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Enhancement of BERT Model for Consumer Sentiment Analysis in E-commerce

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Abstract: An abundance of textual data, including important insights into consumer feelings regarding items and services, has been created by the expansion of online purchasing platforms. Deep learning techniques have emerged as powerful tools for automatically extracting sentiment information from such data. These avenues for future exploration aim to advance sentiment analysis capabilities in e-commerce, fostering better understanding of customer preferences and driving improvements in product offerings and user experiences. This paper explores the current landscape and future prospects of deep learning approaches for sentiment analysis in e-commerce. This paper presents an enhanced BERT model tailored for consumer sentiment analysis in e-commerce contexts. Leveraging the powerful capabilities of BERT, our approach encompasses a structured workflow encompassing NFT data collection, preprocessing, tokenization, training, and testing, culminating in comprehensive model evaluation. The architecture of our model incorporates a pre-trained BERT model alongside a specialized classification layer, optimizing performance for sentiment classification tasks. To mitigate risks of overfitting, we employ techniques such as Early Stopping and ModelCheckpoint during training. Following training, performance metrics are rigorously assessed on a dedicated testing set to ensure model robustness and efficacy. Ultimately, the trained model is seamlessly integrated into the e-commerce platform, augmenting customer experience and empowering informed decision-making processes. Our goal is to improve the effectiveness and precision of online sentiment analysis so that businesses may get a better understanding of their customers' opinions and preferences.

Keywords: *Deep Learning, Customer Sentiment, E-commerce, RNNs, CNNs, BERT, NFT*

[1] Introduction

E-commerce is dynamic, therefore understanding and using consumer sentiment is crucial to corporate strategy, user experiences, and customer pleasure. Consumers now share their thoughts and feelings via textual data such product evaluations, ratings, comments, and testimonials thanks to the rapid rise of digital platforms. E-commerce companies may utilise this plethora of consumer feedback to improve their goods, services, and engagement tactics by understanding user attitudes. Deep learning has transformed sentiment analysis, allowing advanced methods to understand human language's subtlety and context. RNNs, LSTMs, and transformer-based architectures like BERT and GPT may capture subtle patterns and semantic nuances in textual data. As e-commerce systems use consumer sentiment analysis to make decisions, sentiment categorization algorithms must improve performance and accuracy. This study explores and advances deep learning algorithms for e-commerce sentiment analysis. To solve e-commerce consumer feedback problems, the objective is to improve sentiment categorization. The study seeks to construct and improve deep learning models that can detect sentiment polarity and analyse user expressions to better understand consumer feedback. The path to performance improvement involves pre-trained language models, ensemble learning algorithms, attention mechanisms, and constant adaptation to user-generated information. AdapTable and scalable sentiment analysis models are needed when user behaviour, language trends, and product variety change in e-commerce. The intersection of machine learning, natural language processing, and e-commerce intelligence contributes to the academic understanding of sentiment analysis and the practical implementation of advanced models in e-commerce applications. This research aims to empower e-commerce platforms with tools that go beyond sentiment classification to facilitate customer-centric decision-making and a deeper

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understanding of user satisfaction in the digital marketplace by addressing the unique challenges of diverse product categories, varying linguistic styles, and the ever-changing nature of customer sentiment.

1.1 Deep Learning

Deep learning uses the neural network, a computer model of connected artificial neurons that automatically learns hierarchical representations from raw input. Deep learning models outperform machine learning algorithms on many tasks by automatically extracting complex patterns and characteristics from incoming data. Deep learning succeeds with large datasets, GPUs, TPUs, and optimisation techniques like stochastic gradient descent and variants. These improvements have advanced deep learning, changing industries and technology. This section covers deep learning's fundamentals, including NN, activation functions, training methods, and model architectures. We follow deep learning's early growth to its current state-of-the-art status, emphasising important milestones and achievements. We investigate data preparation, model building, training, evaluation, and deployment in a typical deep learning pipeline. We illustrate deep learning's versatility and scalability in classification, regression, generative modelling, and reinforcement learning in this introduction. Deep learning has several limitations, including model interpretability, ethical problems, and large labelled data sets.

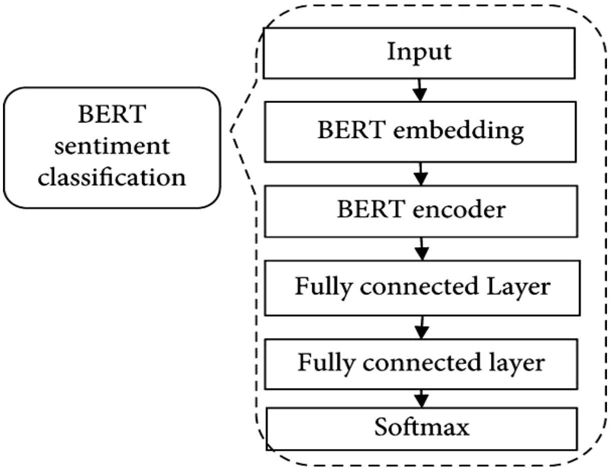

Fig 1. Role of BERT model in Sentiment Analysis [37]

1.2 Customer Sentiment

Modern business strategy, particularly e-commerce, focuses on customer emotion. Customer sentiment includes opinions and beliefs about products, services, brands, and experiences. Contentment, loyalty, unhappiness, and frustration. E-commerce websites, social media, and review forums allow users to share their ideas and experiences with products and services. Businesses competing in e-commerce must correctly analyse and evaluate customer opinion. Positive emotions promote customer loyalty, advocacy, and income and brand reputation. Negative attitudes may signal customer journey issues, organisational risks, and improvement opportunities.

