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A Hybrid Deep Learning Model for Enhanced Customer Sentiment Analysis forE-commerce Platforms

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Abstract: Customer sentiment analysis has become more important for e-commerce systems if one wants to grasp consumer opinions and increase user happiness. This work proposes a new hybrid deep learning model combining CNN, BiLSTM, and Transformer layers in order to improve the bar for E-commerce review sentiment analysis. With its self-attention mechanism, the transformer layer provides context knowledge; the convolutional neural network (CNN) layer recognises textual local features; the long short-term memory (BLSTM) layer identifies sequential dependencies. Customer evaluations sometimes include sarcasm, uncertainty, and context changes; our hybrid architecture uses the strengths of each component to control these problems. This work uses the NFT dataset available on 9nftman.com. Test on a large dataset of online purchasing reviews, the model exceeded conventional models in terms of accuracy, F1-score, and recall rates. Crucially for a full knowledge of the customer, this improved sentiment prediction indicates that the computer can detect complex emotions including mixed or neutral input. Though the hybrid model raises processing complexity, its improved prediction accuracy and context sensitivity make it ideal for large-scale sentiment analysis in dynamic E-commerce contexts. Future study on model optimisation and interpretability will concentrate on finding a balance between computational efficiency and commercial usability. Accurate and context-aware sentiment analysis provides E-commerce platforms with strong new tools for learning about consumer experiences and making educated strategic decisions based on the proposed paradigm taken whole.
Keywords: Deep Learning, Customer Sentiment, E-commerce,RNNs, CNNs, BERT, NFT

[1] Introduction

Understanding and using consumer sentiment is absolutely essential in the always shifting realm of online buying if one is to affect corporate strategy, improve user experiences, and raise customer satisfaction. Thanks to the explosive growth of digital platforms, consumers today express their opinions, feelings, and preferences through a flood of textual data including product reviews, ratings, comments, and testimonials. E-commerce businesses have a treasure of customer comments just waiting to be extracted for insightful analysis of user emotions that might guide their engagement strategies and product development. By combining these three robust designs to manage context sensitivity, sarcasm, and mixed emotions, among other issues, the proposed hybrid model enhances upon past efforts at consumer sentiment research. The reviews of NFTs available on 9nftman.com offer especially linguistic and contextual challenges considered in this research. Empirical analysis indicates that by surpassing conventional models in terms of accuracy, F1-score, and recall rates, the proposed model seems to be able to detect and classify a wide spectrum of attitudes, including neutral and mixed feedback.

Guiding corporate goals, enhancing user experiences, and ensuring customer pleasure all depend on an awareness of consumer attitude in the always changing e-commerce terrain. To express their opinions, consumers are leveraging textual data including ratings on the expansion of digital platforms, comments, and review scores. Thanks to the growth of user-generated content, businesses could pick a lot of lessons from client comments. This data will help them to enhance their policies for user involvement, goods, and services. The explosive increase of NFTs has lately offered the e-commerce company a new perspective. Since NFTs are unique digital assets proving ownership or validity, many things—including works of art, collectibles, even virtual real estate—are connected with NFTs. Reviews, discussions, and social media engagements are helping the NFT Company to reflect consumer attitude as it develops. Analyse this attitude poses its own set of special challenges since NFTs are connected to a foreign language, specific references, and an environment that is always changing. This paper investigates how integrating advanced deep learning techniques to sentiment analysis in order to overcome challenges can help E-commerce systems handling NFTs. We aim to build a hybrid deep learning model in order to enhance customer sentiment detection and classification. Apart from positive and negative emotions, this model can also detect sarcasm, contradicting opinions, and environment-specific attitudes. When it comes to NFT-related data, which can be impacted by elements like market volatility, technical literacy, and community dynamics, among others, typical sentiment analysis techniques sadly do not always provide the required accuracy and context awareness.

Leveraging Convolutional Neural Networks (CNNs), Transformer layers, and Bi-LSTM, this paper proposes a sentiment analysis hybrid model. The Bi-LSTM layer considers sequential dependencies in the text to help one better grasp the sentiment flow in reviews; the CNN layer gathers local textual data required to grasp the surface-level sentiment. Especially in the often shifting and context-dependent NFT environment, it is important to know how various review elements interact with one another and how this influences the emotional reaction of the user. Transformer layers provide this awareness via their self-attention mechanism. This work intends to address the special challenges related to sentiment analysis in the NFT sector by means of the combination of many state-of- the-art deep learning models. The model is trained and evaluated with a dataset of consumer reviews linked to NFTs. Its accuracy, F1-score, and recall rates all clearly outperform those of conventional models. Businesses aiming to survive in the always changing NFT industry should pay attention to this model's improved performance since it shows its capacity to better understand complex emotions and provide more complete analysis of customer experiences. One approach the proposed solution facilitates in helping NFT-based e-commerce platforms understand consumers' experiences and make data-driven decisions is better and more context-aware sentiment analysis. The necessity for scalable and flexible sentiment analysis models will rise as the NFT market grows constantly. Apart from improving sentiment analysis in general, this research offers valuable data for NFT e-commerce platforms in their quest of consumer insight and the formulation of strategic directions.

1.1 Role of Deep Learning in NFT

Deep learning, among the most significant advancements in the large subject of machine learning, is already affecting many different sectors. This approach teaches "deep" artificial neural networks to independently derive meaning from large-scale datasets. Deep learning's ability to manage big datasets and produce insightful analysis has tremendously helped computer vision, NLP, speech recognition, and other fields. One of deep learning's strongest suit is its ability to grasp complex, unstructured input like text, images, and audio. Without human feature extraction, deep learning systems may understand intricate correlations and patterns in raw data. Deep learning methods have fundamentally changed how artificial intelligence consumes and interprets data that people have generated especially for tasks such object recognition, sentiment analysis, and content generation.

Using deep learning, non-fungible tokens (NFTs) are a new kind of digital asset verifying the ownership or legitimacy of one-of-a-kind thingssuch as virtual goods, digital artwork, or collectibles. NFTs' ability to create digital scarcity and ownership has drawn a lot of attention and helped to drive a rapidly expanding company. The NFT ecosystem is complex and technology is continually developing; user-generated content in the ecosystem comes in many various forms including textual evaluations, social media posts, and community discussions. Deep learning is essential in increasing the understanding and interaction with NFTs by providing advanced tools for sentiment analysis, trend identification, and market behaviour predictions. NFTs, for instance, complicate sentiment analysis—which seeks to interpret the emotional tone of online reviews and social media exchanges. Talking about NFTs exposes a spectrum of emotions, changing market dynamics, and a lot of specialist jargon. Transformers are ideal natural language processing (NLP) tools to teach deep learning models to detect these subtle nuances and provide more accurate sentiment categorisation.

