MODELING THE PREDICTIVE POWER OF EMOTION RECOGNITION (VIA CNN) ON SPORTS SOCIAL MEDIA ENGAGEMENT

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Abstract. *Sports Social Media (SM) has become an essential platform for clubs, leagues, and sponsors aiming to promote sustainable practices and engage fans in an emotionally meaningful way. This study explores the predictive power of Convolutional Neural Networks (CNNs) in boosting SM communication by recognizing and interpreting emotional cues in images and video streams captured in sports contexts – live broadcasts, fan-cams, and supporter-generated content. CNNs contribute to tasks such as crowd sentiment analysis, content moderation, deepfake detection, and real-time emotional feedback – all critical for ethical, emotionally intelligent sports marketing. This research presents a neural network model designed to quantify the impact of CNN-based emotion recognition on four key aspects of social media engagement: audience understanding, emotional content triggers, storytelling effectiveness, and responsiveness to social trends. Using a multilayer perceptron architecture trained on facial and webcam data, the model evaluates the relationship between CNN features and sustainability-focused communication outcomes. Findings indicate that CNN training iterations, facial image variability, and real-time webcam data are the most influential predictors of effective sports social media (SM), while emotional labeling and training data diversity play moderate roles. The model demonstrates practical utility for neuromarketing-driven campaign personalization and provides a foundation for ethical, data-informed sustainability messaging. Despite challenges related to privacy and bias, CNN-based AI systems hold significant potential to transform digital marketing strategies into adaptive, responsive, and emotionally intelligent frameworks.*

Keywords*: Artificial Intelligence (AI); Convolutional Neural Networks (CNN); emotion recognition; neuromarketing; sports social media.*

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Introduction

In recent years, social media (SM) has fundamentally reshaped how sports organizations engage with their audiences, allowing for real-time interaction and the promotion of socially responsible values, such as environmental sustainability (Pegoraro et al., 2019; Abeza et al., 2020). Unlike traditional communication channels, SM enables fans not only to consume

content but also to co-create brand narratives through emotionally expressive, user-generated content (Filo et al., 2015). Within this evolving ecosystem, artificial intelligence (AI) – particularly emotion-aware technologies – has become a powerful tool for decoding affective dynamics between teams, athletes, and supporters.

Neuromarketing has emerged as a key interdisciplinary approach that integrates neuroscience, behavioral insights, and data science to optimize emotional engagement (Cheredniakova et al., 2021). In the sports domain, these tools enhance the effectiveness of sustainability campaigns by identifying affective triggers that align with fan values and behavior patterns. Prior research confirms that audience engagement increases when sports messaging blends emotional storytelling with pro-environmental values (Babiak & Trendafilova, 2011; Inoue & Kent, 2014).

Sports-focused social media platforms such as Instagram, TikTok, Twitter/X, and YouTube function as real-time engagement ecosystems where fans, athletes, and brands converge. These platforms enable interactive storytelling through short videos, live streams, and behind-the-scenes content, while amplifying emotional resonance during major events such as Olympic victories or World Cup moments. Fans participate actively through emojis, comments, and reactions that are emotionally expressive and culturally meaningful (Gursoy et al., 2022).

Fan responses on these platforms often reflect dynamics of tribalism, identity, and immediacy – elements best understood and leveraged through emotion-aware AI. Neuromarketing in this context enables the analysis of how emotional triggers influence virality, sentiment diffusion, and long-term loyalty (Hamelin et al., 2020; Hilken et al., 2022). Emotion recognition technologies further allow communicators to tailor narratives to audience moods, identify content themes that stimulate engagement (e.g., nostalgia, rivalry, pride), and promote sustainability campaigns more effectively by anchoring messages in shared emotional values (Gursoy et al., 2022; Brough et al., 2020).

Convolutional Neural Networks (CNNs) are particularly powerful in this space due to their ability to analyze complex visual data by mimicking the human visual cortex (LeCun et al., 2015). CNNs have proven effective in facial expression recognition, emotion classification, and gesture detection, making them particularly suitable when analyzing the highly visual and emotionally dynamic environment of sports media (Cui et al., 2023).

