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Sentiment Analysis for Seller Integrity Authentication on a Business Page

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Abstract
Markets have transformed over time from being predominantly analogue to becoming increasingly digital, presenting a plethora of opportunities for businesses to exploit in terms of improving and streamlining business processes. As technology advanced, the digital markets have given businesses the platform for better visibility and more stability. However, a buyer's inability to accurately evaluate sellers' authenticity, based on ratings and reviews on items they wish to purchase on a business page, presents a significant vulnerability for dubious sellers who may use fraudulent ratings and reviews to exploit unsuspecting buyers. This study adopts a machine learning approach to authenticate seller integrity on business pages through sentiment analysis. Data was extracted from customer reviews and ratings from selected brands of digital products across five major e-commerce sites: Jumia, Konga, Amazon, eBay, and Aliexpress. The model was built using Support Vector Machine algorithm to categorize the sentiments expressed in reviews as positive, negative, or neutral. The machine learning approach was selected due to its effectiveness in pattern recognition, adaptability to evolving data patterns and its suitability in providing high accuracy in sentiment classification. The model's performance was assessed with the training dataset yielding 99.58% accuracy and the test dataset achieving 97.27% accuracy. The results present a reliable method for enhancing consumer trust in online marketplaces by verifying seller authenticity based on their ratings and reviews on a business page.

Keywords: *Sentiment Analysis, Product Rating, Product Review, Machine Learning, Seller Integrity.*

1. INTRODUCTION

Marketplaces have existed since the beginning of time, when humans began exchanging products and services with one another. These marketplace operations were informal and depended on barter systems, in which sellers and buyers exchanged goods and services directly without any standardized exchange medium. As agriculture developed, surplus production informed the establishment of more organized forms of trade. With the emergence of long-distance trade routes, such as the Silk Road, marketplaces became intercontinental as trade extended beyond local boundaries. Emporiums and bazaars became business hubs for trading a variety of exotic goods, such as spices, textiles, and precious metals. [1,2]. Markets have transformed over time from being predominantly analogue to becoming increasingly digital, presenting a plethora of opportunities for businesses to explore [3].
Commerce (or electronic commerce) is a broad term that refers to the act of conducting business or commercial transactions over the internet [4]. The general public did not widely accept e-commerce until the late 1990s, despite technologies like electronic data exchange and electronic money transfer enabling early online commercial transactions as early as 1994. At that time, due to higher security standards and increased internet access availability, it became possible to purchase things using secure payment methods and an electronic checkout process [5].

As technology advances, the value-added value that digital markets provide to businesses becomes more visible and well-established [6]. The online marketplace helps alleviate the stress and hassles associated with shopping in a physical store or market. Individuals can place orders from the comfort of their own homes or from wherever they are at the time of ordering, and they will get

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delivery of their products at the scheduled time. As a result of this transition from the traditional marketplace to a digital alternative, customers now have access to a variety of options, better freedom of choice, and more time to perform other tasks [7].

While an online store is a subset of an e-commerce platform, both are digital marketplaces, it is critical to understand that an e-commerce platform and an online shop are two unique and separate entities. In other words, e-commerce is a marketplace that enables merchants to communicate with and sell their products or services to a targeted customer base via the internet. The owner of an e-commerce website is responsible for connecting suitable sellers and customers in order to create sales via an efficient multi-seller platform. Suppliers benefit from the website's marketing and sales, while the e-commerce website's owner profits from each transaction. On the other hand, an online store refers to a single firm that exclusively operates online, selling either its own products or those of its affiliates. The firm that owns the website and merchandise is solely responsible for marketing and operating them [3].

As is true in other nations, the Nigerian market is gradually transitioning away from traditional retailing and toward internet commerce. As a result of this development, e-commerce platforms such as Jumia, Konga, PayPorte, and others have emerged to serve the local market's needs. With an internet penetration of about 46% and 76.7 million Nigerians being digital shoppers, the number of Nigerian online shoppers is expected to reach 122.5 million by 2025 from the current 76.7 million [8]. Nigerians are increasingly aware of the obvious advantages of these online marketplaces.

