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Detecting Arabic Fake Reviews in E-commerce Platforms Using Machine and Deep Learning Approaches

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Abstract— **With the high spread of technology and e-commerce platforms, especially after the pandemic of COVID-19, customers increasingly rely on product reviews to assess their online choices. However, the usefulness of online reviews can be hindered by fake reviews. Therefore, detection of fake reviews is needed. Unfortunately, the number of studies on the automatic detection of fake reviews is limited. This paper is one of the very few works attempting to detect fake reviews written in Arabic and, to the best of our knowledge, the first paper to evaluate the deep learning architecture for this challenging task. Most reported studies focused on English reviews with little attention to other languages. Thus, this research paper aims to experiment with Arabic fake reviews and investigate how they can be automatically detected using machine and deep learning approaches. Due to the unavailability of the Arabic fake reviews dataset, we used the Amazon e-commerce dataset after translating them into Arabic; first, we have evaluated some traditional algorithms, including logistic regression, decision tree, K-nearest neighbors, and support vector machine (SVM), and compared the results with other state-of-the-art approaches such as Gradient boosting classifier, Random Forest classifier and deep learning structures; AraBERT. Among the traditional methods, the results showed that SVM achieved the highest accuracy of 87.61%. However, AraBERT significantly outperformed the SVM and achieved 93.00 % accuracy in detecting Arabic fake reviews.**

Keywords—: fake reviews, algorithms, e-commerce, machine learning, deep learning

I. INTRODUCTION

The continuous advancements in technology and information system applications have changed our lifestyles and introduced a massive development in business fields. The spread of the internet has enabled companies to sell and market their products and services online, allowing different segments of consumers to change their search for these products and services through E-commerce platforms. According to [1], the rapid growth of the Internet profoundly affects people's daily activities. In line with that explored that the internet has changed the process of searching for information and, therefore, has shaped shopping behavior. Moreover, E-commerce has provided customers with quick and easy ways to write reviews regarding services, which can be used as a valuable source of information. Reviews are considered an essential factor for the quality and authenticity of a business, which can help users make decisions regarding the product. Fake reviews can affect the business integrity and result in trust issues, eventually affecting profit. Recent research states that about 20% of Yelp reviews are fake written by paid writers.

In recent years, and due to the growing use of E-commerce platforms worldwide, automatic fake reviews have received attention from many researchers. According to [2], the automatic fake review detections have been examined by researchers for the last ten years. In the meantime, many approaches and features are proposed for improving classification models of fake review detection. Regarding the meaning of reviews on E-commerce platforms, it is emphasized that reviews express someone's suggestions, opinions, or experiences about any market product. This indicates that users seek to place their reviews on online E-commerce websites in the product form to give suggestions or share their opinions and experiences with other relevant groups, such as product providers, sellers, producers, and new purchasers. Detecting fake reviews in the English language is an active research area. However, very few attempts for Arabic content contributed to fake review detection. We have developed and compared several machine learning classifiers to detect fake Arabic reviews and assessed deep learning models to identify dishonest reviews on an E-commerce platform.

The main contributions of this study are two-fold:

First, we compared different machine learning algorithms for Arabic fake reviews detection on E-commerce platforms.

Second, we focused more on the construction and evaluation of deep learning architectures for the enhancement of the results of this challenging task.

II. METHOD

A. Dataset

We use Amazon Review Data (2018) in this study because it is publicly available and contains 40k reviews. *Table 1* shows a sample of the dataset. It has been structured into four columns: category, rating, label, and text.

TABLE 1.AMAZON REVIEWS DATASET

category	rating	label	text_
Home_and_Kitchen_5	5.0	CG	Love this! Well made, sturdy, and very comfor...
Home_and_Kitchen_5	5.0	CG	love it, a great upgrade from the original. I...
Home_and_Kitchen_5	5.0	CG	This pillow saved my back. I love the look and...
Home_and_Kitchen_5	1.0	CG	Missing information on how to use it, but it i...
Home_and_Kitchen_5	5.0	CG	Very nice set. Good quality. We have had the s...
...	...	...	...
Clothing_Shoes_and_Jewelry_5	4.0	OR	I had read some reviews saying that this bra r...
Clothing_Shoes_and_Jewelry_5	5.0	CG	I wasn't sure exactly what it would be. It is ...
Clothing_Shoes_and_Jewelry_5	2.0	OR	You can wear the hood by itself, wear it with ...
Clothing_Shoes_and_Jewelry_5	1.0	CG	I liked nothing about this dress. The only rea...
Clothing_Shoes_and_Jewelry_5	5.0	OR	I work in the wedding industry and have to wor...

