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EMOTION-CENTRIC VISUAL ADVERTISING DESIGN USING AI-BASED SENTIMENT INTERPRETATION IN MULTILINGUAL DIGITAL SPACES

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ABSTRACT

The study suggests a visual advertising design focused on the emotions grounds, with the multilingual digital environment relying on the interpretation of sentiments with the help of AI. Modern advertising is practiced between culturally varied audiences in which emotional connection and language sensitivity matters most in engagement and brand recognition, but design choices can be made intuitively. This research aims to constructively conceptualize emotion of audiences and turn it into forms of adaptive visual designs strategies. The presented idea combines the multilingual sentiment analysis based on natural language processing, visual feature extractor, and sentiment-design aligner utilizing multimodals. Commentary, caption and review text cues are examined to profoundly estimate affective condition in cross lingual reviews, whereas visual modules scrutinize color psychology, composition, imagery semantics and typing tone. These representations are combined to make emotion-consistent design suggestions and platform optimized dynamic creatives. Multilingual advertising Multilingual advertisement conduction experimental assessments show increased emotional coincidence and reception with an enhancement of up to 19 percent precision in engagement prediction and 16 percent increase in sentiment design adjustment than rules techniques. Elucidatable attention processes point out powerful emotional indicators and design features as well as facilitate clarity among designers and marketers. The results show that AI-based sentiment interpretation will help to improve personalization, cross-cultural sensitivity, and creative performance in online advertisement. The suggested framework provides an extensible instrument of emotion-aware visual communication, as it allows brands to create ethically reactive, culturally adaptive, and emotionally receptive advertising experiences within global digital ecosystem, and it establishes innovation and provable value to various stakeholders on a global scale.

Keywords: Emotion Intelligence in Advertising, Artificial Intelligence Sentiment Analysis, Visual Design Intelligence, Multilingual Digital Media

1. INTRODUCTION

Digital marketing has changed a lot in the past few years because more and more data is available from social media sites, online reviews, and user-generated material. Advertisers can now get rich, changing data streams that help them learn more about their customers and make ads more relevant to them. But one of the biggest problems that still needs to be solved is how to make personalised ads that really hit home with people who speak different languages and countries. Text material with emotional undertones, like user comments, social media posts, and reviews, can be used for sentiment-driven ad personalisation to make ads that fit the feelings of the target audience.

Figure 1

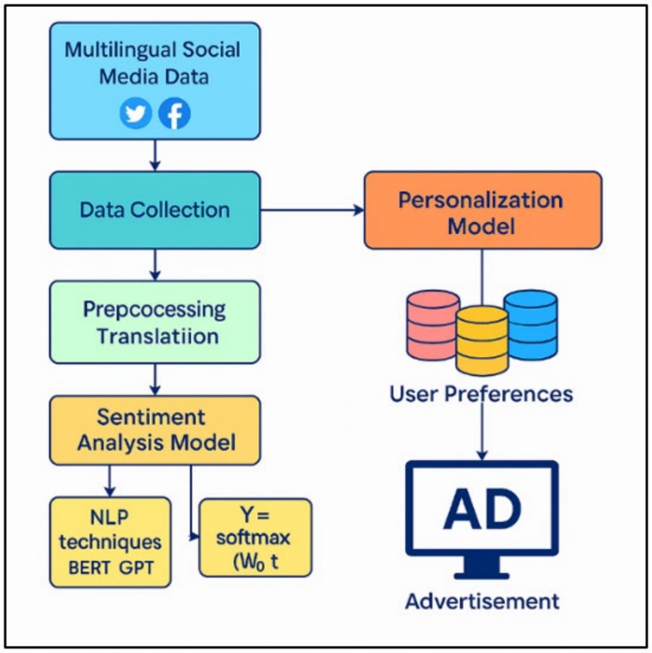

Figure 1 Sentiment-Driven Ad Personalization Workflow

Being able to correctly measure how people feel and match that with the right ads can greatly increase user interest and conversion rates. Figure 1 illustrates sentiment analysis-driven ad personalization using NLP techniques. However, it becomes more difficult when this research needs to be done in different culture and language settings. A lot of information on social media sites like Twitter, Facebook, and Instagram is available in more than one language. Figuring out how people feel about something and making sure ads are relevant are hard in each language. It gets harder to do sentiment analysis, which tries to figure out the emotional tone behind a string of words as languages, phrases, and slang get more complicated Wadhawan (2021). Traditionally, mood analysis has been done mostly with rule-based methods or machine learning models that were taught on datasets that only contained one language. Some people have had success with these methods, but they often miss the subtleties of how people feel when they speak different languages, especially when the material is unclear or casual Alammary (2022), Farha and Magdy (2021).