While e-commerce has eliminated the necessity for physical interaction, it also creates a number of challenges. One of these is the buyer's inability to verify the quality of the goods before making a purchase. To combat this, legitimate e-commerce websites, which are governed by regulations established by a central authority, introduced measures to safeguard buyers from fraudulent sellers who could try to take advantage of the aforementioned challenge [9]. These policies vary among sales channels and applications, but they frequently revolve around safeguarding the buyer's right to get the items they have paid for, as well as their right to a full or partial refund if the product they have purchased does not meet the buyer's expectations. The industry-standard measure of introducing a rating and review system to evaluate sellers in the e-commerce space curtails the activities of fraudulent sellers. Customers can use the site to rate and share the purchasing experience they had with a particular seller and their level of satisfaction with the goods they received [10, 11].

As a result of this ranking, top-rated sellers are more likely to be suggested to customers, since customers are assured of attaining the most value for their money and consequently having a fulfilling shopping experience [9]. The rating and review system established across e-commerce platforms places the onus on sellers to deliver exceptional customer satisfaction in order to obtain favourable ratings and reviews from customers, hence projecting their visibility and authenticity to prospective customers. However, some dubious sellers try to rig the system by placing fake ratings and reviews on their pages in order to gain the same reputation and visibility as pages offering authentic services. Customers may also encounter difficulties purchasing a product from a seller's page due to the plethora of reviews available. As a result of this practice, buyers who rely on the rating and review system to recommend a reputable seller may be exposed to buyer disorientation, impairing their ability to make sound judgments and putting them at risk of being tricked into buying substandard products.

2. RELATED WORKS

This section discusses concepts and previous research work related to the subject matter.

2.1 Related Concepts

Markets have altered over time from being largely analog to being increasingly digital. The online marketplace helps lessen the stress and headaches associated with purchasing in a real store or market. Customers can rest assured that their items will arrive precisely when they need them, regardless of their location at the time of placing their order.

Customers now have more options, greater freedom of choice, and more time to complete other chores as a result of the traditional marketplace's shift.

The goal of natural language processing (NLP), a branch of artificial intelligence (AI), is to enable computers to comprehend texts and spoken language in a way that mirrors human comprehension. NLP is a field that combines computational linguistics (rule-based modeling of human language) with statistics, machine learning, and deep learning to create new ways of understanding and understanding others. Combining these technologies, it becomes easier for computers to process human speech in text or audio form, "unravel" its holistic meaning, including the intent and perception of the speaker or author, and "translate" this understanding into action [12].

Sentiment analysis is focused on extracting subjective information from source documents and assisting businesses to comprehend social sentiment while monitoring online conversations about their brands, products, and services. For collecting insight from textual data on e-commerce websites, sentiment analysis is an essential and frequent approach. Messages, tweets, and comments sent to the e-commerce site generate enormous amounts of text data every day. People can also express their thoughts through emotional expressions like emojis, reviews, and ratings. The extraction of product information from online evaluations aids in customer education and decision-making [13].

The success of e-commerce platforms is dependent on building trust. These systems collect and analyze consumer feedback to generate an overall trust score for sellers. By offering more detailed insights into customer experiences, sentiment analysis of reviews improves these systems. It is crucial to identify and mitigate fraudulent vendor activities in order to preserve the integrity of the online marketplace. Sentiment analysis is efficient in identifying patterns of discontent or deception that may suggest fraudulent behavior [10].

The primary goal of this research is to develop a robust system that deploys sentiment analysis to authenticate the integrity of sellers on e-commerce platforms by providing a robust mechanism for verifying seller integrity using customer sentiments expressed in reviews, thus improving the detection and reduction of fraudulent activities.

2.2 Review of Related Literature

Poomka *et al.,* [14] developed a sentiment analysis model for categorizing product reviews as positive or negative. The classification approach was based on the integration of word processing methods (Bag of Words, BoW, and WordEmbedding) with machine learning algorithms (logistic regression, Naive Bayes, SVM, and NN) and deep learning algorithms (LSTM and GRU).

