جامعة جدة
University of Jeddah

Google Maps Fake Review Detector

by

Weam Ahmad Fallatah 2100314

Manahel Abdullah Aljubairi 2100318

Supervised by

Dr. Rawan Baalous

Feb- 2022

ACKNOWLEDGEMENT

Alhamdulillah, we managed to finish our graduation project after a challenging work. I would like to extend my deep sincere thanks and to our dear supervisor Dr. Rawan Baalous. Thank you for your guidance, friendship, for all the efforts you make to help us grow throughout the project period.

Weam Fallatah

Manahel Aljubairi

UNDERTAKING

This is to declare that the project entitled "Google Maps Fake Review Detector" is an original work done by the undersigned, in partial fulfillment of the requirements for the degree "Master of Science in Cybersecurity" at the Information System Department, College of Computer Science and Engineering, University of Jeddah.

All the analysis, design, and system development have accomplished by the undersigned. Moreover, this project has not submitted to any other college or university.

Weam Ahmad Fallatah (2100314) ………………………….

Manahel Abdullah Almutairi (2100318) ………………………….

ABSTRACT

Google Maps have a review and rating feature. This feature allows consumers to post or see a review of a product, service, or place. These reviews are helpful for business owners to raise their reputation and give the consumers an idea of what he is looking for. However, fake reviews aim to provide deceptive reviews to mislead consumers. Moreover, it can significantly affect the sales reputation of business owners. We propose to develop a tool to analyze automatically, and filter posted suspicious reviews on Google Maps using LSTM and Sentiment analysis and analyze unnatural patterns in ratings and reviews and display a report view with more trustable results.

Table of Contents

Tables List

Table of figures

Chapter 1| Project Outlines

1.1 Introduction

Over the last few years, almost all online platforms have had a review and rating feature. This feature allows consumers to post or see the review and rating of a product, service, or place before purchasing or visiting a specific place. These reviews are helpful for both employers and consumers, as they help business owners raise their know reputation and give the consumers an idea about goods, services, and places. In addition, lots of service providers encourage consumers to post reviews and share their experiences online, for example, Google Maps.

Google Maps is an application that estimates the correct way to the destination and calculates the distance between two locations. Business owners can write down the information that needs like schedules and photos of the place. Likewise, consumers can provide feedback and share their ratings and reviews (google). Google Map encourages its users to post reviews and gives them points and badges based on their contributions to making reviews more helpful. They called these users Local Guides. Local Guide is a service that lets people describe their experience with reviews, update information, or verify and check facts. Consequently, consumers are increasingly dependent on reviews as they become an essential aspect and significantly impact their decision-making(Hollenbeck & Proserpio, n.d.).Due to this, fake reviews have increased recently.

Fake reviews aim to provide deceptive reviews about services, products, or places to mislead consumers. Whether they are negative or positive reviews, they are harmful and deceive consumers as if legitimate and unbiased customers wrote them. Moreover, these reviews can significantly affect sales figures and the online reputation of business owners.(Krügel et al., 2021; Martínez Otero, 2021; Wu et al., 2020)

Some business owners use fake reviews generated by humans to promote low-quality products. That increases their revenue and affects the marketplace for honest business owners(Hollenbeck & Proserpio, n.d.). Accordingly, honest reviews give the business owners a source to improve their quality and give the consumers a source on which they can rely. This paper explores fake reviews published by humans on Google Maps and detecting these reviews.

1.2The Problem

Most consumers prefer to read reviews before making any decision. Google Maps allow users to share their experience and enable them to read and decide according to multiple opinions expressed value or reviews describing the user experience. Still, these reviews may be fake, and it has no credibility.

There are many reasons why people or business owners misuse these reviews. One of these reasons is to destroy a business's reputation or increase sales(Krügel et al., 2021). Thus, both consumers and business owners are affected by fake reviews, whether these reviews were created manually by a human or automatically by a computer program(Salminen et al., 2022). Studies indicate that around 80% of consumers are tempted by other people's reviews and know their opinion about the product or service they want to buy. Manipulated ratings and reviews harm consumers as they may pay more than they should for a lower-quality product (Hollenbeck and Proserpio).On the other hand, business owners are beaning harmed by fake reviews. Whether it is because of the negative review attacks, they wear exposed to, or because other businesses use fake reviews to their advantage, honest business owners may force to close because of their lower ratings than those businesses that use fake reviews.

1.3 The Recommended Solution

We propose developing a tool designed to automatically detect suspicious or biased reviews posted on Google Maps. First, it collects review data by the API from Google Maps to build a dataset. Then detects, analyzes, and filters unnatural patterns in reviews. Finally, it presents results that help consumers make their decisions and business owners to see results that help them improve themselves.

Furthermore, this tool will make it easier for consumers and business owners to save time and effort in filtering reviews manually.

1.4 Clear Statement of Aim

This project aims to develop a web application that automatically detects fake Arabic reviews on Google Maps using LSTM deep learning model with sentimental analysis to help business owners better understand customer experience and consumers see trustworthy reviews.

1.5 Statement of Objectives

The project achieves the following objectives:

- Build a web-based application to detect fake Arabic reviews on Google Maps using deep learning techniques.
- Analyze Arabic reviews posted in Google Maps in terms of the sentiment analysis in the review, average rating, and review length.
- Check and compare ratings before and after detecting fake reviews.

1.6 Project Plan

Clear tasks specification

Initiation phase: The first stage changes the idea to a feasible goal. That needs to develop a business case and create a project charter.

Analysis phase: In this phase, identify the primary tasks and technical also develop a project schedule.

Design phase: We can achieve the project results in the design phase. Include prototypes, flow charts, and HTML screen designs.

Implementation phase: In the implementation phase, the programmers encode the project, which becomes visible to the customer.

Testing phase: Testing Phase, the software Quality assurance, and the requirements complete the program's goal and ensure the units work well together.

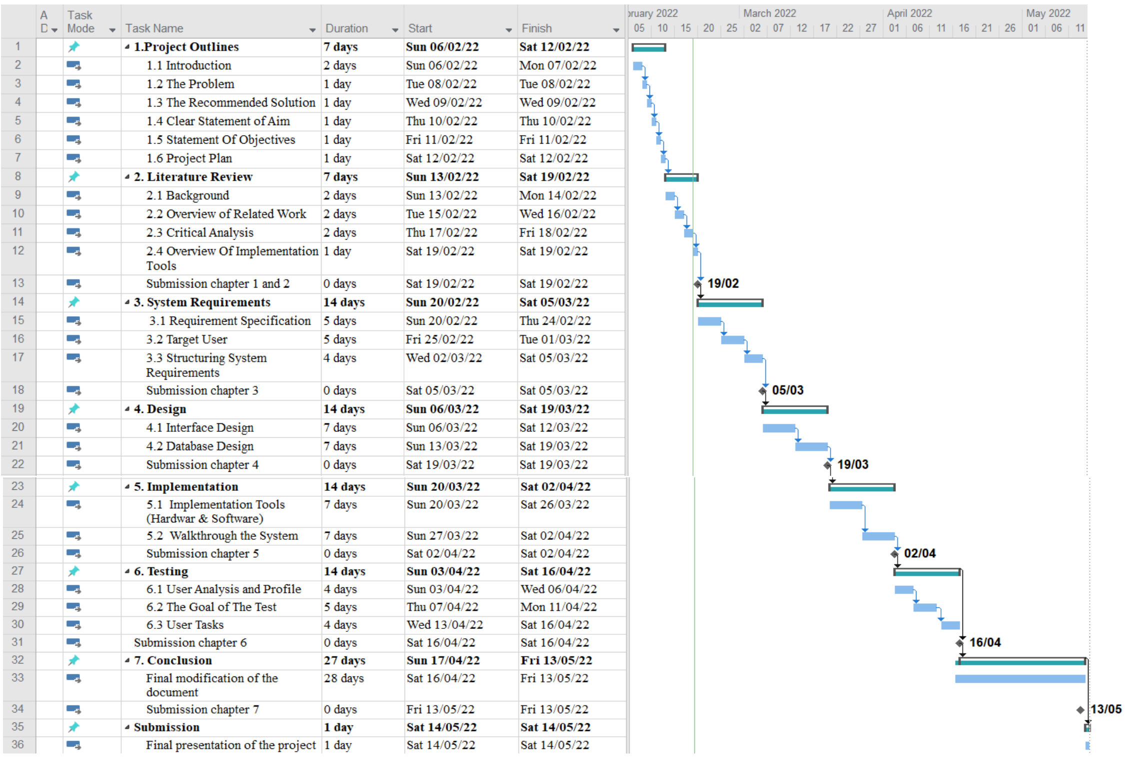
	AD	Task Mode	Task Name	Duration	Start	Finish
1			**1.Project Outlines**	**7 days**	**Sun 06/02/22**	**Sat 12/02/22**
2			1.1 Introduction	2 days	Sun 06/02/22	Mon 07/02/22
3			1.2 The Problem	1 day	Tue 08/02/22	Tue 08/02/22
4			1.3 The Recommended Solution	1 day	Wed 09/02/22	Wed 09/02/22
5			1.4 Clear Statement of Aim	1 day	Thu 10/02/22	Thu 10/02/22
6			1.5 Statement Of Objectives	1 day	Fri 11/02/22	Fri 11/02/22
7			1.6 Project Plan	1 day	Sat 12/02/22	Sat 12/02/22
8			**2. Literature Review**	**7 days**	**Sun 13/02/22**	**Sat 19/02/22**
9			2.1 Background	2 days	Sun 13/02/22	Mon 14/02/22
10			2.2 Overview of Related Work	2 days	Tue 15/02/22	Wed 16/02/22
11			2.3 Critical Analysis	2 days	Thu 17/02/22	Fri 18/02/22
12			2.4 Overview Of Implementation Tools	1 day	Sat 19/02/22	Sat 19/02/22
13			Submission chapter 1 and 2	0 days	Sat 19/02/22	Sat 19/02/22
14			**3. System Requirements**	**14 days**	**Sun 20/02/22**	**Sat 05/03/22**
15			3.1 Requirement Specification	5 days	Sun 20/02/22	Thu 24/02/22
16			3.2 Target User	5 days	Fri 25/02/22	Tue 01/03/22
17			3.3 Structuring System Requirements	4 days	Wed 02/03/22	Sat 05/03/22
18			Submission chapter 3	0 days	Sat 05/03/22	Sat 05/03/22
19			**4. Design**	**14 days**	**Sun 06/03/22**	**Sat 19/03/22**
20			4.1 Interface Design	7 days	Sun 06/03/22	Sat 12/03/22
21			4.2 Database Design	7 days	Sun 13/03/22	Sat 19/03/22
22			Submission chapter 4	0 days	Sat 19/03/22	Sat 19/03/22

Figure 1 Project Plan 1

23			**5. Implementation**	**14 days**	**Sun 20/03/22**	**Sat 02/04/22**
24			5.1 Implementation Tools (Hardwar & Software)	7 days	Sun 20/03/22	Sat 26/03/22
25			5.2 Walkthrough the System	7 days	Sun 27/03/22	Sat 02/04/22
26			Submission chapter 5	0 days	Sat 02/04/22	Sat 02/04/22
27			**6. Testing**	**14 days**	**Sun 03/04/22**	**Sat 16/04/22**
28			6.1 User Analysis and Profile	4 days	Sun 03/04/22	Wed 06/04/22
29			6.2 The Goal of The Test	5 days	Thu 07/04/22	Mon 11/04/22
30			6.3 User Tasks	4 days	Wed 13/04/22	Sat 16/04/22
31			Submission chapter 6	0 days	Sat 16/04/22	Sat 16/04/22
32			**7. Conclusion**	**27 days**	**Sun 17/04/22**	**Fri 13/05/22**
33			Final modification of the document	28 days	Sat 16/04/22	Fri 13/05/22
34			Submission chapter 7	0 days	Fri 13/05/22	Fri 13/05/22
35			**Submission**	**1 day**	**Sat 14/05/22**	**Sat 14/05/22**
36			Final presentation of the project	1 day	Sat 14/05/22	Sat 14/05/22

