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RESEARCH ARTICLE

Spatial Attention-Enhanced EEG Analysis for Profiling Consumer Choices

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ABSTRACT Over the years, research in neuroscience-driven marketing has progressively delved into the conscious and subconscious behaviors of consumers. Existing Electroencephalography (EEG)-based studies related to consumer preferences toward products are not comprehensive. Due to non-stationarity issues of EEG, a significant variance is observed in inter-trial and inter-session EEG signals of a subject, which leads to challenges in building a universal consumer preference model across diverse subjects, sessions, and tasks. Transfer learning mitigates this challenge by utilizing data or knowledge from similar subjects, sessions, or tasks to improve the learning process for a new subject, session, or task, thereby enhancing overall model performance. Moreover, high-dimensional EEG features often lead to poor classification results. Therefore, selecting meaningful or refined features is of utmost importance for classification. Therefore, we propose a robust EEG-based neuromarketing framework combining deep transfer learning, spatial attention models, and deep neural networks. The proposed framework predicts the consumer choices (in terms of "likes" and "dislikes") for e-commerce products. Initially, the knowledge distillation is performed from the pre-trained network to the proposed model, and the model is trained on the connectivity features of EEG. Next, the attention-based features are extracted from high-level connectivity features using the spatial attention model (Convolutional Block Attention Module: CBAM). CBAM extracts the attention feature maps along channel and spatial dimensions for adaptive feature refinement. The refined features improve the classification accuracy. Finally, the attention-based features are passed to the 2D CNN-based deep learning model to evaluate consumer choices. The proposed model achieves 95.60% classification accuracy with the experimental dataset. The proposed model achieves a significant improvement of 2.60% over the existing neuromarketing-based studies.

INDEX TERMS Consumer behavior, deep transfer learning, EEG, neuromarketing, spatial attention.

I. INTRODUCTION

The emerging field of neuromarketing is gaining traction and legitimacy as it integrates neuroscience with consumer psychology, marketing, economics, and decision sciences. In a brief period, consumer neuroscience has successfully established a solid research connection between brain sciences and applied business-related research [1]. It is an emerging research field that aims to capture the response of the human brain to commercials, brands, and marketing stimuli.According to Hubert and Kenning [2], neuroeconomics employs methods originally used in brain research regarding economic problems. Neuromarketing or consumer neuroscience is a sub-area of neuroeconomics that tries to find a solution in the marketing domain. Different physiological measures such as functional magnetic resonance imaging (fMRI) [3], electroencephalography (EEG) [4], magnetoencephalography (MEG) have been used in neuromarketing-based studies, which are related to purchasing preference towards various products, brands [5]. Physiological measure-based studies are useful in various fields of consumer behavior domains, such as formulation

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of policies related to pricing [6], product [5] and brand research [7]. Instead of just asking consumers' preferences, this technology helps to gain access to hidden information about the consumer experience. This ultimately leads to improved product design and increased sales [8]. EEG is a widely used physiological measure in the marketing domain due to its inexpensive experimental setup and high temporal resolution. EEG has been used in different applications such as epileptic seizure detection [9], user verification [10], emotion recognition [11], cognitive workload estimation [12], recommendation system [4], and preference prediction [13]. In an EEG-based neuromarketing study, the brain signal of a consumer is captured while observing a product or watching an advertisement. For example, mutual information-based EEG analysis identified the significant change in the spectral activity while the consumers indicated their preferences. The like/dislike preferences have been identified during watching the products [14]. The intersection of machine learning and deep learning applied to EEG signals has emerged as a compelling research focus, showcasing a burgeoning interest in exploring their combined potential. For example, a 2D convolutional neural network (CNN)-based deep learning model has been used to estimate the customer choice from the product and movie rating dataset [15]. They have achieved a maximum accuracy of 74.57% with the movie rating dataset. Golnar-Nik et al. [16] have implemented a like/dislike prediction framework using EEG band power and SVM classifier with an accuracy of more than 87%. They have identified that centro-parietal locations (Fp1, Cp3, Cpz) of the brain can effectively distinguish the preference classes. Due to the dynamic and non-stationary nature of EEG, a large variance has been observed in inter-trial and inter-session signals of a subject. Therefore, building a robust EEG-based Brain-Computer Interface (BCI) system across different subjects is of utmost demand [17].