The dataset is labeled to OR = Original reviews, and CG= Computer-generated fake reviews using two language models, ULMFit and GPT-2 [3]. *Fig 1* shows the balanced distribution of the data set samples.

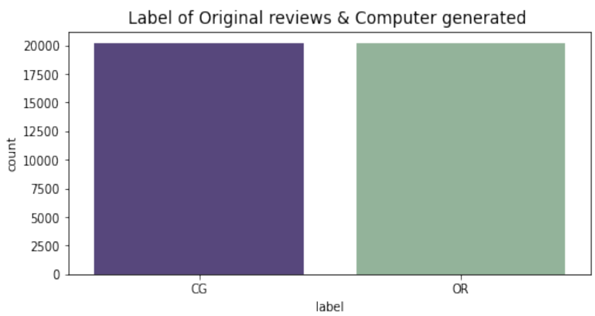

Fig 1.Dataset Labelling for Original and Computer-generated reviews

Fig 2 presents the product categories of the dataset and the number of samples in each category، n. There are ten categories: Kindle Store Books, Pet Supplies, Home and Kitchen, Electronics, Sports and Outdoors, Tools and Home Improvement, Clothing Shoes and Jewelry, Toys and Games, and Movies and TV.

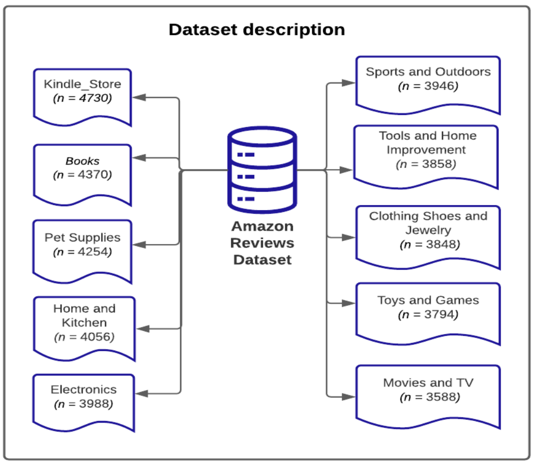

Fig 2.Dataset description

Fig 3, the bar chart represents the distribution of product reviews by categories. The smallest class is the Movies & TV with 3588 samples, and the largest type is the Kindle Store with 4730 samples.

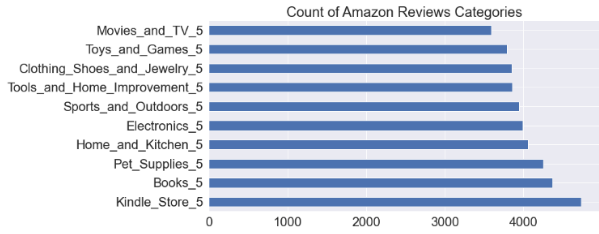

Fig 3Amazon Dataset Reviews Categories

Below Fig 4 shows the rating of the products from one to five. The total highest vote 5 is 24559, and the total lower vote two is 1967.

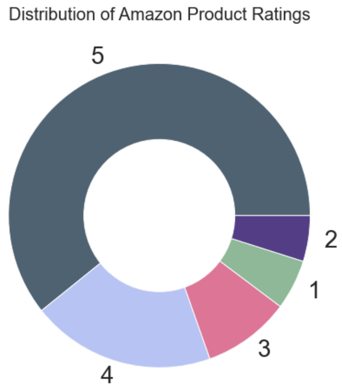

Fig 4.Distribution of Amazon Product Ratings

B. Methodology

Our approach for detecting and classifying Arabic fake reviews is presented in Fig 5 . We have conducted six main steps: In the first step, we translated the reviews by using Google Translate API in Python. In the second step, we preprocessed the data before feeding it to the models to perform word tokenization, remove the stop words, check for missing values, and remove the common affixes (prefix and suffix) from words. The third step was the feature extraction and normalization step to convert the strings of the words into vectors and normalize them. The fourth step was classifying these reviews into fake, non-fake classes. We have trained and evaluated several classifiers, including decision trees, logistic regression, gradient boosting, random forest, K-Nearest, Neighbors, and support vector machines. [4]. We have also evaluated Arabert deep learning architecture. Finally, we have assessed the proposed solution by comparing the performance of each of these models. We used six evaluations of the performances of models via Accuracy, Precision, Recall, F1 Score, and AUC-ROC Curve.