Figure 2 Project Plan 2

1.6.1 Tasks duration



ID	Task Mode	Task Name	Duration	Start	Finish
1		**1.Project Outlines**	**7 days**	**Sun 06/02/22**	**Sat 12/02/22**
2		1.1 Introduction	2 days	Sun 06/02/22	Mon 07/02/22
3		1.2 The Problem	1 day	Tue 08/02/22	Tue 08/02/22
4		1.3 The Recommended Solution	1 day	Wed 09/02/22	Wed 09/02/22
5		1.4 Clear Statement of Aim	1 day	Thu 10/02/22	Thu 10/02/22
6		1.5 Statement Of Objectives	1 day	Fri 11/02/22	Fri 11/02/22
7		1.6 Project Plan	1 day	Sat 12/02/22	Sat 12/02/22
8		**2. Literature Review**	**7 days**	**Sun 13/02/22**	**Sat 19/02/22**
9		2.1 Background	2 days	Sun 13/02/22	Mon 14/02/22
10		2.2 Overview of Related Work	2 days	Tue 15/02/22	Wed 16/02/22
11		2.3 Critical Analysis	2 days	Thu 17/02/22	Fri 18/02/22
12		2.4 Overview Of Implementation Tools	1 day	Sat 19/02/22	Sat 19/02/22
13		Submission chapter 1 and 2	0 days	Sat 19/02/22	Sat 19/02/22
14		**3. System Requirements**	**14 days**	**Sun 20/02/22**	**Sat 05/03/22**
15		3.1 Requirement Specification	5 days	Sun 20/02/22	Thu 24/02/22
16		3.2 Target User	5 days	Fri 25/02/22	Tue 01/03/22
17		3.3 Structuring System Requirements	4 days	Wed 02/03/22	Sat 05/03/22
18		Submission chapter 3	0 days	Sat 05/03/22	Sat 05/03/22
19		**4. Design**	**14 days**	**Sun 06/03/22**	**Sat 19/03/22**
20		4.1 Interface Design	7 days	Sun 06/03/22	Sat 12/03/22
21		4.2 Database Design	7 days	Sun 13/03/22	Sat 19/03/22
22		Submission chapter 4	0 days	Sat 19/03/22	Sat 19/03/22
23		**5. Implementation**	**14 days**	**Sun 20/03/22**	**Sat 02/04/22**
24		5.1 Implementation Tools (Hardwar & Software)	7 days	Sun 20/03/22	Sat 26/03/22
25		5.2 Walkthrough the System	7 days	Sun 27/03/22	Sat 02/04/22
26		Submission chapter 5	0 days	Sat 02/04/22	Sat 02/04/22
27		**6. Testing**	**14 days**	**Sun 03/04/22**	**Sat 16/04/22**
28		6.1 User Analysis and Profile	4 days	Sun 03/04/22	Wed 06/04/22
29		6.2 The Goal of The Test	5 days	Thu 07/04/22	Mon 11/04/22
30		6.3 User Tasks	4 days	Wed 13/04/22	Sat 16/04/22
31		Submission chapter 6	0 days	Sat 16/04/22	Sat 16/04/22
32		**7. Conclusion**	**27 days**	**Sun 17/04/22**	**Fri 13/05/22**
33		Final modification of the document	28 days	Sat 16/04/22	Fri 13/05/22
34		Submission chapter 7	0 days	Fri 13/05/22	Fri 13/05/22
35		**Submission**	**1 day**	**Sat 14/05/22**	**Sat 14/05/22**
36		Final presentation of the project	1 day	Sat 14/05/22	Sat 14/05/22

Figure 3 Tasks duration

Chapter 2 | Literature Review

2.1 Background and Overview of Related Work

2.1.1 Background

We Google Map has become a crucial source of reviews more than other online platforms, significantly after adding the local Guide's feature. Reviews are what truthful users express about their opinions, satisfaction, or dissatisfaction with a particular service or product. Therefore, reviews play an essential role in the reputation of a business and consumer decisions (*Detection of Fake Reviews_ Analysis of Sellers' Manipulation Behavior _ Enhanced Reader*, n.d.).Users often read reviews as it allows them to know the experiences of others and get an actual knowledge of the product or services. More reviews lead to a higher ranking of the business and make it easier for consumers to reach them, thus increasing its revenue. Unfortunately, as a side effect, fake reviews have increased.

One of the main reasons is to promote a low-quality product or service. Otherwise, it damages the reputation of a competitor by misleading potential consumers. All these reasons cause unfair competition between businesses and a loss of consumer confidence in reviews (Saeed et al., 2022)(Martens & Maalej, 2019). Moreover, it has become easy to order a fake review from a third party. These reviews generated by humans or computers using Natural Language Processing (NLP) and Machine Learning (ML).

Additionally, automated fake reviews (generated by computers) are becoming increasingly widely used because they are easier and less costly than those created by humans (Salminen et al.).Furthermore, many companies are willing to spend money on fake reviews that cannot easily be detected(Krügel et al., 2021). Whereas a positive review of the company aims to attract more customers and increase sales, a negative review aims to discredit the target and reduce sales (Salminen et al., 2022).On the other hand, fake positive reviews lead to false visions about the actual consumers' needs and prevent the business owners from improving their quality (Martens & Maalej, 2019). Hence, whether positive or negative, the effect of fake reviews goes beyond being online (reputation) and involves the truthful world. (Monetary cost) (Salminen et al., 2022)

For this purpose, Google Maps have a strict policy on the reviews posted on its platform. Reviews checked and filtered before and after posted on the platform with the help of machine learning (Mathayomchan and Taecharungroj).Despite that, some biased or fake reviews are still being posted, especially by third parties who have become professional in generating them. (Salminen et al., 2022)

The local Guide contributes and makes it easier for other consumers to find their information. (google) Local guide users post reviews more than regular users, letting consumers rely on their opinions. However, the problem still exists as these people can only leave reviews to get points from the Local Guide Program (Borrego & Navarra, n.d.).Therefore, Google provided a way to report reviews that users believe violate the policy, including fake reviews.Human operators review the reported content to determine if this content is fake or not (Mathayomchan & Taecharungroj, 2020). Auditing the reported review takes several days before responding, and during that time, the damage may have already been done to the consumer or business owner (Salminen et al.).In addition, it is not easy to monitor and detect these reviews manually by consumers and business owners. Besides, it is comprehensive and takes a long time, especially with many reviews.

Thus, there is a need to automatically detect fake reviews to protect consumers and businesses. We can detect fake reviews by classifying the reviews and sentimental analysis. Sentiment analysis is a natural language processing (NLP) technique that analyzes the review content, such as users' sentiments or emotions towards a product or service.

Many machine learning and deep learning techniques have been used with sentimental analysis based on previous research. These techniques have used to classify the reviews as positive or negative and get users' opinions. (*Detection of Fake Reviews_ Analysis of Sellers' Manipulation Behavior _ Enhanced Reader*, n.d.)(Alharbi et al., 2020)

2.1.1 Machine Learning Classifiers

Machine Learning has several types of models:

Naïve Bayesian classifier (NB)

In the NB classifier, each attribute used in classification will classified independently. Accordingly, it has the feature of finding noise in data and produces better outcomes when the sample size is small. (Alharbi et al., 2020)

Support Vector Machine classifier (SVM)

SVM is a technique for classifying linear and nonlinear data. The SVM searches for the best linear separator level with a boundary that separates the data of one class from another. Therefore, If the data is linearly inseparable, the SVM transforms the data into a higher dimension by using a nonlinear mapping.(Fang & Zhan, 2015)

K-Nearest Neighbor (K-NN)

(K-NN) a simple classification method developed to perform discriminatory analysis when estimation probability is difficult to determine or unknown. For example, for $k=1$ and $n \to \infty$, the k-nearest-neighbor classification error is a double-bonded Bayes error rate.

2.1.2 Deep Learning Classifiers

Deep learning, also known as Deep Neural Network, is a type of machine learning that allows computers to make predictions more effectively by relying on multilevel learning representation. Deep learning determines the higher levels than lower levels by following human feelings to be accurate results to classify tasks through text or images using neural networks (Bashar, 2019). Deep learning has several types of models:

Convolutional neural networks (CNNs)

A CNN consists of three primary layers: the input layer, multiple convolutional layers known as hidden layers, and the output layer. CNN used in classifying applications of vision and image. On the other hand, studies have shown that CNNs can used to classify texts. (Jain et al., 2019; Umer et al., 2020)

Recurrent neural networks (RNNs)

An RNN consists of three primary layers: an input layer, recurrent units known as hidden layers, and an output layer. RNN typically used to gain a deeper understanding of language and speech recognition by leveraging sequential data. (Umer et al., 2020)

Long Short-Term Memory (LSTM)

LSTM is one type of RNN designed for long-range time series and to mitigate the Problem of RNN short-term memory. LSTM consists of an inputs layer, a hidden layer called memory blocks, and a final output layer. (Wahdan et al., 2020)

2.2 Overview of Related Work

This section presents an overview of previous works related to fake review detection in Arabic and English.

(Ding et al., 2008)(2008) Focuses on positive or negative customer reviews of products on websites. Suggests a lexicon-based dictionary that carries or uses opinion-based words to express products. The new method can improve the context precision when the weakness is that the method is not practical with the context of the comment. For example, the sentence may symbolize being positive or negative at the same time.

(Saeed et al., 2022)(2019) Uses many other Arabic review detection techniques to build and evaluate the group based on integrating a rule-based classifier with machine learning techniques that depend on negation handling N-gram features considered different datasets sizes. Nevertheless, (Alharbi et al., 2020) used N-gram with Naïve Bayesian algorithm, so the results when using large spam messages of Arabic and mixed English and Arabic data model that the most massage published on English on the contrary, the results in Arabic were few compared to the other language. The stronger the stacking group classifier was progressing of other classifiers. The technique showed an increase of 28% in detecting Arabic spam reviews in (seed).

(Martens & Maalej, 2019)(2019) Compared 60,000 fake reviews out of 62 million reviews in the Apple App Store to know manipulation reviews and ratings and how fake reviews are different from regular reviews. In the research using a supervised classifier, the authors automatically detected fake reviews with a recall of 91%.

(Ziani et al., 2021)In 2021 using the semi-supervised SVM (S3VM) for Arabic deception detection. SVM is more flexible and easier to adapt to other technologies, and it improves the system to 85.99%. However, also, it is not easy to deal with the Arabic language.

(Sadiq et al., 2021)In 2021 suggest, Google App numeric reviews ratings sing deep learning approaches. The framework has two phases. The first phase is the contradiction of reviews and sentiment analysis tools. The second phase used star rating whit a deep learning model. After using TextBlob and VADE tool, its division of data is 70% for training while 30% for testing, and the Strengths ability to identify semantic relationships of text in a better way than conventional machine learning. The weakness is that the RNN also faces a problem of vanishing gradients that hinders it from learning long-term dependencies and their correlation.

(Saumya & Singh, 2022) (221) In this proposed use model that combines automatic encryption (LSTM-autoencoder) and long short-term memory (LSTM) networks to sort honest reviews from spam reviews, the model is trained to learn textual honest review patterns without any label, and the results are that the model can separate honest review from unwanted review with the best accuracy.

(Alsubari et al.) (2021) Use the CNN-LSTM model and evaluate two types of in-domain experiments: restaurants, hotels, Amazon, and Yelp. Each dataset applied separately. The other one is across a domain, and all datasets collected, put into one data frame, and evaluated thoroughly. The testing results of the model in domain experiment datasets were 77%, 85%, and 86%.

2.3 Critical Analysis

Author	Detection Language	Detection Technique Classifier	Platform	Datasets size	Performance
(Ding et al., 2008) 2008	English	Lexicon-based	Websites	445 reviews	The average F-score dropped to 87% to poor recall
(Alharbi et al., 2020) 2014	Arabic	• Naïve Bayesian • N-gram	Microsoft Hotmail, Google Gmail, and Yahoo Mail	9697 comments	28% increase in the accuracy of detecting Arabic spam reviews.
(Saeed et al., 2022)	Arabic	• Rule-based • N-gram	Online marketing	1,600 reviews	Accuracy of 95.25% and 99.98% for the two experimented datasets

2019					
(Martens & Maalej, 2019) 2019	English	• Multiple classification algorithms • Supervised classifier	App stores	30,000 reviews per app.	Recall of 91% and an AUC/ROC value of 98%
(Ziani et al., 2021)	Arabic	Support Vector Machine classifier (SVM) with semi-supervised (S3VM)	-	150 reviews	Accuracy 85.99%.
(Sadiq et al., 2021) **2021**	English	• Deep learning models	Google App	502, 658 records	TextBlob shows a total of 124,238 ratings biased out of 502,658 ratings VADER results show that 125,811 ratings biased out of 502,658 ratings
(Alsubari et al., 2021) **2021**	English	CNN-LSTM	hotel, restaurant, Amazon, and Yelp.	• Amazon: 21,000 reviews • Yelp: 9461 reviews • Restaurant: 110 reviews • Hotel:1600 reviews	89% Accuracy
(Saumya & Singh, 2022) **2021**	English	LSTM	YouTube	• Psy: 350 reviews • KatyPerry: 350 reviews • LMFAO: 438 reviews • Eminem: 448 reviews • Shakira: 370 reviews	OneHot Embedding with 0.34 DBI and 0.71 SC scores.
Proposed Model	Arabic	• Rule-based • LSTM	Google Maps	1,021 reviews	77% Accuracy

Table 1 Critical Analysis

2.3 Research Gap

Based on the critical analysis table above and our review of related works, various researchers have covered fake reviews on online platforms and how to detect them using different machine learning techniques. However, little research covered detecting fake reviews automatically in Google Maps, whether Arabic or English. On the other hand, other research has focused on manipulating reviews and ratings and the difference between truthful and fake reviews. Some researchers used traditional machine learning techniques, others used deep learning techniques and neural networks, while some used the two techniques together. Based on research that used both methods together, it found that deep learning techniques provide better accuracy than traditional machine learning techniques. Accordingly, we decided to use the LSTM deep learning model with sentimental analysis. Furthermore, we will develop a web-based tool to classify and detect fake reviews on the Google Map platform in Arabic.