Transfer learning (TL) can overcome this issue by utilizing the knowledge or data from similar or relevant subjects/sessions/tasks to facilitate learning for a new subject/session/task [18]. In deep transfer learning (DTL), an efficient deep neural network performs the knowledge transfer between the source and destination domain. The objective of DTL is to extract high-level abstract features from the source dataset and re-engineer those features in the new dataset to enhance the model performance [19]. A multisource transfer learning framework has been developed for the emotion recognition task [20] to remove the subject-wise signal variation from the same task. He and Wu [21] have developed a label alignment approach to identify different labels of the target domain from the source domain in a cross-task TL-based MI experiment. Xu et al. [22] have developed an efficient DTL model for motor imagery classification using VGG-16 with an average accuracy of 74.2% for all subjects. Tan et al. [23] implemented an EEG-based DTL model using VGG-16, VGG-19, ResNet, and AlexNet for music imagery classification. Duan et al. [24] addressed the challenge of cross-subject EEG classification using meta-learning on constrained transfer learning (MLCL). This study offered an effective solution for personalized EEG classification while minimizing the need for extensive subject-specific data collection. This study achieved an accuracy of 78.6% with the SEED dataset. Xu et al. [22] developed deep transfer CNN framework using VGG-16 for Motor Imagery (MI)-based Brain-Computer Interface (BCI) application. Their study achieved 74.2% classification accuracy, outperforming the existing EEG-based MI studies and offering a promising approach for practical BCI applications. Bird et al. [25] developed EEG and EMG-based transfer learning using Multilayer-layered perception (MLP) and CNN. During the CNN/MLP model training, they used random weight distribution of EMG and EEG and weight transfer learning between EMG and EEG to find the best model. They have achieved maximum classification accuracy of 97.18% with a CNN-based transfer learning model (with weight transfer). Zhang et al. [26] proposed an innovative method for alcoholism diagnosis using EEG signals, addressing the unreliability of patient information with 95.33% accuracy. Aldayel et al. [27] illustrated the impact of employing DTL in the realm of EEG-based emotion recognition and EEG-based preference detection. These models predicted consumer preferences from EEG signals by utilizing the DEAP dataset with 93% accuracy. The identification of class-specific regions from the high-level abstract features (returned from DTL) is important for better classification. The attention mechanism has been effectively used to focus the region of interest of an image [28]. Woo et al. [29] have developed a lightweight visual attention module called Convolutional Block Attention Module (CBAM). In CBAM, the spatial and channel-level attention maps have been merged with the input feature map to produce a final refined feature map. Spatial attention maps have been effectively implemented in image captioning [30], question answering [31].

However, implementing the attention mechanism in EEG-based tasks or neuromarketing applications has not yet been discovered; therefore, building a robust neuromarketing-based model to identify customer choice towards the products is of utmost demand. Moreover, most existing TL-based studies [18], [28] focused only on cross-subject/sessions, but cross-task-based TL task remains mostly unexplored. This is the primary motivation behind this study. In this paper, we implement cross-task-based TL, where knowledge from the image classification task has been utilized for the prediction of customer choice. In this study, we transform the knowledge from the source dataset (i.e., *imagenet*) to the destination dataset (EEG-choice prediction). Initially, we extract the connectivity features from the EEG signal, and the adjacency matrix's image of those features is passed to the pre-trained network (VGG 16). Next, the transformed features are moved to CBAM. Finally, the attention-based features (extracted from CBAM) are passed

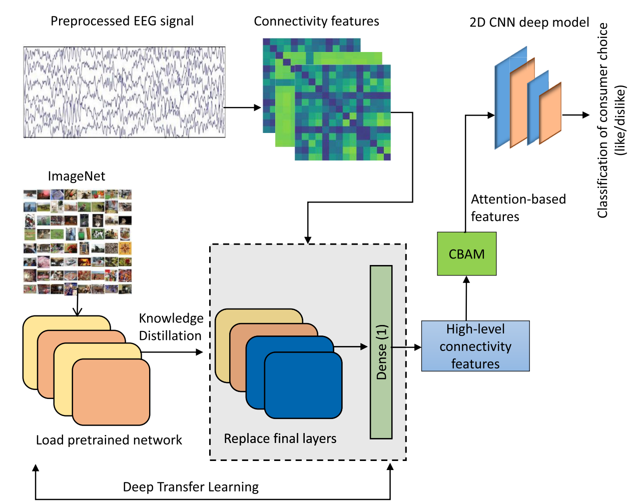


FIGURE 1. Proposed neuromarketing framework consisting of Deep transfer learning, spatial attention, and 2D CNN-based deep learning model for classification of consumer choice. Initially, connectivity features are extracted from EEG, and knowledge transfer is performed from the pre-trained network to the proposed model. Finally, spatial attention is applied using the CBAM, and attention-based connectivity features are passed to the 2D CNN model to evaluate consumer choice.

to the 2D CNN model to identify consumer preferences. The framework of the proposed model is shown in Figure 1. The novelty of this study is illustrated as follows:

1) There exist no studies that aim to combine EEG and consumer preferences using a DTL-spatial attention-based deep learning model.
2) The proposed neuromarketing framework implements a spatial attention mechanism using CBAM that enhances the classification performance.
3) The performance of the proposed model has achieved significant improvement over existing methods of neuromarketing studies.

The rest of this paper is organized as follows;

The detailed discussion of the proposed work is presented in section II. Section III represents the experimental results of the proposed model. A detailed discussion of this study is mentioned in section IV. Finally, in section V, we conclude the paper with future research directions.

II. PROPOSED METHOD

This section consists of three subsections, namely, (a) Data preprocessing (b) Feature engineering, and (c) Consumer behaviour classification.

A. DATA PREPROCESSING

In this study, we have used a public neuromarketing dataset [32]. The dataset consists of EEG signals of 40 subjects (25 male and 15 female) while they were watching e-commerce products. Fourteen different products, each with three varieties, have been selected for the experiment. Therefore, 42 (14 × 3) product images have been used for a single subject, and 1680 (42 × 40) images have been used for all 40 subjects. Each product's images appeared for 4s in the experiment, and EEG signals were recorded in parallel. After showing the image, the user's preference for the product was recorded.

EEG measures the electrical activity in the brain, and the activity is divided into five frequency bands: delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz), and Gamma (30-40Hz) [33]. EEG frequency bands(1-40Hz) provide valuable information about the brain's functional states, cognitive processes, and overall neurological health. As EEG is sensitive to noise, to keep the valuable information of the brain without high-frequency noise, we have applied a bandpass filter between 1 to 40 Hz [34]. Next, independent component analysis (ICA) was used to remove all types of artifacts (ocular and cardiac artifacts) from EEG. The artifact removal has been performed using EEGLAB software [35]. The connectivity feature extraction process has been performed using Brainstorm software [36].

