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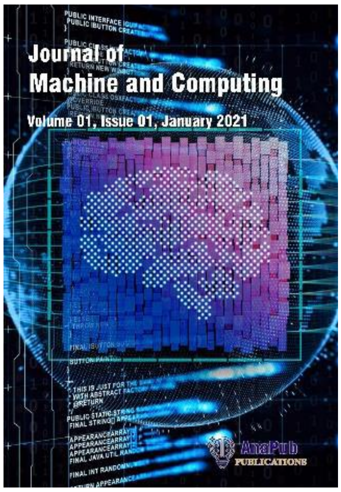

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Multimodal Deep Learning Model for Measuring the Impact of Social Media Advertising Using Visual-Linguistic Representation Learning

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Abstract

The research examines the application of Natural Language Processing (NLP) and Deep Convolutional Neural Networks (Deep-CNN) in forecasting social media activity. The study aims to improve Social Media Awareness (SMA) by integrating these technologies. The research utilizes 500,000 Facebook posts to develop a model that predicts user behavior based on the number of posts, post count, and sentiment. The study found that image and text data performed better than unpredictability methods, demonstrating the importance of data fusion in predicting user behavior. This could revolutionize online advertising methods and establish the basis for a Decision-Making System (DMS) that includes advertising data analytics and Artificial Intelligence (AI). The research project used a hybrid model to predict user participation in advertisements, while a random model predicted post count, share count, and post sentiment for 60% of each blog post. The models accurately predicted post sentiment, post count, and share count 61%, 62%, and 65% of the time, setting an acceptable standard for future studies.

Keywords: Sentiment Analysis, Natural Language Processing, Social Media Advertising, Customer Visions, Machine Learning, Brand Monitoring

1. Introduction

Businesses in the fast-growing field of Social Media Advertising (SMA) are continually seeking new methods to connect with their target audience, win over skeptical customers, and differentiate themselves from other businesses. For these factors, the outside world of Social Media (SM), which is defined by differences generated by consumer information and the scope of its impact, has evolved into a vital tool. An individual's portfolio of actual life events is the thoughts, ideas, and sentiments they communicate on Social Media Networks (SMN). Marketers proficient in collecting information from interactions may significantly benefit from these sentiments, ideas, and perspectives. Sentiment Analysis (SA) is now recognized as an essential tool in this setting for accessing the implicit value of data on sentiment. As Natural Language Processing (NLP) has evolved, this type of outcome is within the scope of the approach [1].

As part of NLP, SA attempts to recognize, classify, and measure the fundamental emotional content of what is said. The abbreviation "Opinion Analysis" can be utilized similarly in this study area. Furthermore, to emphasise elementary, minimal behaviours, advertisers ought to attempt to recognize their users' secret feelings and thoughts. Machine Learning (ML) algorithms and advanced NLP approaches have evolved SA from a simple test into a vital tool for businesses winning in the global SMN market. The primary objective of this work is to provide a comprehensive analysis of SMA within the context of SM. To provide significant insights into the emotional and psychological well-being of the people they serve, businesses can utilize NLP in various approaches. The present article examines these techniques [2].

This paper presents a detailed examination of the issue, addressing the scientific basis of SA and the real-world implications of the marketing techniques analyzed. The impact of SA in an SMA scenario may not be underscored. By applying this technology, companies can evaluate consumer feedback, monitor the general public's perception of their business, assess the success of their advertising efforts, and identify emerging innovations and challenges.

A prevalent feature of data obtained from SMN is an incredible quantity of raw information. An additional benefit is that SA can significantly impact ranking management, the level of customer service, and the production of new goods. However, it maintains its core structure, which is particularly identifiable.

Furthermore, it includes factors such as review and emotional evaluation, which are influenced by contextual factors, addressing major problems for SA. Ethical problems, such as those related to biases in algorithms and privacy, underscore the importance of moral principles and their practical application. It explores the philosophical foundations of SA and presents instances of its implementation in advertising methods, showing its significant influence. Consumers will find this data extremely valuable when processing the regularly developing business. In the marketing model, this article recommends delving into NLP and SA. The article emphasizes the significance of such approaches to assisting data-driven Decision-Making Systems (DMS) in sustaining attractiveness in the rapidly evolving marketing and promotional business.