In sports marketing, CNNs are used to:

- analyze fan reactions during live games (e.g., webcam footage, crowd videos);
- measure emotional engagement across regions and demographics;
- personalize fan experiences via AI-driven recommendation systems;
- predict content virality based on initial emotional responses (Lopez & Ramos-Galarza 2022; Salinas-Medina et al., 2019).

For instance, a CNN may detect high levels of joy or surprise during a decisive goal and anticipate a spike in shares or comments. These insights help clubs and sponsors optimize message timing, visual framing, and content delivery (Ramirez et al., 2022; Yang & Kim, 2020).

The integration of AI - particularly deep learning and CNN-based emotion recognition - enhances the precision and adaptability of social media strategies. It allows marketers to identify emotional triggers, segment audiences by affective profiles, and adjust content

dynamically to maximize relevance and impact (Wang & Deng, 2021; Gursoy et al., 2022). Neuromarketing principles, applied ethically, help identify ideal tone, language, and narrative frameworks for promoting sustainable behaviors, while avoiding manipulation and respecting user autonomy (Lyu & Manas-Viniegra, 2021; Leal et al., 2020; Filipovic et al., 2019; Boz & Kose, 2018; Hamelin et al., 2020; Cenizo, 2023; Dursun & Goker, 2018; Rodrigues et al., 2022).

Despite its promise, CNN-driven emotional analysis raises significant ethical concerns, such as data privacy, algorithmic bias, and the risk of manipulating public sentiment (O'Neil, 2022; Idrobo-Avila et al., 2021). Automated image recognition may infringe on users' privacy, while imbalanced training data can perpetuate harmful stereotypes. Emotionally targeted content, if deployed without transparency or consent, may lead to manipulation rather than engagement.

To mitigate these risks, AI models must be designed with fairness, inclusivity, and accountability - especially when deployed at scale in emotionally sensitive contexts like sports fandom and sustainability communication.

In light of the current literature, this study builds on the following premises:

- social media is a highly emotional and participatory space that shapes how fans engage with sports content;
- motion-aware AI, particularly CNNs, can effectively recognize and classify emotional responses in visual data;
- neuromarketing techniques can enhance message relevance, emotional alignment, and engagement, especially in sustainability communication;
- fan emotional reactions are predictive indicators of social media engagement performance in sports contexts.

This paper analyzes the integration of Convolutional Neural Networks (CNNs) in sports social media marketing, with a specific focus on how CNN-driven emotion recognition can enhance sustainability-oriented communication.

The objective of this study is to quantify the predictive power of CNN features in shaping audience response across four communication dimensions: audience insight, emotional triggers, narrative impact, and trend responsiveness. By quantifying these relationships, the ultimate goal is to enhance the design of emotionally intelligent, data-informed strategies that are both ethically sound and impact-driven.

The research question is: Can machine learning systems, specifically CNN-based emotion recognition, transform expressions into sustainability-oriented, engagement-enhancing outcomes in sports social media communication?

Methodology

Research Design

The methodological approach is exploratory and predictive, combining survey-based data collection with machine learning modeling. According to Bishop (1995) a Multilayer Perceptron (MLP) neural network was implemented in IBM SPSS to assess the relationship between five independent CNN-related variables and four dependent social media outcomes.

The study is grounded in neuromarketing principles, assuming that the emotional impact of marketing content can be objectively analyzed using CNN-derived features such as facial recognition, emotional state detection, and real-time video input.

Instrument Development

A structured questionnaire exploring how rational, emotional, and digital communication factors (including AI and social media) influence consumer decision-making was developed. It evaluates participants' understanding and perceptions of AI-driven communication strategies. The instrument included: a) items measuring awareness and interpretation of facial expressions and emotions; b) perceived effectiveness of AI tools in marketing; c) behavioral indicators related to content engagement and sustainability values. The survey instrument was validated through expert review involving professionals in marketing and social psychology. A pilot study ensured the clarity, reliability, and relevance of all items. The questionnaire contains 39 items in total: 8 demographic & background items (e.g., age group, gender, education, country, expertise); 4 rational decision-making items; 9 emotional decision-making items; 2 risk-avoidance items; 3 awareness-raising items; 13 items on social media marketing, communication, AI, and design.