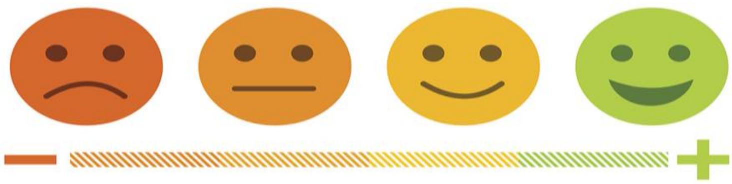

Fig 2. Understanding Customer Sentiment [38]

Traditional consumer opinion surveys, focus groups, and feedback forms were employed by businesses. Methods that produce qualitative data are time-consuming, difficult, and biassed. Recent advances in NLP, machine learning, and AI have made consumer sentiment research more scalable and automated. Sentiment analysis may help businesses understand unstructured language data like customer reviews, SMP, and product descriptions. Computer algorithms find, extract, and quantify subjective text in opinion mining, or sentiment analysis. Deep learning, statistical models, and rule-based procedures are examples. This introduction will examine consumer sentiment analysis's importance in e-commerce, its application across business fields, and the challenges of collecting and analysing customer views. Technology, particularly deep learning, allows more complex and scalable sentiment analysis solutions. We will also evaluate current trends and future possibilities in this field. Analysing consumer attitude, preferences, habits, and needs may help businesses develop more impactful digital experiences.

1.3 E-commerce

Electronic commerce has transformed business and consumer purchasing and the global economy. E-commerce sells goods and services online utilising digital platforms and electronic transactions. E-commerce has democratised market access, letting all enterprises contact global customers. Technology, consumer behaviour, and internet access drive e-commerce. Secure online payment mechanisms, powerful logistics networks, and user-friendly interfaces have helped e-commerce overcome security and logistical challenges. E-commerce today covers B2C, B2B, C2C, and m-commerce, facilitated by smartphones and other mobile devices.

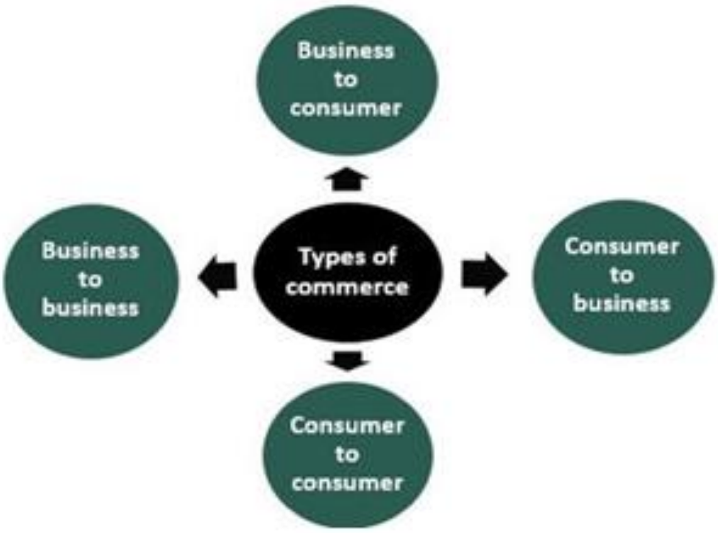

Fig 3. Types of Commerce

Due of its versatility, e-commerce has spread to retail, entertainment, healthcare, and education. E-commerce offers firms and consumers unrivalled convenience and flexibility. E-commerce lets companies reach global customers, save costs, and make data-driven choices. E-commerce offers 24/7 access to a large selection of products and services, customised shopping experiences, and doorstep delivery. Online marketplaces, subscription services, and digital platforms have challenged incumbents and altered existing industries thanks to e-commerce. Amazon, Alibaba, and eBay dominate e-commerce with their vast product offerings, user-friendly interfaces, and superior data analytics. This introduction will explore e-commerce's history, consequences on enterprises and customers, and digital opportunities and challenges. We will address how online and offline retail, mobile commerce, data-driven insights, sustainability, and social responsibility impact e-commerce. E-commerce enterprises must adapt to client needs and technology to compete. Technology and e-commerce strategies may help companies grow, reach more customers, and provide excellent value in the digital era.