The objective of this research is to share knowledge on the possibilities, risks, and ethical issues facing SA and to present an approach for utilizing NLP to identify essential customer data within the framework of SMM.

In today's era of infinite data, companies that are prepared to engage with the views and emotions of their target consumers will have a significant advantage in winning the SMM business. The procedure of retrieving sentiments from linguistic information on SMA networks and online reviews is named NLP, also referred to as SA. It uses ML, practical, and language-related techniques to classify sentiment as positive, neutral, or negative. Primary methods encompass the preprocessing of texts and tokenization, which is a Feature Extraction (FE), among others. ML models such as SVM, Naive Bayes, or LSTM are developed on tagged datasets to classify sentiments. There are several software applications, such as tracking businesses, designing products, analyzing advertising efforts, researching competitors, and enhancing consumer service. Firms can more effectively comprehend their customers' views, address emergencies, identify both the positive and negative aspects of their products, analyze their advertising strategies, and enhance the standard of consumer satisfaction.

Although NLP-based SA has tremendous potential, it faces numerous obstacles. Ambiguity and context play a significant role in determining the meaning of words and phrases, as the context in which they are used can drastically alter that meaning. The ability of SA algorithms to comprehend context is a challenging task. Because sarcasm and irony are frequently communicated through oblique verbal clues, SA has difficulty identifying them in written communication, especially in multilingual analysis. Since SM is a worldwide platform, user SA must consider a variety of languages and dialects. Emojis and Emoticons: Emojis and emoticons may substantially alter the emotion of communication, yet it is not easy to precisely discern what is being said via their use. In many datasets, one sentiment class (*e.g.,* neutral) often dominates, resulting in unbalanced training data and bias in the model. Neutrality may be the most common sentiment class.

Objectives of Research

a) To develop a multimodal DL that combines visual and textual representations for the aim of analyzing the impact of advertisements on social media networks.
b) The purpose of the present investigation is to determine how well this model can predict user involvement, sentiment, and sales metrics.
c) A comparison of the accuracy of the proposed approach with that of conventional unimodal models is to be explored.

The article is systematized as follows: a detailed overview of the impact of social media advertising is given in Section 1, the related works are discussed in Section 2, the proposed Sentiment Analysis using CNN + NLP is given in Section 3, the results and discussion are shown in Section 4, and the article is concluded in Section 5.

2. Related works

Authors' [3] survey found that advertising managers trust SMA analytics, including recognition of the brand (89%), recommendations of interest (88%), customer happiness (87%), user input ([illegible]0%), and internet analytics (80%). Website views, price per 1000 views, and CTR are recommended. [illegible]% of business enterprises will make more investments in the use of SM.

The authors [4] researched mining feedback on social media and correlated images of sentiment using SA. By implementing an object image classification approach, SA classifies the sentiment of these clustered images after an unsupervised system is developed.

SA classifies texts by opinion instead of subject. Data retrieval, NLP, data analysis, and knowledge management are methods to identify qualitative information in enormous amounts of raw data.

The government, e-commerce, and real-time SMA analysis utilize SA. It examines social media comments for their positive and negative aspects. It evaluates e-commerce activities and the quality of goods to convert unhappy consumers into marketers. Tweet feels analyzes Twitter in real-time. Blogger-centric contextual marketing leverages SA to develop brand-focused, customised advertisements. Overall, SA is frequently employed for recognizing and assessing patterns of behaviour and sentiment [5].

Significant ML and DL text classification studies are available. Conventional techniques employ bag-of-words, TF-IDF, handcrafted n-grams, and complex features like phrases containing nouns, part-of-speech tags, and tree kernels for feature engineering and classification. More complicated features have been developed [6-10].