A sentiment analysis model for accurate distinction between positive and negative emotional input was proposed by Rakibul *et al.,* [15]. The model demonstrated sentiment analysis for both fake and authentic reviews. Additionally, utilizing a hotel review dataset, the proposed sentiment model was applied to test the effectiveness of probabilistic sentiment scores in detecting false online reviews.

Mohd Nafis and Awang [16] deployed an improved hybrid feature selection strategy that boosted sentiment categorization using machine learning techniques. The suggested feature selection approach was created and evaluated on two datasets using a hybridization of Term Frequency-Inverse Document Frequency (IF-IDF) and support vector machine (SVM-RFE). TF-IDF was used to quantify the relevance of features, while SVM-RFE assessed and ordered the features iteratively. Accuracy, precision, recall, and F-measure were used to evaluate the performance of the Support Vector Machine (SVM) classifier, which revealed that a reduction rate is critical for optimizing the consumption of computing resources while retaining the classification's efficiency. In addition, the proposed approach outperformed other comparable techniques on several datasets.

Kumaran *et al.,* [17] deployed a system that evaluates numerous feedbacks and user evaluations categorized as negative, positive, or neutral using a probabilistic learning algorithm. Data gathered from real-world users via internet platforms validated the strategy. The researchers used hybrid recommendations as one of the system's primary modules, assisting in overcoming the limitations of conventional collaboration and content-based suggestions. Additionally, the researchers employed a supervised learning method (support vector machine) to enhance the accuracy of their findings. It outperformed prior approaches in terms of performance. The suggested approach assisted individuals in determining the appropriate ranking for their items.

A deep learning model of hybrid masking and attentional techniques based on BertBiGRU Softmax was developed by *Liu et al.,* [18]. The researchers conducted a series of experiments on a massive dataset of over 500,000 product reviews, and the results demonstrated that the proposed model outperformed previous deep learning models such as RNN, BiGRU, and BertBiLSTM. These models attained an accuracy of at least 95.5% and significantly decreased the loss of e-commerce reviews. As a result, recognizing fraudulent reviews is becoming increasingly critical.

The study of Krishnan *et al.,* [19] developed an intelligent technology-based approach to sentiment analysis of product evaluations. The proposed model incorporated six phases: preprocessing, keyword extraction and categorization by emotion, semantic word extraction, semantic similarity testing, feature extraction, and classification. MongoDB first preprocessed a tweet by implementing word deletion prevention, word stemming, and blank removal. The study also collected keywords from preprocessed tweets. Through effective comparison analysis, the new model demonstrated benefits over standard models in terms of positive and negative key performance metrics.

This study was motivated by the deployment of machine learning algorithms to learn, evaluate, and rate products, as well as store information based on consumer experience. Product information and user reviews were gathered from the Unified Computing Reference System (UCS), a server for data-driven computing products optimized for hardware evaluations, support watching, and software administration. In comparison to other current systems, the proposed HRS system had a MAPE value of 96 percent and an accuracy of approximately 98 percent. The average absolute error of the suggested HRS system was close to 0.6, indicating that the system's performance is surprisingly efficient [20].

Deep and Mein [21] proposed a solution to combating the issue of fake online reviews by adopting digital identity verification and user authentication provided by third-party organizations. This approach preserves consumer anonymity while enhancing the credibility and trustworthiness of online businesses.

According to Willianto and Antoni [22], rating data was classified using sentiment analysis algorithms. Sentiment analysis was used to categorize product reviews from e-commerce websites as positive or negative. The data was then further analyzed and utilized to summarize consumer thoughts about a particular product without the need to read individual reviews. The objective of this study was to improve classification performance through the use of feature selection techniques. Finally, to determine the most successful classifier,

Dutta [23] investigated sentiment analysis methods for determining if something is positive or negative. Eleven common machine learning algorithms were used: Multiterm Naive Bayes, Support Vector Machines, Decision Trees, Nearest Neighbors, Gradient Boosting Classifiers and AdaBoost Classifiers. The authors used Logistic regression, Random Forest, Additional Tree, Stochastic Gradient Descent Classifier, and Linear SVM as instruments. The Kaggle website provided approximately 3,600,000 Amazon customer reviews for the dataset. Each algorithm's performance was evaluated using recall, precision, F-score, AUC, and accuracy. Extra trees and Random Forests outperformed other classifiers in the analysis. The Gradient Boosting classifier had the lowest accuracy of all tests.