The questionnaire included items assessing perceptions of artificial intelligence and convolutional neural networks (CNNs) alongside social media (SM) communication influences on decision-making. CNN-related items focused on respondents' cognitive evaluation of AI-supported technologies, for example: *"Artificial Intelligence (AI) technologies help me make better choices"* and *"Artificial Intelligence (AI) helps me decide."* The answer is evaluated on a Likert scale with 5 steps, where 1 is Totally unlikely/ disagree and 5 is Very likely/ Totally agree. These items capture the perceived rational and supportive role of AI-driven systems in individual decision processes. In parallel, social media–related items examined affective and design-oriented responses to digital communication, such as *"Social media reach out to me," "I enjoy visual, interactive, and immersive messages,"* and *"I enjoy messages with humor."* Together, these items operationalize both analytical (CNN/ AI-enabled) and experiential (social media communication) dimensions of decision-making, allowing for an integrated assessment of how advanced technologies and digital marketing stimuli jointly influence consumer judgments and preferences.

Therefore, the questionnaire comprised several sections; however, only two sections: 1) Social media neuromarketing research (SM) and 2) Convolutional neural networks (CNNs) were utilized for the purposes of this study. The items are:

- Convolutional neural networks (CNNs) have been used to identify human emotions or facial expressions from webcam or image data, as follows: A dataset of facial images displaying various emotions is collected (CNNfacial); A CNN architecture is designed for emotion recognition (CNNemotion); The model is trained on the labeled dataset using a large number of iterations (CNNiterations); A separate validation dataset is used to monitor the model's performance during training (CNNtraining); The trained model can then be used to analyze the webcam stream in real time (CNNwebcam).
- Neuromarketing research in social media can contribute to sustainable corporate communication, as follows: Helps companies gain a deeper understanding of the

preferences, emotions, and behaviors of their target audience on social media (SMaudience); Guides the creation of emotionally engaging content that triggers positive emotions related to sustainability (SMtriggers); Guides the development of compelling stories that effectively communicate a company's sustainability initiatives (SMstories); Helps optimize visual content to capture attention, convey messages clearly, and evoke desired emotional responses (SMvisual); Neuromarketing research can reveal the most effective language, tone, and messaging styles for communicating sustainability-related information (SMmsg); Understanding how social media users respond to different types of content can guide companies in encouraging sustainable behaviors (SMbehaviour); Provides real-time interaction and feedback (SMfeedback); Helps companies ensure that their communication efforts are authentic and resonate with their audience's values (SMcommunication); Provides guidance on avoiding manipulation techniques and ensuring that communication efforts respect individual privacy and autonomy (SMGDPR); Provides feedback for continuous improvement, helping companies adapt strategies based on evolving public preferences and societal trends (SMtrends).

From the items included in these two sections, a subset was selected for analysis. Items exhibiting high multicollinearity, as indicated by elevated Variance Inflation Factor (VIF) values, were excluded. The retained variables and their corresponding descriptions are presented in Table 1.

Sample and Data Collection

The study was conducted in Bucharest, Romania, between October and December 2023. A non-probability purposive sampling method was used to target digitally active individuals aged 18 to 40, reflecting the core demographic of social media users. The total number of respondents were 416 (51.2% men and 48.79% women) and the questionnaire was filled face-to-face and the subjects received support and explanations regarding the content of the items. Participants provided informed consent and were briefed on ethical standards, including compliance with the General Data Protection Regulation (GDPR). All responses were anonymous and used solely for academic research.

Neural Network Model Construction

A Multilayer Perceptron (MLP) neural network was configured using the following architecture:

- Input layer: 5 CNN-related predictors: 1) CNN facial – Facial photo variation; 2) CNN emotion – Emotional identification capability; 3) CNN iterations – Number of CNN training cycles; 4) CNN training – Quality/diversity of training dataset; 5) CNN webcam – Real-time webcam input capability.
- Hidden layer: 1 layer with 6 neurons and a Hyperbolic Tangent activation function.
- Output layer: 4 target variables: SM audience, SM triggers, SM stories, SMtrends (Table 1), and the selected error function was the Sum of Squares

- Training/Testing Split: 72.6% Training Set (n = 302) and 27.4% Testing Set (n = 114). This represents an appropriate training/testing split — a standard practice for generalizability and only 1 excluded case (data cleaning seems successful).
- Stopping Rule: One consecutive step with no reduction in error.