B. FEATURE ENGINEERING

Connectivity features provide more discriminative power than traditional EEG features. Power-based connectivity features (coherence and correlation) reveal the information processing between brain regions during the prediction of customer choice (here, "like"/"dislike"). Power changes may indicate positive or negative reactions to specific design elements, helping to predict customer choice preferences [37]. Phase information is essential for understanding the temporal coordination of neural activity. Phase-Locking Value (PLV) specifically provides insights into the temporal sequence of cognitive processes, improving product choice prediction [38].

This section consists of two subsections, namely, (a) connectivity-based feature extraction and (b) feature extraction using CBAM.

1) CONNECTIVITY-BASED FEATURE EXTRACTION

The brain connectivity features are widely used in finding underlying brain patterns during the task [39]. Here, we use power (coherence and correlation) and phase (Phase locking value)–based connectivity features for customer choice prediction. A detailed description of each feature is mentioned in the following subsections.

Power-based connectivity features: The correlation connectivity feature is derived from Pearson's correlation coefficient (PCC). The PCC measures the linear dependency between the two time-series signals ranging from −1 to 1. A higher value of PCC refers to the positive correlation among the two time-series signals, whereas a lower value represents a negative correlation. For the two EEG signals $e_i = \left\{e_i^1, e_i^2, \ldots..e_i^T\right\}$ and $e_k = \left\{e_k^1, e_k^2, \ldots..e_k^T\right\}$ of the i^{th} and k^{th} electrodes, PCC is computed using (1) [38].

$$PCC(i,k) = \frac{\frac{1}{T}\sum_{t=1}^{T}(e_i^t - \mu_i)(e_k^t - \mu_k)}{\sigma_i \sigma_k} \tag{1}$$

where T is the time length of the signals. μ and σ represent the mean and standard deviation of the signal, respectively.

Coherence refers to the degree of similarity between the two signals for the same frequency component. The magnitude of coherence varies from 0 to 1. The coherence of the two EEG signals x and y for the frequency component f is represented using (2) [40].

$$Coh_{x,y}(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f)S_{yy}(f)} \tag{2}$$

where $S_{xy}(f)$ represents the cross-spectral density, $S_{xx}(f)$, $S_{yy}(f)$ are the auto-spectral density of the frequency component f.

Phase-based connectivity features: Due to the rhythmic character of EEG, phase synchronization would bring more robust connectivity results than time-domain metrics. Phase synchronization is expressed by the relative phase difference of two signals, $\Delta\phi_r(t) = |\phi_{x_i}(t) - \phi_{x_j}(t)| mod 2\pi$. The instantaneous phase of the signal, $\phi_x(t)$, is obtained after applying the Hilbert transform to the original signal $x(t)$ at time t. Among the phase synchronization metrics, Phase Locking Value (PLV) describes the variability of the relative phase using (3) [41].

$$PLV(x_i, x_j) = \left| \frac{1}{N} \sum_{n=1}^{N} e^{i\Delta\phi_r(t_n)} \right| \tag{3}$$

2) FEATURE EXTRACTION USING CBAM

After extracting the robust connectivity features from the EEG signal, we implement the CBAM [29] mechanism to compute the attention maps from the input feature descriptor. The CBAM method consists of two attention modules, namely the channel attention module and spatial attention module. The detailed description of each module is discussed in subsequent paragraphs.

Channel attention module: In the input feature map, each channel represents as a feature detector; therefore, channel attention focuses on *what* is meaningful in the input image. Initially, average and max pooling operations have been performed to aggregate spatial information of input features (F). Then, average-pooled (F^c_{avg}) and max-pooled (F^c_{max}) features are passed to a multi-layer perceptron (MLP)-based shared network to generate the channel attention map ($M_c \in \mathbb{R}^{C\times1\times1}$). The hidden activation size of the shared network is $\mathbb{R}^{C/r\times1\times1}$, where C, r are the channel and reduction ratio, respectively. The channel attention map can be represented as follows:

$$\begin{aligned} M_c(F) &= \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \\ &= \sigma(W_1(W_0(F^c_{avg})) + W_1(W_0(F^c_{max}))) \end{aligned} \tag{4}$$

where, σ is the sigmoid function, $W_0 \in \mathbb{R}^{C/r\times C}$, and $W_1 \in \mathbb{R}^{C\times C/r}$. The weights ($W_0$ and W_1) of MLP are shared for channel and spatial inputs.

Spatial attention module: In spatial attention, we identify the inter-spatial relationship of features. This module extracted the max-pooled and average-pooled features along the channel axis and concatenated them to get an efficient feature descriptor. Then, a convolution layer is applied over the concatenated feature descriptor to generate the spatial attention map ($M_S(F) \in \mathbf{R}^{H\times W}$). The spatial attention map is computed as follows:

$$\begin{aligned} M_s(F) &= \sigma(f^{x\times x}([AvgPool(F); MaxPool(F)])) \\ &= \sigma(f^{x\times x}([F^s_{avg}; F^s_{max}])) \end{aligned} \tag{5}$$

where, $f^{x\times x}$ denotes the convolutional operation with the filter size of ($x \times x$). $F^s_{avg}, F^s_{max} \in \mathbb{R}^{1\times H\times W}$ represents the 2D spatial feature maps.