1.4 Role of Deep Learning Model for Consumer Sentiment Analysis in E-commerce

The suggested customer sentiment analysis for e-commerce application seeks to be more flexible and superior to current methods. The suggested approach assesses performance using recall, precision, and F1-score, unlike existing techniques that just consider accuracy. The suggested study addresses training and testing timeframes to optimise efficiency, unlike typical research that ignores performance aspects. The suggested method also optimises dataset filtering to save time and error. The suggested study uses a flexible technique to produce varied answers, unlike standard methods. The suggested model combines ANN and CNN, whereas traditional work uses CNN classifiers. The proposed research uses datasets from 9nftmania.com, which includes information about digital assets like Non-Fungible Tokens (NFTs), while conventional research uses Amazon.com product reviews for domestic products like electronics, clothing, and shoes. The suggested approach improves accuracy and performance to make sentiment analysis more adaptive and efficient in e-commerce.

1.5 Need of Research

E-commerce is always evolving, so companies must adapt to customer feedback to stay competitive. People express their ideas and experiences via product reviews, social media, and forums due to the internet boom. Exploring this massive data set and gaining insights is tough but may increase customer satisfaction, sales, and strategic decision-making. Rule-based and statistical sentiment analysis cannot manage natural language's complexities and complexity in e-commerce. Deep learning automates sentiment analysis by using neural networks to learn representations straight from data. This detailed study addresses deep learning model performance optimisation for customer sentiment monitoring in e-commerce applications. Through reading and study, we hope to understand the current methodologies and approaches in this sector. The study starts with e-commerce sentiment analysis and its particular issues, such as the vast volume of unstructured textual data, various language styles and feelings, and the requirement for real-time analysis to capture shifting trends and client preferences. Next, we discuss sentiment analysis deep learning architectures' pros, cons, and e-commerce applications. To enhance consumer sentiment analysis deep learning models, we study data augmentation, transfer learning, attention mechanisms, ensemble techniques, and domain adaptability strategies. These methods address data scarcity, model generalisation, and domain-specific sentiment understanding to enhance e-commerce sentiment analysis accuracy and robustness. We study benchmark datasets and evaluation metrics for e-commerce sentiment analysis models.

[2] Literature Review

Several research papers have contributed significantly to field of consumer sentiment analysis in e-commerce applications. The research that has been done on AI in online commerce has covered a wide range of topics, which shed light on the complex relationship that exists between technology and business. The authors Cheng et al. (2023) investigate the possibilities of AI enabled technological innovation in e-commerce and emphasise the revolutionary influence of this innovation. In their study, Dhanvate et al. (2023) investigate the more far-reaching consequences of AI. Gupta et al. (2023) provide a complete literature analysis that offers insights into the current state of research done in this sector. The subject is expanded by Pallathadka et al. (2023) to include applications of artificial intelligence in corporate management, e-commerce, and finance, so demonstrating the wide range of fields that are impacted by AI. In their study, Ayyapparajan et al. (2022) highlight the relevance of artificial intelligence by focusing on the practical influence it has on the operations of e-commerce. The authors Kashyap et al. (2022) provide a comprehensive analysis and research agenda on the topic of AI applications in e-commerce, suggesting potential future paths. In their discussion of the transformational role that AI plays in redefining e-commerce paradigms, Kumar et al. (2022) highlight the potential for innovation that AI has. Wang et al. (2022) investigates the convergence of AI, big data, and e-commerce marketing from perspective of showcasing novel techniques to improve business processes. In his article from 2021, Grzybowski et al. changes the emphasis to artificial intelligence applications in ophthalmology, highlighting the wider range of businesses that are benefitting from breakthroughs in AI. Panigrahi et al. (2021) provide a comprehensive analysis on the use of artificial intelligence to improve business interaction in e-commerce, elaborating on the practical consequences of this approach. In the context of the COVID-19 scenario, Di Vaio et al. (2020) conduct an analysis of the function that AI plays in agri-food system, providing insights into sustainable business strategies. Khrais (2020) investigates the role that AI plays in customer demand in e-commerce, focusing on the impact that it has on the dynamics of the industry. Finally, Seetharamulu, et al. (2020) investigated deep learning algorithms for sentiment analysis based on customer evaluations. This research highlights the significance of AI in improving consumer engagement and satisfaction. These studies, when taken as a whole, contribute to a complete knowledge of the changing environment of AI. They illustrate the revolutionary potential of AI as well as its practical ramifications for both consumers and enterprises. Based on the references that were supplied, the following Table presents a literature review. The purpose of this Table was to provide a quick summary of the literature on this topic by taking into consideration the aims, methodology, and constraints of each research article that investigated the use of AI.