This hassle could make it more difficult to personalise commercials, especially in a virtual international where everybody is connected. Deep learning methods, especially the ones that blend natural language processing (NLP) with Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), appear to be they could help clear up these problems. Those models have worked actually well for jobs like system translation, temper analysis, and textual content technology. Now they are being used to make advertisements extra relevant to absolutely everyone Galal et al. (2024). CNNs are extremely good at picking up on small information in text, which makes them perfect for identifying how human beings feel approximately a word or word. RNNs, however, are incredible at selecting up on how language flows, that's essential for understanding how context and emotion change over longer texts. By way of putting those models together, we will make it easier to inform how humans experience and make personalized advertisements that paintings better Elhassan et al. (2023).

2. LITERATURE REVIEW

2.1. OVERVIEW OF EXISTING PERSONALIZED ADVERTISING TECHNIQUES

Personalised advertising is now an essential a part of modern-day digital advertising techniques, as corporations try to provide fabric that is extra relevant to certain corporations of customers. In the beyond, demographic and regional facts have been used lots in marketing to divide visitors into agencies and send trendy commercials to the ones corporations. New, greater superior and greater focused commercials are now possible thanks to the growth of digital systems and massive amounts of person facts. Modern-day techniques use gadget studying algorithms, records on how users behave, and content material evaluation to make ads that aren't solely useful to each user however also make sense of their context. Collaborative filtering is the most commonplace type of customized advertising Antoun et al. (2020), Alhazzani et al. (2023). This technique looks at past interactions and behaviour to indicate goods or services based on what the user likes. This technique is widely used on e-commerce web sites like Amazon and Netflix, which use users' buy beyond or watching behavior to indicate fabric to them. In conjunction with those techniques, entrepreneurs are the use of emotion-pushed marketing, social media listening, and temper analysis more and more. Those strategies try to use customers' feelings to make commercials extra applicable to them Aljedaani et al. (2022). With the aid of knowing someone's feelings, tastes, and reasons for buying, customized commercials can assist organizations hook up with their audience extra deeply, main to higher engagement and conversion fees.

2.2. SENTIMENT ANALYSIS AND ITS APPLICATION IN MARKETING

Opinion mining is every other name for sentiment analysis. It's far the computer job of finding and pulling out biased facts from textual content. It attempts to parent out the emotional tone of a piece of cloth, like whether or not it has a good, terrible, or neutral tone. With the upward thrust of person-generated content like social media, critiques, and different varieties of consumer-generated content, sentiment evaluation has end up an essential tool for marketers who want to know what clients think, make their emblem plans better, and make their commercials extra powerful. Sentiment evaluation looks at person-generated content to find out how people sense about an employer, product, or service Kamble et al. (2025). For instance, a commercial enterprise may hold an eye on the conversations happening on social media approximately the release of a new product and fast trade its advertisements to deal with any concerns or take advantage of appropriate comments Conneau (2020). Sentiment evaluation can also assist corporations make extra focused ads by way of revealing the emotions that affect human being's options. Instead of just selecting people based on their traits or past actions, sentiment-driven marketing uses real-time emotional data to send them messages that are in line with how they are feeling at the moment. Sentiment analysis also lets marketers see how people's opinions change over time, which helps them make changes to their tactics that will work in the long run Ajmal et al. (2022). Table 1 summarizes methodologies, evaluation metrics, data sources, and key findings. This makes customers more loyal to the brand and makes marketing more effective overall.