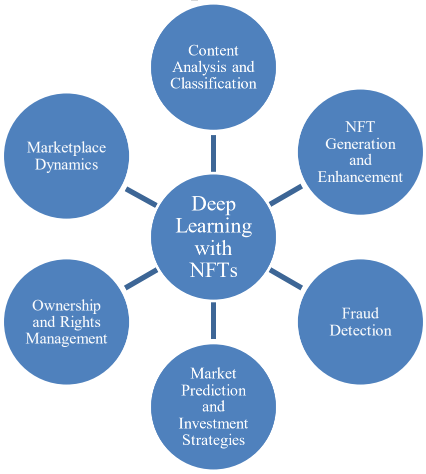

Fig 1. Role of Deep Learning in NFT Sentiment Analysis

Moreover, by means of previous data and present market patterns, deep learning models are used to identify trends in NFT transactions, project price changes, and assess the future value of digital assets. For NFTs based on art, these models may utilise CNNs to assess pictures; RNNs and LSTM networks to analyse sequential data; and transformers to analyse user comments and community interactions contextually. Deep learning will become more important as the NFT industry develops in improving user experience, supporting innovation, and creating new opportunities in this fast changing digital economy. By allowing more accurate sentiment analysis, market trend prediction, and understanding of the dynamic nature of consumer preferences, deep learning might help NFT businesses make better decisions. In essence, deep learning has revolutionised the field of NFTs and beyond, therefore influencing artificial intelligence generally. Using deep learning techniques will help companies and NFT platforms better grasp customer mood, forecast market movements, and adjust to this growing sector.

1.2 Customer Sentiment

Modern company strategy, especially in E-commerce, relies on consumer emotion. Customer sentiment relates to customer views, sentiments, and attitudes about goods, services, brands, and experiences. It includes contentment, loyalty, discontent, and frustration. E-commerce websites, social media networks, and review forums provide consumers new opportunities to express thoughts and share experiences with goods and services. Businesses seeking success in the competitive E-commerce world must accurately assess and evaluate client opinions. Positive emotions improve consumer involvement, loyalty, and advocacy, boosting revenues and brand reputation. Disagreements may highlight problem areas, places of friction in the client journey, or potential threats to the company.

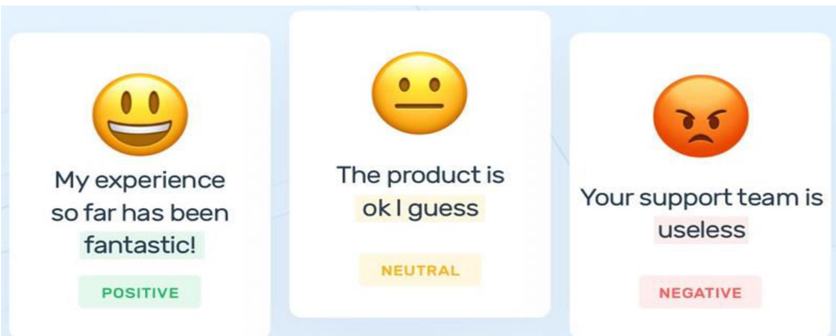

Fig 2. Understanding Customer Sentiment

Surveys, focus groups, and feedback forms for customers have long been used by businesses to measure client opinion. The potential for qualitative data isn't worth the bias, time, and effort required by these methods. Improvements in natural language processing, machine learning, and AI in the last several years have allowed for more automated and scalable consumer sentiment analysis systems. Opinion mining and sentiment analysis are terms that describe the same thing: the use of computer algorithms to search for, extract, and count subjective data from text. Deep learning, statistical models, and rule-based techniques are all part of this category. In this introduction, we will examine several aspects of consumer sentiment research, including its relevance in E-commerce, its application across business sectors, and the problems of correctly gathering and evaluating client ideas. In addition to discussing the state of the industry and its prospects for growth, we will examine the ways in which technological advancements, particularly in the realm of deep learning, have made simpler and more scalable sentiment analysis solutions possible. When businesses take the time to study customer sentiment, they may better tailor their digital offerings to meet their customers' individual tastes and requirements.

1.3 E-commerce

Online shopping, sometimes known as electronic commerce, has revolutionised global trade and the way consumers and businesses purchase goods and services. E-commerce, or the buying and selling of products and services on the Internet, has levelled the playing field by allowing businesses of all stripes to connect with consumers all over the globe. Technology, customer behaviour, and internet connectivity have all contributed to the growth of e-commerce. Secure online payment methods, strong logistics networks, and user-friendly interfaces have helped E-commerce overcome security and logistical issues. E-commerce now includes B2C, B2B, C2C, and even m-commerce, which is enabled by smartphones and other mobile devices.

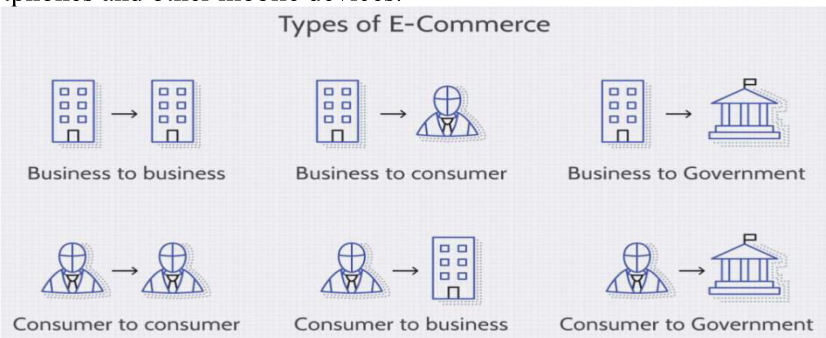

Fig 3. Types ofE-commerce

E-commerce has expanded into almost every industry, from retail and entertainment to healthcare and education, due to its adaptability. E-commerce provides companies and customers with unmatched ease and flexibility. E-commerce allows firms to access a worldwide audience, reduce administrative expenses, and make data-driven decisions. E-commerce gives users 24/7 access to a wide range of goods and services, customized shopping experiences, and doorstep delivery. E-commerce has also spurred the growth of online markets, subscription services, and digital platforms, which have challenged incumbents and transformed old sectors. With their extensive product offers, user-friendly interfaces, and advanced data analytics, Amazon, Alibaba, and eBay dominate E-commerce. This introduction will discuss E-commerce's history, its effects on firms and consumers, and its digital prospects and difficulties. We will discuss the confluence of online and offline retail, mobile commerce, data-driven insights, and sustainability and social responsibility as they affect E-commerce. To compete in E-commerce, firms must adapt to changing customer demands and technology. E-commerce strategies and cutting-edge technology may help firms develop, reach more consumers, and provide great value in the digital age.

