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AI in Detecting inappropriate and misleading content on E-commerce Platforms

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At

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Abstract

The gradual expansion of e-commerce stores has caused the emergence and proliferation of false and inappropriate e-commerce-related information, including inauthentic and inaccurate customer reviews, false ad notifications, and inappropriate product offerings. This kind of information harms customer trust, distorts purchasing behavior, and decreases site authenticity.

The purpose of the study is to design and develop a sophisticated system that identifies and classifies false reviews in the Arabic language for e-commerce applications, utilizing machine learning approaches.

Data preprocessing, feature engineering, and model training sequentially evaluate tools in the proposed approach. With the aid of the aforementioned NLP techniques, the Arabic text refinement stage of the process is accomplished by Tokenization, Stopword Removal, and Stemming.

Feature extraction and model training are accomplished by TF-IDF, which records a word's frequency, and Word2Vec, used for concept mappings. LR, Naive Bayes, and Linear SVM are the obtained supervised ML algorithms, and are assessed using a set of metrics; accuracy, precision, recall, and F1-score. The trained model tools are embedded in a streaming application using Streamlit. Users of the application can upload and compare a set of documents, and the individual review analysis will aid model performance analysis.

More customer trust on online shopping due to review analysis automation was the main impact of the presented ML model. This also acted as a stepping stone for ML and AI in e-commerce.

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List of Abbreviations

- **NLP:** Natural Language Processing
- **ML:** Machine Learning
- **SVM:** Support Vector Machine
- **DL:** Deep learning
- **LR:** Logistic Regression

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Chapter 1: Introduction

The increasing reliance on e-commerce platforms has made user reviews an important factor used to influence other user potential customer's buying decisions. The aim of these reviews are to help potential customers make an informed decision on a product. Unfortunately, the emergence of fake reviews has created a new problem for potential customers and online merchants. Fraudulent reviews create an imbalanced alter reality on the perceived value of a product and e-commerce via online reviews.

The Saudi Vision 2030, a blueprint of the Kingdom's e-commerce, relies on a large number of e-commerce merchants and online customers. The Saudi Data and Artificial Intelligence Authority (SDAIA) has spearheaded several businesses to use artificial intelligence to bridge the gap between online merchants and customers, most especially within the e-commerce platforms.

The aim of this project is to develop a Machine Learning tool to process and analyze the attributes of reviews. The project has its aim to plan and support e-commerce platforms in the user trust retention in order for them to build a highly sophisticated response to the challenges.

1.1 Problem Definition

As there is more and more user-generated review content on e-commerce site, it is becoming more and more difficult to determine user-generated reviews that are fake or misleading. While reviews should help consumers make better purchases, fake, misleading and poorly written reviews seriously distort a review of a product. This damage s the online marketplace, trust of the consumer, and impacts consumer behavior.

Thus, the main concern the current project is trying to address is:

How can an automated system be made that accurately and reliably identifies fake or misleading reviews in the Arabic language on e-commerce platforms?

As is to be expected, there are some challenges that arise from this.

- News and shiny. Most Arabic review text is unstructured, and informal language, slang, and other forms of noisy content can be expected.
- There are many fine and subtle linguistic features that can be learned by a model to identify genuine and deceptive reviews.
- There is a need to accurately determine the authenticity of the review text via the application of machine learning.
- The ability to access a review text that is either in a large collection of review documents or in an isolated state, and in either case to provide the user with an environment that is responsive.

There is machine learning content, and it will make a clear contribution to e-commerce platforms content moderation.

1.2 Thesis Objectives

The main objective of this project is to develop a model that detects inappropriate and misleading content across e-commerce platforms. The project goals include the following objectives:

- Detecting fake reviews: This aspect involves identifying and classifying misleading or fake reviews, which helps prevent consumers from relying on inaccurate information when making purchasing decisions.
- Identifying Misleading Product Descriptions: This aspect aims to uncover discrepancies between the advertised product descriptions and their actual features, thus helping to protect consumers from making purchasing decisions based on false or exaggerated claims.
- Improved Content Management: This aspect aims to increase the efficiency and effectiveness of content management processes on e-commerce websites by automating the detection of harmful content, thereby improving accuracy.