2.4 Overview of Implementation Tools

The tools that will enable us to build the web-based tool are:

- C# Programming Language using ASP.net.
- JavaScript scripting language.
- Python Programming Language
- Visual studio.
- Microsoft SQL Server.

Chapter 3 | System Requirements

3.1 Requirement Specification

3.1.1 Data collection and Analysis

A questionnaire designed using Google forms to collect data about functional requirements. The questionnaire consists of two parts, the first part is for consumers, and the other is for business owners who use Google Maps. The aim is to know the extent of the Google Maps user's knowledge about fake reviews and their impact, and the need for a tool to detect them. We present the statistics results of the questionnaire conducted on (221) people (16) of whom were business owners.

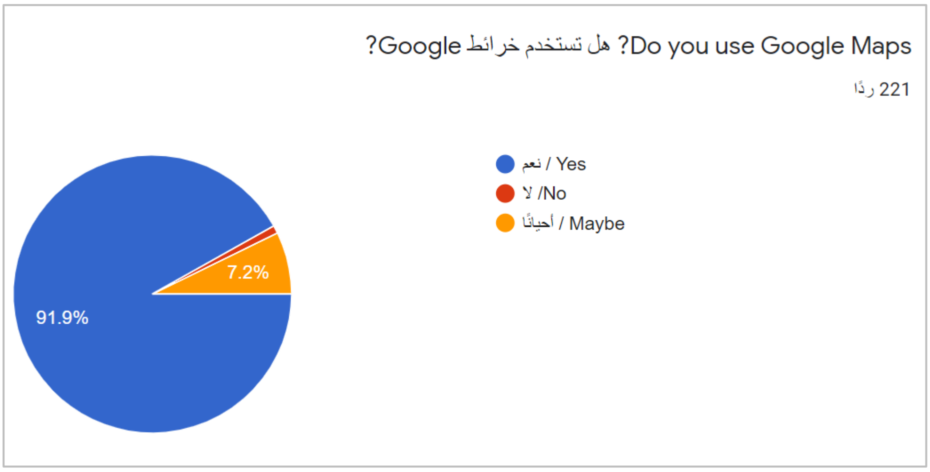


Figure 4 Result of Question1

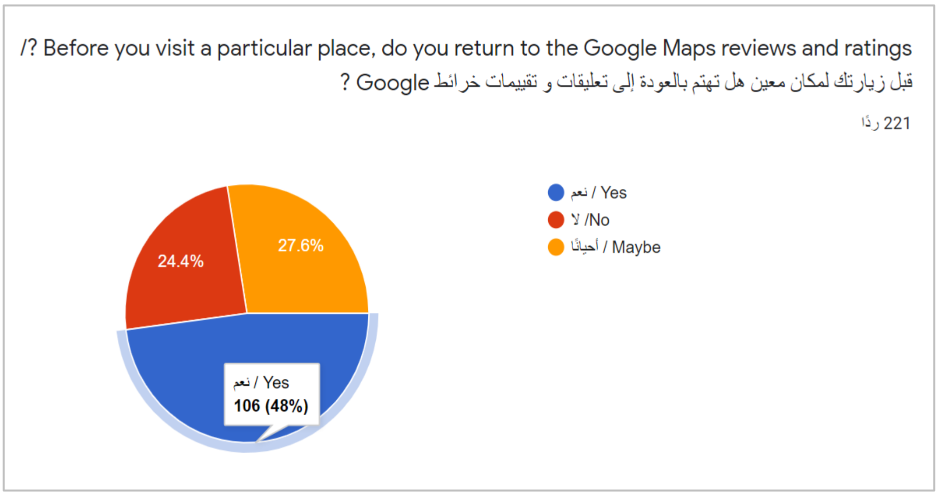


Figure 5 Result of Question2

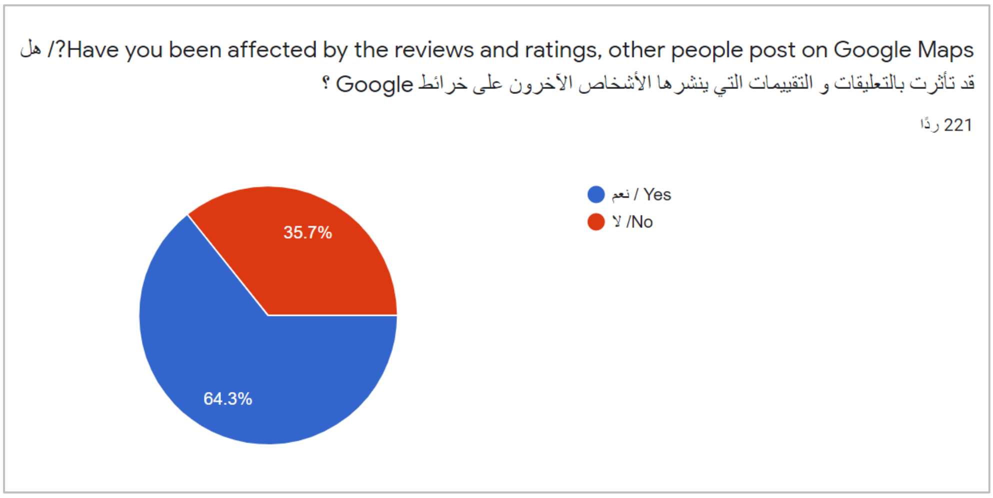


Figure 6 Result of Question 3

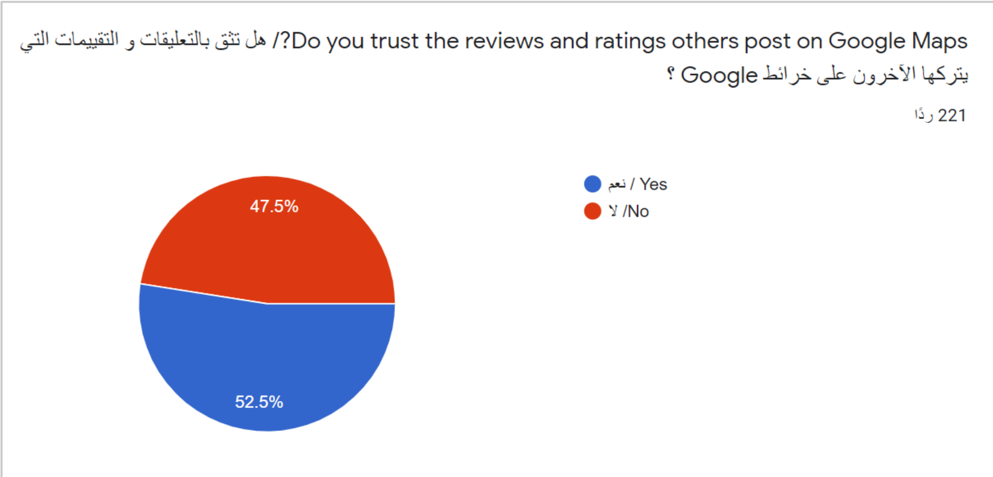


Figure 7 Result of Question 4

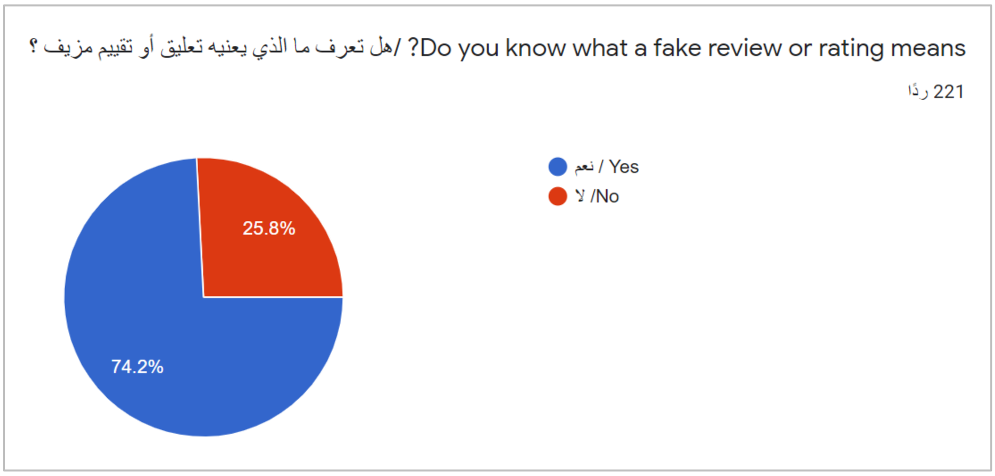


Figure 8 Result of Question 5

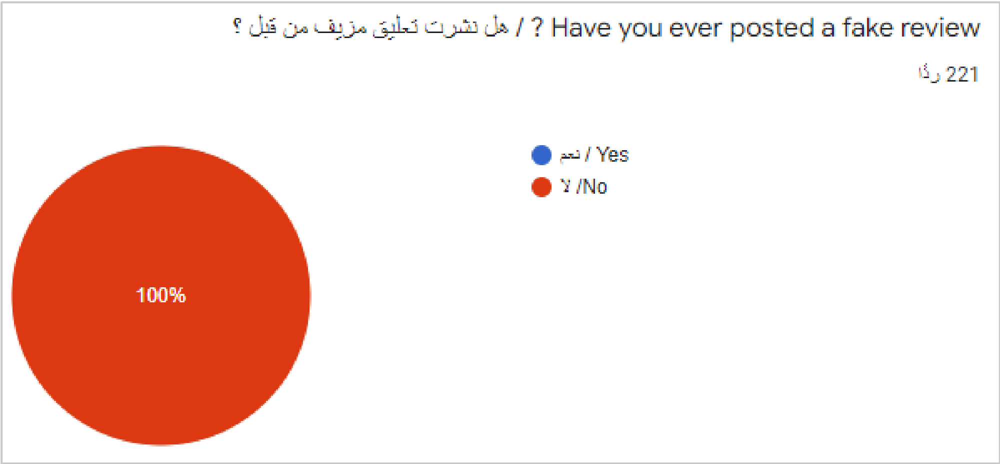


Figure 9 Result of Question 6

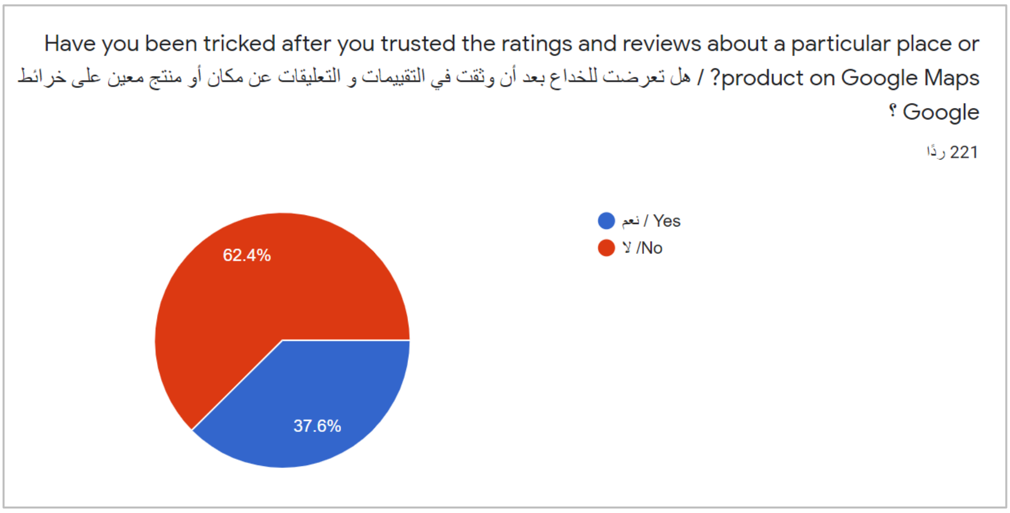


Figure 10 Result of Question 7

Figure 11 Result of Question 8

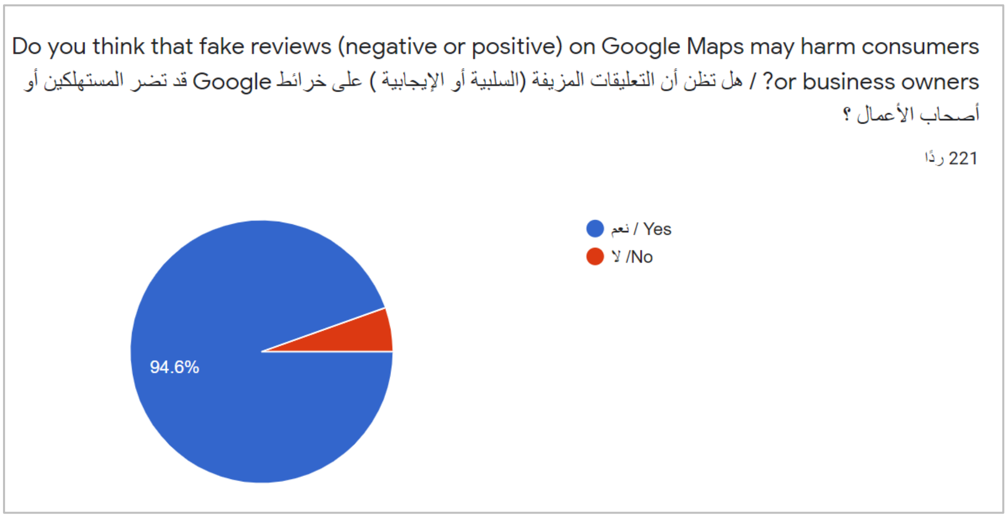


Figure 12 Result of Question 9

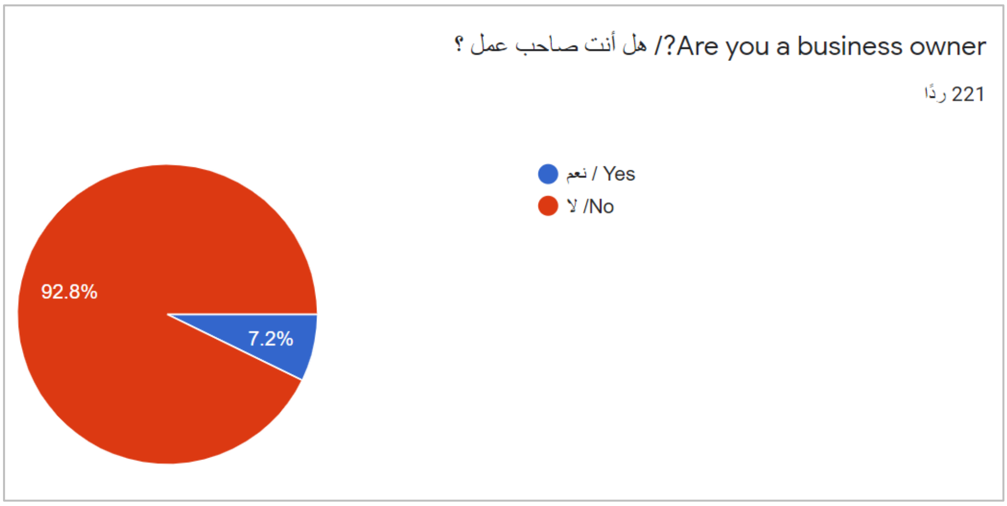


Figure 13 Result of Question 10

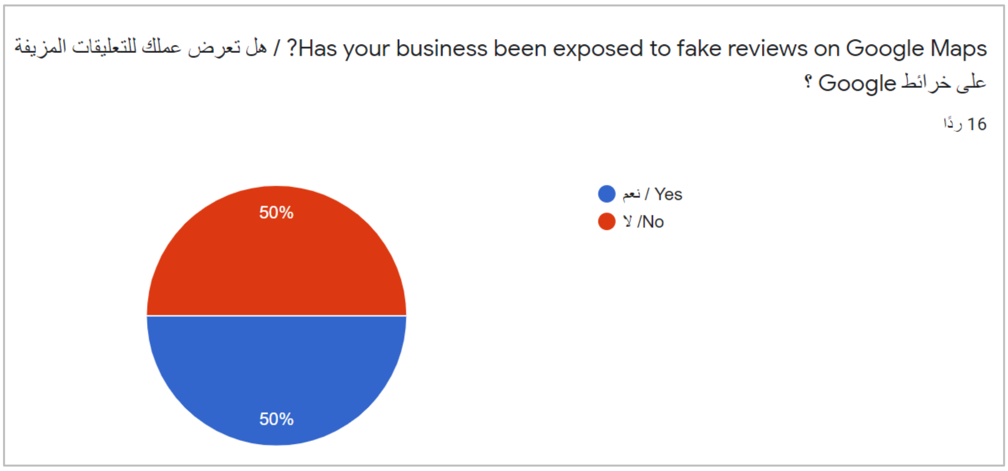


Figure 14 Result of Question 11

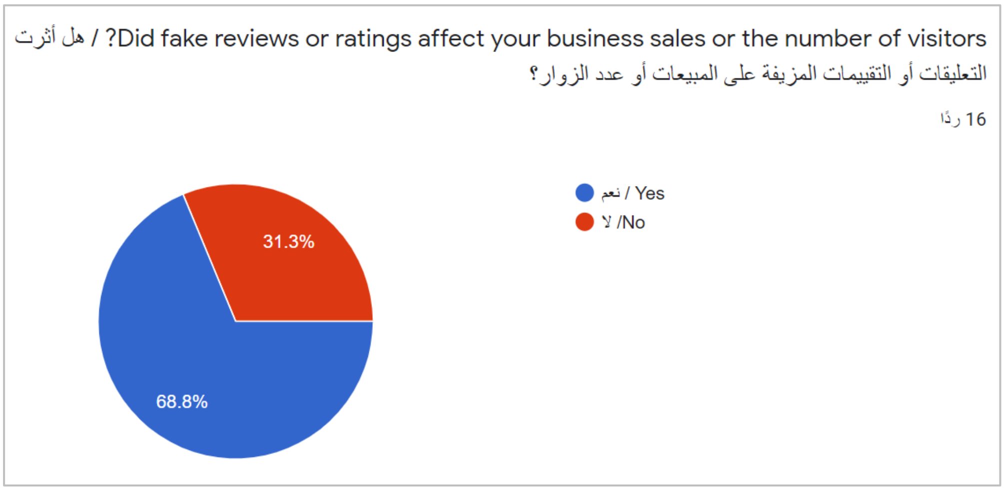


Figure 15 Result of Question 12

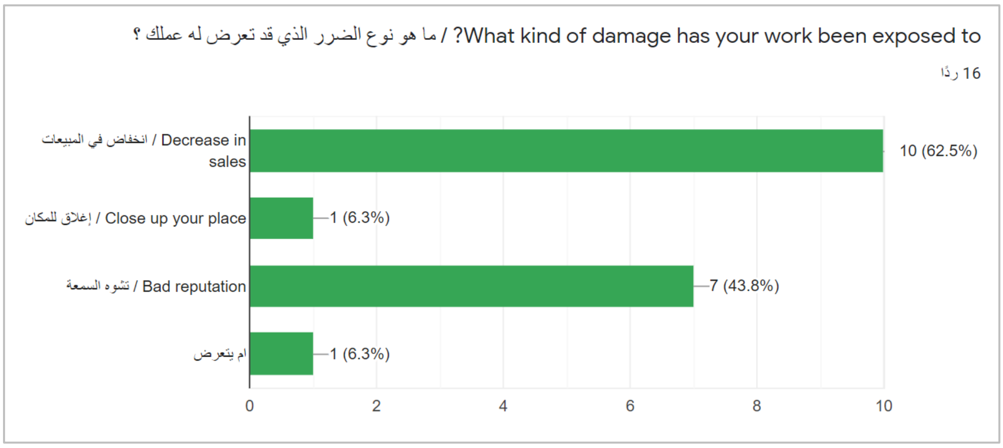


Figure 16 Result of Question 13

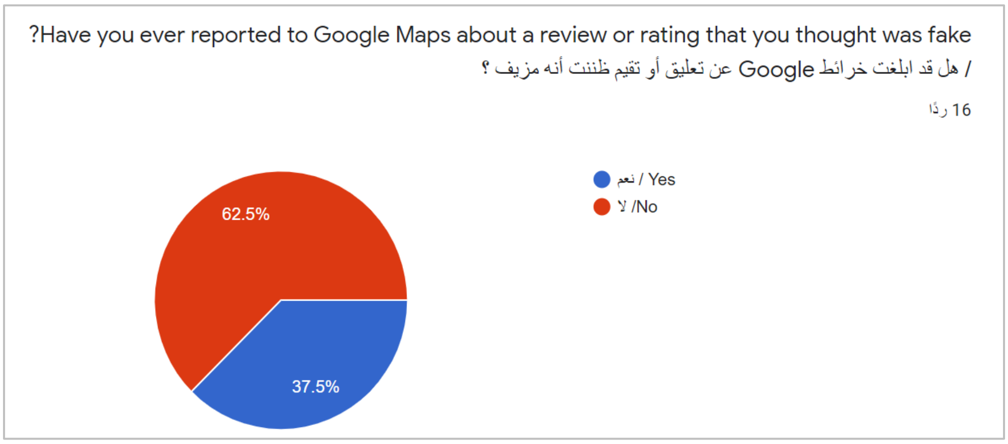


Figure 17 Result of Question 14

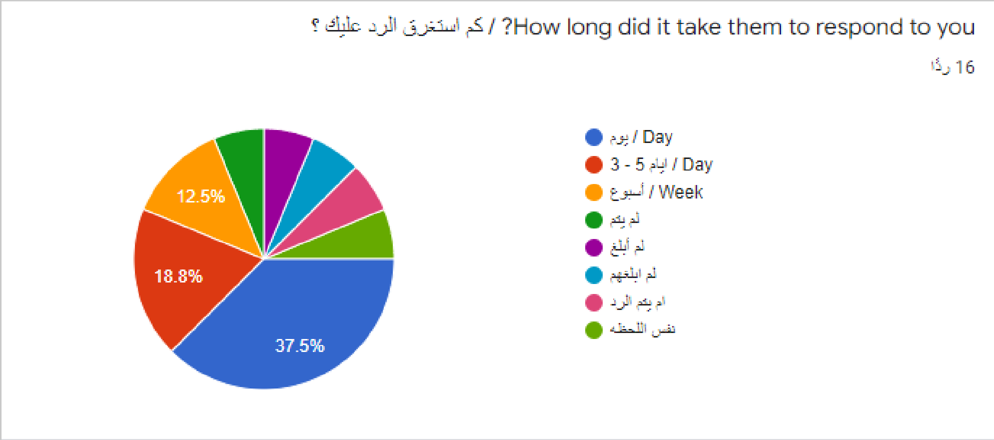


Figure 18 Result of Question 15

Based on the analysis of the questionnaire results, we found that 91% use Google Maps, and 48% refer to reviews before making decisions. Furthermore, 64% influenced by reviews, and 52% said they trusted reviews left by other people. 37% said they defrauded before by the fake reviews. 94% agreed that fake reviews harm consumers and business owners, and 95% said it is better to have a tool that helps detect fake reviews.

In the section of the business owners, 50% said they exposed to fake reviews, 62% said it had affected their sales, and 43% their reputation. 37% reported fake reviews to Google Map, and 37% said that the response took a day. 18% said it took 3 to 5 days, while 12% said it took a week to respond to them.