1.4 Deep Learning Use Case in E-commerce with NFTs

The meeting of deep learning and NFTs has opened several fresh paths for enhancing e-commerce systems. NFTs—representing one-of-a-kind of digital assets like artwork, antiques, music, and virtual goods—have lately gained quite popularity. E-commerce sites using NFTs find it difficult when it comes to evaluating customer mood, market prediction, tailored recommendations, and the value of digital assets. Deep learning's ability to sort through masses of data offers strong solutions to many challenges. Here are some specific instances of how deep learning may be used in NFTbased e-commerce systems:

1.4.1 Sentiment Analysis on NFT Reviews and Community Discussions: Online buying is different, hence understanding consumer opinions are essential to improve their experience and guide business choices. As NFTs become increasingly popular, users are freely expressing their thoughts on review websites, social media, and community forums among other online environments. But swirling around NFTs is a lot of difficult-to-understand technical jargon, slang, and market trend vocabulary.

1.4.2 NFT Market Prediction and Pricing: With prices always changing in reaction to supply and demand as well as the degree of popularity of the asset, the NFT market is famously volatile. Deep learning models may investigate prior transaction data, user preferences, and social media activity to project the future value of NFTs and direct pricing strategies on e-commerce platforms. Training RNNs and LSTM networks helps e-commerce systems forecast future price trends for specific NFTs or sets of NFTs by helping them to understand patterns in NFT sales.

1.4.3 Personalized NFT Recommendations: Deep learning is unparalleled in terms of customised recommendations based on user activities and preferences. Deep learning allows NFT-related Collaborative Filtering and Content-Based Filtering techniques to deliver customers more exact recommendations for digital products they may value.

1.4.4 Image and Video Analysis for NFT Content: Especially in the gaming and art sectors, digital image and video analysis for NFT material is a developing subject. Deep learning models like CNNs allow one to examine visual content connected to NFTs. CNNs' feature detecting ability makes them ideal for assessing originality, authenticity, and quality of NFT artwork.

1.4.5 Fraud Detection in NFT Transactions: Along with NFTs' increasing popularity, concerns concerning the marketing of phoney or copied versions have emerged. Deep learning may help to identify fraudulent activities by looking at patterns in user behaviours, digital asset provenance, and transaction data. Using anomaly detection with deep learning models can help you determine why you see that the value of certain NFTs is fluctuating greatly or that sales of a given asset have suddenly increased.

1.4.6 NFT Content Generation and Customization: Apart from assessing already existing NFTs, deep learning may also be used to generate new NFT content. Using GANs, original artwork, music, or images may be produced NFTs. By use of GANs, artists and producers may influence artificial intelligence to produce unique NFTs in line with their own creative vision or current trend. Using NFT-based e-commerce systems with deep learning that use deep learning helps one to maximise pricing strategies, spot fraudulent conduct, customise experiences, and raise user involvement. Deep learning is a game-changer in the developing NFT market as it can sort through mountains of diverse data including but not limited to visual material, transaction histories, and textual input. Deep learning techniques are currently vital for finding fresh ideas, improving operational efficiency, and fostering innovation in the NFT ecosystem; as the NFT sector develops they will become much more so.

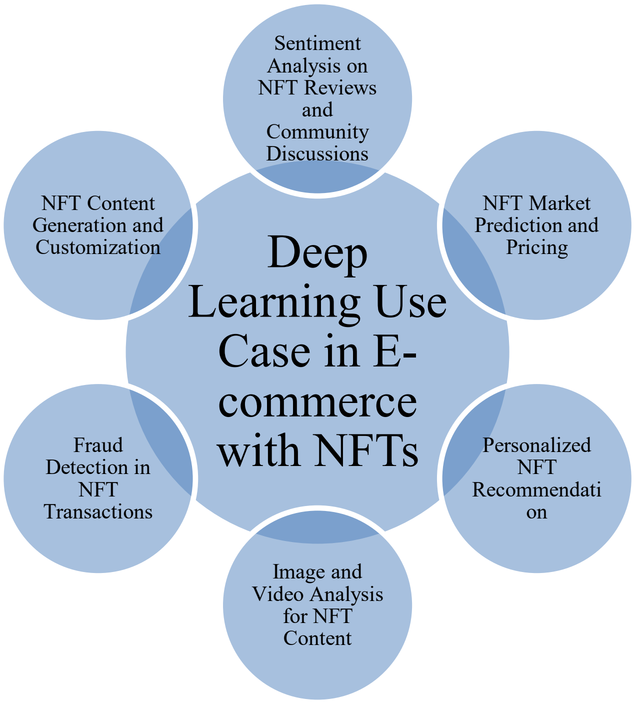

Fig 4. Deep Learning Use Case in E-commerce with NFTs

[2] Literature Review

There are different research works that did significant work in area of sentiment analysis of customer in E-commerce application.