1.3 Thesis Contribution

In the most recent works about Arabic Language Processing and the issues of deceptive content on e-commerce platforms this research does the following:

- **Building an Arabic Fake-Review Identification Tool:** A fully automated ML-based fraud detection system for Arabic deceptive reviews. The system incorporates a complete preprocessing, feature extraction, model training, and modeling assessment pipeline structured around the complex and rich system of the Arabic language. .
- **Alternative ML Models Assessment:** Inclusion of different classification algorithms: LR, Naive Bayes, Linear SVM, and Word2Vec models. A spate of models are utilized in an assessment of the models and review their performance in a classification task. This assessment adds to the Arabic review authenticity classification.
- **Cleaning and Structuring Arabic Reviews Dataset:** The developed model includes the +2,000-strong Arabic Dataset dedicated to fake reviews. The Dataset undergoes a full cycle of Processing in the domain of Dirty Data, in a structured format, available, and Accessible. The dataset available increases the limited structured resources around the Arabic language.
- **Implementation of an Interactive Tool for Real-World Use:** A practical Streamlit-based application is developed that enables users to analyze individual reviews or batch datasets and visualize model performance. This tool demonstrates the real-world applicability of the research and supports potential integration into e-commerce moderation systems.
- **Contribution to Arabic NLP Research and E-Commerce Transparency:** The thesis discusses Arabic text analysis challenges in misleading-content detection and proposes techniques to address ever-present challenges. The results contribute to avoiding trust erosion in automated solutions in e-commerce and provide building blocks for future studies to automate solutions that nurture trust on e-commerce platforms.

1.4 Thesis Organization

In this thesis its organized to present the research in a clear, logical, and systematic manner. In the structure it guides the reader from introduction, project context, and literature review to the proposed methodology, implementation, and conclusion of results. This organization ensures a better understanding of the research process and highlights how each component contributes to achieving the study's objectives.