3.1.2 Functional requirement

Functional requirements describe the activities or processes that the system must perform or support. The main requirement of the "Fake Review Detector Tool" are the following:

- **Register to the system:** The system should allow visitors to register.
- **Log in to the system:** The system should allow members to log in and authenticate their identities.
- **Request Location Rating:** Visitors and members can search for the actual rating for a particular location in Google Maps.
- **Analyze Location Information:** The system should analyze the reviews for the entered location, remove the fake reviews, and recalculate the new rating.
- **Show Results:** The system should view the results reports to all users.

- **Save Resalt:** Only members have the right to save the results report. Members can view previously saved reports.
- **Manage Members:** The system should allow the admin to ban users when they notice abnormal behavior.
- **Manage Analyze Technique:** Admin can update the analyze technique information such as (modify, add, or delete) words. In addition, the system should allow the admin to view the locations that users search.

3.1.3 Other non-functional requirements

The non-functional requirements describe the criteria that determine the quality of the system operation and the limitation of its functionality.

- **Performance:** The tool will provide good throughput and reasonable response time; end-users do not need to wait for a long time.
- **Usability and Accessibility:** The tool will be easy to use with a friendly interface and designed to reach the results of the reviews in a few straightforward steps. Also, it will have a meaningful name and logo so the user can access it easily.
- **Scalability:** Given how the tool works, it will support the expansion and add new data to enhance the result.
- **Portability and Maintainability:** The web-based tool will support and work on different platforms, and it should be easy to maintain.

3.2 Target User

The targeted users of our web-based tool are:

- **Consumers:** They are the people who refer to the ratings and reviews on Google Maps.
- **Business owners:** They are the people who have an account, such as restaurants in Google Maps.

3.3 Structuring System Requirements

The following diagrams illustrate the relationship between the “Fake Review Detector Tool” and the actors. We have used the use case diagram and data flow diagram to describe this.

3.3.1 Use case model

Use cases describe the interaction scenarios between the tool and users to execute a task refer to figure 19.