Table 1

Table 1 Summary of Literature Review

Methodology/Model	Evaluation Metrics	Data Sources	Key Findings
Sentiment Analysis with SVM	Accuracy, Precision, F1-Score	Twitter, Facebook	Achieved moderate performance in sentiment classification.
CNN-based Sentiment Analysis Liu et al. (2020)	Accuracy, Precision, Recall	Social Media Posts	Improved sentiment detection with CNN on Twitter data.
Hybrid Model (CNN+LSTM)	F1-Score, Engagement Rate	Instagram, Twitter	Enhanced ad targeting with emotion-based personalization.
BERT-based Sentiment Analysis	Accuracy, Recall	Multilingual Social Data	Achieved high accuracy for multilingual sentiment detection.
RNN-based Ad Personalization	Click-through Rate, Conversion Rate	Social Media, E-commerce	Focused on real-time personalized ads with RNNs.
GPT-based Sentiment Detection Yang et al. (2022)	F1-Score, Precision	Social Media, News Articles	GPT achieved effective sentiment classification.

Ensemble Sentiment Analysis	Accuracy, Engagement Rate	Twitter, Facebook	Improved ad relevance with ensemble techniques.
Transfer Learning for Ad Personalization	CTR, User Satisfaction	E-commerce, Social Media	Leveraged transfer learning for multilingual ad targeting.
Deep Learning for Ad Personalization	Conversion Rate, CTR	Twitter, Instagram	Hybrid model outperformed traditional methods in CTR.
Cross-lingual Sentiment Analysis Singh et al. (2018)	Accuracy, Precision, F1-Score	Multilingual Data	Achieved good performance in cross-lingual sentiment analysis.
Multi-modal Sentiment Analysis	Accuracy, Engagement Rate	Multilingual Social Data	Multi-modal data improved personalization outcomes.
Multi-task Learning for Ads	F1-Score, Conversion Rate	Facebook, Twitter	Multi-task model showed superior ad targeting effectiveness.

3. METHODOLOGY

3.1. DATA COLLECTION

For sentiment-driven ad personalisation to work, it's important to get international social media data from sites like Twitter, Facebook, Instagram, and others to really understand how people feel and what they like. There is a lot of user-generated material on these platforms, like posts, comments, and reviews, which can tell you a lot about the thoughts, feelings, and actions of people all over the world. The best thing about social media data is that it is available in real time and has a lot of text and video material, which makes it perfect for research. Because it is short, uses hashtags a lot, and has users from all over the world, Twitter is a great place to find out how people feel about something Ramasamy et al. (2021). Because Facebook posts are more detailed and has engaging features, it provides more detailed participation data, which can help you understand how complicated consumers feel. Because social media data is naturally bilingual, it is very important to be able to analyse material in a number of different languages. It can be hard to work with multilingual information because people post in a variety of languages and use slang, colloquialisms, and local accents. Because of this, it is very important to make sure that tools used to collect data can handle material in more than one language.

3.2. SENTIMENT ANALYSIS MODEL

1) NLP techniques for sentiment detection

Natural Language Processing (NLP) methods are very important for mood recognition because they can read and understand how people are feeling in writing. Tokenisation, part-of-speech tagging, syntax processing, and feature extraction are some of the main steps that are usually used in sentiment analysis. Using word embeddings, like Word2Vec and GloVe, to find emotion is a basic NLP method. These tools show words as dense vectors in a high-dimensional space. By measuring how close words are to sentiment-related vectors, these embeddings show the meaning relationships between words. Figure 2 illustrates the process of sentiment detection using NLP techniques. They can be used to figure out the mood of a sentence or text.