Table 1 provides an overview of the variables under analysis.

Table 1. *The variables analyzed*

Variable	Label	Description
CNN	NEmotional	CNN facilitates the identification of emotional issues.
	NIterations	CNN employs a lot of iterations.
	NPhotos	Different emotions may be seen in facial photos.
	Nmodel	A different training dataset is utilized to track the model's effectiveness.
	Nwebcam	After that, the model may be used to instantly examine webcam feeds.
SM	Smaudience	Help companies gain a deeper understanding of their target audience's preferences, emotions, and behaviors on social media.
	SMtriggers	Guide the creation of emotionally engaging content that triggers positive emotions related to sustainability.
	SMstories	Guide the development of compelling stories that effectively communicate a company's sustainability initiatives.
	Smtrends	Provides a feedback loop for continuous improvement by helping companies adapt their strategies based on evolving audience preferences and societal trends.

Model Validation and Ethical Considerations

The model's performance was evaluated using: 1) Sum of Squares Error (SSE) for training and testing sets; 2) Relative Error across each output dimension, and 3) Normalized importance scores to assess predictor contribution.

The results showed acceptable generalization capacity with stronger predictive accuracy for SM audience and SM triggers. Ethical safeguards were applied throughout the study to ensure transparency, anonymity, and compliance with EU data protection standards.

Results

The neural network architecture – input, hidden and output layer – is presented in Table 2. The model proposes that *emotion detection tech* (CNN variables) can predict how emotionally effective and adaptive a company is on social media, particularly in the context of sustainability narratives (Emotion AI meets Sustainability Strategy). This setup links computer vision, marketing, and environmental communication, representing an emerging area of interdisciplinary research. The neural network tries enhance the dissemination of sustainability-related content by analyzing emotional cues derived from facial data.

The use of tanh and identity functions suggests that the modeling is nonlinear, but interpretable outcomes – suitable for strategy refinement and scenario analysis (e.g., "What happens to SM stories if CNN webcam is deployed in real time?").

Table 2. *Neural Network Structure*

Network Information			
Input Layer	Factors	1	CNNfacial
		2	CNNemotion
		3	CNNiterations
		4	CNNtraining
		5	CNNwebcam
	Number of Units[a]		25
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		6
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Smaudience
		2	Smtriggers
		3	Smstories
		4	Smtrends
	Number of Units		4
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

The Model Summary (Table 3) provides us insight into the model's performance, including both training data and unseen testing data.

Table 3. *Performance Overview*

Metric	Training	Testing
Sum of Squares Error (SSE)	463.110	132.833
Avg. Overall Relative Error	0.769	0.602
Training Time	0.08 seconds	–
Stopping Rule	Early stopping (1 step without error decrease)	–

Sum of Squares Error (SSE) is lower on the test set than the training set, but this is expected since the training set is larger. What matters more is *relative error*. Average Relative Error (ARE): Training: 0.769, Testing: 0.602. The testing error is lower, which could signal some over-regularization or early stopping, but mostly this indicates that the model generalizes reasonably well. A value of 0.60 suggests the model captures about 40% of the predictive structure. This suggests a moderate predictive performance, indicating meaningful but limited explanatory power. For human behavior and emotion-related tasks, this is within range, given complexity and variability (Table 3).

Table 4. *Per-Output Variable Performance*

Output	Relative Error (Train)	Relative Error (Test)	Performance
SMaudience	0.749	0.532	Best
SMtriggers	0.717	0.599	Good
SMstories	0.759	0.664	OK
SMtrends	0.852	0.618	Lower

SM audience has the lowest relative error (0.532) suggesting the model best predicts how well CNN data can anticipate audience behavior/preferences. SM trends is the hardest to predict, which makes intuitive sense – societal trends evolve from complex, emergent patterns beyond facial cues or CNN features (Table 4).

Stopping Rule *"1 consecutive step(s) with no decrease in error"*. The model stopped training early after detecting a plateau in error reduction. This helps prevent overfitting and is a standard practice, but with only one step, it's possible the model didn't explore enough depth to optimize further.

This model represents a promising prototype, especially for predicting audience engagement and emotional resonance in sustainable messaging. It has practical utility for guiding: Campaign personalization (especially via SM audience); A/B testing emotional content (via SM triggers) and less so for long-term strategic planning (SM trends), but this could improve with additional trend-level features (e.g., hashtags, engagement growth rates).