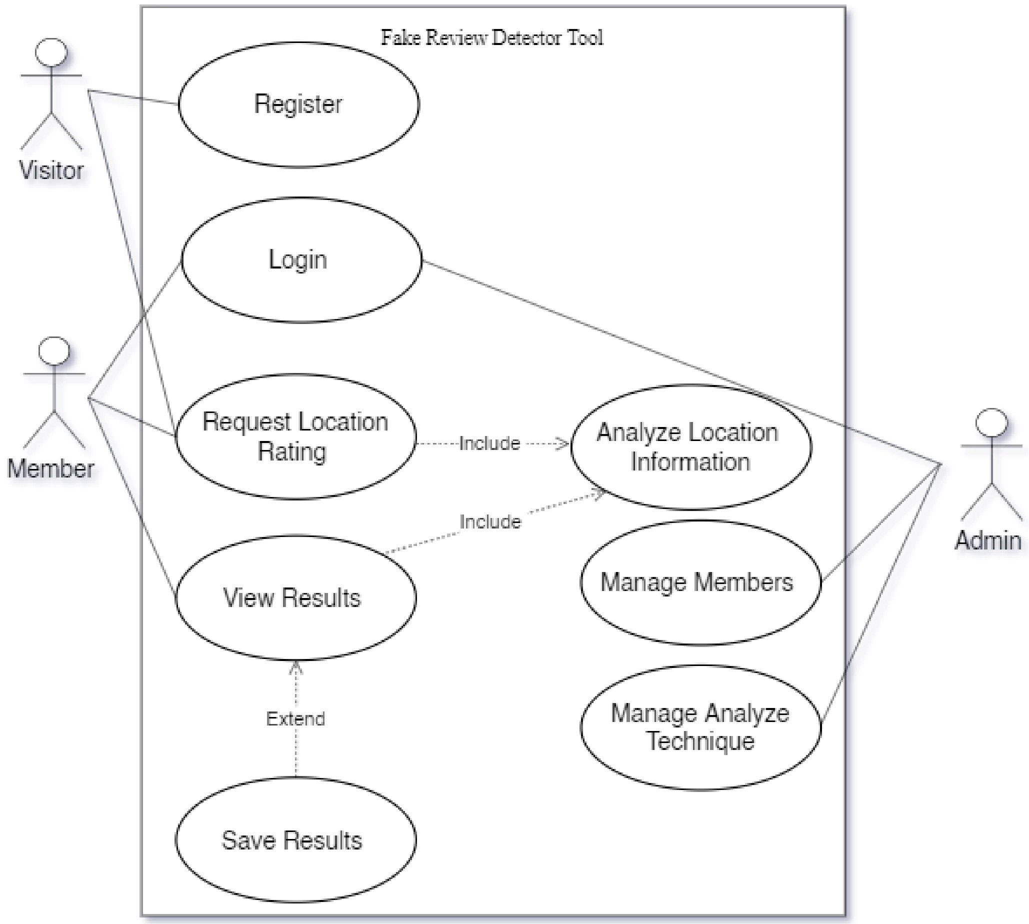


Figure 19 Use case Diagram

Each use case described separately in detail in the following tables refer to tables 2-9.

Use case name	**Register**	
Actors	Visitor	
Description	The user registrar information such as (username, password, email, consumer, business owner, etc.)	
Pre-conditions	-	
Post-conditions	Successful registration.	
Basic flow	**Actors**	**System**
	1-The user enters registrar information. 2-The user submits information.	3- Validates user information. 4-Display homepage.

Table 2 Register use case.

Use case name	**Login**	
Actors	Member, Admin	
Description	Users' login using username and password.	
Pre-conditions	Users should have an account.	
Post-conditions	Successful login.	
Basic flow	**Actors**	**System**
	1- The user enters the username and password. 2-The user submits a username and password.	3-Validates user credentials. 4-Display homepage.

Table 3 Login use case.

Use case name	Request Location Rating	
Actors	Visitor, Member	
Description	The user enters the link of the desired place to view its reel rating.	
Pre-conditions	Entering veiled location.	
Post-conditions	-	
Include Use case	Analyze Location Information.	
Basic flow	**Actors**	**System**
	1- The user enters the place link.	2- Triggers analyze location information use case.

Table 4 Request Location Rating use case.

Use case name	Analyze Location Information	
Actors	**Visitor, Member**	
Description	The system analyzes review information to identify fake reviews.	
Pre-conditions	-	
Post-conditions	Location rating successfully analyzed.	
Basic flow	**Actors**	**System**
	-	1-Analyzes the review content. 2-Identifies fake reviews. 3-Removes fake reviews. 4-Recalculates the rating.

Table 5 Analyze Location Information use case.

Use case name	**View Results**	
Actors	Visitor, Member	
Description	Users view the result report of the new recalculated rating.	
Pre-conditions	-	
Post-conditions	The system displays the rating report results page.	
Include Use case	Analyze Location Information.	
Basic flow	**Actors**	**System**
	2- User view result report.	1- Display the results page. 3- (Extension point: Save Resalt)

Table 6 View Results use case.

Use case name	**Save Resalt**	
Actors	Member	
Description	The user saves the results of the report.	
Pre-conditions	The user must be a member.	
Post-conditions	The report is saved.	
Basic flow	**Actors**	**System**
	1- The user enters the save button.	2-The system saves the report in the database. 3-Display-saved massage.

Table 7 Save Resalt use case.

Use case name	**Manage Members**	
Actors	Admin	
Description	Admin can remove or update members' information.	
Pre-conditions	Admin must be logged in.	
Post-conditions	Successfully remove or update members.	
Basic flow	**Actors**	**System**
	1- Admin selects a particular memb to remove.	2-The system removes a member from the database. 3-Display removed member massage.

Table 8 Manage Members use case.

Use case name	**Manage Analyze Technique**	
Actors	Admin	
Description	Admin can add, remove, or update words used in analyzing the results.	
Pre-conditions	Admin must be logged in.	
Post-conditions	Successfully add, remove, or update the database.	
Basic flow	**Actors**	**System**
	1- Admin selects specific data to updated.	2-The system updates the data. 3-Display updated massage.

Table 9 Manage Database use case.

3.3.2 Data flow diagram

DFD describes the flow of data between components of a system in figure 20.

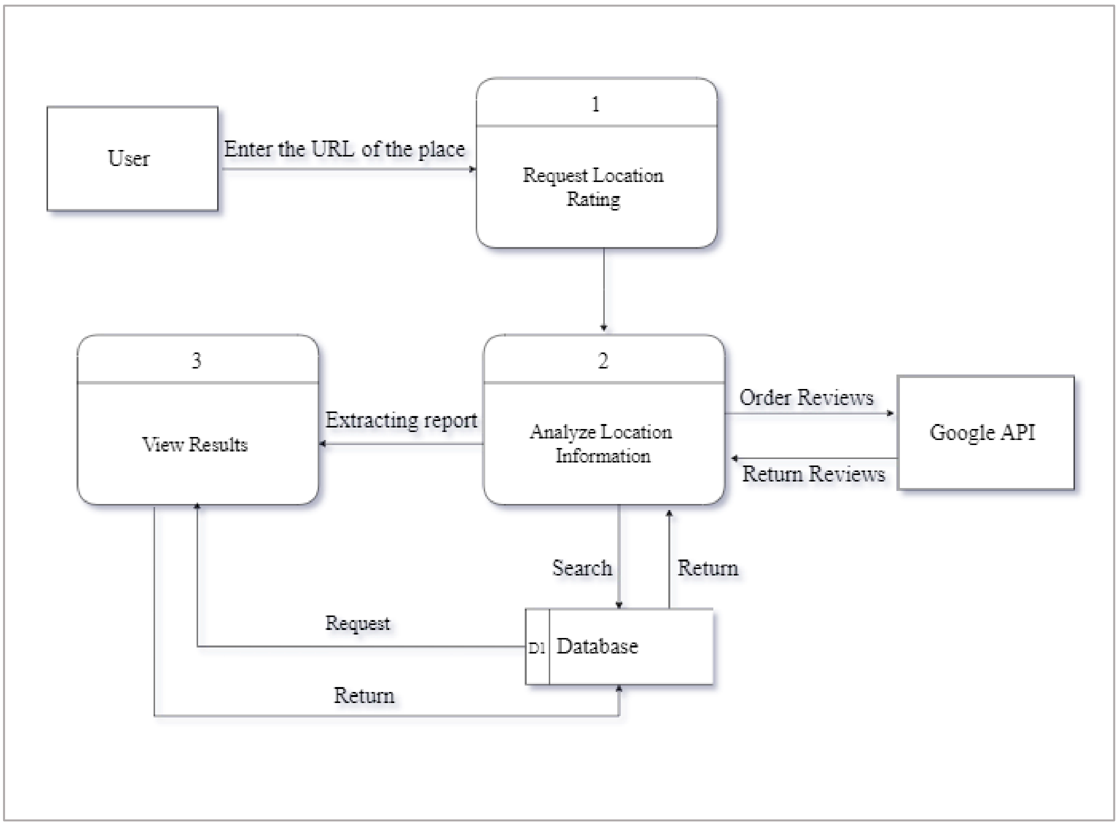


Figure 20 Data flow diagram

The data flow in the system is as follows: In (Process 1), the user enters the address of the place he/she would like to know its actual rating. Then, the information sent to (Process 2) to analyzed while the review information fetched from the Google Maps API, and essential data for the analysis brought from the database. After the analysis finished, the results report displayed in (Process 3) after bringing the report information from the database.

Chapter 4 | Design

4.1 Interface Design

This section previews the prototype design for a " Deep Review Checker " website tool, its functionality, and how it works.

4.1.1 Homepage

Figure 21 shows the main interface of the system. First, the user (member or visitor) copies the link of the place he\she wants to know it is reel rating from Google Maps, puts the link in the search box, and clicks the check button. Then the system will start processing and analyzing the content of the reviews. After that, the system directs the user to the report display page.

Figure 21 Homepage

4.1.2 View report Page

The report page shows details about the place that the customer wants to view its actual rating. In addition, it shows the number of reviews that checked, the number of fake reviews, and the percentage of fake reviews to the total number of reviews. Furthermore, it shows the detailed rating of the place in Google Maps and the adjusted rating of our tool, as shown in Figure 22. Also, the report shows the most and least trusted reviews based on our tool's criteria, as shown in Figure 23. The visitor and the member can browse the report page, but logging in if the user wants to save the report requires logging in.

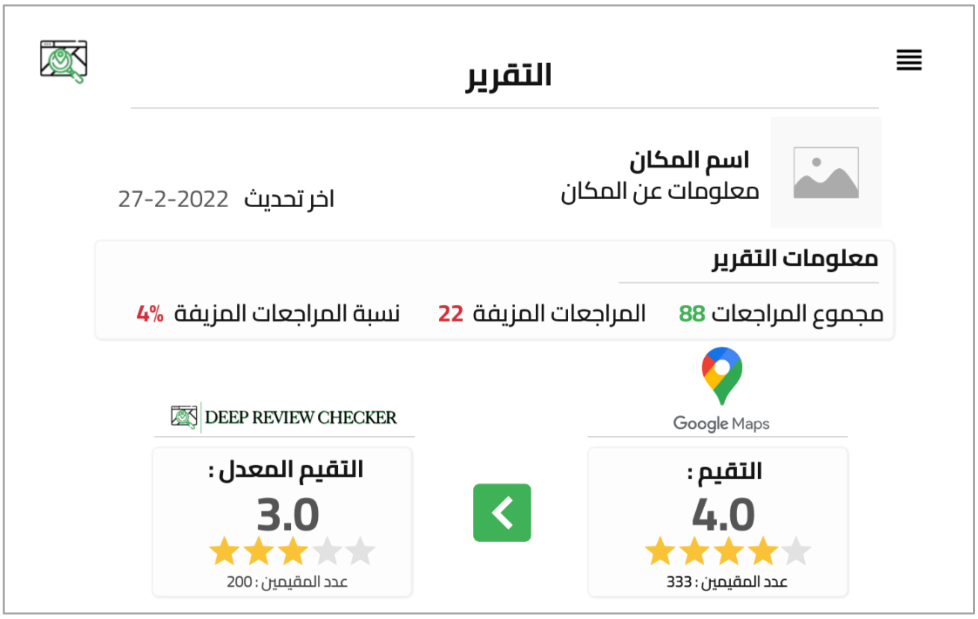


Figure 22 View report page 1

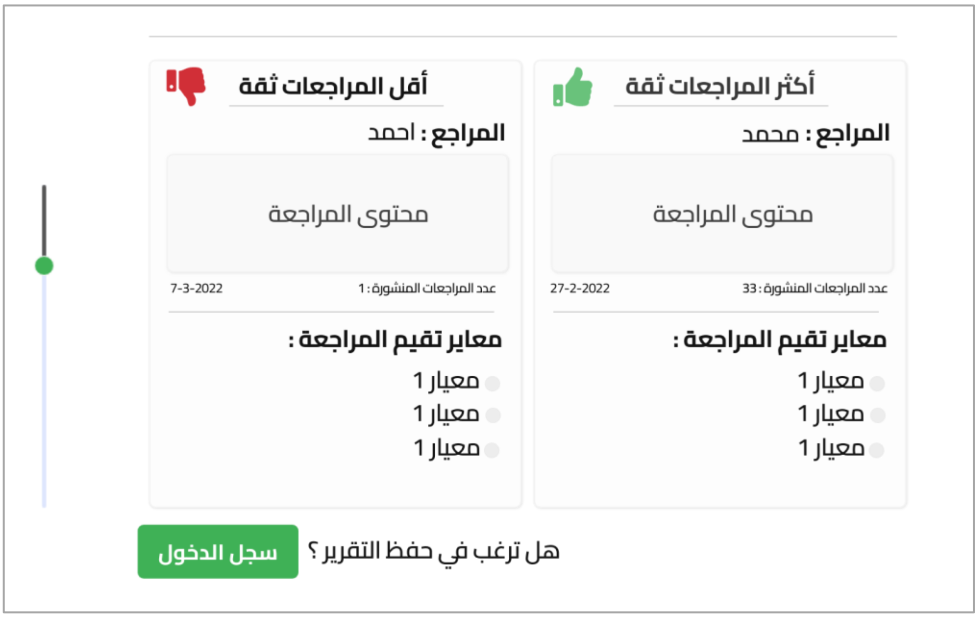


Figure 23 View report page 2

4.1.3 Login Page

The users must provide valid credentials for successful entry to the system. The system does not require users to log in to use the tool; it is optional if users want to save their information and view it later; refer to the login page in Figure 24.