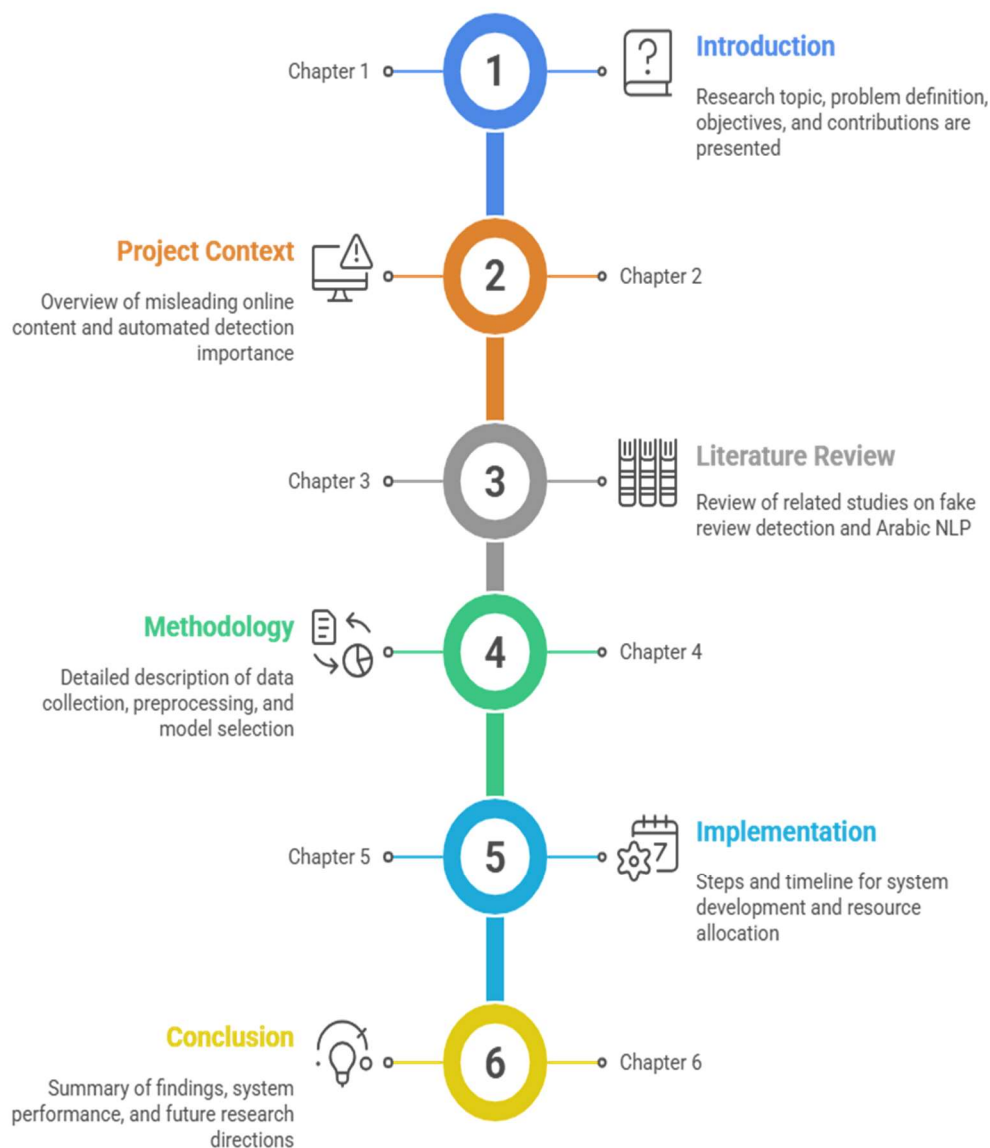


Figure 1 Thesis Organization and Development Process.

Chapter 2: Overview

2.1 Project Overview

E-commerce platforms are integral to modern-day shopping experiences, but their expanding user base has created an increase in deceptive content, which includes fake product reviews, deceptive ads, and misleading product information. This misrepresentation not only damages the trust consumers place in these platforms but also results in financial loss and even legal challenges for businesses. Consequently, the development of robust automated systems capable of detecting and mitigating deceptive content has become essential.

The solution to this problem lies in leveraging machine learning techniques to automatically analyze, identify, and classify misleading information, particularly false customer reviews written in the Arabic language. Unlike traditional manual moderation methods, automated detection systems can efficiently process large volumes of user-generated content while maintaining consistency and scalability.

The solution to this problem lies in leveraging machine learning techniques to automatically analyze, identify, and classify misleading information, particularly false customer reviews written in the Arabic language. Unlike traditional manual moderation methods, automated detection systems can efficiently process large volumes of user-generated content while maintaining consistency and scalability.

Accordingly, this project focuses on designing and implementing a machine learning-based framework that detects false and misleading Arabic e-commerce reviews. By enhancing content authenticity and reliability, the proposed system aims to protect consumers from deceptive practices, strengthen trust in e-commerce platforms, and promote a safer and more transparent online shopping environment.

Chapter 3: Related Work

3.1 Introduction

As e-commerce evolves, online ratings and reviews now have a greater impact on consumer purchasing decisions than ever before. Reviews are left by previous buyers and provide shoppers insight into product quality, seller reputation, and overall shopping experience. However, the growth of e-commerce has also led to the rise of false and misleading reviews, exaggerated claims regarding product features and benefits, and predatory advertising. Such false advertising has negative consequences as it decreases consumer trust, adversely impacts consumer decisions, and threatens the reputation of e-commerce platforms.

Studies show that misleading reviews and fraudulent advertising generate more than half [3], [7], of the online friction entered into content moderation systems. The volume of online content generated by users within a particular marketplace makes the challenge of effective moderation manual reviews burdensome and practically impossible. Fortunately, the need for efficient reviews and misleading content moderation systems has led to the incorporation of Artificial Intelligence (AI) and Natural Language Processing (NLP) into systems designed to limit potential harm and provide efficient and effective solutions. [4].

A good number of early studies using traditional text analysis methods produced great outcomes. However, most of this research concentrated on English text, whereas the Arabic language, despite the numerous Arabic speakers and the extensive use of online shopping in the Arab world, has attracted little attention. Including Arabic text in research is much more complicated because of the language's complex morphology, dialectal variation, grammatical richness, and the scarce amount of available annotated datasets, which complicates the construction of efficient systems of text classification, and detection in particular [5].

There is, therefore, a growing need for automated systems that can detect Arabic reviews that are fraudulent, unethical and misleading. Recent studies have also stated the importance of such systems in providing a safer online shopping experience to the users [6]. This study is aimed at proposing an improved, more efficient method for the detection of misleading reviews in Arabic to meet such a need.