The technique extracts *'k'* essential text features in absolute order through several temporal *k*-max-pooling layers. The length of the sentence and layer order impact *'k'*. CNN classifies brief texts following word vector clustering [11].

BiLSTM-CRF extracts target words from subjective sentences and classifies the results into three categories for better sentence-level SA. Dividing sentences based on different thought targets increases SA [12].

Table 1. A comparison summary of related works

Model/Methodology	Modality	Dataset	Key Findings	Strengths	Weaknesses

Multimodal CNN + LSTM	Visual + Textual	Social Media Ads Dataset	Proposed a combined CNN and LSTM model for sentiment analysis in social media content.	Improved sentiment prediction with a multimodal approach.	Limited dataset size, focused only on sentiment.
Multimodal Deep Learning (MDL)	Visual + Textual	VisualQA, MSCOCO	Introduced an end-to-end architecture to fuse visual and textual data for image captioning and question answering.	Advanced fusion techniques for multimodal data.	Primarily focused on image captioning and QA, not directly on advertising.
Multimodal CNN + RNN	Visual + Textual	Instagram Ad Dataset	Designed a deep learning framework combining CNN for image processing and RNN for text.	Achieved high accuracy in engagement prediction.	Performance drops with noisy data and user comments.
Multimodal Emotion	Visual + Textual	Movie Reviews,	Used attention	Strong performance	Does not account for

Recognition with Attention Networks		Social Media	mechanisms to combine visual and textual features for emotion recognition.	in understanding emotional engagement.	conversion-based metrics in advertising.
Visual-Linguistic Pretrained Transformers	Visual + Textual	Social Media Content	Introduced a transformer-based multimodal model for brand-related sentiment analysis.	Robust performance with pretrained models, scalable.	High computational cost, requires extensive fine-tuning.

3. Proposed Methodology—Sentiment Analysis (SA)

The research methodology for the study employs a systematic approach for collecting, analyzing, and evaluating data about SA in the context of SMA. The study examined the impact of leveraging NLP for Customer Insights. This analytical phase involves a comprehensive investigation of the theoretical foundations of SA and NLP, as well as their dynamic role in the SMA field. Researchers work hard to understand the complexities of these fields, from the most basic principles to the most recent and cutting-edge breakthroughs [13-15].

In the context of SMA, this conceptual inquiry provides a framework for setting research questions, establishing hypotheses, and designing an organizational method that effectively matches SA's intricacies. In addition to conceptual comprehension, the researchers also investigate the current state of the relevant technology background. Researchers address the most current advances in the tools, systems, and inventions within the contexts of NLP and SA. With the support of these scientific questionnaires, participants could select the correct study metrics, which put the examination at the cutting edge of the most modern scientific developments. It prevents the SA from utilizing the most recently developed and cutting-edge tools to extract valuable data from the massive amount of data collected from SMN sites [16-17].

A. Data Cleansing (DC)

The DC method is a key introductory phase in the study's method, which demands significant focus on data. During this stage, a coordinated effort is made to eliminate any unwarranted activity that might render the subsequent estimation inaccurate. The elimination of irrelevant words, unique symbols, and emojis, along with the collection of essential data, is all part of this procedure. The studies ensure that the following analysis will be achieved on an error-free and significant dataset by filtering the data using this method. The investigation findings are then more precise and trustworthy due to the analysis.

B. Tokenization

The next step, which occurs after the data cleansing process is complete, is to tokenize the textual data. The method divides the constant text flow into segments, including phrases, paragraphs, or single words. Tokenization is essential since it develops the text required for the following analysis. Through employing this approach, analysts may probe deeper into the data in search of sentiments, syntax, and semantic correlations. Once data is classified, it provides the analysis model and is processed using various NLP [18].