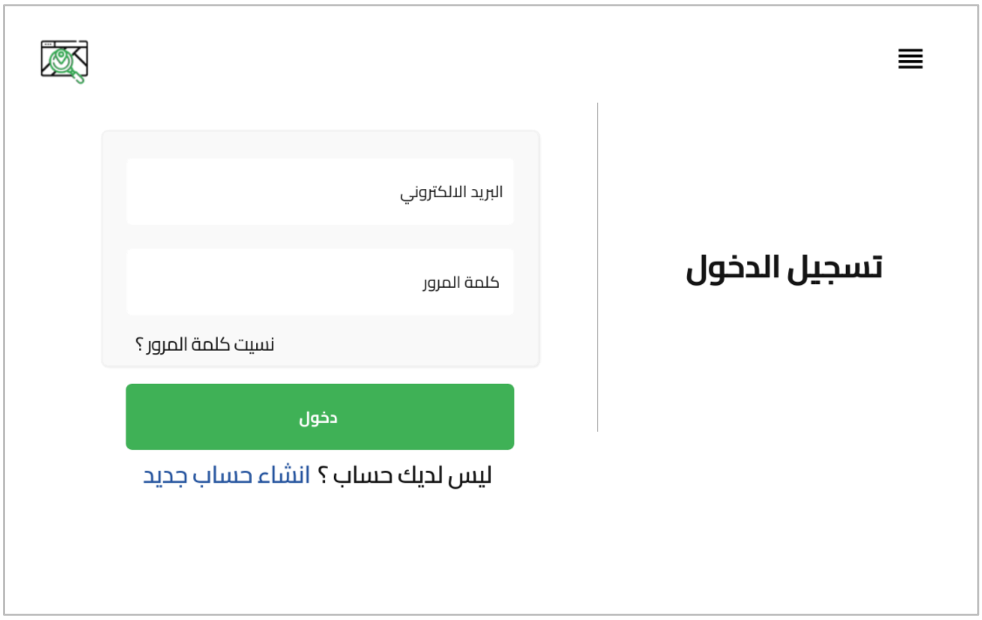


Figure 24 Login page

4.1.4 Register page

If the user does not have an account, he\she must create a new account and enter basic information such as name, email, and password, as shown in Figure 25.

Figure 25 Register page

4.1.5 Account page

After the user logs in, he\she can view his\her account page where the user's basic information is in addition to previous search records and saved reports. Figure 26 shows the account page.

Figure 26 Account page

4.1.6 About us page

Figure 27 shows the about tool page, which displays how the tool works.

Figure 27 about us page

4.1.7 Contact us page

The Contact Us page makes it easy for customers to communicate with us if they encounter problems using the tool. Figure 28 shows Contact Us page.

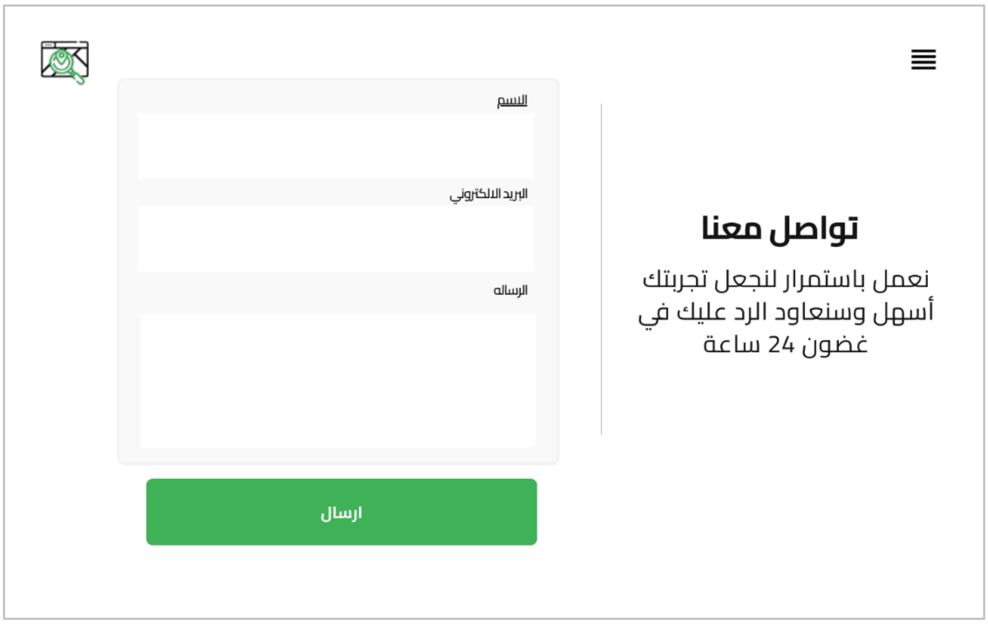


Figure 28 Contact us page

4.2 Database Design

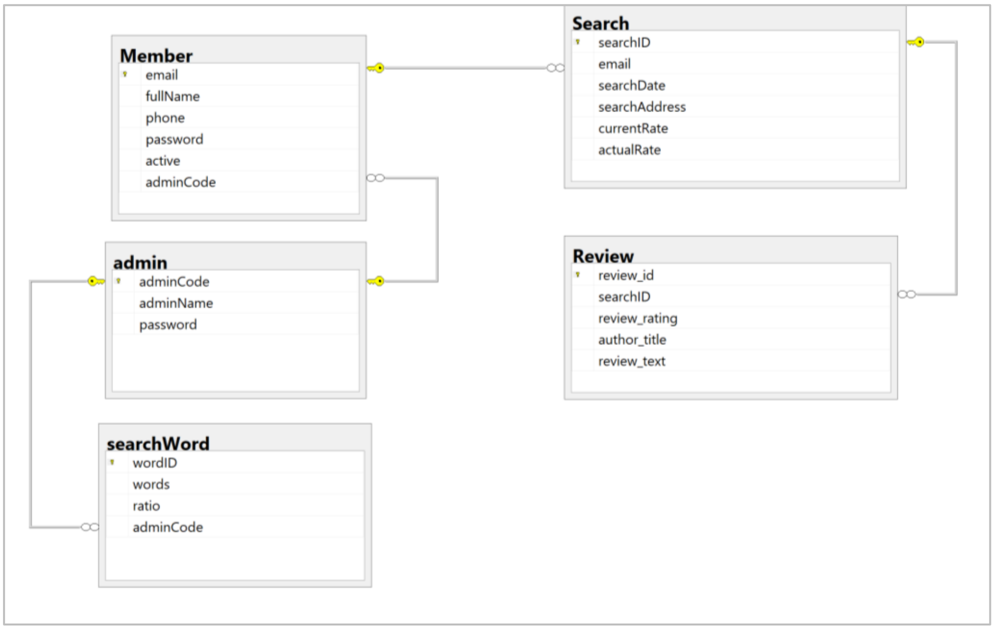


Figure 29 Database Design

Chapter 5 | IMPLEMENTATION

This chapter displays the software tools used in our project to start the implementation and the interfaces description section for the system.

5.1 Implementation Tool

5.1.1 Software Tools

- **Visual studio**

Microsoft's development environment to develop computer programs and websites. For example, we have used it in building the GUI of our web applications and the database schema.

- **JavaScript**

It is a programming language developed to display websites and make web pages interactive. Provides improved services which are better than HTML and CSS.

- **Microsoft SQL Server**

It used to manage and store information C# It is a programming language using ASP.net used for low-level functionalities and device connectivity.

- **Outscraper API**

It is a website that scraps reviews from Google Maps of a given place based on a specific search query.

- **Visual Studio Code**

It is a code editor for building and debugging web and cloud applications. It used in building the LSTM model with the help of Python language.

- **Python**

Is programming language considered a scripting language used to create Web applications, and it contains an open-source library and tools to develop a model for ML and AI. Main Libraries Used:

  - **Pandas**

It is a data manipulation and analysis library which offers data structures and operations for manipulating tables.

- **NLTK**

Natural Language Toolkit libraries used for statistical natural language (NLP) preprocessing and corpora analysis.

- **Numpy**

It provides a high-level math function used in neural networks for faster computations of the weights (gradients).

- **Keras**

It is an open-source library that enables fast experimentation with deep neural networks.

5.1.2 Hardwar Tools

Desktop computer or laptop

5.2 LSTM-Based Fake Review Identification Deep Learning Model

For detecting and identifying fake reviews, we adopted a deep learning technique to build the long short-term memory (LSTM) model. In the first step, we used a Rule-Based classifier to label the unlabeled dataset as a fake or truthful review. The next step is word Embedding, which used to transform each word in the training data into a vector, meaning the words in the dataset transformed into numerical form. Then, split the dataset into a training dataset and a test dataset. Next, the training dataset used to train and build the LSTM model then the model will use the test dataset in the prediction possess. Lastly, we evaluate the performance of the classifier using accuracy. Figure 39 illustrates the structure of the proposed LSTM model used for identifying fake reviews. The components of the proposed LSTM model are as follows.

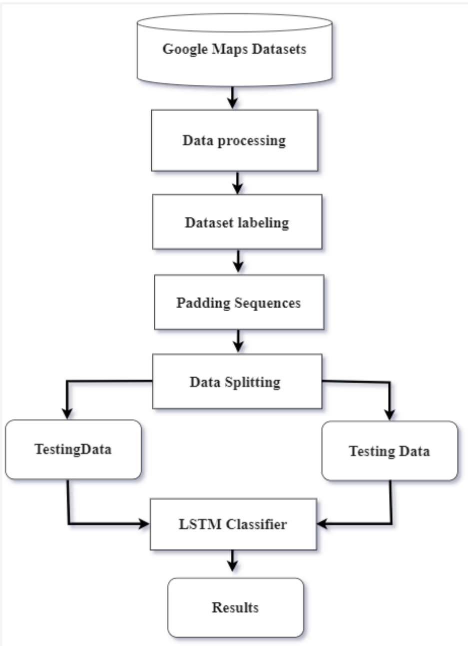


Figure 30 LSTM-Based Fake Review Identification Deep Learning Model Overview

5.2.1 Datasets

Web scraping used to collect Google Maps dataset that contains (1000) Arabic reviews for hotels, markets, shops, restaurants, and others in Jeddah city, see Fieger

30. The dataset has features such as place name, average review rating, author id, author name, the review text, and reviewer rating. In addition, the collected dataset contained row data that is unlabeled to fake or truthful reviews. Dataset shown in Fieger 31.

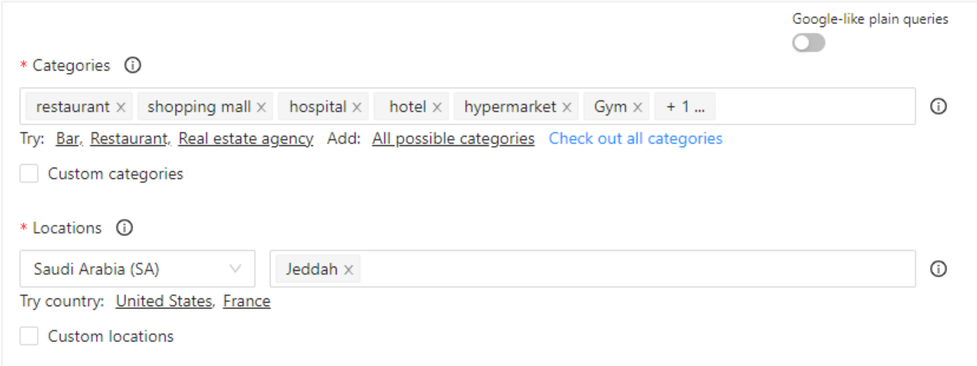


Figure 31 web scraping

	name	rating	author_title	author_id	review_text	review_rating
0	مطعم فردوس	3.7	محمد الحرطانى	118175926849080754067	...جيد واسعارها لابأس بها ولا كن لا يوجد لديهم جه	3
1	مطعم فردوس	3.7	omar almadani	101725960596666716788	...من افضل مطاعم الباكستانين الا بالمنطقة وافضل م	5
2	مطعم فردوس	3.7	ADEL HAMAD	107861058010757228769	...مطعم حلو ولكن ما اكلت عنده إلا عدس وكان جميل ج	4
3	مطعم فردوس	3.7	النيل	115852311212023045023	ممتاز جدا ماشاءالله ربنا يوفقكم وخدمات ممتاذه	5
4	مطعم فردوس	3.7	ابو يمان اليافعي	105163089334133871511	المطعم طيب والاكل طيب بس مشكلته تاخر الطلب	3

Figure 32 Dataset

5.2.2 Data Preprocessing

In this step, the data cleaned, refined, and prepared for the next step using Natural Language Processing. In Fieger 32, an overview of the data preprocessing phase. That includes removing duplicate records, records that do not content review text, punctuation marks, movements for Arabic letters, and removing stop words from the review dataset. First, punctuation marks in reviews removed and replaced with white spaces. Refer to Fieger 33. Next, tokenization used to divide each review text into small words. After that, stop words removed. Stop words are frequently used words in the text, such as prepositions like على) ,الى), و. Refer to Fieger 34.