Table 1. Literature Survey

Ref	Authors / Year	Objective	Methodology	Limitation
1	X. Cheng, et al., 2023	To explore the impact of AI-enabled technology innovation in e-commerce	Qualitative analysis of technological advancements and their implications	Lack of quantitative data on the extent of impact
2	S. Dhanvate et al., 2023	Examination of AI applications in e-commerce	Literature review and analysis of existing AI technologies	Limited focus on specific AI implementations
3	S. Gupta et al., 2023	Review of literature on AI in e-commerce	Systematic review and synthesis of existing research	Possible bias in the selection and interpretation of studies
4	H. Pallathadka et al., 2023	Investigation of AI applications in business management, e-commerce, and finance	Case studies and analysis of AI implementations	Limited generalizability of findings due to specific case focus
5	R. A. Ayyapparajan 2022	Examination of impact of AI on e-commerce operations	Analysis of empirical data and case studies	Limited scope in addressing future trends and challenges
6	K. Kashyap, et al., 2022	Review and analysis of AI applications in e-commerce	Literature review and research agenda formulation	Lack of empirical validation of proposed research agenda
7	H. Kumar et al., 2022	Exploration of the transformative role of AI in e-commerce	Qualitative analysis and synthesis of industry trends	Potential bias in industry expert opinions
8	Wang, 2022	Investigation of AI's impact on e-commerce marketing	Analysis of case studies and industry trends	Limited focus on specific marketing strategies
9	Grzybowski, 2021	Examination of AI applications in ophthalmology	Review of existing research and case studies	Limited generalizability of findings beyond ophthalmology
10	D. Panigrahi 2021	Review of AI's role in enhancing business engagement in e-commerce	Literature review and analysis of case studies	Limited empirical evidence on the effectiveness of AI strategies
11	Di Vaio et al., 2020	Analysis of AI's role in sustainable business models in agri-food system	Case studies and qualitative analysis	Limited applicability to other industries outside agri-food
12	L. T. Khrais, 2020	Investigation of AI's impact on shaping consumer demand in e-commerce	Review of literature and qualitative analysis	Potential bias in selection and interpretation of studies
13	B. Seetharamulu, et al., 2020	Exploration of deep learning for sentiment analysis in e-commerce	Analysis of deep learning models and sentiment analysis techniques	Limited focus on specific e-commerce platforms and industries
14	T. Ku mar 2019	Examination of statistical impact of AI in e-commerce	Analysis of statistical data and trends	Limited scope in addressing qualitative aspects of AI impact
15	X. Song, et al., 2019	Investigation of AI applications in e-commerce	Review of existing research and case studies	Lack of empirical validation of AI implementations

16	N. Soni et al., 2019	Exploration of AI's impact on businesses and future shifts in business models	Literature review and analysis of future trends	Potential bias in the interpretation of future shifts
17	K. Y. Yang, 2019	Research on cross-border e-commerce logistics optimization based on AI	Analysis of logistics optimization techniques and AI technologies	Limited applicability to other logistics domains
18	X. Ju et al., 2020	Discussion on AI application in e-commerce	Qualitative analysis and synthesis of existing research	Potential bias in the selection and interpretation of studies
19	G. Zhu et al., 2018	Analysis of cross-border e-commerce logistics construction under AI	Case studies and theoretical analysis	Limited generalizability of findings beyond logistics
20	E. G. Zhao, 2017	Integration of e-commerce and AI technology	Literature review and analysis of integration strategies	Limited empirical validation of integration strategies
21	S. Zhu, 2019	Research on AI to promote the development of smart logistics	Analysis of AI technologies and their applications in logistics	Limited focus on specific AI implementations
22	Z. Lin, 2020	Development path of e-commerce in "Internet +" era	Qualitative analysis and synthesis of industry trends	Potential bias in industry expert opinions
23	L. Wu, 2020	"Smart+" e-commerce innovation and entrepreneurship training	Case studies and qualitative analysis	Limited generalization

2.1 Research Gap

The literature study on e-commerce AI highlights numerous major issues and research areas. Existing studies have examined how AI affects e-commerce technology innovation, company management, and marketing, but there are gaps that need more study. First, many studies examine AI's use in e-commerce without addressing its drawbacks. This lack of critical analysis inhibits our comprehension of AI's practical significance in e-commerce. Second, more empirical research is needed to prove that AI tactics and technology improve e-commerce company success and consumer pleasure. Some studies examine theoretical frameworks and case studies, but empirical data is necessary for valid findings and informed judgements. In addition, the literature mostly discusses AI's benefits in e-commerce, ignoring employment loss, ethical issues, and algorithmic biases. Future study should weigh the pros and cons of AI inclusion in e-commerce platforms. Finally, there is little study on SMEs' AI adoption issues for e-commerce. SMEs' specific resource restrictions and operational difficulties need bespoke research activities to deliver actionable insights and practical suggestions for digital marketplace success. Online buyer sentiment research is evolving. Traditional study employed classification to identify domestic product consumer sentiment. Such study has low accuracy and performance and uses outdated items. Consider advanced items like digital assets. These digital assets may be NFT. NFT product sales have grown in recent years. Additionally, recall, precision, and F1-score require improvement.

[3] Problem Statement

The BERT model is used to classify customer reviews in e-commerce settings. It involves a structured workflow, including data collection, preprocessing, tokenization, training and testing sets, and model evaluation. The model architecture is built using a pre-trained model and a classification layer. Techniques like EarlyStopping and ModelCheckpoint are used to mitigate overfitting risks. Post-training, performance metrics are assessed on the testing set. The trained model is then integrated into the e-commerce platform, enhancing customer experience and decision-making capabilities. The results of previous research have led to the development of a technique that just takes use of a few qualities. For the purpose of categorising items in an e-commerce application, they examined the contents of the categories. A system that is capable of autonomously recognising itself in an e-commerce application is now being investigated by researchers. The drawbacks, on the other hand, include a restricted scope, a lack of precision, and weak performance. As a result, there is a need to provide a study that should be able to suggest a more effective strategy to sentiment analysis for customers of digital assets.