Existing sentiment analysis models in e-commerce often suffer from limited sentiment granularity, contextual misinterpretation, scalability challenges, insufficient multilingual support, poor adaptability to evolving language patterns, and inadequate fraud detection capabilities.

3. PROPOSED MODEL

This section will present the proposed model, "SentiCheck," for extracting and analysing sentiments to determine seller integrity on a business page. The strategic approach of the proposed system comprises gathering reviews on digital products in the electronics category from the five selected e-commerce sites: Jumia, Konga, Amazon, eBay, and Aliexpress. Data pre-processing is performed on the unstructured product reviews to extract features on which comments are made, and the polarity of the reviews is calculated to produce feedback for prospective buyers.

3.1 Machine Learning Algorithm

This study adopted the Support Vector Machine (SVM) algorithm. SVM is a highly regarded supervised learning algorithm that is widely used for classification and regression tasks. SVM applications span a wide range of fields, such as image classification, pattern recognition, and anomaly detection. SVM algorithms are designed to identify an optimal hyperplane that effectively separates distinct classes of data in a high-dimensional space by maximizing the distance between the nearest points within each class, known as support vectors [24]. Mathematically, the SVM hyperplane is depicted as:

$$w.x + b = 0 \tag{1}$$

where:
w: Weight vector (normal to the hyperplane).
x: Input feature vector.
b: Bias term.

The multiple binary SVM classifier approach (One-vs-Rest approach) was adopted because our model is aimed at classifying the sentiments into three classes (positive, neutral, and negative). The decision function for classifying a new data point x in multiple binary SVM
classifications is mathematically represented as:

Classifier 1: Positive vs. (Neutral + Negative)

$$f_1(x) = sign(w_1.x + b_1 \tag{2}$$

Classifier 2: Neutral vs. (Positive + Negative)

$$f_2(x) = sign(w_2.x + b_2) \tag{3}$$

Classifier 3: Negative vs. (Positive + Neutral)

$$f_3(x) = sign(w_3.x + b_3) \tag{4}$$

The decision function value for each classifier is computed and assigned a class based on the highest confidence score.

Using Support Vector Machine algorithm, the reviews are categorized as positive, neutral, or negative; these categorizations are then used to analyze product-based reviews. The results of the analysis of these reviews were used to determine if a seller's rating prestige corresponds to the sentiments stated in the reviews, which will be recommended to a buyer. Figure 1 shows the structure of customer reviews on one of the e-commerce websites considered in this study.

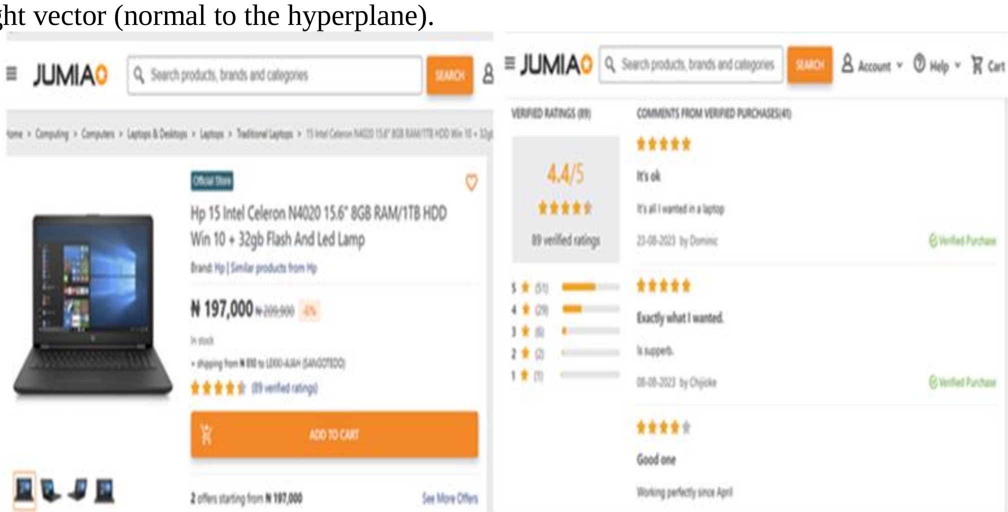

Figure 1: An example of review from Jumia website showing customer reviews and ratings of a HP laptop product (www.jumia.com.ng).