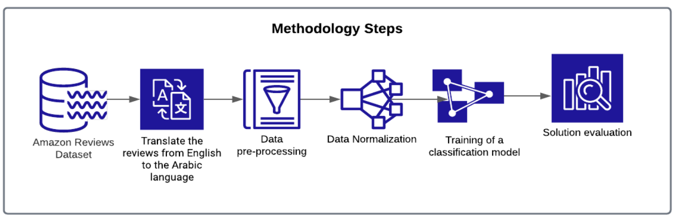

Fig 5.Methodology Steps

C. Translate Reviews

We translated the reviews by using Google translate API in Python. It uses Google's neural machine translation technology to translate texts instantly[5]. *Table 2* represents samples of some reviews after the translation step. It is worth noting that we have also hired some human translators to perform the translation task. However, we found no significant differences between the two translations.

TABLE 2.SAMPLE OF THE DATASET AFTER TRANSLATION TO ARABIC

category	rating	label	text_
Home_and_Kitchen_5	5	CG	احب هذا! مصنوع بشكل جيد ومتين ومريح للغاية. أن...
Home_and_Kitchen_5	5	CG	أحبها ، ترقية رائعة من النسخة الأصلية. لقد كنت...
Home_and_Kitchen_5	5	CG	هذه الوسادة أنقذت ظهري. أنا أحب شكل وملمس هذه ...
Home_and_Kitchen_5	1	CG	معلومات مفقودة حول كيفية لفكرة ، منتج رائع بال...
Home_and_Kitchen_5	5	CG	مجموعة لطيفة جدا. جودة جيدة. كانت لدينا المجمو...
...	...	...	...
Clothing_Shoes_and_Jewelry_5	4	OR	لقد قرأت بعض المراجعات التي تقول إن حمالة الصد...
Clothing_Shoes_and_Jewelry_5	5	CG	لم أكن متأكدة بالضبط ما سيكون. إنه كبير قليلاً...
Clothing_Shoes_and_Jewelry_5	2	OR	يمكنك ارتداء غطاء المحرك بمفرده أو ارتدائه مع ...
Clothing_Shoes_and_Jewelry_5	1	CG	لم يعجبني أي شيء في هذا الفستان. السبب الوحيد ...
Clothing_Shoes_and_Jewelry_5	5	OR	أعمل في صناعة الزفاف ويجب أن أعمل أيامًا طويلة...

D. Data Cleaning

Data Pre-processing is a crucial step. This process transforms raw data into an understandable and readable format. We pre-process the data before using it by extracting the words tokenization, removing the stop words, checking for missing values, and removing the common affixes (prefix and suffix) from words. Below are the steps we have followed for cleaning and processing the dataset:

- Check the null variable. We check null variables. When there are nulls, either we remove that row or column or fill it with an average value.
- Normalizing Alif and Tah Marbotah. We Normalized characters with different forms that could be used interchangeably by a general form. An example of that is the [ا-أ -إ - آ] to an [ا]. Similarly for [ة - ه] to [ه]. We import normalize alef maksura ar and normalize tah marbuta ar from camel *Fig 6* tools sample of review before and after normalized characters.

```
before:  سهل الاستخدام. يبدو أنه طريقة سهلة لعمل عصير صغير.
after :  سهل الاستخدام. يبدو انه طريقه سهله لعمل عصير صغير.
```

Fig 6.Normalization for the reviews

- Tokenization *Fig 7* shows a sample of reviews before and after tokenization. It split up the text of the review into words. From camel tools, we import a simple word tokenizer. It is an essential step for developing good models and allows for a better understanding of the text we have[7].

```
before:  كبيرة جدًا ، الشيء الوحيد الذي لم يعجبني هو حجم ملف
after :  ['كبيرة', 'جدًا', '،', 'الشيء', 'الوحيد', 'الذي', 'لم', 'يعجبني', 'هو', 'حجم', 'ملف']
```