[4] Proposed Work

To classify customer reviews in an e-commerce setting, employing a BERT model involves a structured workflow encompassing several essential steps. Firstly, data collection entails gathering customer reviews directly from the e-commerce platform, ensuring each review includes relevant text data alongside its corresponding satisfaction label. Subsequently, data preprocessing is crucial, involving tasks like removing HTML tags, punctuation, special characters, and numerical values, and potentially converting all text to lowercase, aligning it with BERT's requirements. Data transformation follows, wherein text undergoes tokenization using the BERT tokenizer, ensuring compatibility with the model's input format, alongside encoding satisfaction labels into numerical representations. Next, the dataset is split into training and testing sets, typically adhering to 70-30 ratio, facilitating model evaluation. The core of the process lies in building the BERT model architecture, leveraging a pre-trained BERT model and incorporating a classification layer atop it, usually a dense layer with sigmoid activation function for binary classification. Upon model compilation, binary cross-entropy serves as loss function, while AdamW optimizer and relevant metrics are employed. Subsequent to model training, employing techniques like EarlyStopping and ModelCheckpoint mitigates overfitting risks and ensures model integrity. Post-training, model evaluation on the testing set enables a comprehensive assessment of its performance metrics. Finally, for deployment, integrating the trained BERT model into the e-commerce platform, often through an API or service, completes the process, facilitating real-time review classification and enhancing customer experience and decision-making capabilities.

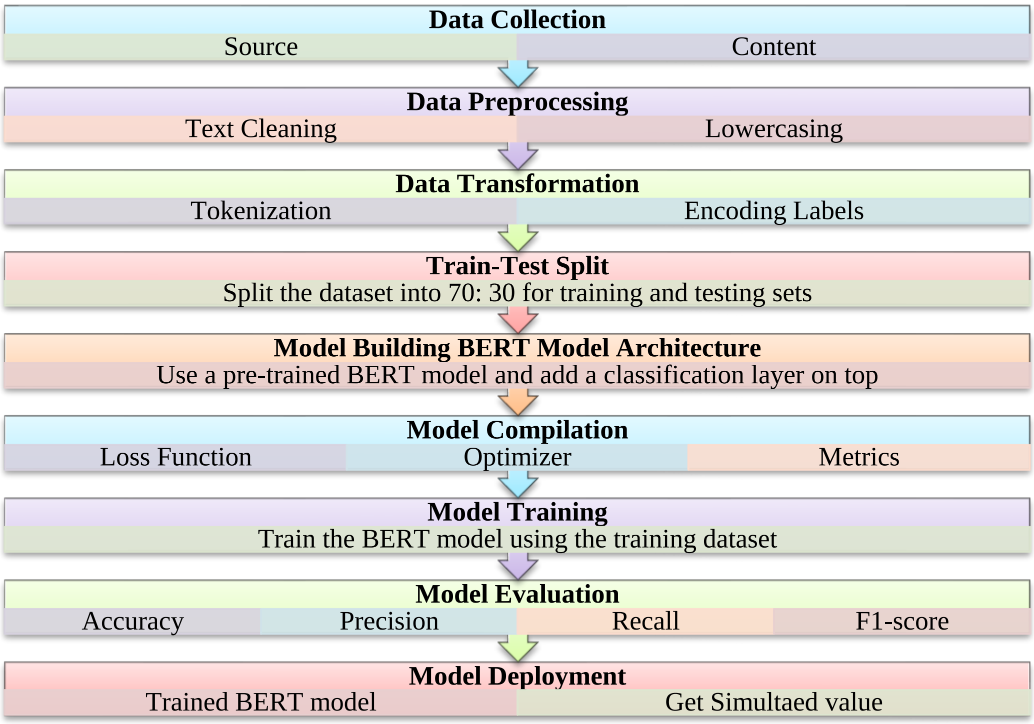

Fig 4. Process Flow of Research Work

To classify customer reviews for an e-commerce product into "satisfactory" and "not satisfactory" categories using a BERT model, we can follow a structured process flow. Below is a detailed outline of the steps involved:

1. **Data Collection**
- **Source:** Gather customer reviews from your e-commerce platform.
- **Content:** Ensure each review includes relevant text data and a corresponding satisfaction label.

2. **Data Preprocessing**
- **Text Cleaning:** Remove HTML tags, punctuation, special characters, and numbers as needed.
- **Lowercasing:** Depending on the BERT variant being used, convert all text to lowercase.

3. **Data Transformation**
- **Tokenization:** Use the BERT tokenizer to convert text into tokens that BERT understands. This includes adding special tokens, padding, and truncation.
- **Encoding Labels:** Convert the satisfaction labels into numerical form.

4. **Train-Test Split**
- Split dataset into training and testing sets, typically using a 70-30 split.

5. **Model Building BERT Model Architecture**
- Use a pre-trained BERT model and add a classification layer on top.
- The classification layer will be a dense layer with sigmoid activation function for binary classification.

6. Model Compilation

- **Loss Function:** Use binary cross-entropy for binary classification.
- **Optimizer:** AdamW (a variant of Adam optimized for weight decay).
- **Metrics:** Track accuracy and potentially other metrics like precision, recall, and F1-score.