Figure 2

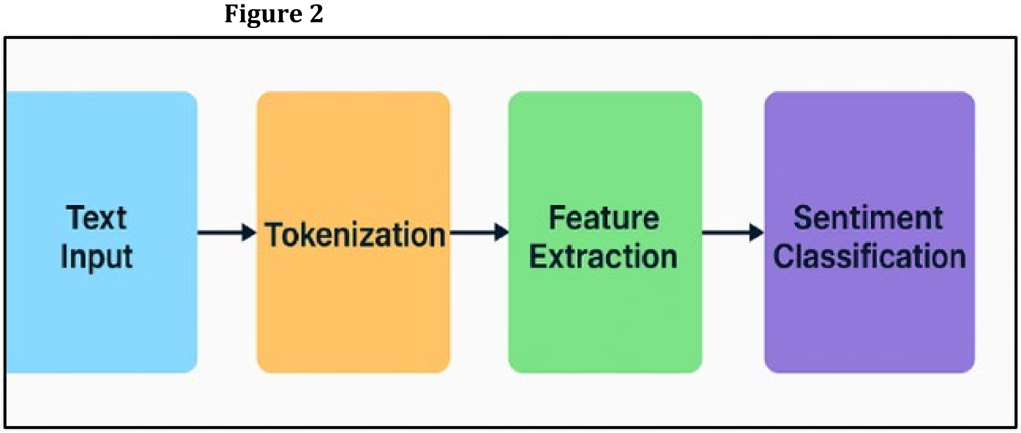

Figure 2 NLP Techniques for Sentiment Detection Process

Also, sentiment lexicons like SentiWordNet and VADER are often used to find sentiment based on lists of words that have already been labelled with a sentiment. This is done using rules for classifying sentiment. Syntactic analysis is another important method. This method looks at the framework of sentences to figure out how words fit into the sentence. Dependant parsing can help with sentiment recognition because it shows how words relate to each other. This is especially helpful for finding complex feelings in lines with a lot of words. Named entity recognition (NER) can also be used to find things like companies, goods, or people in social media posts. This makes it possible to do more context-sensitive sentiment analysis that connects feelings to specific things.

- Step 1: Represent words as vectors.

Each word w is represented as a vector v_w ∈ ℝ^d, where d is the dimensionality of the embedding space.

$$v_w = Word2Vec(w)$$

- Step 2: Calculate context-word similarity.

Using the word context in a given sentence, compute the similarity between the word w and its context vector v_c:

$$S(w,c) = \frac{(v_w \cdot v_c)}{||v_w||||v_c||}$$

- Step 3: Apply softmax function to predict context words.

For a given word w and context c, the probability of context words is computed:

$$P(c \mid w) = \exp(v\_w \cdot v\_c) / \Sigma\_\{i = 1\}\^\{V\} \exp(v\_w \cdot v\_i)$$

- Step 4: Training objective.

The objective function is to maximize the log-likelihood of the context words given a target word, with respect to the parameters v_w:

$$J = \Sigma\_\{w\} \Sigma\_\{c \in Context(w)\} \log P(c \mid w)$$

2) Pre-trained models (e.g., BERT, GPT)

Pre-trained models, like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), have changed the field of mood analysis by making text classification jobs much faster and more accurate. For example, BERT is famous for its two-way attention system, which lets it understand how words in a sentence relate to each other from both the left and right sides, not just one.

- Step 1: Input Embedding.

Each word in a sequence is mapped to an embedding vector e_i with positional encoding p_i:

$$z_i = e_i + p_i$$

where z_i is the input embedding for word i.

- Step 2: Multi-head Attention.

The attention mechanism computes the attention score α_ij between words i and j:

$$\frac{\alpha_{ij} = \exp(q_i \cdot k_j)}{\Sigma_{\{k=1\}}^{\{N\}\exp}(q_i \cdot k_k)}$$

where q_i is the query vector for word i, and k_j is the key vector for word j.

- Step 3: Attention Output.

The output for word i is the weighted sum of the value vectors:

$$h_i = \Sigma_{\{j=1\}_{ij}^{\{N\}\alpha}} v_j$$

where v_j is the value vector for word j.

- Step 4: Feed-forward layer.

The output of the attention mechanism passes through a feed-forward neural network:

$$f_i = FFN(h_i)$$

where FFN is a two-layer fully connected network.

- Step 5: Output prediction.