3.2 Progression in Fake Review Detection Techniques

The initial attempts for the automated detection of fake reviews involved the application of traditional supervised machine learning techniques which include Logistic Regression, Naive Bayes, and Support Vector Machines (SVM). The representation of the texts for these models were done through Bag-of-Words and TF-IDF. Though these techniques were simplistic and were applied with greater efficiency, the techniques had issues in understanding the deeper reasoning and the contexts in the reviews [3], [10].

The comments made by Géron [1] were that the classical machine learning models had a great performance, however, the performance was dependent on the feature engineering that was applied. Unfortunately, the features that were designed did not seem to generalize to other problem domains or other languages. This especially became a constraint in the problem of deceptive reviews that are contextual and very subtle in their nature.

The advent of the different word embedding techniques including Word2Vec and GloVe and fastText were great improvements in the area. These techniques were able to better achieve the encoding of individual words that helped models to encapsulate the semantic contextual information better [2]. The use of embeddings with traditional classifiers to improve the performance of detection, especially for subtle contextual cues in the reviews had been reported in a number of studies [9].

The latest research revolves around deep learning techniques such as CNNs, RNNs, and LSTM networks, which learn complex text features automatically and don't require manual effort on feature crafting. For instance, deep learning models trained on large datasets, such as Amazon reviews, significantly outperformed older ML techniques [11]. However, large amounts of labeled data as well as computational power are required which makes such models ill-suited for low-resource languages like Arabic.

3.3 Arabic Fake and Misleading Content Detection

Very few studies pertain Misleading Content In Arabic. The studies explain the complexity associated with the Arabic language. The studies cite the extremely varied Arabic dialects, the lack of available datasets, the missing of datasets being unified, the datasets not being annotated, the datasets being of poor quality, inconsistency, the innate complexity of Arabic morphology [5]. These studies will probably lead the modeling frameworks to generate poor quality to extremely poor quality results.

Some studies have tried to implement deep learning models for the purpose of classifying Arabic text. The results, however, have not been successful, and the outcomes have seen great variability, and the variability has stemmed from insufficient amounts of training data for the deep learning models. Other studies suggest overrated and excessive fitting. The newer studies that have been published prioritize the implementation of deep learning models that have not been fully encapsulated, suggesting that the models should implement other methods of feature extraction and semantic representation. The studies state that older feature extraction frameworks should be incorporated for optimal result efficiency in Arabic text automation at a reasonable computation cost [7], [9].

The research surrounding automation of fraudulent review detection in e-commerce is where the primary purpose of these studies lie. For example, the

integration of review validation and artificial intelligence for reputation model frameworks aims to improve trust in the field of online trade. These studies show the need for implementing high accuracy in the noticed review detection systems in the field of online trade.

3.4 Research Gap and Contribution

There are still notable gaps in the literature in spite of the extensive contributions on fake review detection. These gaps include:

- An overwhelming majority of the studies focus on English datasets and Arabic reviews are not given attention.
- Most methods assess one model and offer limited insights in terms of comparison.
- Practical constraints such as deployment and resource requirements are generally overlooked by the deep learning solutions.
- There is a paucity of studies that offer user-centric applications which demonstrate genuine usability.
- This project is designed to address the following gaps by:
- Performing a comparative assessment of different machine learning models.
- Combining TF-IDF and Word2Vec representation of the text to derive the statistical and the semantic information of the text.
- Targeting misleading reviews written in Arabic which is a neglected area in the NLP research.
- Building a user-friendly application based on Streamlit that bridges the gap between theoretical research and application.
- Owing to these contributions, the system is able to provide a reliable and efficient means of detecting misleading reviews in Arabic across e-commerce platforms.

Chapter 4: Proposed Approach

In addressing the goals of this research, a multi-step approach was taken to develop an effective system to detect fraudulent Arabic reviews. This approach takes a methodical path, as each stage is designed to guarantee the model's ability to comprehend Arabic texts while ensuring the effective extraction of patterns to discriminate between actual reviews and fraudulent ones.

4.1 Data Collection

This project entails the collection of a large volume of data such as consumer reviews and product descriptions from disparate e-commerce platforms. This data will be collected from the public domains of websites such as Kaggle and Amazon, bearing in mind the legal implications and acceptable use policies of each platform. This data will take the form of text, in the comments of the users, and the titles of the products along with their descriptions to form a detailed database for the later stages of analysis and modeling.