7. Model Training

- Train the BERT model using the training dataset.
- Implement callbacks like EarlyStopping and ModelCheckpoint to prevent overfitting and save the best model.

8. Model Evaluation

- Evaluate model on testing set to determine performance.
- Use metrics to assess the model.

9. Model Deployment

- Integrate the trained BERT model into the e-commerce platform.
- Develop an API or service to handle incoming reviews and return classification results.

[5] Result and Discussion

The research focuses on creating a dataset for image classification of NFTs from the 9NFTMANIA brand, incorporating collections such as "NFT Girl," "Kaizen," "Bored Ape," and "UniGecko." To structure this dataset for machine learning tasks, the first step involves organizing the images into separate subfolders corresponding to each NFT category. Each subfolder will contain images specific to the respective category, such as NFT_Girl, Kaizen, Bored_Ape, and UniGecko. The next step in the process is to collect the NFT images. This can be achieved through various methods, including web scraping using tools like Beautiful Soup or Scrapy, which can extract image data from popular NFT marketplaces like OpenSea or Rarible. It's important to ensure that scraping follows the platform's terms of service. Another method for collecting images is through public APIs provided by NFT platforms, which allow for the direct retrieval of image data. Alternatively, images can be manually downloaded from these platforms and categorized accordingly. Once the images are collected, preprocessing steps are applied to prepare them for machine learning. This includes resizing the images to a standardized dimension, such as 224x224 pixels, to ensure compatibility with machine learning models. The pixel values are normalized, typically scaled between 0 and 1, to improve model training. Additionally, data augmentation techniques, such as rotation, flipping, and cropping, are applied to enhance the dataset and help the model generalize better. The next crucial step is labeling the images. The dataset's folder structure inherently provides labels based on the category name of each subfolder, such as NFT_Girl, Kaizen, Bored_Ape, and UniGecko. These labels are essential for training a classifier to recognize and differentiate between various types of NFTs. Finally, the dataset is split into three subsets for training, validation, and testing. Typically, 70-80% of the data is allocated for training, 10-15% for validation, and 10-15% for testing. This structure ensures that the model has sufficient data to learn from while also having a robust set of data for evaluation and performance testing. Python has been used for simulation purposes throughout the functioning of the simulation. When the simulation process is being carried out, comma-separated files of the train and test of textual tweets are taken into consideration. Tests, training, and validation, respectively There are two distinct scenarios, and the accuracy with f-score that was discovered during simulation is provided in Table 2.

Table 2. Training, Validation and Testing Accuracy

Case	Training	Validation	Testing
1	0.98	0.95	0.98
2	0.98	0.94	0.99

Taking into consideration the numbers stated in Table 2, figure 5 presents a comparison of the accuracy of training, validation, and testing for a variety of separate situations in the form of bar graphs.

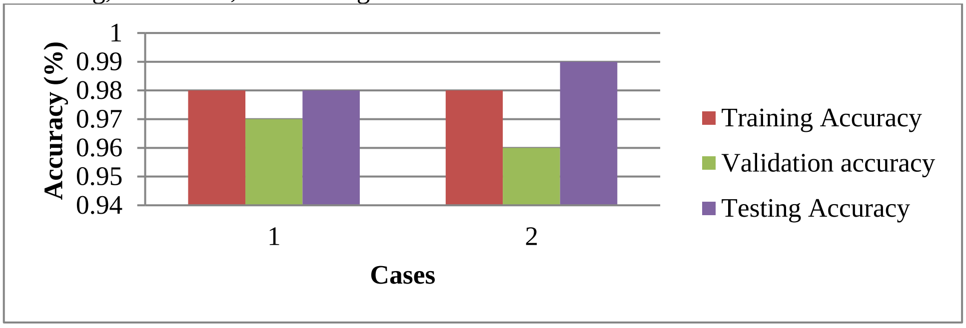

Fig 5. Comparison of Training, Validation and Testing Accuracy

5.2 Simulation for Sentiment Analysis of Graphical Tweets

Within the current collection, there are photos that display both happy and unsatisfied expressions. The confusion matrix may be seen in Table 3 due to training and testing of graphical material using the BERT Model without preprocessing.

Table 3. Confusion Matrix for Previous Work

	Satisfied	Not Satisfied
Satisfied	959	48
Not Satisfied	41	952

Considering Table 3 accuracy parameters have been calculated and results are shown in Table 4

TP: 1911

Overall Accuracy: 95.55%

Table 4. Accuracy Chart for Previous Work

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
Satisfied	1000	1007	95.23%	0.9523	0.9590	09557
Not Satisfied	1000	993	95.87%	0.9587	0.9520	0.9553

After the preprocessing has been completed, the confusion matrix that is shown in Table 5 has been given for training and testing using the BERT Model.