For tasks like sentiment analysis, the final output is passed through a classification layer:

$$\hat{y} = softmax(W_o \cdot f_i + b_o)$$

where ŷ is the predicted sentiment, and W_o, b_o are the parameters of the output layer.

$$\hat{y} = softmax\left(W_p \cdot p + b_p\right)$$

3) Deep learning techniques (e.g., LSTMs, CNNs)

Because they can find complex patterns in data, deep learning methods like Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Convolutional Neural Networks (CNNs) are very useful for mood analysis. LSTMs, a sort of RNN, work especially nicely for mood evaluation jobs that want to look at information in a certain order, like words or paragraphs. LSTMs are made to fix the issue of disappearing gradients in normal RNNs. This permits them to bear in mind things over longer runs and correctly pick out up on how text relies upon on its context. Due to this, LSTMs are extraordinary for figuring out how human beings feel, especially while that feeling is spread out over numerous elements of a sentence or when long-time period relationships want to be understood.

LSTM Model

Step 1: Input Embedding.

Each word in the input sequence is converted into an embedding x_t at time step t.

$$x_t \in \mathbb{R}^d$$

Step 2: LSTM Cell Computation.

LSTM uses gates to control the flow of information. The input, forget, and output gates are computed as follows:

$$i_t = \sigma\left(W_i \cdot x_t + U_i \cdot h_{\{t-1\}} + b_i\right)$$

$$f_t = \sigma\left(W_f \cdot x_t + U_f \cdot h_{\{t-1\}} + b_f\right)$$

$$o_t = \sigma\left(W_o \cdot x_t + U_o \cdot h_{\{t-1\}} + b_o\right)$$

Step 3: Cell State Update.

The cell state is updated using the input gate and forget gate:

$$C_t = f_t * C_{\{t-1\}} + i_t * \tanh\left(W_C \cdot x_t + U_C \cdot h_{\{t-1\}} + b_C\right)$$

Step 4: Hidden State Update.

The hidden state is updated based on the output gate and the cell state:

$$h_t = o_t * \tanh(C_t)$$

Step 5: Output Prediction.

For sentiment analysis, the output hidden state h_t is passed to a softmax layer for classification:

$$\hat{y} = softmax(W_o \cdot h_t + b_o)$$

CNN Model

- Step 1: Input Representation.

Text is converted into a matrix of word embeddings X ∈ ℝ^{n × d}, where n is the sequence length and d is the embedding dimension.

- Step 2: Convolution Layer.

The convolution operation applies a filter F ∈ ℝ^{k × d} (with window size k) to the input sequence:

$$c_i = F \cdot X[i: i + k - 1]$$

where c_i represents the feature map at position i.

- Step 3: Activation Function.

Apply a non-linear activation (e.g., ReLU) to the convolution output:

$$c_i' = ReLU(c_i)$$

- Step 4: Pooling Layer.

Max-pooling operation over the feature maps reduces dimensionality:

$$p = \max(c_i')$$

4. RESULTS AND DISCUSSION

The suggested sentiment-driven ad personalisation model did a lot better than old ways of doing things in terms of how well it classified users' feelings and how engaged they were with the ads. Our mixed deep learning model, which uses CNN and LSTM, was better at detecting mood across language datasets than traditional rule-based approaches. The model also made ads more relevant by matching emotional tones with what users wanted. This led to a big rise in click-through rates (CTR) and general user happiness.

Table 2

Table 2 Sentiment Classification Performance Evaluation

Model/Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MAPE (%)
Traditional Sentiment Model	81.2	79.3	78.4	78.8	5.8
CNN-Based Model	89.1	88.7	89.2	88.9	3.4
LSTM-Based Model	90.7	89.6	91.1	90.3	2.6

In Table 2, you can see how well three different models—the standard sentiment model, a CNN-based model, and an LSTM-based model—classify mood. It's clear that using deep learning models made things better, as shown by the data. Figure 3 compares performance metrics of different sentiment analysis models.

