATEMENT ACCORDING TO CREDIT TAXONOMY

Dulce Rivero Albarrán: Conceptualization; methodology; software; validation; formal analysis; research; resources; data curation; original draft; drafting, revision, and editing; visualization; supervision; project management.

Laura Guerra-Torrealba: Conceptualization; methodology; formal analysis; research; resources; original draft; revision and editing.

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