C. Feature Engineering

To support the actual examination of the data as text, modern NLP methods, such as word encoding and Term Frequency-Inverse Document Frequency (TF-IDF), are employed. These methods convert the text into statistical data, thereby rendering it accessible to statistical analysis. One technique for recording the semantic relationships between words is word encoding, which involves mapping words into high-dimensional vector spaces. TF-IDF is a method that sets a numerical value to phrases to evaluate their importance in an article compared to a database. As a result, feature engineering is a vital part of preparing the data for SA and following ML[19].

Convolutional layers process the incoming data by applying filters or kernels to it. Sliding over the input feature maps, these filters multiply elements by themselves and then add the results to create feature maps that depict local patterns [20]. These regional patterns may indicate significant word or phrase combinations that impact sentiment in the context of SA. The network may learn an increasing number of abstract and sophisticated characteristics by stacking convolutional layers, Equation (1):

$$z_{i,j} = \sum_{m=1}^{f} \sum_{n=1}^{f} x_{i+m-1,j+n-1} \cdot w_{m,n} + b \qquad (1)$$

Where,

- $z_{i,j}$ is the feature map in the output form
- The feature map in the input is given as $x_{i,j}$
- Weight filters are indicated by $w_{m,n}$
- The filter size is given as *'f'*

- The bias is given as *‘b’*.

The resulting feature maps are subjected, element by element, to an activation function after each convolutional layer. The Rectified Linear Unit (ReLU) is a popular option that introduces non-linearity to the model by preserving positive values and setting negative values to zero [21]. To enable the network to learn intricate correlations between input variables and outputs, non-linear activation functions are essential, as shown in Equation (2).

$$h_{i,j} = ReLU(z_{i,j}) \tag{2}$$

Where,

- The activation function in the output layer is indicated by $h_{i,j}$.

Pooling layers preserve significant information while reducing the spatial dimensions of the feature maps. For instance, max pooling downsamples the feature map by choosing the most critical value from a range of values [22].

The average value inside the frame is calculated by average pooling. By pooling the input data, the network’s computational cost may be decreased, and the learned features become more resilient to slight distortions or translations, Equation (3):

$$MaxPooling(x) = \max\left(x_{i:i+s-1,j:j+s-1}\right) \tag{3}$$

Where,

- The window size is signified as *‘s’*.

The output is flattened into a 1-D vector after the pooling layers. The multi-dimensional feature maps are rearranged throughout this step to create a format that can be entered into the fully linked layers. While the input is converted into a format that can be handled by Conventional Neural Network (CNN) layers, flattening maintains the spatial connections that the convolutional layers have learnt [23].

Dense layers, or Fully Connected (FC) layers, acquire high-level representations of the characteristics that the convolutional layers have collected. Every neuron in the layer above it is coupled to every other neuron in an FC layer [24]. The network can record intricate relationships between several input data components to these layers, which collect and integrate the information discovered by the convolutional layers, as shown in Equation (4).

$$y = SoftMax(W_x + b) \tag{4}$$

Where,

- The weight matrix is specified as *‘W’*
- Bias is assumed as *‘b’*
- The output SoftMax activation function is exposed as SoftMax.

The network’s output layer comprises SoftMax units representing several emotion classifications

(Positive, Negative, and Neutral). Each class's probabilities are generated using the SoftMax activation function, and the total equals 1. The emotion of the supplied text is predicted to be the class with the greatest likelihood. This last layer in SA enables the network to categorize the input text's sentiment using its learnt features [25].

4. Results and Discussion

A study of the SA in SMA, which has been rendered feasible by the tools of NLP, has resulted in several important and helpful findings that emphasise the revolutionary nature of the field. The results demonstrate that the domain has the potential to modernise the industry. This section provides an easily understood overview of these realizations by highlighting two essential features: the inherent value of SA and its impact on advertising strategies.

A further source of data, demonstrating that SA is not only an innovation in technology but also an imperative for contemporary technology businesses operating in the digital commerce era, is presented in the research results of this study. Measuring and quantifying sentiments that customers exhibit across SMA sites provides businesses with valuable insights into their target consumers' psychological reactions, likes, dislikes, and opinions. Implementing this knowledge serves as a guide for informed decisions in marketing, product development, and customer meeting systems.