C. CONSUMER BEHAVIOUR CLASSIFICATION

This section consists of two subsections: (a) deep transfer learning and (b) spatial attention & deep classification model. A detailed description of each subsection is mentioned below.

1) DEEP TRANSFER LEARNING

In deep transfer learning (DTL), a robust pre-trained deep transfer learning network is used to learn a new similar kind of task. Two models are used in transfer learning for transferring the effective features across a similar domain: source pre-trained model and target model. Here, we used the retraining approach of DTL, where we used the pre-trained weights ('imagenet') to train the DTL. We replace the final fully connected layer of the pre-trained network with a layer matching the binary classes ('like' and 'dislike') of the experimental dataset. The output of the source pre-trained network is passed as the input of our target model. Next, the adversarial cross-validation is performed over the target model to effectively distinguish the train and test set based on their feature distribution. The training of the target model is performed based on the resized connectivity images (as per the image size of the *imagenet* dataset) extracted from the preprocessed EEG data. The adversarial cross-validation estimates the best-split point of train/test data to evaluate the proposed deep learning model. In machine learning, adversarial cross-validation (CV) is effectively used to reduce overfitting.

2) SPATIAL ATTENTION AND DEEP CLASSIFICATION MODEL

Once the transformed features are obtained from the DTL model, we perform a spatial attention mechanism over those features to identify the region of interest within that feature. The attention-based transformed connectivity features extracted from the CBAM module are passed to the deep learning model. The proposed deep learning model consists of three convolutional layers to classify consumer choice (Figure 2). The first convolutional layer takes the feature map of size: 224 × 224×3 as input and performs the filter operation with eight filters of size 7 × 7. The normalized and pooled output of the first convolutional layer is passed as the inputs to the second convolutional layer that uses 16 filters with size 5 × 5. Similarly, the normalized and pooled

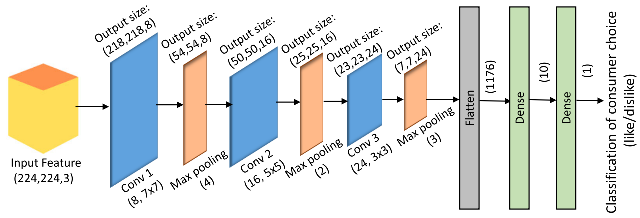


FIGURE 2. Proposed 2D CNN deep learning model for consumer choice classification. Transformed attention-based features passed as an input to the model. The deep learning model consists of three convolutional-max polling layers followed by fully connected layers.

TABLE 1. Results of proposed model according to different pretrained networks.

Pretrained Network	Trainable layer	Acc %(Train/Test)
Resnet 101	Conv 5	97.10/90.88
Resnet 50	Conv 5	95.77/92.23
VGG 16	Block 5	**99.23/95.60**
VGG 19	Block 5	98.19/93.79
DenseNet 121	Conv 5	95.33/89.90

output of the second convolutional layer is passed to the third convolutional layer that has 24 filters with a size of 3×3. The output of the third convolutional layer is passed to the flatten layer to project the image features into a 1D feature vector. Finally, two fully connected layers consisting of ten neurons followed by one neuron finished the model configuration. For normalizing the output, a batch normalization layer is applied after each CNN layer.

III. RESULTS AND ANALYSIS

This section divides into five subsections, namely, (a) Analysis based on different pretrained networks, (b)Analysis of the CBAM model, (c) Classification analysis of the proposed deep learning model, (d) Consumer behavior analysis, and (e) Comparative analysis.

A. ANALYSIS BASED ON DIFFERENT PRETRAINED NETWORKS

This section identifies the optimal network after analyzing the results of different pretrained networks (Resnet 101, Resnet 50, VGG 16, VGG 19, DenseNet 121). The analysis is done based on the same image size (224×224) of each pretrained network while varying the final layer of each network. The performance analysis of the proposed model using different pretrained networks is discussed in Table 1. It can be observed that the proposed model achieves the maximum accuracy of 95.60% while using the VGG 16 as a pretrained network. Therefore, we use VGG 16 as the final pretrained network for future analysis. In pretrained networks, deeper layers extract higher-level features, which are constructed using the lower-level features of earlier layers [42]. The earlier layers extract shallower features having higher spatial resolution.

B. ANALYSIS OF THE CBAM MODEL

After extracting the abstract level connectivity features from the best DTL model (i.e., VGG 16), we extract the attention-based spatial features using CBAM. The CBAM model consists of spatial and channel modules, so the performance of the proposed deep learning model can change with different configurations of CBAM's modules. In this section, we perform the analysis based on different configurations of an individual module (filter sizes, number of filters of spatial module, and pooling operation of channel attention module). From Table 2, we can conclude that the CBAM with sequential configuration (channel-spatial) outperforms other configurations with a maximum classification accuracy of 95.60% (marked as bold in Table 2).

C. CLASSIFICATION ANALYSIS OF THE PROPOSED MODEL

This section subdivides into three subsections, namely, Output and performance analysis, Ablation study and Subject-wise analysis.