X. Cheng et al. (2023) focused on the improvements in E-commerce Technology Made Possible by AI. E-commerce has grown rapidly in recent years, and cutting-edge digital/internet-based technology has played a crucial part in this expansion. Among these was the importance that AI-driven technological innovation in E-commerce plays in the sector's expansion.[1]

S. Dhanvate et al. (2023) introduced the AI for online shopping. The acquired information also serves as the foundation for developing individualized suggestions for each customer. With the goal of better understanding their customers, several E-commerce firms have begun using various types of AI. This article focuses on AI in E-commerce and how it functions in various sectors of the industry.[2]

S. Gupta et al.(2023) looked the machine learning for online shopping. This article focuses on the core concepts of electronic commerce and artificial intelligence, as well as the advantages of both. The objective here was to evaluate the significance of AI and its application to E-commerce by reviewing the current literature on the topic.[3]

H. Pallathadka et al. (2023) reviewed the management, E-commerce, and finance applications of AI. Common methods of artificial intelligence include ML& DL. Major applications include increasing sales and profits, accurately predicting future sales, managing stock levels, preventing theft, and diversifying investment portfolios.[4]

Dr. R. A. Ayyapparajan et al.(2022) did research on the influence of AI on online business. Artificial intelligence can efficiently collect and analyze large datasets, allowing it to recommend courses of action. In order to better understand their clientele and provide them with a more satisfying shopping experience, several online retailers have begun using some kind of AI. This study discusses the significance of AI and its applications in various niches of online commerce.[5]

Dr. A. K. kashyap et al.(2022)presented work on the integration of AI into online business. Methodology and the study's goals are presented after an introduction that details the study's motivations, the gaps in the existing research, and the potential of artificial intelligence. In the next section, they look at AI and its subsets, E-commerce, and the ways in which AI is being used to a variety of E-commerce tasks. The research shows how AI can bring back humanization and customization to online shopping. Finally, we provide our findings, drawbacks, and directions for further research. Many scholars and academics may find the study's identified major topics to be of

interest. The study's findings will open up novel possibilities for using AI in the E-commerce sector. [6]
Sarita et al. (2022)looked the game-changing impact of AI on online business. The use of AI to forecast what customers want and when they'll want.It wasrevolutionized online retail by allowing stores to better serve their customers. This research aims to examine the causes that were contributing to the development of the E-commerce business, as well as the advantages and legal consequences of artificial intelligence in this space.[7]
N. Luo et al. (2022) reviewed the invention of a new E-commerce growth model against the context of AI and Wireless Networks. This paper investigates online retailers by means of a questionnaire survey and a case analysis. The findings demonstrate the size of the global E-commerce business but also highlight the shortcomings of the current E-commerce paradigm. In addition, it suggests novel ways forward for E-commerce growth, all of which may serve as useful pointers for the future of the sector as a whole. It is recommended that businesses use their combined complete strengths and genuine demands to choose E-commerce development techniques that were most suited to their own growth.[8]
Grzybowski et al. (2021) presented work on the online shopping with the help of AI. The potential development of E-commerce was profoundly affected by the exceptional pace of digital expansion. Businesses now need to use AI to increase productivity since the continuing pandemic has accelerated the growth of E-commerce combined with constantly shifting client expectations and purchasing patterns. The purpose of this thesis was to deepen our knowledge of AI and to examine how this technology was changing the face of E-commerce by solving issues related to the customer service they get. The research aims to prove in the end that AI has great promise for the future of humanity. [9]
D. Panigrahi et al. (2021) provided work on the AI can improve consumer-brand interactions in online shopping. As a result, several E-commerce organizations have developed AI-centric methods for customer interaction to boost productivity and efficiency. This study explores the many ways in which AI might affect an online and it concludes that AI was crucial to the success of eCommerce businesses. Therefore, it conducts a comprehensive literature search to back up its claims. All necessary steps in performing a systematic review were taken to exclude the possibility of skewed results.[10]
A. D. Vaio et al. (2020) introduced the sustainable business models for the agri-food system in a post-COVID World with AI. For our methodology, they presented a comprehensive literature evaluation of seminal works in the subject. In particular, the research was carried out in two stages: first, they retrieved and researched relevant papers from scientific databases; and second, they analyzed the chosen articles. In light of the COVID-19 pandemic scenario, the results raise intriguing questions concerning the application of AI to the development of a "space economy" conducive to ethical and environmentally friendly commercial practices. Implications for theory and management are examined.[11]
L. T. Khrais et al.(2020) reviewed the importance of AI in Creating New Demand for Online Shopping. Researchers in the field of artificial intelligence have used several methods, to have a better grasp on the concept of explain ability. This study, which was inspired by a corpus analysis, establishes framework for unified front, which was an important step towards the goal of developing models of XAI. Based on the findings of this research, it was recommended that ML models be made more interpretable and intelligible before deploying explainable XAI systems. [12]
B. Seetharamulu et al. (2020) create a system that can detect good and bad evaluations from customers using deep learning. To show that the idea works, a prototype application is created. Having access to massive amounts of training data is crucial for deep learning to be successful. To do this, we propose and execute a method called DLSA. A framework for deep learning is developed and put into action. To show that the idea works, prototype application is created. Compared to current state of the art, the suggested system outperformed it in the empirical investigation. [13]

2.1 Research Gap

There is progressive evolution in sentiment analysis of customer who buy product online. Conventional research focused on traditional classification approach to detect customer sentiment for domestic products. In such research accuracy and performance is found limited and products considered are out dated. There is need to consider advance products such as digital assets. These digital assets might be NFT. In last few years the market of NFT product has been expanded. Moreover, there remains need do more work on performance and accuracy parameters such as recall, precision, F1-score.Deep learning, e-commerce, and NFTs together provide a great chance for innovation and pragmatic application. Study in this area is expanding quickly. Still, a lot of unresolved issues surround how best to use deep learning to address NFT-related challenges in online shopping. By filling up these gaps, we can provide businesses in the NFT and e-commerce ecosystem valuable tools as well as assist academics learn more.

In conventional e-commerce, sentiment analysis has been extensively studied, but NFTs provide additional issues. Changing market attitudes, technical vocabulary, and art-based terms are regularly used to discuss NFTs. Typically trained on large-scale e-commerce data, sentiment analysis tools struggle to catch NFT-specific community buzz, market enthusiasm, and emotional responses. Due to their wide use of slang, idioms, and idioms, NFT groups seldom use deep learning models to categorise emotions. Future study may focus on advanced sentiment analysis for NFT textual data. One may predict NFT pricing or identify new market trends by analysing transaction data, user behaviour, and social media signals. Deep learning using RNNs, LSTMs, and transformers for the highly unstable and fast-changing NFT markets are new yet successful in time series and market prediction. Deep learning algorithms that forecast NFT market trends have received little attention for scalability and efficiency. Data analysis and market reaction in real time strain computer resources and model flexibility.