3.2 High-Level Design of the Proposed System

Figure 2 represents the high-level model of the proposed "SentiCheck" system; it depicts the interaction of the system's components, which constitute the complete system for determining seller integrity based on the analyzed sentiments. Figure 2 shows the processes, categorized into three phases. Phase 1 involves collecting review data from the sellers' business page, extracting sentiment sentences, and concluding with part-of-speech tagging. Phase 2 commences with the identification of sentence phrases, is followed by the computation of sentiment scores, and ends with the generation of feature vectors. Phase 3 begins with the categorization of the sentiment polarity, leading to result interpretation, which concludes the high-level design for the system.

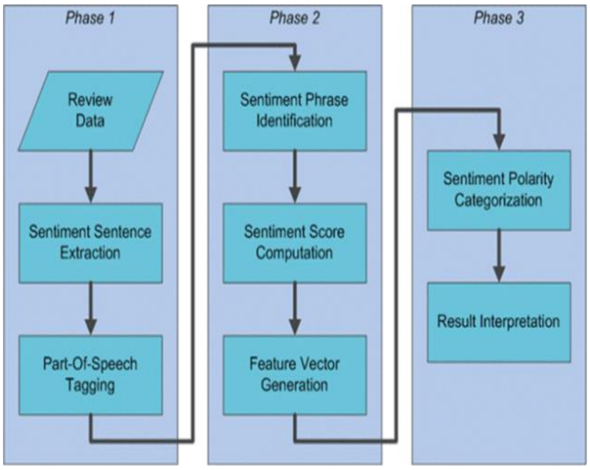

Figure 2: High level design of the proposed system

3.3 Data Flow Diagram (DFD) of the Proposed System

The data flow diagram (DFD) depicts the movement and organization of information within a process or system. It is a visual representation of each entity's inputs and outputs, as well as the overall process. The proposed "SentiCheck" system's data flow diagram, as depicted in Figure 3, shows data flow disintegrating into data collection, sentiment analysis, feature vector generation, sentiment polarity categorization, and seller integrity authentication, respectively.

3.4 Architectural Design of Products/Brand Authentication System

The architectural design establishes the relationships and connections among the components to accomplish the system's objective. Figure 4 presents the architectural plan for the proposed "SentiCheck" system, demonstrating the use of input review data for tokenization and, subsequently, review padding as may be needed. Sentiment Sentence Extraction and Sentiment Phase Identification will be conducted using the Support Vector Machine algorithm, which leads to the output in the form of a predicted sentiment category (positive, neutral, or negative).