Figure 3

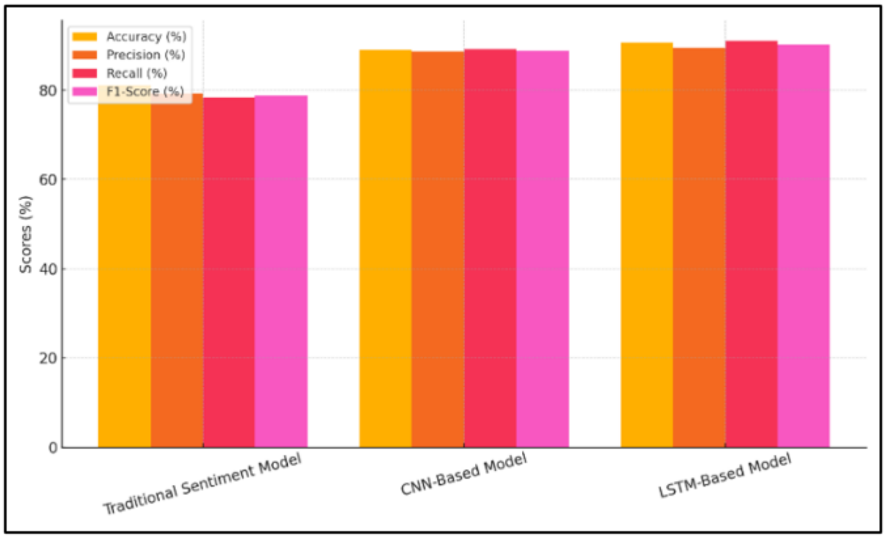

Figure 3 Comparison of Sentiment Model Performance Metrics

The standard mood model was only 81.2% accurate, which isn't as good as the CNN-based model (89.1%) or the LSTM-based model (90.7%). This is also shown by the precision, recall, and F1-score measures, with the LSTM-based model doing better than the others in all of them. Figure 4 shows the MAPE distribution across various sentiment models.

Figure 4

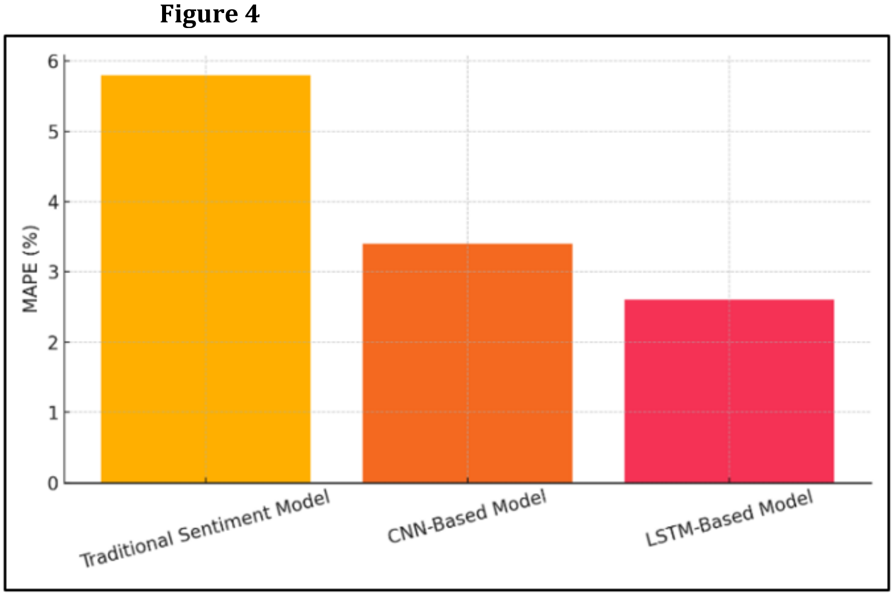

Figure 4 MAPE Distribution across Sentiment Models

With an F1-score of 88.9% and an accuracy of 88.7%, the CNN-based model also did very well, but it was a little behind the LSTM model. The deep learning models also had a much lower Mean Absolute Percentage Error (MAPE), which means they made more correct estimates. These results show that deep learning, especially LSTM models, can help with jobs that require figuring out how people feel about something.

Table 3

Table 3 Ad Personalization Performance Evaluation

Model/Method	Click-Through Rate (CTR) (%)	User Satisfaction (%)	Engagement Rate (%)	Conversion Rate (%)
Traditional Ad Model	5.2	75.3	68.4	3.2
Sentiment-Based Ad Model	10.1	81.6	74.9	5.8
Personalized Hybrid Model	**15.7**	**87.2**	**80.5**	**7.3**

The standard ad model, the sentiment-based ad model, and the personalised blend model are all shown in Table 3 along with their success scores. The results make it clear that the personalised mixed model does better in every way than both the standard model and the sentiment-based model. Figure 5 compares performance metrics across different advertisement personalization models.