4.2 Data Preprocessing

In a bid to allow the machine learning models to function optimally, the Arabic reviews must go through a number of pre-processing stages that work to clean and format the text before looking to train the models. Such tasks as removal of text noise, character canonicalization, removal of extraneous punctuation, and other Arabic language processing techniques are used to standard the text before training. Such measures are taken to the training and test sets to increase result reliability and model calibration.

- Removing specific patterns: Previously existing URLs and non-Arabic characters are expunged and also editing text blocks in accordance to predefined word formats.
- Tokenization: The cleaned text is divided into symbols (words) based on the number of whitespaces or white characters in general.

- **Stopwords Removal:** Using NLTK, Arabic stopwords (e.g. على، من) or tokens are removed so that resulting tokens have, or preserve, some semantic content.
- **Stemming:** The NLTK's ISRIStemmer is used to stem or truncate words to their roots, etc. which also increases generalization and lessens the size of the vocabulary.
- **Feature Representation or Extraction:** for TF-IDF and for word embeddings(turning text to numeric for machine learning) two widely used feature extraction or representation methods would be carried out.

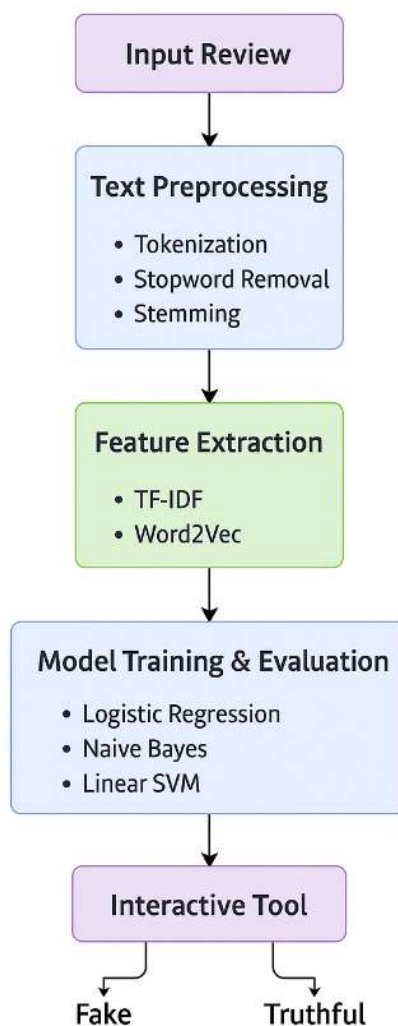


Figure 2 Proposed Framework.

4.3 Model/Method Selection

Out of the three machine learning models and the embedding-based model, the machine learning models were chosen based on their ability to handle text, so as to compare the performance of each of the models on the content classification business task, while each of the models provided a different functionality to focus on distinct evaluation of text representation.

- The TF-IDF + LR model is a benchmarked and recognized linear classifier that is highly efficient and effective due to its simplicity for text classification, and also for sparse text feature classification and evaluation in order to identify and filter out fraudulent or counterfeit reviews.
- TF-IDF + Linear SVM is a boundary-based classifier which performs very well for high-dimensional text data and achieves high accuracy rates on binary classification problems.
- TF-IDF + Naive Bayesian is one of the fastest methods and is a very effective classifier for short texts. Therefore, it is a very low-cost, effective and fast algorithm for this task.
- Word2Vec + LR adds a dense word embedding layer to capture the meaning and context of what is being said. Other than TF-IDF, this adds a richer linguistic detail.
- Evaluating these models helps us to understand their effect and ascertain a suitable one for detecting misleading data on E-commerce sites.

4.4 Testing and Evaluation:

Some of the evaluation metrics to be used include:

- **Accuracy:** the rate at which the model classifies the content correctly. This is the overall classifier performance.
- **Precision:** This is the percentage of misleading content that is relevant to the flagged content.

- **Recall:** This is the percentage of misleading content that the model was able to uncover.
- **F1-Score:** This is the evaluation of average between Precision and Recall and used to give a balancing metric.

For the model to be accepted, it should demonstrate the ability to perform on different strata of the data and be able to generalize. This will be captured through cross-validation.