SA enables businesses to recognise emerging developments, analyse the impact of advertising tasks, and rapidly address problems or negative sentiment surges. It also reveals the complex patterns of customer sentiment, which exhibit the most profound levels of customer sentiment. It also renders it more accessible to implement a client-centric approach, where businesses adapt their goods, services, content, and messaging to the prevailing sentiment. As a result, this contributes to improved client satisfaction and brand loyalty.

The processing efficiency of the proposed model can be determined by the time required for model training and prediction. The architecture is executed on one Intel 1.8-GHz PC with a GPU and 32 GB of memory. The initially generated sample Twitter set needed 2 hours of training and 5 seconds of prediction. Due to the small sample size, the second set was trained for 15 hours, and the third was trained for 20 minutes.

4.1. Data Context

Consumers respond to text and images in SM messages, which this research analyses. Post meta data contains likes, shares, reactions, tags, and timestamps. The data is derived from customer interactions, including comments, likes, and shares. Advertiser profiles on Facebook featured ratings, followers, and lively comments. Page data, posts, post data, and comments are employed to research Facebook user behaviour. According to Facebook's privacy policy, comments and replies are confidential. Subscriber webpages are typically banned, so the app cannot see user information.

4.2. Data Origin

The advertising software company Ad helps advertisers create and advertise their advertisements on various platforms. The online platform provides Facebook advertising guidance and over 2500 test advertisements. The tool enables advertisers to send advertisements to multiple platforms from a single location. The article collected sample advertisements for SA.

4.3. Data Collection

The Python web scraper searches websites on Facebook utilizing its Graph API. No more than 3000 posts were obtained through scraping per page to limit ML presumption and Facebook's everyday API session limit. Over 3000 posts have been collected. Text data was obtained and stored in a central repository, while image URLs minimized space. The result illustrates the data extraction procedure and a graph of the Facebook site comments collected. A user-friendly and ordered Facebook API enables URL prefixes for visiting children's objects. The URL can be amended with posts and comments via "/Posts" or "/Comments". Collecting data is more accessible and less prone to error. URLs serve as distinctive passwords for the text on a page element. The URL is the database's key element, featuring 500,000 comments and sharing rates, as well as 100,000 post sentiment samples in the resultant graphs.

4.4. Text Processing

Text data will be processed into NN vectors in the context of the research. Blank space is employed to divide text into words, generate word tokens, arrange them into sentences, lowercase words, eliminate stopwords, and delete words with fewer than three characters. Port stemmers cause stems for all words, and POS tag repositories tag parts of speech. Word lemmatizers extract stems from the stem and POS tags and send them into TD-IDF vectorizers for generating word vectors. These vectors represent NN features. "DL with Keras" includes an example.

In the context of SA, visual representations play a crucial role in elucidating numerous data and model performance features.

Figure 1. Word cloud.

Figure 1, the Word Cloud, provides a visually striking depiction of the most prominent words within the dataset, offering insights into the prevalent themes and SA.

Figure 2. Classification accuracy for different epochs.

Figure 2, Classification Accuracy for Different Epochs, charts the evolution of model accuracy over time, serving as a diagnostic tool to assess convergence or divergence during training.