Fig 7.Tokenization for the reviews

- Remove English Text *Fig 8* presents a review sample before and after removing English text. It is not helpful in the classification process.

```
before:  بالارتفاع المناسب التنظيف ، DVR أرفف جميلة ، تحمل.
after :  أرفف جميلة ، تحمل ، بالارتفاع المناسب التنظيف.
```

Fig 8.Remove English Text

- Remove Punctuation: *Fig 9* shows a review sample before and after removing punctuation. It helps to eliminate unhelpful parts of the data or noise.

```
before:  في احسن الاحوال. أحب كل شيء عنهم. تبدو رائعة في مطبخي.
after :  في احسن الاحوال أحب كل شيء عنهم تبدو رائعة في مطبخي
```

Fig 9 .Remove Punctuation

- Stop-words removal. We would not want these words to take up space in our database or valuable processing time. We can remove them using simple word tokenization from camel tools and stop words from nltk *Fig 10* sample of review before and after removing Stop words.

```
before:  كبيرة جدًا ، الشيء الوحيد الذي لم يعجبني هو حجم ملف
after :  ['كبيرة', 'جدًا', '،', 'الشيء', 'الوحيد', 'يعجبني', 'حجم', 'ملف']
```

Fig 10.Stop-words removal

The pre-processing has been applied to a review. In *Table 3* below are the results obtained after cleaning.

TABLE 3.DATASET AFTER CLEANING

	category	rating	label	text_
0	Home_and_Kitchen_5	5	CG	احب مصنوع بشكل جيد ومتين ومريح للغايه انا احبه...
1	Home_and_Kitchen_5	5	CG	احبها ترقيه رائعه النسخه الاصليه لقد كنت املك ...
2	Home_and_Kitchen_5	5	CG	الوساده انقذت ظهري انا احب شكل وملمس الوساده
3	Home_and_Kitchen_5	1	CG	معلومات مفقوده حول كيفيه لفكره منتج رائع بالنس...
4	Home_and_Kitchen_5	5	CG	مجموعه لطيفه جدا جوده جيده كانت لدينا المجموعه...
...	...	...	...	...
40427	Clothing_Shoes_and_Jewelry_5	4	OR	لقد قرات المراجعات تقول ان حماله الصدر كانت صغ...
40428	Clothing_Shoes_and_Jewelry_5	5	CG	اكن متاكده بالضبط سيكون انه كبير قليلاً بالنسب...
40429	Clothing_Shoes_and_Jewelry_5	2	OR	يمكنك ارتداء غطاء المحرك بمفرده او ارتدائه غطا...
40430	Clothing_Shoes_and_Jewelry_5	1	CG	يعجبني اي شيء الفستان السبب الوحيد جعلني اعطيت...
40431	Clothing_Shoes_and_Jewelry_5	5	OR	اعمل صناعه الزفاف ويجب ان اعمل ايامًا طويله عل...

E. Machine Learning Algorithms

- Logistic regression is a primary classification approach that belongs to the category of linear classifiers and is similar to polynomial and linear regression. Logistic regression is a simple model that can be used to explain all result [8].
- Decision tree classification in machine learning is one of the most popular algorithms used today. It is a supervised learning technique that can be used for both classification and regression problems. However, it is preferable to solve mainly classification problems. The goal is to build a model that predicts the value of a target variable by learning simple decision rules

derived from the features of the data. This algorithm divides the population into two or more homogeneous groups based on the most important independent characteristics/variables. Decision trees learn from the data to approximate a sinusoid with a set of "if yes" decision rules. The deeper the tree, the more complex the decision rules and the more appropriate the model [9].

- Gradient boosting classifiers are a set of machine learning algorithms that combine multiple weak learning models to create a robust predictive model. Gradient boosting is often used when doing decision trees. Incremental augmentation models have become popular due to their effectiveness in classifying complex datasets. It is an optimized algorithm that produces highly accurate predictions when processing large data sets [10].
- Random forests are one of the algorithms of supervised learning. It can be used for classification and regression and is one of the most flexible and easy-to-use algorithms. It is said that the more trees in a forest consisting of a group of trees, the stronger the forest is. Each tree is classified to classify a new object based on its attributes, and the tree for that class is voted on. The classification with the most votes (over all the trees in the forest) is chosen. The mechanism of this algorithm can be explained as follows: If the number of states in the training set is N, N states are randomly sampled. This sample will be the training set for tree growth. If there are variables entered M, a number m < < M will be selected so that the m variables at each node will be randomly selected from M, and the best split on that m will be used to split the node. The value of m is kept constant during this process. Each tree is planted as far as possible without pruning it[11].
- K-Nearest Neighbor is one of the simplest implemented machine learning algorithms based on supervised learning technology. It stores all available data and classifies new data points based on their similarity. With the help of the K-NN algorithm, we can easily classify new data if it appears in a well-set category. The K-NN algorithm is widely used to solve classification, regression, and order problems. It is a non-parametric algorithm, which means that it makes no assumptions about the underlying data. It is called a lazy learner algorithm because it does not learn immediately from the training set, but stores the data set at the time of classification and performs an action on the data set [12].
- Support Vector Machine It is one of the supervised learning methods used for classification, regression, and outlier detection. It can solve linear and nonlinear problems and works well with many practical problems. The idea of SVM is simple: the algorithm creates a line or hyper level that separates the data into categories[13].