Synaptic Weight Insights (Figure 1) reveal which hidden neurons contribute most to each SM output by the number and thickness of lines leading into a specific output node.

- Hidden nodes like H (1:2) and H (1:5) appear to have more dark blue connections to certain outputs, which implies negative influence (e.g., a rise in CNN emotion might reduce SM triggers in some contexts).
- SM audience and SM triggers are more densely connected, reflecting their higher performance (as indicated by the error metrics presented earlier).
- CNN webcam appears to feed heavily into H (1:3) and H (1:6), which may suggest a relationship to trend prediction (SM trends), albeit weaker.

The model let us know that "Emotion recognition has stronger influence on audience prediction than trend forecasting".

The Parameter estimated emphasize that H (1:1) is a strong inhibitor, especially for SM audience and SM triggers. Meanwhile, H (1:2) and H (1:3) are activators, influencing almost all SM outputs positively (Figure 1).

Strengths: The model is sensitive to variations in facial recognition and emotion detection, especially at extreme values. The output for SM audience and SM triggers is largely shaped by strong negative and positive balancing forces – excellent for nuanced audience modeling.

Weaknesses: Some hidden neurons (e.g., H (1:5)) have mostly weak influence – maybe underutilized. SM trends depend heavily on just 1–2 hidden units, which may explain its lower predictive accuracy (per your earlier error metrics).