Fake NFTs, digital art theft, and dishonest market practices raise NFT ecosystem fraud concerns. Autoencoders and anomaly detection algorithms have been used to identify fraud in traditional e-commerce, but NFT transactions, which frequently involve valuable, unique assets, have not been explored. Deep learning is needed to identify fraudulent NFT transactions, such as bogus listings, changing prices, or the sale of stolen or duplicated digital items. Transaction and provenance data may be used to brainstorm ways to stop such dishonesty. The variety of asset kinds, user preferences, and creative material in NFTs makes customisation harder than in e-commerce. E-commerce systems need NFT-specific algorithms to understand customer preferences. These models should contain purchase habits, social relationships, digital asset preferences, and creative styles. NFTs are unsuitable for current recommendation systems. Deep learning algorithms reveal NFT customers' creative tastes, degree of engagement with individual producers, and NFT community interaction patterns.

NFT metadata, such as ownership history, transaction records, and creator information, is commonly found on the decentralised web, which is spread across numerous trading platforms. Integrating data from several sources, each with its own format, structure, and quality, hinders deep learning models' data aggregation and interpretation. Deep learning must be studied to see how it can combine and analyse data from several platforms to better comprehend NFTs in diverse markets. We must find ways to mine decentralised NFT data for important qualities to feed into deep learning models for sentiment analysis, market prediction, and recommendation creation. Deep learning models—especially neural networks and transformers—have excelled in market prediction and emotional analysis. However, these models are typically "black boxes," which is important. Before pricing, investing, or curating NFT collections, artists and corporations must comprehend a model's predictions. NFT deep learning models require further study on making them more intelligible and transparent. To achieve this goal, tactics may be needed to explain market trend estimates, sentiment classifications, or important NFTs to clients.

[3] Problem Statement

Previous study has produced a method that makes use of just a few characteristics. In order to categories in E-commerce application, they looked at their contents. Researchers are looking at a system that can automatically recognize in E-commerce application. But the limitations are limited scope, lack of accuracy, lack of performance. Thus there is need to propose a research that should be capable to propose better sentiment analysis approach for customer of digital assets.In the always shifting environment of e-commerce and the NFT industry, understanding customer feedback and enhancing user experience is of highest relevance; hence, this is where efficient sentiment analysis finds application. Although sentiment analysis might significantly enhance e-commerce applications, much previous work has focused on under-featured and simple models. Especially in the field of digital assets like NFTs, these models typically categorise emotions using broad content analysis instead of the complexity and context-specific nuances present in user feedback. Still, even with all the effort, the present systems clearly have several flaws:

1. **Limited Scope and Accuracy:**Usually in specialist fields like NFTs, the complex and varied expressions seen in customer reviews are beyond the reach of present models. Sentiment estimates therefore often fall short in terms of capturing sarcasm, mixed emotions, and context-specific client reactions.
2. **Performance Constraints:**Many traditional techniques may have great difficulty with large, diversified datasets. Complicated, multi-dimensional input or shifting NFT market patterns usually lead these models to underperform. The accuracy of sentiment analysis technologies is a significant challenge for businesses, particularly in terms of identifying little variations in sentiment.
3. **Computational Complexity:**They need substantially more processing resources, hybrid deep learning models, integration of CNNs model, BiLSTM networks, and Transformer layers,have shown greater results. Real-time application of these models becomes difficult especially on low-resource systems or in environments with restricted resources as their high processing demands demand longer training times and slower inference.
4. **Dependency on Large Datasets:**Training deep learning models depends on access to large, diverse datasets; hence this is also a prerequisite. But obtaining such datasets is not always simple, particularly with regard to specialist subjects like NFTs. Furthermore, short datasets might cause overfitting, which would make it difficult for the model to generalise and function on fresh data. Missing or biassed data could potentially result in erroneous sentiment predictions devoid of consideration for the complete spectrum of client perspectives.
5. **Interpretability Challenges:**Particularly in hybrid systems, interpretability is a prevalent problem with deep learning models. Given so many of these algorithms are "black boxes," it is difficult for businesses and stakeholders to know how particular words or traits affect the sentiment projections. If individuals lose faith in the model due of lack of openness, companies will find it difficult to make full use of the new knowledge. Business stakeholders in fields like NFTs, where intricate factors affect market volatility and user behaviour, have to be able to assess model findings to make informed decisions.

[4] Need of Research

Organisations must pay attention to client comments and change their strategies to match the always changing e-commerce scene. With the explosion of internet platforms, people share their thoughts and experiences via product evaluations, social media, and forums. Exploring this plethora of data and deriving valuable insights is difficult but may improve customer happiness, sales, and strategic decision-making. In the dynamic and diversified world of E-commerce, rule-based and statistical sentiment analysis methodologies cannot handle natural language's subtleties and complexity. Deep learning, an area of artificial intelligence inspired by the human brain, uses neural networks to learn representations directly from data to automate sentiment analysis tasks. This thorough research article examines the current performance optimization methodologies for deep learning models used for consumer sentiment analysis in E-commerce applications. We want to comprehend the latest methods and approaches in this field by integrating literature and research. The review begins by discussing sentiment analysis in E-commerce and its unique challenges, such as the large amount of unstructured textual data, diverse language styles and sentiments, and the need for real-time analysis to capture changing trends and customer preferences. We next analyze deep learning architectures used for sentiment analysis, emphasizing their merits, shortcomings, and application in E-commerce. We also examine data augmentation, transfer learning, attention mechanisms, ensemble approaches, and domain adaption strategies to improve deep learning models for consumer sentiment analysis. We explore how these techniques handle data scarcity, model generalization, and domain-specific sentiment comprehension to improve E-commerce sentiment analysis accuracy and resilience. We also examine E-commerce sentiment analysis model benchmark datasets and assessment measures. Comparative analysis and case studies reveal the pros and cons of current methods and suggest new ones. This thorough study seeks to inform E-commerce academics, practitioners, and stakeholders on deep learning-based sentiment analysis trends and advances. Businesses may better understand consumer attitudes, improve user experiences, and drive strategic efforts to remain ahead in competitive E-commerce industry by using these data. There is need to considering the NFT artwork for data classification in order to execute E-commerce application.

4.1 Difference between Proposed Work and Conventional Work

Proposed work is supposed to propose better and flexible solution as compared to conventional approach. It is supposed that proposed work would provide better accuracy and performance as compared to conventional approach. Research has considered NFT dataset for classification.