F. *Deep Learning Algorithms*

- AraBERT is from Transformers and stands for Arabic Bidirectional Encoder Representations. It employs a transformer, which is an attention device that discovers contextual linkages between words or sub worlds in a text. The transformer encoder scans the complete word sequence in one go. It is thought to be bidirectional. This feature helps the model to learn the word's context from its surroundings (left and right of the word). The input consists of a series of tokens that are embedded in vectors before being processed by a neural network. The result is an H-dimensional sequence of vectors, each of which corresponds to an input symbol with the same index [14], shown in Fig 11.

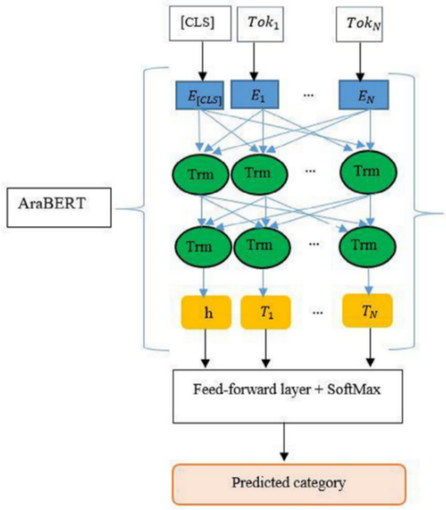

Fig 11.Architecture of AraBERT model [15]

- HybridNLP repository provides multiple Natural Language Processing models on different tutorials, one of which is the NLP Deep Learning classification model. Internally this model depends on the TensorFlow library as its base. Furthermore, the model provides a series of functions that helps to pre-process the dataset, such as cleaning the dataset from stop words and unwanted characters, tokenizing the texts into tokens, i.e., individual words, and indexing the data for lookups and mapping between words and embeddings. Moreover, the library uses Neural Networks with input, embedding, LSTM, and dense layers. It allows us to hyper-tune the training experiment. It is possible to enable or disable the Long Short-Term Memory layer, i.e., LSTM, a bi-directional layer. The library uses the n_cross_val method when training the data. Behind the scenes, it splits the data, trains it, then evaluates it and returns the trained model. As an input, it expects a tensor, given that it uses Tensorflow as the foundation[16].

III. RESULTS AND DISCUSSION

This section addresses the evaluation and discussion of the achieved results and the validity and reliability of the experiments for the models of various machine learning algorithms and deep learning algorithms. The main aims of the comparison were to evaluate the effectiveness of the different machine learning and deep learning algorithms to determine the highest performance algorithm. The machine learning algorithms we used were Logistic Regression, Decision Tree, Gradient Boosting, Random Forest, K-Nearest Neighbors, and Support Vector Machine. Also, we used AraBERT as a deep learning algorithm.

A. Result of Machine Learning Algorithms

The F1 score is defined as a measure of accuracy and recall. It is also the weighted average of accuracy and recall. They are used to compare classifiers to determine which one is more accurate. The following *Table IV* compares the F1 score and the classifiers, from highest to least accurate. Compares the F1 score and the classifiers.

TABLE 4. COMPARISON BETWEEN THE F1 SCORE AND THE CLASSIFIER

Model	Accuracy
Support Vector Machine	0.8761
Logistic Regression	0.87016
Random Forest Classifier	0.85198
Gradient Boosting Classifier	0.79028
Decision Tree	0.73983
K-Nearest Neighbors	0.50179

The AUC-ROC curve is used to compare the classifiers. The ROC curve is a sensitivity plot on a graph. On the y-axis versus one on the x-axis for variable values of threshold t. The ROC curve is the 45° diagonal line connecting (0,0) to (1,1).