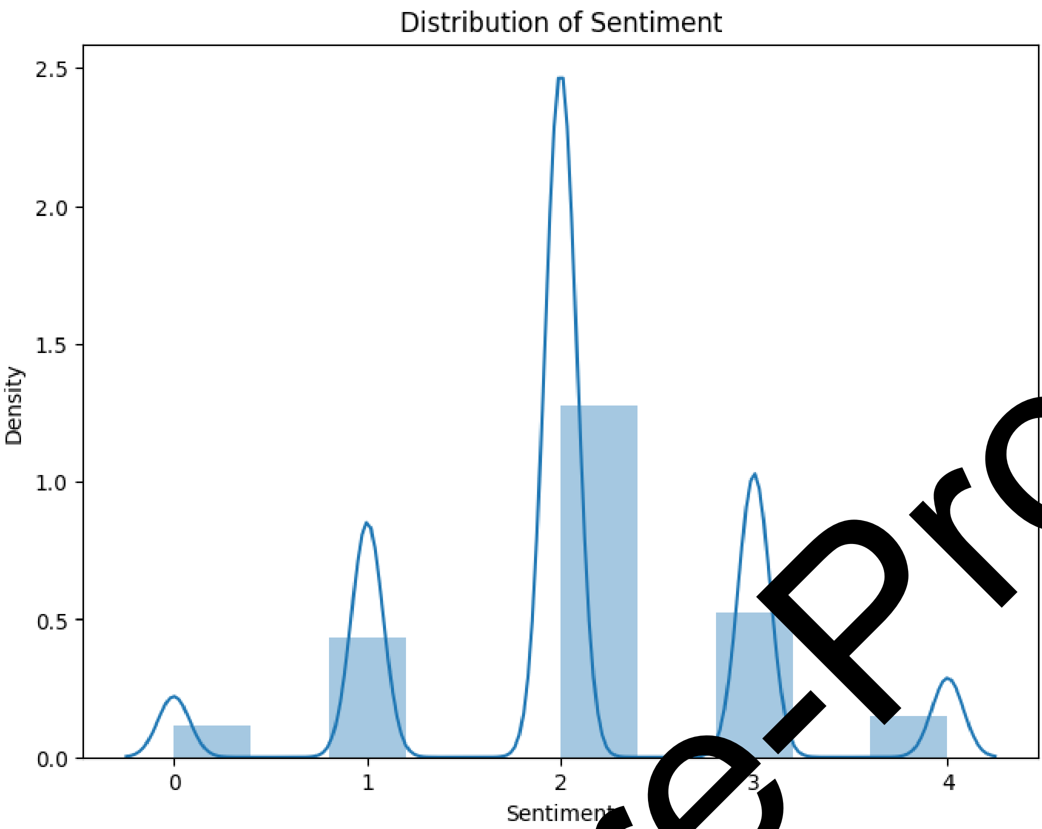

Figure 3. Sentiment distribution.

Figure 3, Sentiment Distribution, offers a comprehensive view of the SA by illustrating the distribution of different SAs across the dataset, aiding in understanding the overall SA.