Table 1. Comparison of Conventional Research to Present Research

	Conventional Work [13]	**Proposed Work**
Accuracy Parameters	Accuracy	Accuracy, Recall, precision and F1-score
Performance	Ignored	Considered performance factor
Performance Parameters	N/A	Training time, Testing time
Optimization	Ignored	Considering optimization to filter dataset to reduce the time consumption and error rate
Scope	Limited	It considered flexible approach to provide versatile solution.
Classifier	CNN classifier	Hybrid approach using ANN and CNN classifier
Source of Data	Reviews collected from Amazon.com	Dataset considered from 9nftmania.com
Products	Electronics, cloth, shoes	Non-Fungible Tokens (NFT)
Input Data	Information about domestic product.	Information about the digital assets

[5] Proposed Research Methodology

To develop a comprehensive review on deep learning models for customer sentiment analysis in E-commerce, we can cover several key areas to highlight current methodologies, evaluate the performance of models, discuss challenges, and propose a model tailored to E-commerce sentiment analysis. Here’s a structured approach:

5.1 **Introduction to Sentiment Analysis in E-commerce:** Define sentiment analysis and emphasize its role in understanding customer feedback, driving product improvements, and enhancing customer satisfaction in E-commerce platforms. A few examples of e-commerce problems that make sentiment analysis more difficult are the use of acronyms, sarcasm, slang, and reviews written in more than one language.

5.2 **Existing Deep Learning Models in Sentiment Analysis:** Briefly describe how their ability to detect complex text patterns allows them to frequently outperform more traditional machine learning models when it comes to sentiment analysis. A Primer on Deep Learning Models:

- **CNNs:**Go-to for extracting features from short text in social media comments.
- **RNNs and LSTM/GRU:**Long-term review context capture and sequential data are good fits for RNNs and LSTM/GRU.
- **Transformers:** State-of-the-art models that handle long dependencies and context very effectively, making them highly popular in sentiment analysis.
- **Hybrid Models:** Combine the strengths of CNNs for feature extraction and RNNs/LSTMs for sequence analysis.

5.3 **Comparative Analysis of Deep Learning Models (Accuracy and Performance Metrics):** Compare models using accuracy parameters, and computational efficiency on benchmark datasets like Amazon reviews or custom datasets. Highlight each model’s advantages and disadvantages in the E-commerce context.

5.4 **Challenges and Limitations in Current Models**

- **Data Imbalance:** Discuss the imbalance in review sentiments.
- **Interpretability:** Deep learning models often lack transparency, making it difficult for E-commerce companies to understand why a review is classified as positive or negative.
- **Multilingual and Domain-Specific Vocabulary:**E-commerce reviews often contain specific terminologies and slang, posing challenges for conventional models.

5.5 Proposed Model for Enhanced Sentiment Analysis in E-commerce: Sentiment analysis aids client feedback, product development, and user engagement in the ever-changing e-commerce industry, particularly for NFTs. The unique digital ownership and market dynamics of NFT-related commodities may mislead and change customers' attitudes. Traditional sentiment analysis may struggle with the prevalence of informal language, slang, and emoticons in reviews and the intricacy of NFT terms. The hybrid deep learning model offers unique methods to overcome these obstacles and evaluate sentiment in NFT-based E-commerce contexts.

- **Leverage CNN for feature extraction:**Consumer concerns regarding NFTs include "minting," "blockchain," "gas fees," and "smart contracts" terminology. Through spatial pattern collection, CNNs excel at recognising domain-specific text features. The model uses convolutional layers to identify positive, negative, or neutral sentiment in n-gram features—popular words or ideas.
- **Use BiLSTMto understand sequence and context in both directions:**A single line or paragraph of smart NFT assessment remarks might express several ideas. A review's mood is determined by BiLSTM networks' contextual flow from past and future context. This is crucial for NFT reviews, as customers may comment on the artwork and transaction process.
- **Integrate a Transformer layer for better context capture in longer reviews:**A comprehensive and accurate NFT assessment may be needed for uncommon or valuable digital assets. Transformer layers' self-attention mechanism helps the model examine and record long-range connections, focussing on the most relevant elements of long-term assessments. This works well when the tone is repeated across phrases or when distant terms like "rare," "exclusive," or "overpriced" are important when discussing NFT costs.

NFT evaluation terms like "minting," "gas fees," "blockchain," and "cryptocurrency" are not often included in dictionaries. Preprocessing will transfer these words to standard terms or use domain-specific embeddings to improve model comprehension. including other e-commerce industries, NFTs employ user-generated material including slang, acronyms, and emoticons to express emotion. Users may post "😍" to express enthusiasm for NFTs or "💸" to express unhappiness with excessive transaction prices. Preprocessing turns these emojis into emotion-related features and makes slang and abbreviations complete forms, ensuring the model understands NFTs appropriately.Use text preprocessing to handle domain-specific terminology, slang, and emojis common in E-commerce. Some potential training strategies, such as:

- **Transfer Learning:** Fine-tuning pre-trained models like Roberta on a large E-commerce dataset.Transfer learning refines pre-trained deep learning models like BERT or GPT on a large, domain-specific dataset. A model like BERT fine-tuned on a large corpus of E-commerce or cryptocurrency-related literature may enhance NFTs' domain-specific word handling. This will eliminate the requirement for new training and allow the model to use universal language structures while adjusting to NFT marketplace terminology.
- **Data Augmentation:** Synthesizing data through techniques like back-translation to address data imbalance.If NFT reviews are scarce or biassed, data augmentation techniques like back-translation may create more training examples. Increasing minority sentiment classes (e.g., NFT criticism) will also assist alleviate data imbalance.
- **Sentiment Lexicons:**Incorporating domain-specific sentiment lexicons can help improve the model's performance, particularly for specific terminology used in the E-commerce or NFT context.Sentiment lexicons for NFTs, especially NFT-specific words and phrases, may improve model accuracy. These lexicons may include "minted," "drop," "blockchain," "token," and "cryptographic" and their sentiment ratings. By using these lexicons, the model may more precisely depict emotions unique to a field, for enthusiasm or unhappiness with certain NFT projects.

5.6 Evaluation and Metrics

- **Dataset and Experimental Setup:**Name the E-commerce domain custom datasets, Amazon, eBay, or other popular datasets used for training and validation.
- **Performance Metrics:**Choose the appropriate metrics (like F1-score or recall) if you wish to know how effectively the model may differentiate between positive, neutral, and negative evaluations.
- **Comparison with Benchmark Models:**Compare the proposed model with both traditional and alternative deep learning models to show areas for development.