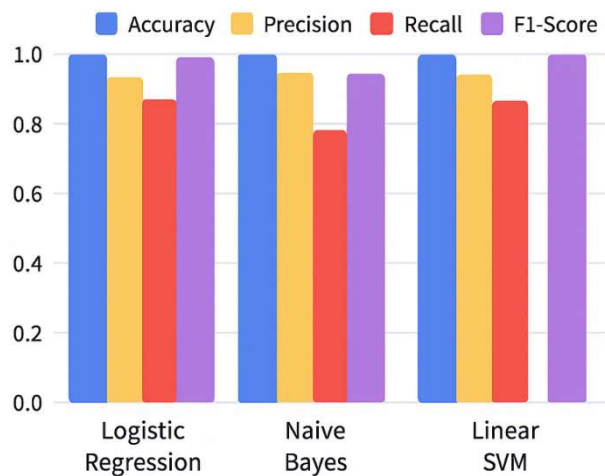


Figure 3 Model Performance Chart.

4.5 Expected Results

Here are the expected outcomes of the project:

- **Gained Enhanced Detection of Misleading Content:** With the project's developed machine learning models, e-commerce platforms are expected to have greater capability of misleading reviews, inappropriate product descriptions, and more, thereby increasing exposure to fraudulent data and reducing user trust.
- **Gained Additional Knowledge for Arabic NLP:** Integrating several preprocessing techniques, the project aims to compare the classical machine learning models and embedding techniques to provide additional knowledge for Arabic NLP.

Chapter 5: Project Steps and Timeline

This chapter explains what the proposed system will look like, and how it will function, detailing the workflow from initial data collection through to the last step, evaluation and reporting. The project will happen in data preparation, model development, performance evaluation, and final fitting, all of which happen in four main steps.

5.1 Step one: Data collection and preparation

This stage is the extraction of relevant data sets with product descriptions and customer reviews. After relevant data are collected, they are subjected to data cleaning and improvement of quality and consistency factors such as removal of URLs, Arabic text normalizing, stop word removal, tokenization and stemming. After data cleaning, the text data will be processed and converted to numerical data with TF-IDF and Word2Vec techniques. Then, the dataset will be split to training and testing to enable evaluation of the model with some level of confidence.

5.2 Step 2: Developing and training the model

This is the phase that training happens. The focus should be on model training, which comprises of some machine learning models such as Logistic Regression, Naive bayesian, Linear Support Vector Machine, and Word2Vec model, in addition to a model training custom-built interface on Streamlit designed for ease of user testing and interaction to be flexibly added to the system.

5.3 Step 3: Testing and Evaluation

- Standard metrics like accuracy, precision, recall, and F1 score, will be used on the trained models and assessed, focusing on the performance of the models and determining their overall effectiveness and their strengths and weaknesses. In addition, this evaluation phase seeks to determine how well the models can be used on completely new and unseen data.

- Analyze errors and identify strengths and weaknesses in each model.
- Test models on new data to ensure generalizability and minimize overlearning.
- Update the tool's interface to display evaluation results interactively and clearly.

5.4 Step 4: Final Adjustments and Reporting.

- Improve the model's performance and the tool's interface based on the evaluation results.
- Document the steps, methods, experiments, results, and challenges in the final project report.
- Prepare presentations and visual materials to showcase the project.