1) OUTPUT AND PERFORMANCE ANALYSIS

This section discusses the output and performance analysis of the proposed deep learning model. A binary cross-entropy loss function has been used for two-class classification (like and dislike). The model has been trained with a batch size of 32 for 100 epochs. Adam optimizer, with an initial learning rate of 0.002, has been used. We combine the data of all the subjects for classification. The dataset is divided into training, validation, and testing set with the ratio of 7:1:2. The proposed model achieves 95.60% classification accuracy. The classification results of the proposed model for two classes (like and dislike) is shown in Table 3. The result is produced based on classification metric such as precision, recall and f1-score. The most important metric for balanced classification results is the f1-score, which combines the optimal balance of recall and precision to get a better result.

The Receiver operating characteristic (ROC) curve is generally used in binary classification to evaluate the model performance. Here, we compare different 2D CNN models with different configurations and evaluate the performance of each model using the ROC curve. The ROC curve of the proposed deep learning model (2D CNN model2) and other deep learning models are presented in Figure 3. The Area Under Curve (AUC) region in the ROC curve defines how the model separates the two classes; therefore, a higher AUC score leads to better classification results. From Figure 3, we can conclude that the proposed model covers the maximum AUC region leading to the highest AUC score over other deep learning models.

2) ABLATION STUDY

As the proposed model consists of three components, namely DTL, CBAM and deep 2D CNN model, it is important to measure the classification performance of individual components. In the ablation study, we perform the classification analysis based on the following three model variants:

Model 1: 2D CNN

Model 2: CBAM + 2D CNN

Model 3: DTL + CBAM + 2D CNN (proposed)

TABLE 2. Classification analysis of the proposed deep learning model (2D CNN) based on different CBAM configurations.

CBAM configuration	Spatial module	Channel module	Accuracy(%) (Train/Test)
	conv:1, k=7	Max pool	88.33/78.36
	conv 10(k=5)-conv 1(k=7)	Max pool	90.91/82.86
	conv:1, k=7	Avg pool	86.36/76.96
Sequential: Channel-Spatial	conv 10(k=5)-conv 1(k=7)	Avg pool	93.96/89.69
	conv:1, k=7	Avg+Max pool	**99.23/95.60**
	conv 10(k=5)-conv 1(k=7)	Avg+Max pool	96.34/91.13
	conv:1, k=7	Max pool	89.23/82.56
	conv 10 (k=5)-conv 1 (k=7)	Max pool	91.66/77.96
	conv:1, k=7	Avg pool	91.56/80.44
Sequential: Spatial-Channel	conv 10 (k=5)-conv 1 (k=7)	Avg pool	88.56/74.69
	conv:1, k=7	Avg+Max pool	90.56/70.36
	conv 10 (k=5)-conv 1 (k=7)	Avg+Max pool	91.56/76.23
	conv:1, k=7	Max pool	78.69/69.36
	conv 10 (k=5)-conv 1 (k=7)	Max pool	90.56/76.16
	conv:1, k=7	Avg pool	86.05/71.33
Parallel: Channel+Spatial	conv 10 (k=5)-conv 1 (k=7)	Avg pool	89.56/76.39
	conv:1, k=7	Avg+Max pool	94.05/83.56
	conv 10 (k=5)-conv 1 (k=7)	Avg+Max pool	96.23/90.55

TABLE 3. Classification analysis of the proposed model.

Class	Precision (%)	Recall (%)	f1-score (%))
Like	96.20	89.33	92.63
Dislike	85.17	93.04	88.93

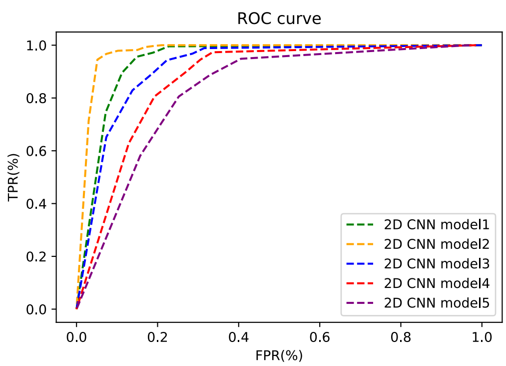


FIGURE 3. Performance analysis of the proposed deep learning model (2D CNN model2) over other deep learning models using the ROC curve. Configurations of each 2D CNN model are as follows: model1: C6-M4-C12-M2-C18-M2-D1, model2: C8-M4-C16-M2-C24-M3-D10-D1, model3: C24-M2-C48-M2-D20-D1, model4: C16-M4-C32-M4-C48-M2-C64-M2-D100-D1, and model5: C128-M4-C256-M2-D50-D1. Here, C, M, and D denote the convolutional, max-pooling, and dense layers. The filter sizes of the first, second, third, and fourth convolutional layers are 7 × 7, 5 × 5, 3×3, and 3×3, respectively.

For each case, the classification analysis is performed based on the best 2D CNN model (model 2 of Figure 3). The result of the ablation study is presented in Figure 4. It can be concluded that the proposed model (model 3: the combination of DTL, CBAM, and 2D CNN) outperforms the other models with maximum classification accuracy.

3) SUBJECT-WISE ANALYSIS

To evaluate subject-wise evaluation for all products, we implement the Leave-subject-out experiment, where the training and testing set contains entirely different subjects.