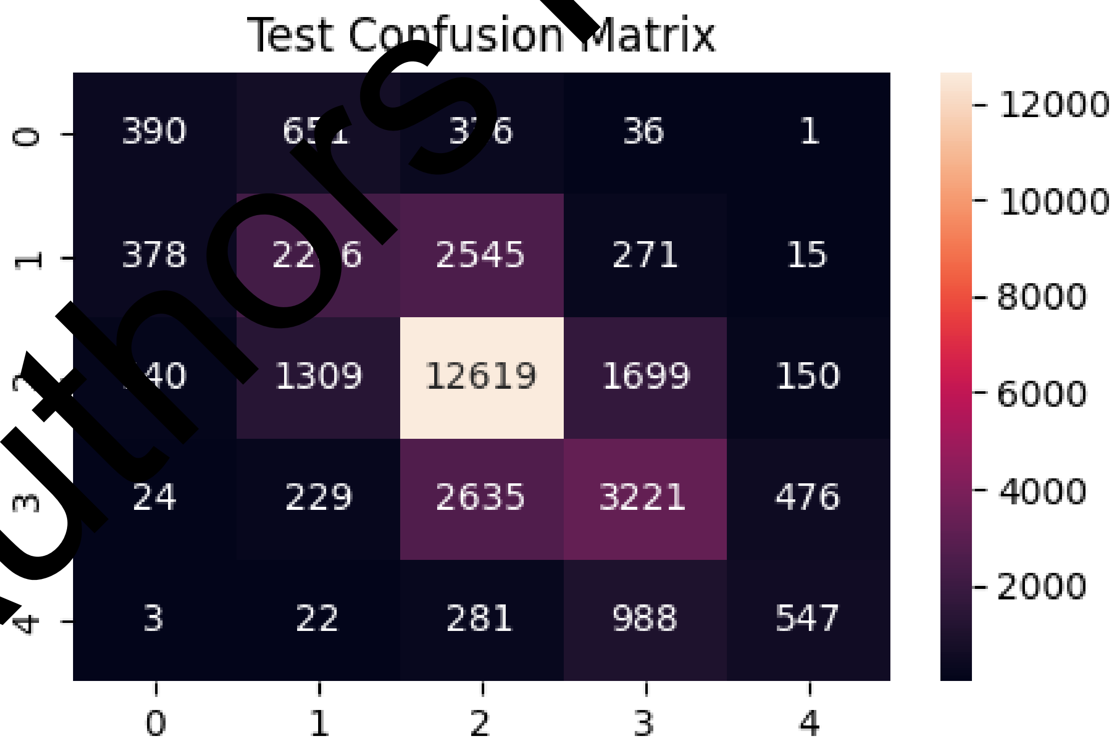

Figure 4. Confusion matrix.

In the end, **Figure 4**, the Confusion Matrix, shows the predicted labels compared to the accurate labels for each sentiment class, demonstrating how well the model performed. This matrix measures SA algorithms' accuracy, precision, recall, and F1-score. These visual representations enable SA researchers and practitioners to increase complete identifications, find patterns, and improve SA models.

The present research provides insight into the life-changing impact that SM can have on marketing methods. Technology-driven promotion enables businesses to communicate more effectively and directly with their target audience. First, SA may impact advertisements and other communications based on consumer sentiment. It enables the most effective methods of communication and timing, thereby increasing the likelihood that the target customer will appreciate the data being provided. SA also helps businesses monitor consumer sentiment in real-time. The result is that enterprises adapt rapidly to problems and possibilities. It enables companies to manage adverse reviews and prevent emergencies, making it essential to manage reputation resources effectively.

Table 2: Statistical Results on the Test Set

Model	Accuracy	Precision	Recall	F1-score	AUC (ROC)	MSE	Sentiment Accuracy
Proposed Multimodal Model	**96.14%**	**95.13%**	**94.[illegible]%**	**[illegible]5.40%**	**0.934**	**0.15**	**94.16%**
Visual-only Model (CNN)	89.77%	87.65%	86.42%	86.68%	0.88	0.27	89.2%
Text-only Model (RNN)	91.82%	89.3[illegible]%	88.77%	89.21%	0.89	0.25	92.3%
Traditional Regression	83.9[illegible]%	81.42%	80.31%	80.16%	0.78	0.37	78.8%

5. Conclusion and Future Work

This investigation extends to the current state of the literature regarding forecasting user interactions. A data-driven advertising method leverages data from the intended consumer's electronic interactions, rather than emotions, when making decisions. This study integrated image and text-based models, with mid-model fusion predicting more significant user interaction. The CNN network performed well in terms of SM statistics, and the combined models outperformed the text-based NN and image-based CNN in all parameters. Image-based models are superior to text-based models, particularly with complex datasets. Online businesses require SA to address problems and concentrate on customers. SA transforms advertising through interacting with customers and correlating content to sentiments. SA secures a business's reputation by providing instant feedback from customer data to solve problems and capitalize on opportunities. It extends beyond essential marketing and provides several advertising approaches.

The research work predicted user participation for both advertisements employing a hybrid model. The random model forecasted post count, share count, and post sentiment for 60% of the period for each blog post. The combination of the models accurately predicted post sentiment, post count, and share count 61%, 62%, and 65% of the time, defining an acceptable standard for future studies.

AI has revolutionized product development, enabling businesses to tailor products to meet consumer demands and enhance consumer satisfaction and trust. Improved NLP algorithms can successfully identify irony and sarcasm in multiple languages, making this enjoyable for SMM.

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