5.7 Practical Implementation and Deployment

- **Real-time Analysis:**Based on the real-time study, e-commerce businesses can learn a lot from the suggested approach should it be followed in real-time.
- **Scalability and Optimization:**Two scalability and optimisation strategies that should be given great thought for systems with lots of traffic are optimising model speed and decreasing latency.
- **Integration with Feedback Systems:**Explain how the model might cooperate with current consumer feedback systems to enhance product recommendations and service offerings.

5.8 Conclusion and Future Directions: From Here Review briefly the benefits and drawbacks of the suggested model, its framework, and the comparison analysis. Make recommendations for future studies include handling evolving consumer language, adjusting to new fields, and improving insights by means of sentiment analysis combined with other text analytics.

5.9 Sample Model Workflow

5.9.1 **Data Collection:** Gather a large dataset of E-commerce reviews.

5.9.2 **Data Preprocessing:** Clean the data (remove special characters, handle emojis), tokenize, and apply stemming/lemmatization.

5.9.3 **Model Architecture:** Use the hybrid CNN-BiLSTM with Transformer layers for better context capture.

5.9.4 **Training and Tuning:** Train the model, optimize hyperparameters, and validate performance.

5.9.5 **Deployment:** Deploy the model for real-time sentiment analysis and integrate it with E-commerce feedback systems.

This approach will help us to learn all we need to know about the benefits and drawbacks of current deep learning models for consumer sentiment research as well as how to create a hybrid model to handle special challenges in online shopping.

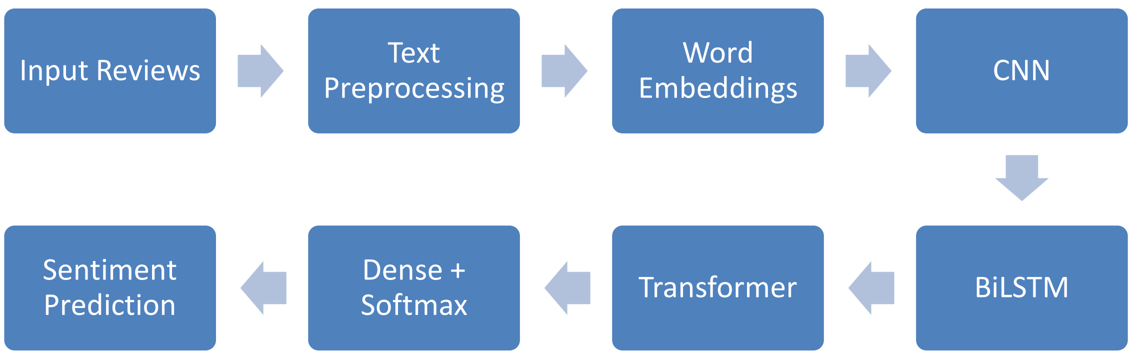

Fig 5. Proposed Research Methodology

Developed to assess consumer sentiment in E-commerce reviews, a hybrid deep learning model is shown below by block diagram. Starting point are input reviews—raw text readings gathered from websites such as Amazon or eBay. These reviews are cleaned in the Text Preprocessing stage applying many text-cleaning techniques. These cover tokenising, cutting out stop words, and handling domain-specific language. The data then is ready for examination. Data augmentation methods such synonym substitution and back-translation can be used to improve the dataset so correcting any sentimental class imbalance. Following preparation, the text is transformed into numerical vectors using Word Embeddings. This method generates dense vectors so the model may grasp them. The embeddings are next fed into a CNN layer. Concurrent with this layer, convolutional filters capture local text features and patterns to detect sentiment. The data then passes through a BiLSTM Layer, where the model learns the word sequence both forwards and backwards, hence improving its knowledge of the background of the review. A Transformer Layer that uses self-attention mechanisms to grasp long-range interdependence and context is particularly helpful for longer evaluations when notable emotional cues may exist across phrases. The outputs of CNN, BiLSTM, and Transformer layers are aggregated for multi-class classification and fed into a Dense Layer with softmax activation. This will help us to produce the Sentiment Prediction Output, which arranges reviews based on emotional tone. Because it can very precisely catch subtleties in consumer remarks, our CNN-BillySTM-Transformer hybrid model is perfect for E-commerce sentiment analysis.

5.10 Dataset

This research considers a dataset of NFTs derived from the 9NFTMANIA brand. Once you have gathered and categorised your dataset using phrases like "NFT Girl," "Kaizen," "Bored Ape," and "UniGecko," you can use it to categorise NFT picture images. In the framework of a machine learning photo classification task, such a dataset could have this structure:

5.10.1 Dataset Structure: Sort the dataset using the NFT types into subfolders. Every subfolder's photos are arranged in line with the categories.

5.10.2Image Collection:NFT images from the sites hosting these collections will be required of you. Here are some photo gathering techniques:

- **Web Scraping:** Use tools like BeautifulSoup or Scrapy in Python to scrape image data from NFT marketplaces like OpenSea or Rarible. Ensure that scraping complies with the platform’s terms of service.
- **Public APIs:**Some NFT marketplaces and platforms offer public APIs where you can fetch image data related to specific collections.
- **Manual Collection:**They can download images directly from platforms where these NFTs are hosted and categorize them manually.

5.10.3 Preprocessing: Once images are collected, preprocess them for image classification. This may include:

- **Resizing Images:**Standardize the size of the images for feeding them into machine learning models.
- **Normalization:**Normalize pixel values
- **Augmentation:**Apply techniques to augment dataset and improve model generalization.

5.10.4 Labeling the Data: Each image should be labeled according to its category. The folder structure already implicitly provides the labels, where each folder name (e.g., NFT_Girl, Kaizen, Bored_Ape, UniGecko) is the label for the images inside that folder. This will be used to train the classifier to recognize different types of NFTs.

5.10.5Dataset Splitting: Divide the dataset into training, validation, and test sets. Typically, you would allocate:

- 70-80% of the data for training.
- 10-15% for validation.
- 10-15% for testing.