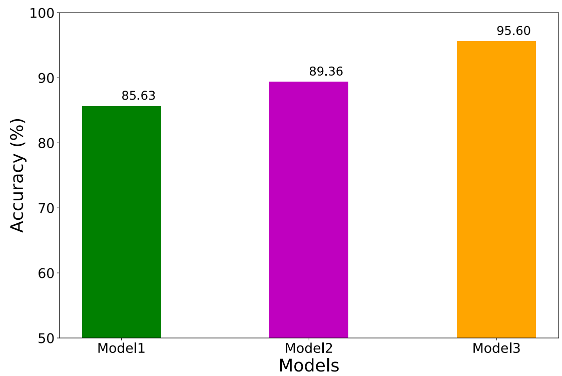


FIGURE 4. Result of the ablation study. Model 1: 2D CNN, Model 2: CBAM + 2D CNN and Model 3 (proposed): DTL + CBAM + 2D CNN. Maximum accuracy of 95.60% is achieved using the model 3 approach.

Here, the proposed model is trained with 39 subjects and tested with the remaining one subject (i.e., 'Subject in Test set' in Figure 5). The result of the Leave-subject-out experiment is shown in Figure 5. The model achieves the maximum and minimum accuracy of 99.25% and 87.59% for subject 18 ('S18') and subject 34 ('S34'), respectively.

D. CONSUMER BEHAVIOUR ANALYSIS

This section is divided into three subsections, namely product-wise analysis, identification of most liked or disliked products, and impacts of gender on consumer preference.

1) PRODUCT-WISE ANALYSIS

In Figure 6, we execute the proposed model for individual products rather than all 14 products. Therefore, EEG signals of each product (with three varieties) are selected for classification. As the EEG signals (inputs) of different products are different, the classification accuracy also varies across products. This experiment proves the generalization of the proposed model not only for all products but also for individual ones. It can be observed that the highest (98.88%)

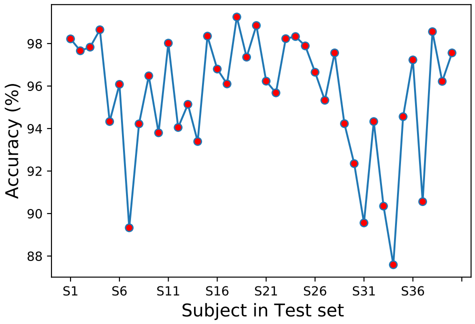


FIGURE 5. Subject-wise prediction for all products. The analysis is performed using the Leave-subject-out experiment. The maximum and minimum accuracy of 99.25% and 87.59% are obtained for subjects 'S18' and 'S34', respectively.

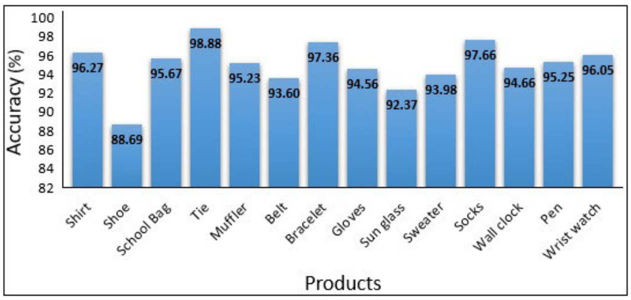


FIGURE 6. Product-wise analysis of the proposed model. The maximum and minimum accuracy is achieved for 'Tie' and 'Shoe', respectively.

and lowest (88.69%) accuracy are achieved for the product categories 'Tie' and 'Shoe', respectively.

2) IDENTIFICATION OF MOST LIKED OR DISLIKED PRODUCT

In an e-commerce application, it is important to identify the most liked or disliked product, which highlights the customer feedback in the marketing domain. This section highlights the selection of the most liked/disliked product out of 14 products. The experimental dataset consists of 40 subjects with 42 product variations (14 products, each of three variants/brands) when a subject likes or dislikes an individual product. We combine the like and dislike choices for an individual product of all subjects to find out the most liked and disliked product. The product-wise like/dislike case is plotted in Figure. 7. It can be observed that 'socks' (P11) and 'sweater' (P10) are marked as the most liked and most disliked products by subjects.

In a neuromarketing study, it is important to highlight the underlying brain activity for most liked or disliked products to understand the relationship between consumer behavior and the activated brain region. In the experimental dataset, the ERP signal is generated for the most liked (socks) and disliked (sweater) products by trial-wise averaging of those products' signals across all the subjects. The ERP event timings are 0.5-10 sec. and 10.5-20 sec for the most liked and most disliked products, respectively. Then, we identify the activated EEG channels for the most liked and disliked event from the highly activated region from the specific ERP

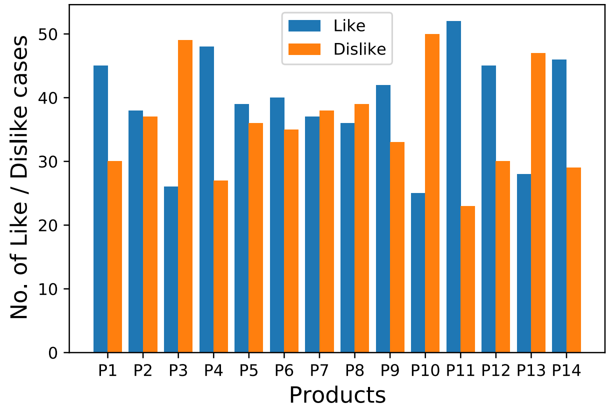


FIGURE 7. Product-wise like/dislike analysis to select the most liked and disliked product. Note: P1: Shirt, P2: Shoe, P3: School Bag, P4: Tie, P5: Muffler, P6: Belt, P7: Bracelet, P8: Gloves, P9: Sunglass, P10: Sweater, P11: Socks, P12: Wall clock, P13: Pen and P14: Wristwatch.

peak (most liked: 6.773 sec. and most disliked: 13.844 sec.). The brain activation using the topographical plot of the beta band (best band as per Figure 10) for the most liked and disliked product is shown in Figure 8. For the most liked case, maximum activation is observed at frontal channels (AF3, AF4, F3, F4), whereas for the most disliked case, maximum activation is observed at frontocentral channels (F4, FC6).