They are equivalent to random chance. The ROC curves, in general, fall somewhere between these two extremes. The area under the ROC curve is a summary assessment of diagnostic accuracy across a range of test values. AUC is commonly regarded as the likelihood that the model outperforms chance. The AUC value for a model with full precision is 1.0, while the AUC value for a model with perfect precision is 0 [17]. The results *Fig 12* show that our classifier and support vector machines in scored the highest (AUC = 0.95), followed by the logistic regression (AUC= 0.94) shown in *Fig* 13,Fig *14*. as a random forest (AUC=0.92). As shown in *Fig 14*.

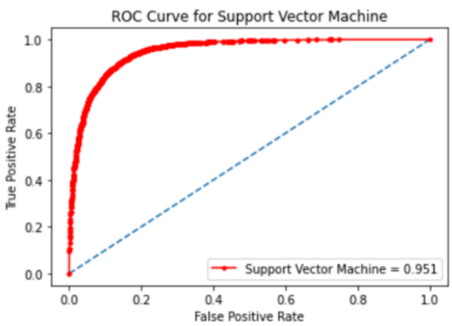

Fig 12.Roc Curve for Support Vector Machine

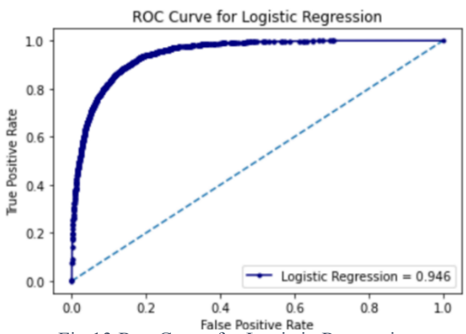

Fig 13.Roc Curve for Logistic Regression

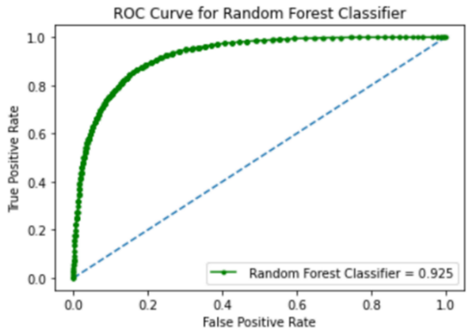

Fig 14.Roc Curve for Random Forest Classifier

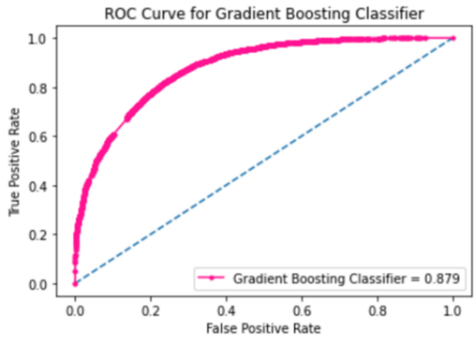

Fig 15. Roc Curve for Gradient Boosting Classifier

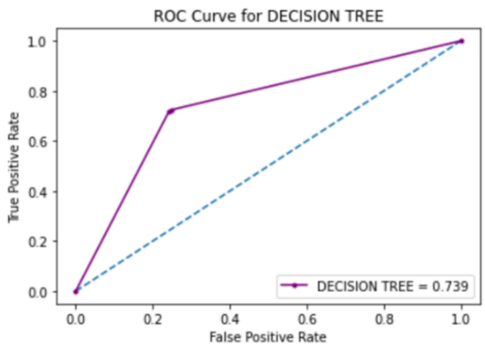

Fig 16.Roc Curve for Decision Tree

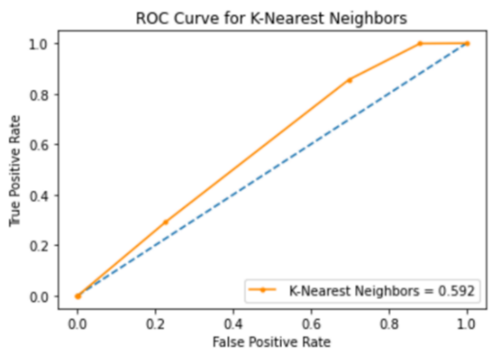

Fig 17.Roc Curve for K-Nearest Neighbors

B. Result of Deep Learning Algorithms

1) AraBERT: The results in when the model predicts that a review is fake, it is correct at 92%. Also, our model's recall is 0.92 — it correctly identifies 92% of all fake reviews. Table 5 show that our model has a precision of 0.92. In other words, when the model predicts that a review is fake, it is correct at 92%. Also, our model's recall is 0.92 — it correctly identifies 92% of all fake reviews. Table 5 *We employed the area under the Receiver Operating Characteristic Curve (AUC-ROC) for the classification task.*