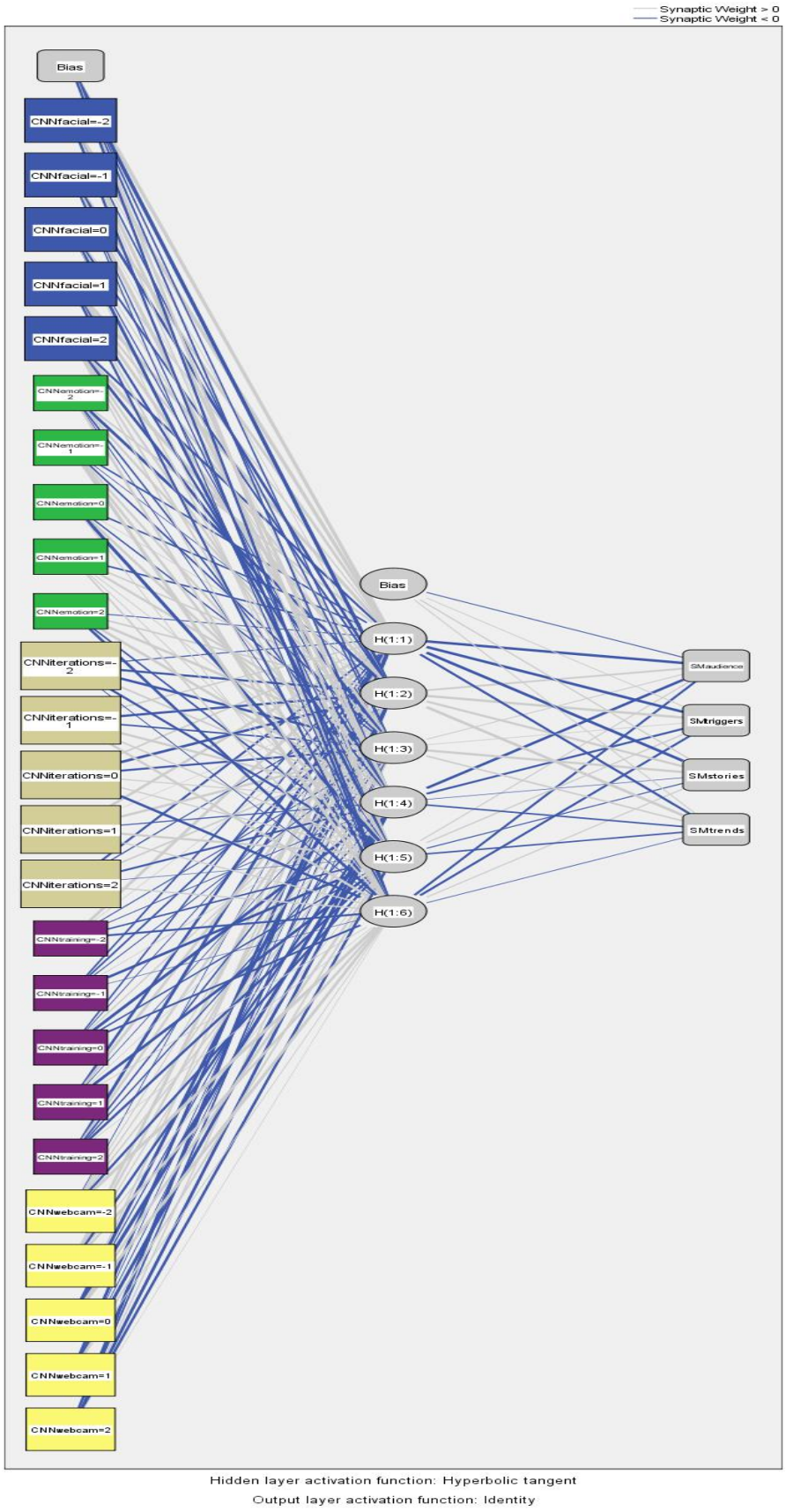

Figure 1. Synaptic Weight Insights

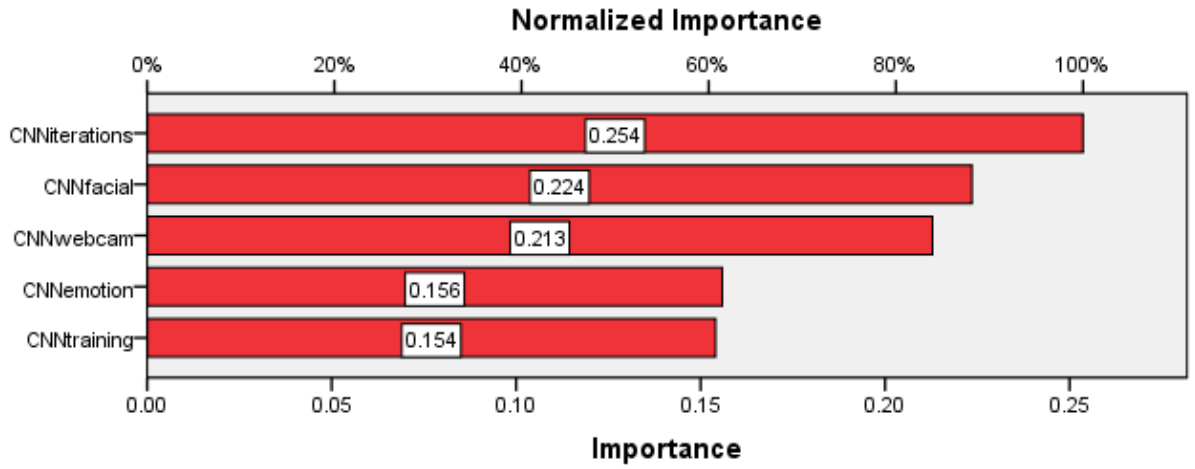

Figure 2. Normalized importance – neural network

Figure 2 represents the Normalized Importance of each input variable in your neural network model – in other words, how much each input contributes to predicting the outputs (SM audience, SM triggers, SM stories, and SM trends). The input with the highest impact is assigned a value of 1 (or 100%) – all other inputs are shown as a percentage relative to that. These values are derived from the sum of squared connection weights between each input and the hidden layer(s), across the entire model.

Table 5. *Variable Rankings (from most to least important)*

Variable	Normalized Importance	Interpretation
CNNiterations	0.254 (100%)	Most important. The number of CNN iterations used in training strongly impacts how well the model predicts emotional-social outcomes. It likely reflects model learning capacity.
CNNfacial	0.224 (88%)	Very important. The presence/variation of facial photo data helps the model discern emotional context.
CNNwebcam	0.213 (84%)	Nearly tied with facial. Real-time webcam data seems to significantly influence the prediction of social media variables.
CNNemotion	0.156 (61%)	Moderately important. Emotional labeling from CNN helps, but it's less powerful than expected. Possibly due to overlap or less variance.
CNNtraining	0.154 (61%)	Similar to CNNemotion – contributes modestly. Likely reflects that training dataset diversity, while useful, is not the main driver.