3) IMPACTS OF GENDER ON CONSUMER PREFERENCE

In this section, we identify the gender-wise most liked or most disliked product. The dataset includes EEG recordings of 25 male and 15 female subjects. For a product, we compute all like and dislike choices for all the male and female subjects and produce the like-dislike ratio (LDR) for that product. The LDR score (6) calculates the preference of each product. In Figure 9, gender-wise like and dislike ratios (computed from LDR score) are calculated for all the products. The most preferred products (having maximum LDR score) for male and female subjects are 'shirt' and 'bracelet', respectively.

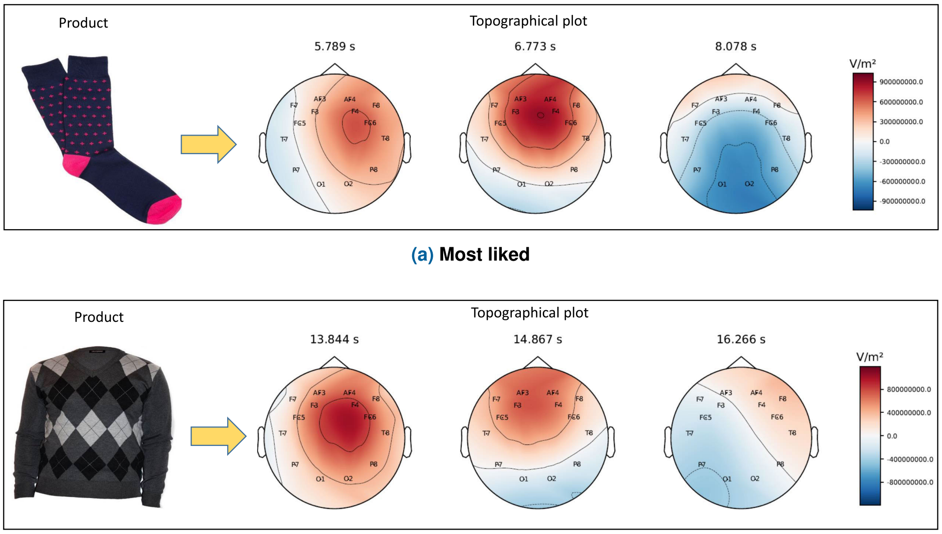
$$LDR = \frac{No.\ \ of\,(likes/dislikes)/product}{No.\ \ of\,(likes + dislikes)/product} \tag{6}$$

E. COMPARATIVE ANALYSIS

This section consists of two subsections, namely, a comparison based on EEG bands and comparison with existing neuromarketing-based studies.

1) COMPARISON BASED ON EEG-BANDS

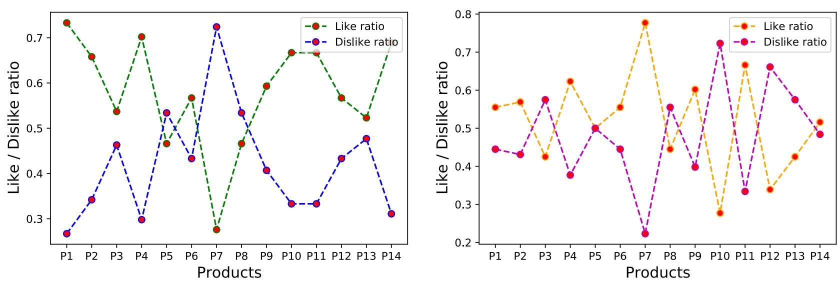
Here, we compare the performance of the proposed deep learning model based on different EEG bands (delta, theta, alpha, beta, and gamma). The connectivity features are extracted based on different frequency ranges of respective EEG bands, and the proposed model is analyzed using each of the band-specific features. The band-wise classification result of the proposed model is plotted in Figure 10. It has been observed that the beta band (16-31 Hz) has achieved maximum accuracy over other EEG bands.



(a) Most liked

(b) Most disliked

FIGURE 8. Brain activation (using the topographical plot) for the most liked (socks) and most disliked (sweater) products. ERP peak timing for each topographical plot is shown at the top of the individual map for the most liked (0.5-10 sec.) and disliked (10.5-20 sec.) events. In the most liked case, maximum activation is observed at frontal channels (AF3, AF4, F3, F4), whereas for the most disliked case, maximum activation is observed at frontocentral channels (F4, FC6). The optimal channels are selected based on the highest activation-based topographical plot at 6.773 sec. (most liked) and 13.844 sec. (most disliked).



(a) Male (b) Female

FIGURE 9. Product-wise like/dislike analysis based on gender. The score of each product is reported based on like/dislike ratio (LDR). Note: P1: Shirt, P2: Shoe, P3: School Bag, P4: Tie, P5: Muffler, P6: Belt, P7: Bracelet, P8: Gloves, P9: Sunglass, P10: Sweater, P11: Socks, P12: Wall clock, P13: Pen and P14: Wristwatch.