TABLE 5. CLASSIFICATION REPORT FOR ARABERT

	precision	Recall	F1-score	support
0	0.92	0.93	0.93	1614
1	0.93	0.92	0.93	1606
Accuracy			0.93	3220
macro avg	0.93	0.93	0.93	3220
weighted avg	0.93	0.93	0.93	3220

We used a training set to train the prediction model and then optimized it using the AUC-ROC measure from the validation set. Our classifier, AraBERT, had a high score (AUC = 0.93), as shown in Fig 18.

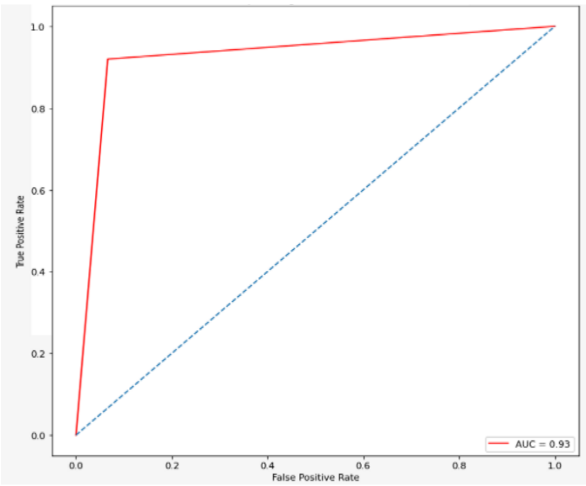

Fig 18.Roc Curve for AraBERT

2) *NLP hybrid model*: The results in Table 6 recorded that the accuracy of our model is 0.75. Therefore, when the model predicts that the review is fake, it is 75% correct. Meaning our model call accuracy is 0.75, which correctly measures 75% of all fake reviews.

TABLE 6.CLASSIFICATION REPORT FOR NLP HYBRID

	precision	Recall	F1-score	support
0	0.67	0.99	0.80	6027
1	0.98	0.52	0.68	6103
Accuracy			0.75	12130
macro avg	0.83	0.76	0.74	12130
weighted avg	0.83	0.75	0.74	12130

The scale for the classification task is shown by the area under the Receiver Operating Characteristic Curve (AUC-ROC). After training the prediction model and improving it based on the AUC-ROC scale of the validation set for the classification task. Our classifier, the NLP hybrid model, has a high score (AUC = 0.76), as shown in *Fig 19*.

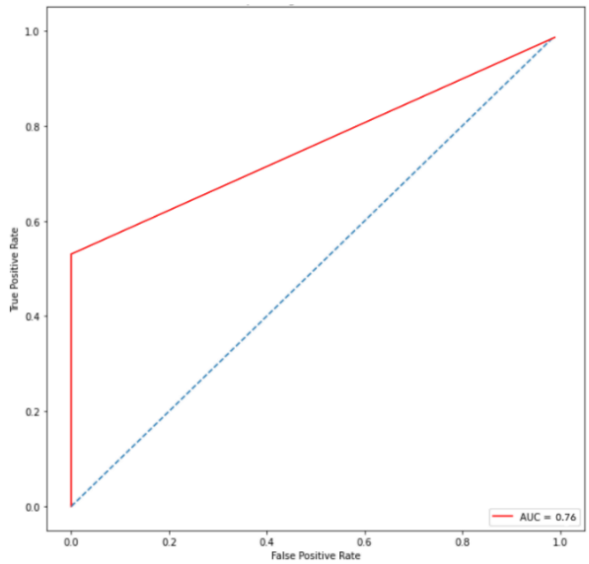

Fig 19.Roc Curve for NLP hybrid model

To evaluate the effect of the Arabert and NLP hybrid model algorithm, we compare the performance of accuracy and summarize the results in *Table 7* We found that the impact of algorithms AraBERT performance is highest.