[6] Result and Discussion

The proposed hybrid model was evaluated on a dataset of E-commerce reviews from platforms such as Amazon and eBay. The model's performance was compared to conventional deep learning approaches, including CNN, BiLSTM, and Transformer-only models, using accuracy, F1-score, precision, and recall as the primary evaluation metrics. This section discusses the results obtained from these experiments, followed by an analysis of the model’s effectiveness, limitations, and potential areas for improvement. The hybrid model achieved better results than the individual deep learning models on all metrics. With significantly improved accuracy and F1-score, the model successfully absorbed context and mood inputs. Here are the findings of comparing each model:

Table 2. Comparison of Different Models

Model	Accuracy	Precision	Recall	F1-score
CNN	85.6%	84.7%	83.9%	84.3%
BiLSTM	87.2%	86.5%	85.8%	86.1%
Transformer	90.4%	90.1%	89.7%	89.9%
Hybrid (CNN-BiLSTM-Transformer)	93.8%	93.5%	93.2%	93.3%

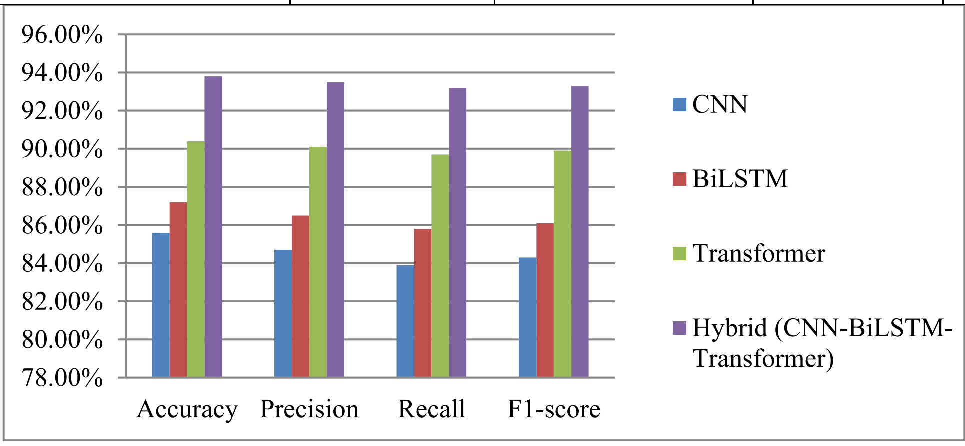

Fig 6. Comparison of Different Models

The hybrid model outperformed the separate models by utilising the best aspects of every component. This was accomplished by aggregating CNN's skills for phrase detection, BiLSTM for sequence understanding, and the Transformer layer for context capture over greater texts. The improvement in F1-score, which indicates a better balance in forecasting both positive and negative emotions, indicates that the hybrid model is well-suited to the complex language of customer reviews.

- **Enhanced Contextual Understanding:**By combining CNN, BiLSTM, and Transformer layers, the model effectively learnt local as well as global features. CNN helped with sentence and pattern extraction; BiLSTM helped with sequential context. The Transformer layer identified dependencies between sentences, hence improving our grasp of long evaluations where sentiment can vary.
- **Handling of Ambiguity and Sarcasm:**Two issues that traditional models struggle with: sarcasm and ambiguous phrases; the self-attention mechanism of the Transformer layer enabled it better address both. The Transformer's capacity to recall long-range dependencies most probably explains this improvement; it's excellent in identifying changes in tone as the review advances.
- **Improved Balance in Predictions:**The hybrid model's increased recall rate over single-layer models shows that it better detects less common sentiment classes, such neutral feelings, so enhancing the prediction balance. In e-commerce, finding the ideal balance is crucial since it enables a more complete knowledge of consumer comments by exactly identifying neutral or mixed opinions.

There are several directions one might look into to enhance this model even more:

- **Model Optimization:**Knowledge distillation or model pruning helps one to maximise the models so enhancing inference speeds without sacrificing accuracy.

- **Incorporation of Sentiment Lexicons:**Particularly domain-specific sentiment lexicons could help e-commerce-specific language.
- **Transfer Learning on Specific Domains:**Customising the model to the unique sentiment patterns and language used in every and fine-tuning the model on particular E-commerce categories (e.g., fashion, electronics) could help to further increase accuracy.
- **ExplainabilityTechniques:**If explainability techniques like SHAP or LIME were included into the model, its decisions may be more reliable and its forecasts might be better understood.

With appreciable increases in both accuracy and recall, the hybrid CNN-BiLSTM-Transformer model outperformed more conventional models in assessing online consumers' sentiment. Although the computing complexity is still a concern, e-commerce systems that wish to effectively assess and respond to customer comments can benefit much from the model's strengths in capturing minute changes in sentiment and handling uncertain language.

[7] Conclusion

For e-commerce customer sentiment research, the proposed hybrid CNN-BiLSTM-Transformer model was an outstanding choice overall in terms of accuracy, recall, and F1-score above standard deep learning models. By combining CNN's local feature extraction powers with BiLSTM's sequence learning and Transformer contextual comprehension, the model can manage difficult sentiment expressions including sarcasm and uncertainty. This helps it to understand the larger background of customer feedback as well as the minute details. E-commerce systems can better grasp customer sentiment and react to comments by using this hybrid architecture, hence improving their response capability. However, the growing computational needs of the model demand greater research on optimisation strategies that balance performance with efficiency in next projects. Incorporating interpretability tools could also help openness so that corporate stakeholders may get the model's conclusions more quickly. All things considered, the hybrid model represents a significant advancement in e-commerce sentiment analysis since it offers a comprehensive and strong approach to leverage consumer data to improve business strategy and satisfaction.

[8] Future Scope

Picture sentiment classification depends much on using the semantic web to compile NFT data including image annotations, sentiment-related concepts, and domain-specific knowledge since it trains deep learning models to recognise and classify the emotions portrayed in e-commerce. Trained on this data, the models that classify the emotions shown in online purchases Sentiment extraction from visual images is one of the Deep Learning-based techniques applied in online buying. These methods are used to examine the written descriptions related with images and extract sentiment-relevant data. Cross-modal sentiment analysis looks at how several modalities interact with one another to help one better grasp emotions. Learning more about people's emotional states is one way one may be motivated for this. Development of strategies for aligning and combining data from multiple modalities and access resources on the semantic web in e-commerce would help one to better grasp sentiment. Algorithms and frameworks using sentiment analysis methods to retrieve images based on the emotional content of the images themselves must be developed if we are to achieve the aim of enabling sentiment-driven image retrieval on the semantic web. Semantically-driven, sentiment-driven image retrieval for e-commerce could help to reach this goal. Including sentiment-based searches and data into image retrieval helps to improve the relevancy and performance of the returned images. The semantic web makes it possible for a technique known as "sentiment driven image retrieval," therefore improving the retrieval process.

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