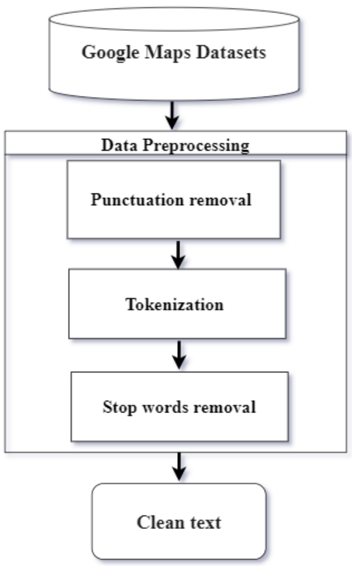


Figure 33 Data Preprocessing Overview

```
text = data[['review_text']]
# Removes all special characters and numericals leaving the alphabets
def clean_text(text):
    search = ["أ","إ","آ","ة","_","-","/",".","،"," و "," يا ",'"',"ـ","'","ى",
              "\\",'\n', '\t','&quot;','?','؟','!' ]
    replace = ["ا","ا","ا","ه"," "," ","","",""," و"," يا",
               "","","","ي","",' ', ' ',' ',' ? ',' ؟ ', ' ! ' ]
```

Figure 34 punctuation marks in reviews removed

	name	rating	author_title	author_id	review_text	review_rating	Cleaned_Reviews	Tokeniz_Reviews
0	مطعم فردوس	3.7	محمد الحرطاني	118175926849080754067	جيد واسعارها لابأس بها ولا كن لا يوجد لديهم جه...	3	جيد واسعارها لاباس بها ولا كن لا يوجد لديهم جه...	جيد واسعارها لاباس يوجد لديهم جهاز سحب للحساب ...
1	مطعم فردوس	3.7	omar almadani	101725960596666716788	من افضل مطاعم الباكستانين الا بالمنطقة وافضل م...	5	من افضل مطاعم الباكستانين الا بالمنطقة وافضل م...	افضل مطاعم الباكستانين الا بالمنطقة وافضل الاب...

Figure 35 After preprocessing

5.2.3 Dataset labeling

After preprocessing supervised Rule-Based classification method used to label the dataset. The criteria that we relied on in determining whether a review is fake or truthful are:

- Length of the review (Average number of words)
- Review rating
- Sentiments in the review (Percentage of positive/negative words in each review)

We first start by specifying the length of the review and its word count. Studies have indicated that short reviews are usually fake, while reviews with average word lengths of 200 words tend to be more truthful. (Alsubari et al., 2022)

The code calculates the word count for each review and then calculates the average length for all reviews. The length of the review compared to the average length of the reviews:

If Review length >= Average length

Then the review is most likely to be reel.

else

The review is most likely to be feck.

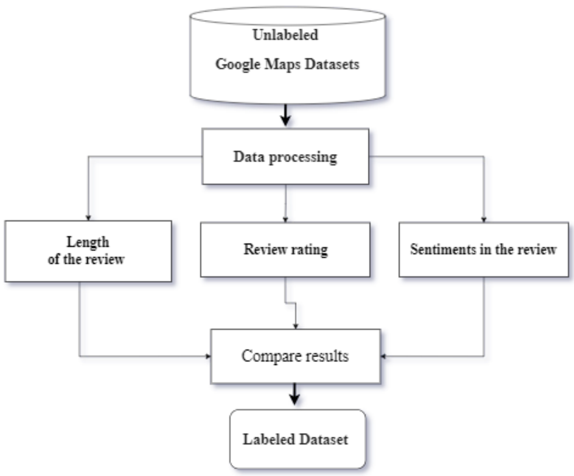


Figure 36 Dataset labeling Overview

In the next step, the rating of each review compared with the average rating of all reviews. According to studies, fake reviews tend to have an extreme rating compared to truthful reviews. (Rout et al., 2017)

The last step analyzes sentiment for each review using the NLTK module. Vader Sentiment word dictionaries used for sentiment polarity score. The code calculates each review's negativity, positivity, and neutrality scores. Based on studies, fake reviews contain exaggerated sentiment compared to truthful reviews. (Moon et al., 2021)

The code collects the sum of positive and negative sentiment percentages and compares the result with the neutral sentiment percentage. If the sentiment percentage in the review is greater than or equal to the neutral sentiment percentage, then the review is most likely fake; otherwise, it is truthful.

In each of the previous steps, the result will be 0 if the review is feck and 1 if truthful. Finally, in the last step in the dataset labeling process, the final result will calculate according to the criteria scours. If two or more criteria indicate that the review is fake, it labeled Fake; otherwise, it is Truthful. Refer to Fieger 36. In Fieger 37, the ratio of fake reviews to truthful ones.

	dc_Avgwords	dc_rating	dc_sentiment	label
0	0	0	0	FAKE
1	0	0	0	FAKE
2	0	0	0	FAKE
3	1	0	1	REAL
4	1	0	1	REAL

Figure 37 Dataset labeling

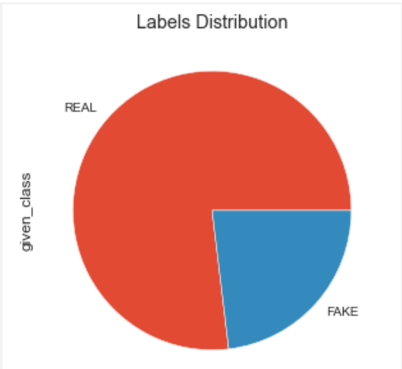


Figure 38 the ratio of fake reviews to the real review

5.2.4 Padding Sequences

This step converts reviews to sequences because deep learning algorithms require a fixed length for input sequences in text classification and then apply the padding. Therefore, in this step in the learning process, 150 words will used as the maximum length for each review using the padding sequence method. Refer to Fieger 38.

```python
# We will be using only 150 words for learning for each review
def trim_data_lem(text):
    text = word_tokenize(text)
    temp = " ".join(x for x in text[:148])
    return temp
data['trim_data_lemmatized'] = data['Translated_Reviews'].apply(lambda x : trim_data_lem(x))
maxReviewLength = 155
```

✓ 0.8s Python

Figure 39 apply padding

5.2.5 Data Splitting

The dataset has divided into 70% as a training set, 10% as a validation set, and 20% as a testing set. Then, we used a network model consisting of a long short-term memory (LSTM) to detect and classify the review text into a fake or truthful review.

5.2.6 Results and Analysis

We analyze the performance of the LSTM model on google review datasets. The final Test Accuracy that the model presented was 0.77. Refer to Fieger 40 and Fieger 41.

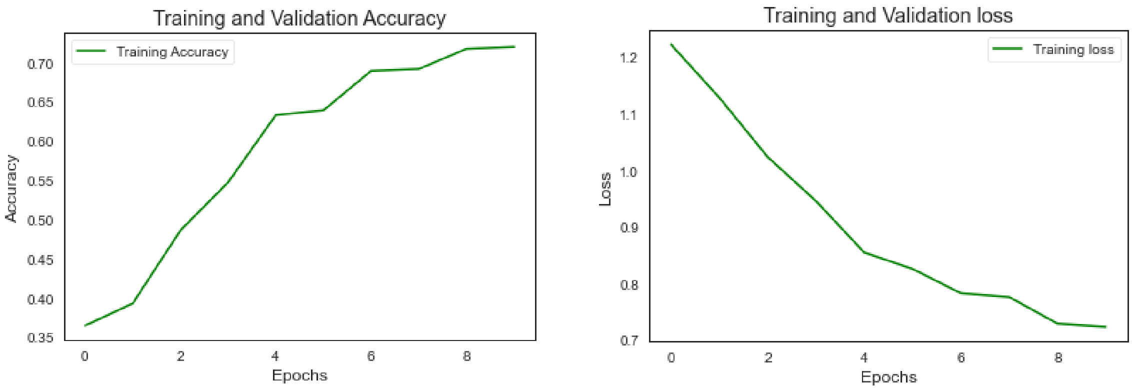


Figure 40 The performance and loss of the LSTM model on cross-domain datasets.

	precision	recall	f1-score	support
0	0.77	1.00	0.87	158
1	0.00	0.00	0.00	47
accuracy			0.77	205
macro avg	0.39	0.50	0.44	205
weighted avg	0.59	0.77	0.67	205

Figure 41 classification report

5.3 Walkthrough the System

In this section, we explain our web application " Deep Review Check" code and its main pages. When the user opens the website the first page that will appear is the main page. The user puts the name or the URL of the place he/she wants to search for his/her credible rating in the search box. After the user presses the check button, the website will fetch the reviews of the place using the Outscraper API tool. A message will appear to users if the search button is pressed before the URL is placed alerting them to put it. Figure 42 illustrates the line of code that fetches reviews from Google Maps.

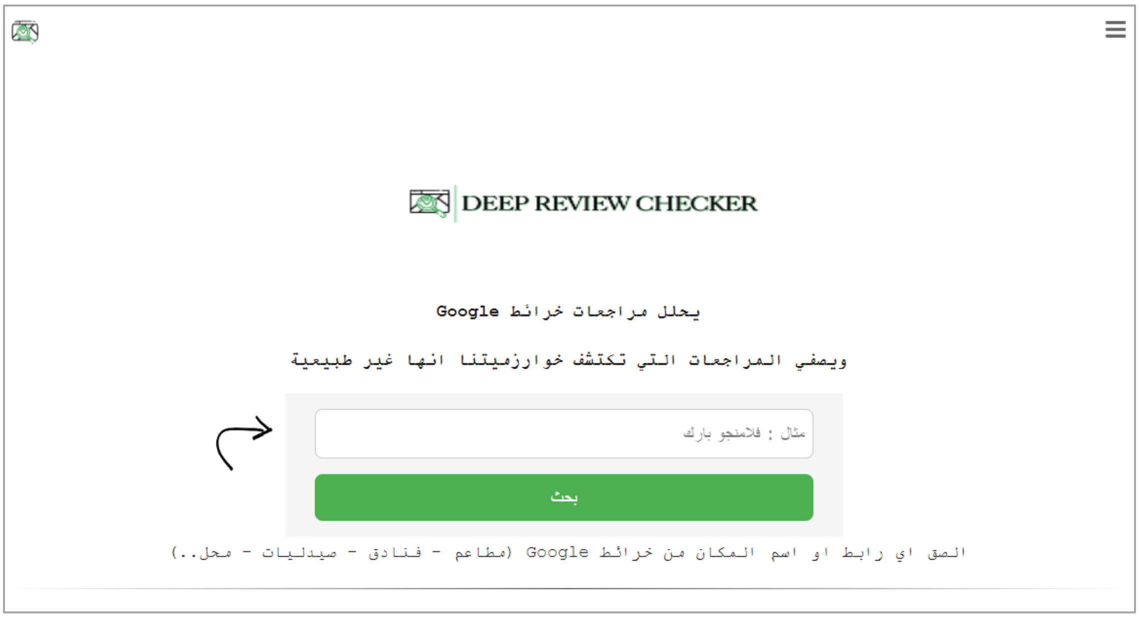


Figure 42 main page

Figure 43 illustrates the line of code that gets reviews from Google Maps.

```
$.ajax({
    type: "GET",
    url: "https://api.app.outscraper.com/maps/reviews-v2?async=false&apiKey=Z29vZ2xlLW9hdXRoMnwxMDEyOTQ2MjUxMzg0MTA2NTg5Mzh8OTJlNjY5NGUzYg&reviewsLimit="
        + sampleNo + "&query=" + location + "&language=" + language,
```

Figure 43 URL Outscraper API

After clicking on the search box, the website analyzes these reviews in the background using sentiment analysis. When the analysis is complete, the report will appear down the page. The report summary contains information about the place, Google Maps rating, the rating of our website "Deep Review Checker" and the number of all the reviews of the place, the number of fake, and truthful reviews. The report displays additional information such as all reviews of the place and shows reviews that we believe are fake and reliable. Figure 44 shows the report page.