TABLE 7.COMPARISON OF DEEP LEARNING ALGORITHMS

Classifier	Label	Performance measure			
		F1 Score	Recall	Precision	Accuracy
AraBERT	OR	0.92	0.93	0.93	0.93
	CG	0.93	0.92	0.93	
NLP hybrid model	OR	0.80	0.99	0.67	0.76
	CG	0.68	0.52	0.98	

To successfully determine whether Arabert's prediction helped to detect fake reviews. We made a prediction from the reviews in our dataset as to whether it will predict correctly is fake or not. Let's see this example:

جاء مكسور المقبض قطعه مكسوره

The dataset is labeled as OR which means it is an original review. Now we want to check whether it predicts OR or CG. *Fig 20* shows the prediction result; it is correct and works well.

Fig 20.OR prediction

Another example of the fake review's prediction is shown in *Fig 21.*

كبيرة جدًا، الشيء الوحيد الذي لم يعجبني هو حجم ملف

The results of the prediction of CG computer generation working correctly.

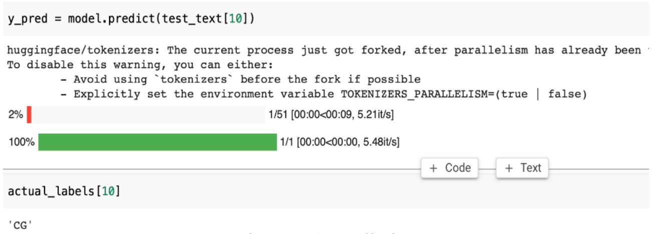

Fig 21.CG prediction

IV. Conclusion

In this research, several machine learning methods have been verified on the Amazon reviews dataset that contains two labels: fake reviews and honest reviews. We have discussed several experiments conducted to analyze current advances in deep learning and machine learning models for the Arabic language fake reviews detection. Our experimental results demonstrate that AraBERT outperformed other approaches. On the other hand, the SVM has performed better than traditional machine learning algorithms.

Although this work contributes to realizing Arabic fake review detection, we observed several limitations and challenges. First, regarding the data, we used an English reviews dataset; we translated the reviews by using Google API translator because no labeled Arabic data is available for fake reviews. In the future, we will consider developing a comprehensive Arabic fake reviews dataset and study other factors associated with reviews, such as the time of the review. The time-based datasets will allow us to compare the user's timestamps of the reviews to find if a particular user is posting too many reviews in a short period. Also, we aim to employ unsupervised learning for unlabeled data to detect fake reviews.

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الكشف عن المراجعات المزيفة باللغة العربية في منصات التجارة الإلكترونية باستخدام أساليب التعلم الآلي والعميق

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المستخلص. مع انتشار التكنولوجيا والتعامل معها في معظم جوانب الحياة، وخاصة في التجارة الإلكترونية، أصبح العملاء يعتمدون على المراجعات والتعليقات للوصول والحصول على معلومات حول المنتجات المختلفة. من ناحية أخرى، يلجأ البعض إلى مراجعات مزيفة تعيق فائدة المراجعات الصادقة عبر الإنترنت التي تعطي صورة غير صحيحة عن جودة بعض المنتجات. لهذا السبب، أصبح من الضروري إيجاد حلول للكشف عن المراجعات المزيفة. في هذه الورقة البحثية، يتمثل التحدي الذي يواجهنا في كيفية اكتشاف المراجعات المزيفة باللغة العربية، و سنتعرف على طرق إيجاد حلول للكشف عن المراجعات المزيفة في مجموعة بيانات التجارة الإلكترونية في أمازون بعد ترجمتها إلى اللغة العربية باستخدام خوارزميات التعلم الآلي مثل (الانحدار اللوجستي، تصنيف شجرة القرار، مصنف تعزيز التدرج، مصنف الغابات العشوائي، أقرب الجيران K-، دعم آلة المتجهات) باستخدام خوارزميات التعلم العميق مثل (نموذج AraBERT و NLP الهجين) ، من خلال مقارنة نتائج التنبؤ التي نحصل عليها من التعلم الآلي و خوارزميات التعلم العميق في مجموعة البيانات للعثور على النتائج الأكثر دقة و التوصية باستخدامها.

الكلمات المفتاحية: مراجعات مزيفة، خوارزميات، تجارة إلكترونية، تعلم آلي، تعلم عميق