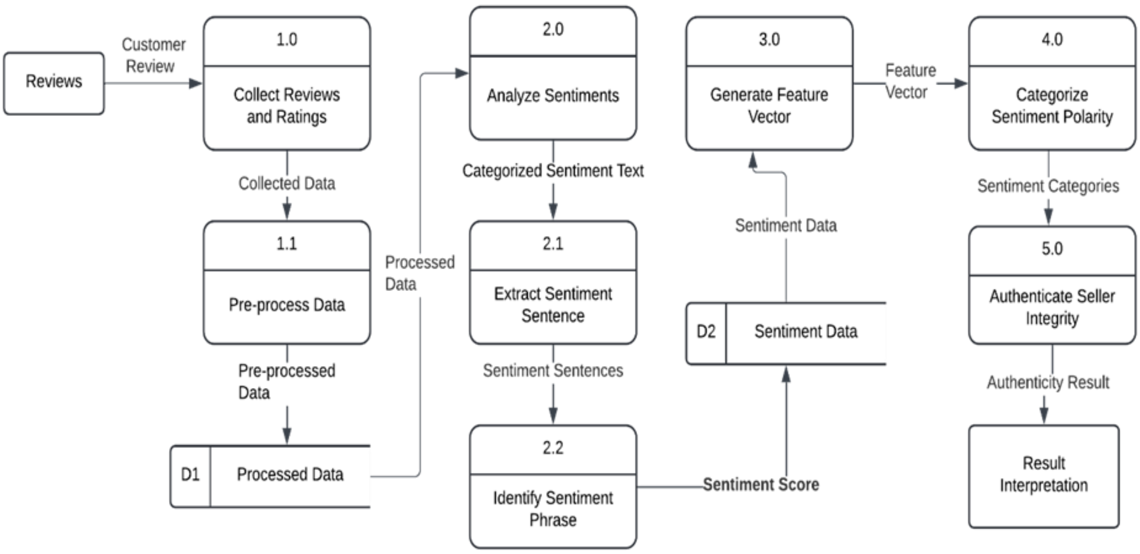

Figure 3: Data flow diagram of the proposed system.

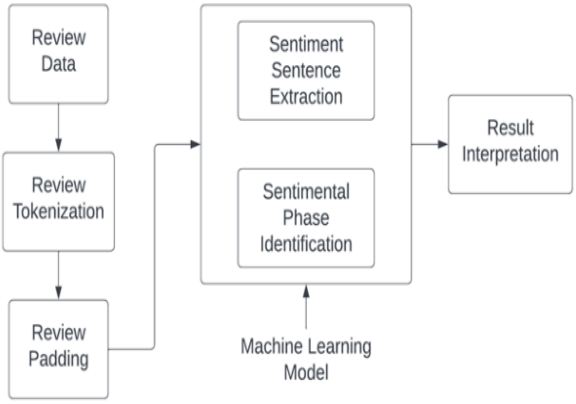

Figure 4: Architectural design of products/brands integrity authentication system.

4. RESULTS AND DISCUSSION

This section discusses the results obtained by translating the stated user requirements into a tangible and insightful system implementation. This section also undertakes the evaluation and verification of the system's performance.

4.1 The Dataset

The dataset used for the study consisted of review sentences obtained from selected business pages for successful sales of laptops by a particular brand. We extracted the data from five e-commerce websites, as Table 1 below illustrates:

Table 1: Statistics of datasets and sources

Source	Size of Dataset
Jumia	1,230 sentences
Konga	1,423 sentences
Amazon	2,805 sentences
eBay	2,100 sentences
Aliexpress	2,670 sentences

As seen in Table 1, the datasets sourced from Jumia, Konga, Amazon, eBay, and AliExpress were 1,230, 1,432, 2,805, 2,100, and 2,670 sentences, respectively. To train the machine learning models, 70% of the entire data was used, while 30% was used to test the models. This study considered the use of HP laptops based on customer reviews from Jumia, Konga, Amazon, eBay, and AliExpress e-commerce websites.

4.2 Result

The study was carried out in two phases: the first involved building a model using a machine learning algorithm, and the second involved the deployment of the model. This section documents the results obtained from the evaluation of the model and shows the user interface used to interact with the deployed system.

4.2.1 Model Performance Evaluation

The "SentiCheck" model was evaluated to determine how well it performs in terms of achieving the verification objective. The researchers used the inbuilt model evaluation metrics (.evaluate) for the performance evaluation to determine accuracy. With a train accuracy of 99.58% and a test accuracy of 97.2%, the model demonstrated efficiency in achieving its set objectives. Table 2 displays the accuracy of the train and test datasets for the support vector machine algorithm.

Table 2: Model accuracy for seller integrity authentication

Model	Train Result	Test Result
Support Vector Machine	99.58%	97.27%

4.2.2 User Interface of the Seller Integrity Authentication System

The user interface design offers an application environment that ensures the user's interaction with the system is easy and effective in order to achieve user goals, including how the user performs specific interactions and the usability of the interface design. The system employs a Gradio-generated user interface. Figures 5 and 6 depict the deployed system's user interface.