Figure 44 Report page

Figure 45 shows part of the report page code where the sentiment analysis for each review is computed.

```
var sumValue = 0;
var sumWord = 0;
console.log(text.data[0].reviews_data[i].review_text);
var ReviewWords = text.data[0].reviews_data[i].review_text.split(" ");
for (var m = 0; m < ReviewWords.length; m++) {
    var str = filter(ReviewWords[m]);
    for (var n = 0; n < words.length; n++) {
        console.log(str + " word  " + words[n].words + "  " + str.includes(words[n].words) + "  " + words[n].ratio);
        if (str.includes(words[n].words)) {
            sumWord = sumWord + 1;
            sumValue = sumValue + parseFloat(words[n].ratio);
        }
    }
}
```

Figure 45 new rating equation

The new rating is calculated after removing the fake reviews based on the equation in Figure 46.

```
var ratio = (sumValue / (ReviewWords.length * 1.0)) * 100;
ratio = ratio.toFixed(1);
console.log(ratio + " sum value " + sumValue + " length " + ReviewWords.length);
if (ratio >= Database_ratio) {
    rateFake = rateFake + text.data[0].reviews_data[i].review_rating;
    Fakeno = Fakeno + 1;
    fake += "<p class='w3-container' style='text-align:right'> التقيم :" + text.data[0].reviews_data[i].review_rating + "</p>";
    fake += "<p class='w3-container' style='text-align:right'> التعليق </p>";
    fake += "<p class='w3-container' style='text-align:right'>" + text.data[0].reviews_data[i].review_text + "</p>";
}
else {
    rateGood = rateGood + text.data[0].reviews_data[i].review_rating;
    goodno = goodno + 1;
    good += "<p class='w3-container' style='text-align:right'> التقيم :" + text.data[0].reviews_data[i].review_rating + "</p>";
    good += "<p class='w3-container' style='text-align:right'> التعليق </p>";
    good += "<p class='w3-container' style='text-align:right'>" + text.data[0].reviews_data[i].review_text + "</p>";
}
```

Figure 46 new rating equation

Chapter 6 |Testing

6.1 Introduction

This chapter is the final stage of the project. Building a successful and effective website must follow six system development life cycle phases. Now we are in the final stage, which is the testing phase. First, the developers will test the website to ensure it matches the primary purpose. This testing will cover usability and performance and evaluate the website interfaces and the tools to ensure they are working as expected.

6.2 User Analysis and Profile

To test the functionality of our project, we asked five people to use our website, and they were between the ages of 20 to 50 years, including consumers and business owners. Suppose they can register, create a new user in the system or log in from the side menu. The users can access every website page for testing, including searching for the actual rating for a particular location in Google Maps, displaying truthful and fake reviews, and viewing the results from the report and account pages. Also, non-users can search the actual rating for allocation in Google Maps from the search page. As the services provided by our project received more positive feedback, and they said that our web application is straightforward to use, and they do not need any help from anyone else. The website was easy to deal with multiple devices and screens and showed the review report promptly.

6.3 The Goal of The Test

The testing goals are based on ensuring that the services provided by the project that consumers and business owners needed the It. The user expects to register to the system or log in and request a location rating; it also can show results and save results.

6.4 User Tasks

Table10 displays the user's tasks on the website, such as creating a new user account, accessing the website, inter URL to search the location, and showing the report.

Task	User Type
Register: Create a new account	User
Puts the link in the search box and click the check button.	User
Show previous search records and saved reports	User
It shows the about tool page, which displays how the tool works.	User
It shows details about the place where the customer wants to view its actual rating and the number of reviews on the report page.	User
Search without login and show the report	User
Manage members and ban users	Administrators
Update the analyze technique information modify, add, or delete words	Administrators
View the locations that users search	Administrators

Table 10Tasks for different users

6.5 Tester Profile and Analysis

<table>
<tr><td rowspan="2">Test information</td><td>Full name</td><td colspan="3">Amal</td></tr>
<tr><td>User Type</td><td colspan="3">User</td></tr>
<tr><td rowspan="5">Testing task</td><td colspan="2" rowspan="2">Task</td><td colspan="2">Result</td></tr>
<tr><td>Pass</td><td>Not pass</td></tr>
<tr><td colspan="2">create a new account</td><td>√</td><td></td></tr>
<tr><td colspan="2">Puts the link in the search box and directs to the report display page.</td><td>√</td><td></td></tr>
<tr><td colspan="2">Saved reports</td><td>√</td><td></td></tr>
</table>

Table 11 test user tasks

Test information	**Full name**	Abdullah	
	User Type	User	
Testing task	**Task**	**Result**	
		Pass	**Not pass**
	Log in to the system	√	
	Puts the link in the search box and directs to the report display page.	√	
	It shows about the tool page.	√	

Table 12 test user tasks

Test information	**Full name**	Razan	
	User Type	User	
Testing task	**Task**	**Result**	
		Pass	**Not pass**
	Log in to the system	√	
	Puts the link in the search box and directs to the report display page.	√	
	Show previous search records	√	

Table 13 test user tasks

Test information	Full name	Sidra	
	User Type	User	
Testing task	Task	Result	
		Pass	Not pass
	Open the system without logging	√	
	Puts the link in the search box and directs to the report display page.	√	
	Show report	√	

Table 14 test use tasks

Test information	Full name	Manahel	
	User Type	Administrator	
Testing task	Task	Result	
		Pass	Not pass
	Open the system	√	
	Manage members and ban users	√	
	Update the analyze technique information and modify words	√	
	View the locations that users search	√	

Table 15 test user tasks

Chapter 7 |Conclusion

In the last years, Deep Neural Network models have been used to improve the performance of machines to learn better semantic representations in NLP tasks. Our web application "Deep Review Checker" uses LSTM deep neural network models and sentiment analysis to analyze and detect fake Arabic reviews on Google Maps.

7.1 Challenges

In We were unable to find an available dataset containing Arabic Google Map reviews, as the few existing datasets were in English or other languages. To overcome this, we have used Outscraper API to extract reviews directly from Google Map.

Another challenge we faced was the dataset labeling as the dataset we extracted using the API was unlabeled. We solve this challenge after reading multiple research papers related to dataset labeling and then we used the Roll-Based Method to label the data.

We had difficulty with deep learning techniques when building our model as they were new to us, and our experience was not enough. Through great effort in researching and reading, we were able to overcome many of the difficulties we faced.

Lastly, time was the biggest challenge for us, as we had to learn new information and apply it in a short time, and through time management, we were able to overcome this challenge.

7.2 Future works

In the future, we aspire to add enhancement to the LSTM model to show better results. Moreover, Improve the performance of the model, as well as speed up the outputs on the website. In addition to using a larger database to help in producing more accurate results.

Chapter 8 |References

Alharbi, A., Algethami, W., Alghamdi, A., Albahar, M., & Ibrahim, S. (2020). Detecting Spam Messages on Social Networks in Saudi Arabia. *IJCSNS International Journal of Computer Science and Network Security* (Vol. 20, Issue 5).

Alsubari, S. N., Deshmukh, S. N., Al-Adhaileh, M. H., Alsaade, F. W., & Aldhyani, T. H. H. (2021). Development of Integrated Neural Network Model for Identification of Fake Reviews in E-Commerce Using Multidomain Datasets. *Applied Bionics and Biomechanics*, *2021*. https://doi.org/10.1155/2021/5522574

Alsubari, S. N., Deshmukh, S. N., Alqarni, A. A., Alsharif, N., Aldhyani, T. H. H., Alsaade, F. W., & Khalaf, O. I. (2022). Data analytics for the identification of fake reviews using supervised learning. *Computers, Materials and Continua*, *70*(2), 3189–3204. https://doi.org/10.32604/cmc.2022.019625

Bashar, Dr. A. (2019). SURVEY ON EVOLVING DEEP LEARNING NEURAL NETWORK ARCHITECTURES. *Journal of Artificial Intelligence and Capsule Networks*, *2019*(2), 73–82. https://doi.org/10.36548/jaicn.2019.2.003

Borrego, A., & Navarra, M. C. (n.d.). *What users say about public libraries: an analysis of Google Maps reviews*. https://doi.org/10.1108/OIR

Detection of Fake Reviews_ Analysis of Sellers' Manipulation Behavior _ Enhanced Reader. (n.d.).

Ding, X., Liu, B., & Yu, P. S. (2008). *A Holistic Lexicon-Based Approach to Opinion Mining*. http://wordnet.princeton.edu/

Fang, X., & Zhan, J. (2015). Sentiment analysis using product review data. *Journal of Big Data*, *2*(1). https://doi.org/10.1186/s40537-015-0015-2

Hollenbeck, B., & Proserpio, D. (n.d.). *Stanford Graduate School of Business, D'Amore-McKim School of Business at Northeastern, USC Marshall marketing workshop, UCLA Anderson marketing workshop*.

Jain, N., Kumar, A., Singh, S., Singh, C., & Tripathi, S. (2019). Deceptive Reviews Detection Using Deep Learning Techniques. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11608 LNCS*, 79–91. https://doi.org/10.1007/978-3-030-23281-8_7

Krügel, J. P., Paetzel, F., Greiff, M., Greiner, B., Heinrich, T., Sausgruber, R., & Traub, S. (2021). *The Impact of Fake Reviews on Reputation Systems and Efficiency **. https://ssrn.com/abstract=3710843

Martens, D., & Maalej, W. (2019). Towards understanding and detecting fake reviews in app stores. *Empirical Software Engineering*, *24*(6), 3316–3355. https://doi.org/10.1007/s10664-019-09706-9

Martínez Otero, J. M. (2021). Fake reviews on online platforms: perspectives from the US, UK, and EU legislations. *SN Social Sciences*, *1*(7). https://doi.org/10.1007/s43545-021-00193-8

Mathayomchan, B., & Taecharungroj, V. (2020). "How was your meal?" Examining customer experience using Google maps reviews. *International Journal of Hospitality Management*, *90*. https://doi.org/10.1016/j.ijhm.2020.102641

Moon, S., Kim, M. Y., & Iacobucci, D. (2021). Content analysis of fake consumer reviews by survey-based text categorization. *International Journal of Research in Marketing*, *38*(2), 343–364. https://doi.org/10.1016/j.ijresmar.2020.08.001

Rout, J. K., Singh, S., Jena, S. K., & Bakshi, S. (2017). Deceptive review detection using labeled and unlabeled data. *Multimedia Tools and Applications*, *76*(3), 3187–3211. https://doi.org/10.1007/s11042-016-3819-y

Sadiq, S., Umer, M., Ullah, S., Mirjalili, S., Rupapara, V., & Nappi, M. (2021). Discrepancy detection between actual user reviews and numeric ratings of Google App store using deep learning. *Expert Systems with Applications*, *181*. https://doi.org/10.1016/j.eswa.2021.115111

Saeed, R. M. K., Rady, S., & Gharib, T. F. (2022). An ensemble approach for spam detection in Arabic opinion texts. *Journal of King Saud University - Computer and Information Sciences*, *34*(1), 1407–1416. https://doi.org/10.1016/j.jksuci.2019.10.002

Salminen, J., Kandpal, C., Kamel, A. M., Jung, S. gyo, & Jansen, B. J. (2022). Creating and detecting fake reviews of online products. *Journal of Retailing and Consumer Services*, *64*. https://doi.org/10.1016/j.jretconser.2021.102771

Saumya, S., & Singh, J. P. (2022). Spam review detection using LSTM autoencoder: an unsupervised approach. *Electronic Commerce Research*, *22*(1), 113–133. https://doi.org/10.1007/s10660-020-09413-4

Umer, M., Imtiaz, Z., Ullah, S., Mehmood, A., Choi, G. S., & On, B. W. (2020). Fake news stance detection using deep learning architecture (CNN-LSTM). *IEEE Access*, *8*, 156695–156706. https://doi.org/10.1109/ACCESS.2020.3019735

Wahdan, A., Hantoobi, S., Salloum, S. A., & Shaalan, K. (2020). A systematic review of text classification research based on deep learning models in Arabic language. *International Journal of Electrical and Computer Engineering*, *10*(6), 6629–6643. https://doi.org/10.11591/IJECE.V10I6.PP6629-6643

Wu, Y., Ngai, E. W. T., Wu, P., & Wu, C. (2020). Fake online reviews: Literature review, synthesis, and directions for future research. *Decision Support Systems*, *132*. https://doi.org/10.1016/j.dss.2020.113280

Ziani, A., Azizi, N., Schwab, D., Zenakhra, D., Aldwairi, M., Chekkai, N., Zemmal, N., & Salah, M. H. (2021). Deceptive Opinions Detection Using New Proposed Arabic Semantic Features. *Procedia CIRP*, *189*, 29–36. https://doi.org/10.1016/j.procs.2021.05.067