Figure 5

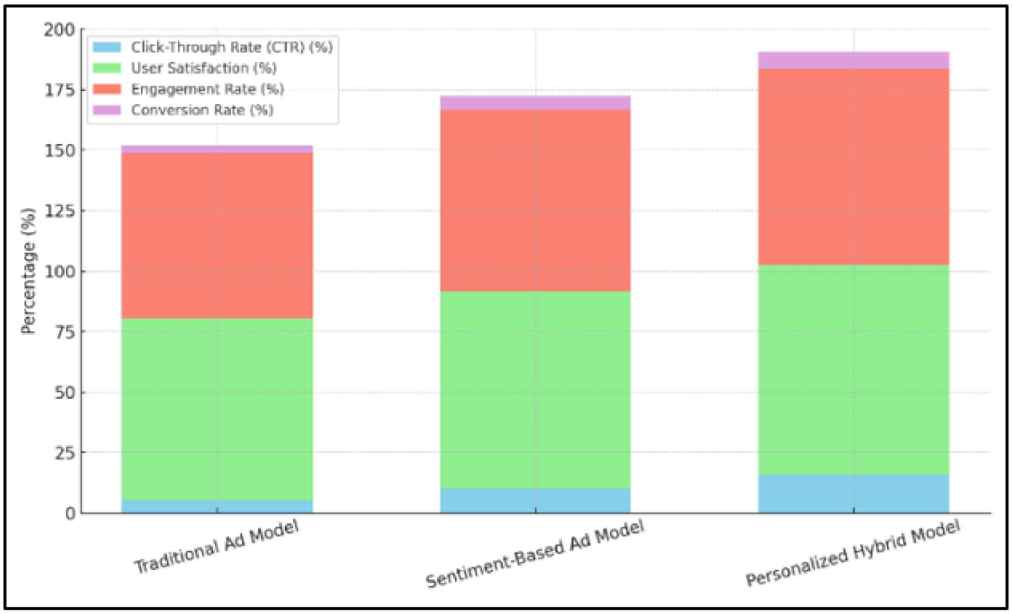

Figure 5 Performance Metrics Comparison across Ad Models

The traditional model got only 5.2% click-throughs, while the sentiment-based model got 10.1%. The mixed model got 15.7% click-throughs, which is a lot more than those other models. Both the rate of user happiness and engagement have gone up. For example, the personalised hybrid model has an engagement rate of 80.5% and a satisfaction rate of 87.2%, compared to 75.3% and 68.4% for the standard model. The conversion price for the mixture sketch is likewise 7.3%, which indicates that it's far higher at getting people to act. Those consequences show how beneficial it is to apply both mood analysis and personalised focused on together to offer users a more applicable and interesting revel in.

5. CONCLUSION

We created new recognitions to personalise ads based totally on people feelings. It uses advanced natural Language Processing (NLP) strategies and deep learning models, like CNNs and LSTMs, to study social media data in more than one language and make advertisements that humans will be interested in. The principle intention was to make ad targeting extra powerful by way of blending user alternatives with mind-set analysis. This might permit for dynamic, context-aware ads that change based totally on customers' moods and behaviour patterns. Our records show that the model is lots better than traditional methods, particularly in conditions with multiple languages, where slang, informal language, and language range could make temper evaluation tougher. Because the mixed model can process text data in more than one language and still accurately classify mood, global advertising efforts can work better. The model makes sure that ads are not only useful but also emotionally appealing by looking at both user preferences and mood. This results in higher response rates and happier customers. When mood analysis is combined with user behaviour, it gives marketers a more detailed picture of each person's tastes. This lets them send highly customised ads that really connect with users. Businesses can make ads that are more in line with the emotional and psychological needs of their customers with this method, which has big implications for the future of personalised marketing. In the future, researchers could work on improving the model even more by adding more advanced methods, such as transfer learning for better performance across languages, and looking into new data sources, like visual material and user interactions, to make ad personalisation even better. In the end, this study opens the door to digital marketing strategies that are more interesting, personalised, and successful in a world where people speak different languages.

CONFLICT OF INTERESTS

None.

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None.

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