Figure 5: The input page of the product/brand authentication system

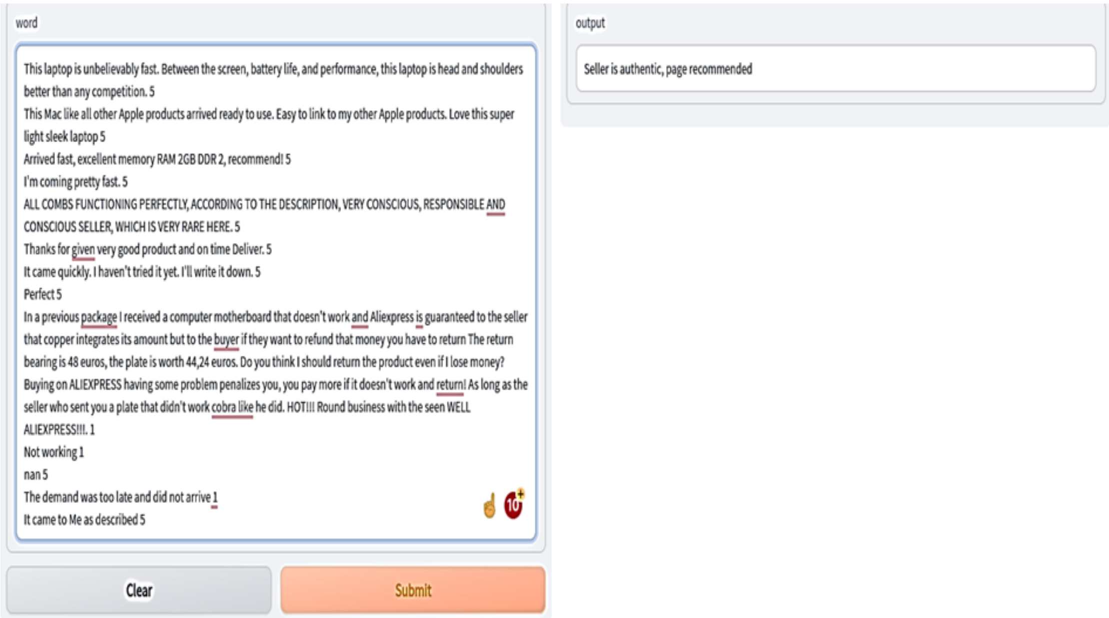

Figure 6: The result page of the product/brand authentication system.

5. Conclusion

In this study, we have provided a solution for quality assurance and seller integrity authentication for e-commerce brands. Our research successfully developed the "SentiCheck" model, a valuable tool that businesses and consumers can use to build trust in the products being sold through authentication of the integrity of sellers on e-commerce platforms. The authentication system was achieved by scraping reviews and ratings on HP laptop brand products from sellers selected from five top e-commerce platforms. The data was subjected to a series of data cleaning and preprocessing steps before being used to build a machine learning model with it. The model was deployed on a web-based application that helps users authenticate the integrity of brand owners and protect buyers' interests.

By analyzing sentiments, the "SentiCheck" model provides a reliable method to detect fraudulent sellers and ensure authentic transactions on e-commerce platforms, as it demonstrated high accuracy in classifying customer reviews in the three categories. Hence, the model's ability to provide accurate sentiment-based feedback boosts customer confidence in online shopping environments. This research contributes to the field by applying a tri-sentiment classification model to e-commerce with the goal of enhancing seller verification processes. The model has shown that it has the capacity to strengthen e-commerce platforms with data-driven insights and enable proactive measures against fraudulent activities.

Future research could explore the integration of advanced artificial intelligence approaches, such as deep learning, to enhance sentiment classification accuracy. Furthermore, real-time sentiment analysis research can provide immediate feedback to customers and sellers, improving the buyer's shopping experience. Expanding the model to support multiple languages will serve a broader audience and make it more adaptable to international e-commerce platforms. More complex insights might be gained by advancing research to include additional features such as context-aware and aspect-based sentiment analysis.

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