2) COMPARISON WITH EXISTING NEUROMARKETING-BASED STUDIES

This section highlights the comparative study between the proposed model and existing neuromarketing-based studies. The comparison is performed based on methodology and applied tools. From the comparison study (Table 4), it can be observed that the proposed model achieves a significant improvement over other neuromarketing-based studies.

IV. DISCUSSION

Neuroscience-based marketing has made substantial strides in understanding consumer behavior over the past decade [48]. This study contributes to the field by proposing a robust EEG-based neuromarketing framework that combines DTL, spatial attention methods, and deep neural networks. The primary aim of this framework is to predict consumer choices for e-commerce products, offering a nuanced understanding of preferences through an innovative approach. Transfer learning emerges as a crucial aspect of this study, addressing

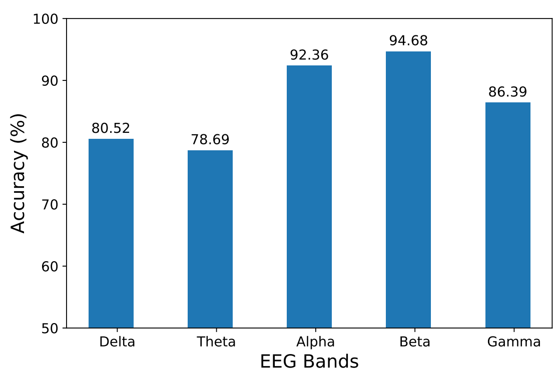


FIGURE 10. Comparative analysis between five EEG bands with different frequency ranges. The comparison is performed based on the band-wise prediction results of the proposed model.

TABLE 4. Comparison with existing neuromarketing-based studies. The abbreviations are as follows: Accuracy (Acc), Power spectral density (PSD), Random Forest (RF), Time-Frequency Analysis (TFA), Fast Fourier transform (FFT), Deep neural network (DNN), Support Vector Machine (SVM) and K-nearest neighbors (kNN).

Study	Methodology	Signals & Marketing element	Acc(%)
Smith *et al.* [43]	Bayesian Regression	fMRI-50 pairs of snacks	68.20
Telpaz *et al.* [44]	Cardinal analysis	EEG-10 product images	65.00
Yadava *et al.* [32]	HMM classifier	EEG-42 product images	70.33
Aldayel *et al.* [45]	PSD + DNN	EEG-42 product images	93.00
Kim *et al.* [46]	FFT + SVM	EEG-53 Preferred, Unnoticed images	88.54
Chew *et al.* [47]	TFA + kNN	EEG-60 3D bracelet images	80.00
Proposed	DTL + CBAM +2D CNN	EEG-42 product images	**95.60**

the non-stationarity challenges inherent in EEG experiments [18]. By leveraging data or knowledge from comparable subjects, sessions, or tasks, the proposed framework enhances its adaptability to diverse scenarios [18]. This addresses a significant gap in existing EEG-based studies on consumer preferences, which often struggle to create universal models due to variations in subjects, sessions, and tasks. The result of the proposed model with different pre-trained networks is shown in Table 1. Incorporating a spatial attention model using CBAM further enhances the performance of the proposed framework. The CBAM improves classification accuracy by extracting attention-based features from high-level connectivity features. CBAM achieves the highest classification accuracy with sequential mode (channel-spatial) in Table 2. The experimental results demonstrate the efficacy of the proposed model, achieving an impressive 95.60% classification accuracy. This noteworthy accomplishment represents a significant advancement, surpassing existing neuromarketing-based studies by 2.60% (refer to Table 4). As the experimental dataset consists of 42 different product variants, identifying the most liked ('socks') or disliked product ('sweater') can be a relevant and significant finding (Figure 9) for future research of product-based neuromarketing applications. We also evaluate the prediction rate (in terms of accuracy) of the proposed model for each product (Figure 7). Identifying the most liked/disliked product overall (for all subjects) and in a gender-wise manner provides a guideline for marketers to devise segmentation, targeting, and positioning strategies.

It further aids many marketing-domain-related decisions like pricing, promotional strategy formulation, and product-catalog design for e-commerce companies. All of these above-mentioned initiatives ultimately lead to more customer acquisitions, improved customer retention, and increased customer loyalty, which are the ultimate goals of any business unit. Real-time applications of our model in marketing scenarios are a promising prospect, allowing businesses to adapt swiftly to immediate consumer preferences. Ethical considerations in neuromarketing, encompassing the responsible use of neuroscientific methods in influencing consumer choices, also present a compelling area for investigation.

V. CONCLUSION

We have implemented a robust hybrid framework consisting of DTL, spatial attention, and a deep learning model to evaluate consumer behavior while watching a product. The EEG data were collected while they watched the products, and their choice (like/dislike) was recorded for that product. As the proposed model combines three components (DTL, CBAM, and deep network), therefore we evaluate the significance of individual components using the ablation study (Figure 6). We observe that the proposed model (model 3: DTL + CBAM + 2D CNN of ablation study) reaches the highest classification accuracy of 95.60%, which outperforms all the existing neuromarketing-based studies (Table 4).

The eye movement of a user while watching the product is an important factor in product preference. In the near future, we will combine eye movement with EEG signals to build a robust multimodal deep-neuromarketing framework to improve the prediction results. Additionally, building upon the success of our current research, future directions in this field are poised to explore more personalized marketing strategies, aligning with individual consumer behavior.

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