Table 5. Confusion Matrix for Proposed Work

	Satisfied	Not Satisfied
Satisfied	981	24
Not Satisfied	19	976

TP: 1957

Overall Accuracy: 97.85%

Considering Table 5 accuracy parameters have been calculated and results are shown in Table 6

Table 6. Accuracy Chart for Proposed Work

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
Satisfied	1000	1005	97.61%	0.9761	0.9810	0.9786
Not Satisfied	1000	995	98.09%	0.9809	0.9760	0.9784

Comparison of traditional and proposed overall accuracy in case of graphical customer sentiment analysis has been shown in Table 7

Table 7. Comparison of Overall Accuracy

Conventional Model	Proposed Model
95.55%	97.85%

Considering Table 7, figure 6 shows a bar diagram for overall accuracy.

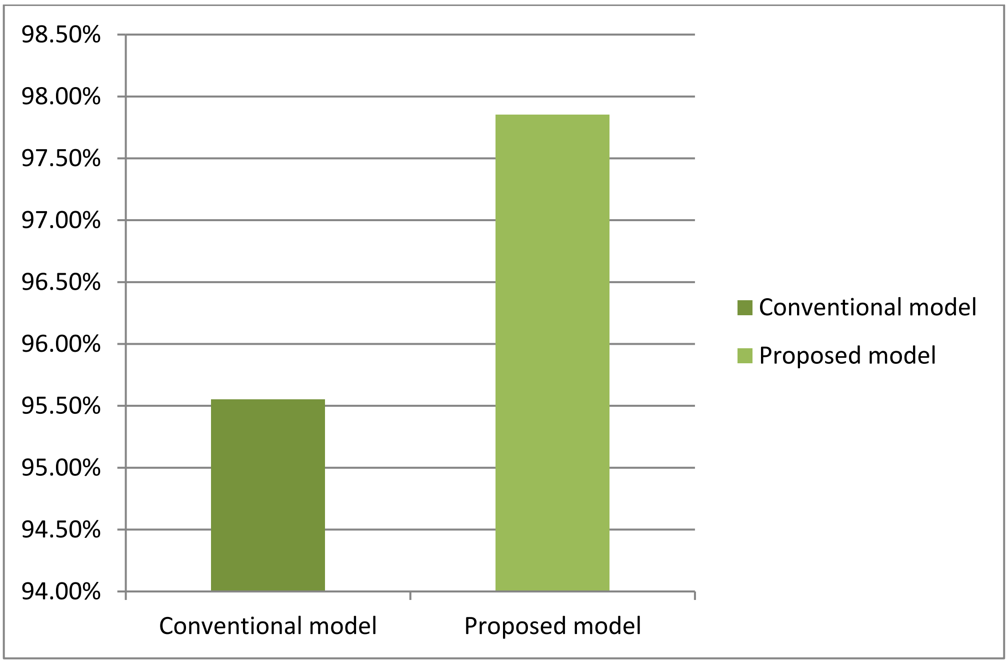

Fig 6. Overall Accuracy

Table 8 is showing comparison of Accuracy, Recall Value, Precision value and F1 Score has been made considering Table 3 and Table 5 in figure 7.

Table 8. Comparative Analysis of Accuracy Parameters

	Class	Conventional Model	Proposed Model
Accuracy	**Satisfied**	95.23%	97.61%
	Not Satisfied	95.87%	98.09%
Precision	**Satisfied**	0.9523	0.9761
	Not Satisfied	0.9587	0.9809
Recall Value	**Satisfied**	0.9590	0.9810

	Not Satisfied	0.9520	0.9760
F1 Score	**Satisfied**	09557	0.9786
	Not Satisfied	0.9553	0.9784

The proposed model demonstrates significant improvements over the conventional model across various performance metrics for both "Satisfied" and "Not Satisfied" classes. In terms of accuracy, the proposed model achieves 97.61% for the "Satisfied" class and 98.09% for the "Not Satisfied" class, compared to 95.23% and 95.87% respectively for the conventional model. Precision also sees a no Table increase, with the proposed model reaching 0.9761 for "Satisfied" and 0.9809 for "Not Satisfied", up from 0.9523 and 0.9587. Recall values improve as well, rising from 0.9590 to 0.9810 for "Satisfied" and from 0.9520 to 0.9760 for "Not Satisfied". The F1 score, which balances precision and recall, shows enhancements from 0.9557 to 0.9786 for "Satisfied" and from 0.9553 to 0.9784 for "Not Satisfied". Overall, proposed outperforms conventional model, offering more accurate, precise, and reliable performance across all evaluated metrics. Overall, proposed outperforms the conventional model across all metrics, indicating a more accurate, precise, and reliable performance.