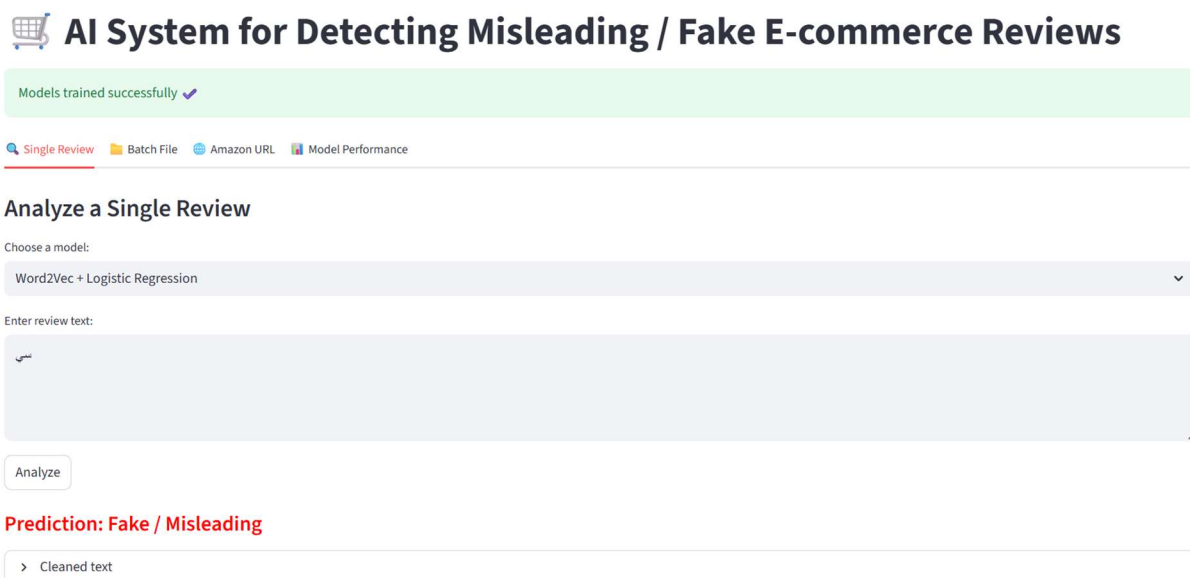


Figure 4 Streamlit UI Screenshot.

5.5 Resources Needed

- **Software and Tools:**
 - Language:
 - The primary programming language for the project is Python
 - ML Libraries:
 - Scikit-learn for traditional machine learning (ML) models and TensorFlow for potential DL extensions.
 - NLP Libraries:
 - NLTK for Arabic text preprocessing and Gensim for Word2Vec embeddings.
 - User Interface framework
 - Streamlit to building an interactive tool to display results.
- **Datasets:**
 - The dataset from Kaggle contains Arabic reviews categorized as Fake or Truthful.
 - Additional datasets from e-commerce platforms may be integrated into future projects.
- **Computing Resources**
 - A computer with moderate processing power for training models.
 - Google Colab to support faster model training if needed.

Chapter 6: Conclusion and Future Work

This thesis describes an intelligent system for detecting misleading Arabic reviews from e-commerce sites using Natural Language Processing and Machine Learning. The approach taken was a series of interconnected steps including, first, text pre-processing and feature extraction with both TF-IDF and Word2Vec. Then, a number of models were trained, including Logistic Regression, Naive Bayes, and Linear SVM, and performance of the models was evaluated using a range of well-established scientific performance indicators. The results showed Naive Bayes the best overall performance, demonstrating an ability to analyze short, direct Arabic texts.

In addition, this research has produced a functioning application on Streamlit, to analyze single reviews or entire datasets, thus making the system operational. This work goes some way to filling a significant research gap in the detection of misleading Arabic reviews and will support efforts to advance the development of other systems.

6.2 Future Work

Working with cutting-edge technological advancements, the developed tool demonstrates effectiveness in identifying deceptive Arabic reviews, however, certain aspects remain to be developed in order to facilitate overall effectiveness and versatility. Work in the future could involve the inclusion of more sophisticated deep learning models, the diversification of the dataset to encompass more types of reviews, and enhancements in the application interface to improve usability and flexibility for end-users. Some of the spearheaded potential modifications may involve Looking through the prism of potential future enhancements, the hub of activities for the future lies in the following for the initial actions/ steps, it covers the following:

1. Integrating the system with e-commerce platforms via APIs

Due to technical limitations in collecting reviews directly from sites like Amazon and AliExpress, as a result of their anti-scraping and security systems, the current model does not include a live review fetching process.

- In future developments, the system can be integrated with e-commerce platforms through:
- Using official APIs or external APIs (such as RapidAPI) to fetch reviews directly.
- Analyzing the content of dynamic pages using advanced tools such as Selenium or Playwright.
- Integrating the tool with a real platform that automatically reads and categorizes reviews as soon as they are published, without human intervention.
- Adding this step will make the system more practical and prepare it to be part of a company's content moderation system.

2. Use DL models (Transformers) such as BERT or AraBERT to improve understanding of linguistic context, especially in complex or long texts.

These models may offer higher accuracy but require more computing resources and more data.

3. Expand the size and quality of the data The model's performance can be enhanced by expanding the dataset to include: reviews from multiple platforms, different Arabic dialects, and longer, more detailed texts.

4. Integrate additional non-textual features such as star count, user behavior, review posting frequency, and review date (the time the review was written). These features can help detect fake reviews more accurately.

5. Develop a more integrated interface. In the future, the system could be integrated with e-commerce platforms via API to enable automatic and real-time review monitoring.

6. Expand the system to be multilingual, supporting both Arabic and English reviews, especially for international stores.

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