CNN iterations lead the pack: A well-trained model (with more training epochs/iterations) enhances prediction quality of audience behavior and emotional triggers on social media.

- CNN facial and CNN webcam are close seconds – what is seen (facial data) and when it's seen (real-time feeds) are both critical to forecasting emotional responses and trend engagement.
- CNN emotion is only moderately important, suggesting that raw emotion tagging alone isn’t enough – it may need to be combined with timing (webcam) or context (facial inputs) to matter.
- CNN training is useful but has limited standalone power – possibly due to consistent quality across datasets or a narrow range of variation in your sample.

The model doesn't just learn from what emotions are *named*, but it learns from how they're trained, how many times, and how real-time they appear. It is clear that model performance is influenced by both training depth and real-time data integration.

Discussions

This study provides valuable insights into the integration of Convolutional Neural Networks (CNNs) in the strategic design of emotionally intelligent communication on social media, particularly within sports campaigns. By modeling the predictive relationship between CNN-based emotion detection and audience engagement outcomes, we bridge AI-based visual recognition technology with neuromarketing and environmental communication strategies.

The results reveal that CNN iterations, CNN facial, and CNN webcam are the most significant contributors to predicting communication effectiveness. These findings underscore the importance of not only the quality of input data (e.g., emotional cues or facial features) but also the depth of learning and training exposure in machine learning systems. This aligns with previous research emphasizing that deeper, well-trained models provide more reliable pattern recognition in emotionally nuanced tasks (Wang & Deng, 2021; Zhang et al., 2020).

Importantly, the model demonstrated strong performance in forecasting audience understanding (SM audience) and emotional responsiveness (SM triggers). These dimensions are directly influenced by the system's ability to recognize emotional cues in visual data and process them in real time, suggesting that CNNs can meaningfully inform the timing, tone, and framing of marketing content. This reinforces existing claims in the literature that emotion-aware AI tools can enhance content relevance and resonance (Kietzmann et al., 2018).

On the other hand, the model showed lower predictive accuracy for SM trends, indicating the complexity and unpredictability of social trends, which often evolve from external socio-political and cultural factors not easily captured by emotion recognition systems. This limitation points to a potential area for future model enhancement, perhaps by incorporating external data sources such as social listening, hashtags, or news event timelines.

Moreover, the study confirms that emotion detection alone is not sufficient. While CNN emotion contributed to performance, it was less influential than training depth and data modality. This suggests that emotion recognition technologies are most effective when embedded in dynamic, iterative, and context-aware systems, rather than used as static classifiers.

From a practical standpoint, these findings have several implications:

- companies should invest in iterative model training and real-time emotion detection technologies to improve campaign personalization;
- CNN-powered emotion analysis tools can support A/B testing, audience segmentation, and micro-targeting strategies in sustainability communication;
- ethical considerations remain crucial, especially regarding user privacy, bias in training data, and the potential emotional manipulation of audiences. These issues must be carefully navigated to ensure responsible AI deployment in marketing.

Conclusion

This study explored the integration of Convolutional Neural Networks (CNNs) into social media communication strategies, focusing on their role in enhancing audience engagement through emotional recognition. By developing and testing a Multilayer Perceptron neural network, the research demonstrated that CNN-derived features, particularly training iterations, facial data, and real-time webcam input are strong predictors of emotional resonance and strategic effectiveness in sustainability-oriented campaigns.

The model showed promising predictive accuracy for understanding audience preferences (SM audience) and triggering emotional responses (SM triggers), validating the potential of AI-based tools in neuromarketing and digital storytelling. Although the model's performance was lower for forecasting societal trends (SM trends), this finding underscores the need for more complex, multi-source input models that incorporate social context and real-time feedback.

Overall, this research contributes to the growing intersection of AI, marketing, and sustainability communication by demonstrating how CNNs can serve as both analytical and creative tools. As organizations seek to humanize their messaging and connect with audiences on an emotional level, the ethical and effective application of CNN-based models will play a central role in the development of future communication strategies.

Future studies should consider expanding the model with multimodal inputs (e.g., voice, text sentiment, and environmental cues), testing across broader demographics, and exploring the long-term behavioral impact of AI-personalized sustainability messaging.

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