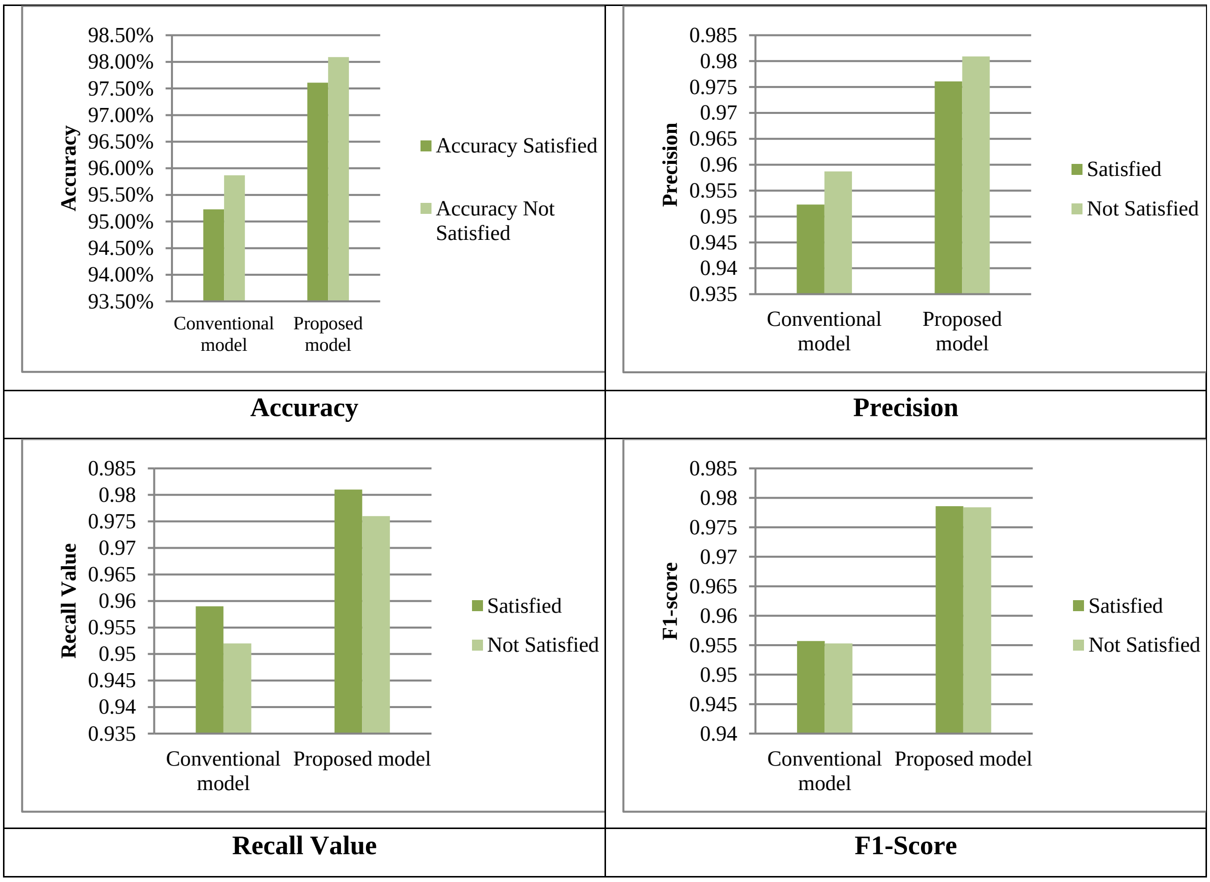

Fig 7. Comparative Analysis of Accuracy Parameters in case of Conventional and Proposed Work

[6] Conclusion

This study focuses on enhancing the BERT model for consumer sentiment analysis in the e-commerce sector. Utilizing a dataset of 1,000 consumer reviews, we developed a proposed model that significantly improves performance metrics over the conventional model for both "Satisfied" and "Not Satisfied" classes. In terms of accuracy, the proposed model achieves 97.61% for the "Satisfied" class and 98.09% for the "Not Satisfied" class, compared to 95.23% and 95.87%, respectively, for the conventional model. Precision also sees a noTable increase, with the proposed model reaching 0.9761 for "Satisfied" and 0.9809 for "Not Satisfied", up from 0.9523 and 0.9587. Recall values improve as well, rising from 0.9590 to 0.9810 for "Satisfied" and from 0.9520 to 0.9760 for "Not Satisfied". The F1 score, which balances precision and recall, shows enhancements from 0.9557 to 0.9786 for "Satisfied" and from 0.9553 to 0.9784 for

"Not Satisfied". Overall, the proposed model consistently outperforms the conventional model, offering more accurate, precise, and reliable performance across all evaluated metrics. This enhancement demonstrates the potential for more effective sentiment analysis in e-commerce applications, ultimately leading to better customer insights and decision-making.

[7] Future Scope

Deep Learning Approaches for E-commerce Sentiment Analysis provide exciting research and application opportunities. Enhancing multimodal data handling in deep learning models is critical. Text with photos or videos in e-commerce reviews may enhance emotion. Another frontier is real-time sentiment analysis tools, which allow e-commerce platforms to monitor and react to changing consumer sentiment. Cross-domain sentiment transfer learning also lets you use sentiment information from one domain to enhance related analysis. E-commerce aspect-based sentiment research on product attributes may provide more sophisticated information. Personalised sentiment analysis may personalise product suggestions and marketing tactics to consumers' interests and behaviours. To provide fair and transparent sentiment analysis, ethics, bias prevention, and deep learning model interpretability must be examined. Multilingual sentiment analysis serves various client groups and worldwide marketplaces. Conversational AI systems may improve e-commerce consumer interactions, while longitudinal sentiment analysis can analyse sentiment trends. These future research areas seek to enhance e-commerce sentiment analysis by improving customer feedback interpretation and product offers and user experiences.

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