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Ensemble Based Low Complexity Arabic Fake News Detection

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***Abstract**:* Nowadays, Due to the growth of online communication, many people use social media platforms and produce a lot of content. Fake news creates negative perceptions of society. The rise of social media networks has given fake news a platform to rapidly gain popularity among users. Identifying and labelling Arabic fake news represents a big challenge because of the large amount of heterogeneous content in addition to the limited related Arabic datasets available. machine learning (ML), Natural language processing (NLP) and deep learning (DL) are commonly used to increase the speed and automate the analytical process of this huge amount of content and to transform unstructured text into structured form. In this study, a corpus of news websites is developed to determine fake news using some machine learning techniques; this includes a dataset 3185 fake news articles and a new dataset consists of 1453 real news articles. This paper shows that, using an aggregation of machine learning and ensemble methods, we can make a prediction model for fake news that has an accuracy of up to 100%. with low complexity, which can save power and energy, and we can use it as a reference for the detection of fake news in Egypt and Arab countries.

Keywords: *Machine learning, Deep learning, Natural Language Processing, Fake News, Arabic Fake Detection (AFD), Ensemble Learning (EL).*

1. Introduction

The increase of multiple media platforms and the digitization of society have contributed to the increase in fake news, which has a direct impact on the community [1]. Fake news is described as anything that has been presented as "real news" to society through social media [2]. The openness of the internet and social media and the consequent absence of active content monitoring are two of the main causes of the rise in fake news [2]. Fake news is dangerous and affects the less informed members of society [3]. The credibility of journalism is seriously challenged by false information and fake news and have also created sociable problems (i) within the economy [4], (ii) in the political world [5][6], and even (iii) in human life.

These threats increase noticeably with the assistance of the Internet and social media, and other Web resources to spread fake news [7]. So, propaganda and fake news were named as one of the most significant challenges we faced in the twenty-first century [8]. Individuals and society have suffered of the growth of low-quality news on social media because fake news often misleads people and make wrong perceptions about society [9].

networks perform when given pretrained word embeddings as input for identifying Arabic fake news articles. The techniques of machine learning can achieve a lot, as they solve the problem of detecting fake news and can improve accuracy with deep learning algorithms. Ensemble learning is considered a process for collecting a lot of "weak learners" and combine them in an attempt to develop a "strong learner." Typically, approaches that use a single base learner to generate many hypotheses are referred to as "ensemble" [10]. On the other hand, standard machine learning methods aim to learn a single hypothesis from training data. Ensemble algorithms can enhance results, minimize the overfitting and offer the flexibility to handle various tasks by merging numerous learners and fully utilizing these learners. Three well-known ensemble approaches that can be applied practically include bagging, boosting, and stacking [11].

In this study, our work has been arranged in the following ways: The introduction is described in Section 1. The related works are shown in Section 2. The classification approaches are given along with the data processing and representation in Section 3. The proposed model architecture and workflow are displayed in Section 4. Section 5 provides the analysis and discussion of results, and finally, I conclude this paper and make some remarks and future work in section 6.

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2. Related Works

Fake news has become a general term within the human language [12]. Using click stories and videos, which are frequently used in public news, misinformation can spread quickly [13]. For a number of various reasons, blogs, headlines, and social media posts may be purposely deceptive. They might aim to influence elections or policies, engage in cyberwarfare between states, boost the influence and power of one person, or weaken an opponent [14]. The noun-to-verb ratio has a significant difference between veracity and pretend corpora, according to Marquardt D. [15].

The ratio is larger in the true news, with a mean of 4.27 as opposed to 2.73 in the fake news corpus. The mean of the news corpus is 20.5 words in reality as opposed to 14.3 words in the fake news corpus [16]. Fatemeh Torabi Asr [17] also discovered that fake newspapers typically employ more words associated with sex, death, and fear. Real News, in comparison, contains a greater percentage of words relating to business and economy.

Hancock et al. [18] examined 242 manuscripts and discovered which liars added more words as well as words with sense connotations, such as hearing and speaking.

Rashkin et al. [19] investigated the relationship between particular grammatical patterns and incorrect information. They came to the conclusion that purposefully deceptive sources tend to use phrases that are prone to exaggeration more frequently. Superlatives like "best" and "worst" as well as supposedly subjective phrases like "brilliant" and "awful" were among these terms. The false information seems to refer to "reality" and "democracy" in general terms. Jack Grieve [20] noted that academics don't necessarily monitor the genre, and therefore the linguistic variations seen above may only lead to the difference between a more formal newspaper article and a more informal Facebook post. Alfalahi et al. [21] presented that algorithms were trained on a collection of poems written by a well-known poet, identifying the features of the author. As a result, scientists were prepared to create highly accurate classifiers.

The flexibility of identifying the author of the Arabic text using the SVM algorithm was covered by Baraka et al. [22]. Feature extraction from the input text was necessary for the text classification's author identification and was completed in five steps: collecting of documents, processing of data groups, feature extraction, selection of optimization features, and creation of the classification model.

To identify fake news, P'erez-Rosas et al. (2018) primarily examined word choices and grammatical variations in the title and body of reports. To identify fake news, several studies look at both the text and the images in news reports [23].

A replacement n-gram model was created by Ahmed et al. [24] that has a specific emphasis on fake comments and fake news to automatically detect incorrect information. They used TFIDF for feature extraction and different machine learning classification techniques.

Different types of news item features, such as sources and social media posts, were presented by Reis et al. [25]. To automatically identify fake news, they discuss a set of features and put KNN, NB, RF, SVM, and XGB's predictive capabilities to the testing. The model XGB with the highest accuracy 86%. With a focus on contextual consideration, Asghar et al. [26] studied the topic of rumor detection by investigating various deep learning models. A coevolutionary neural network is used to implement bidirectional long-dependent immediate memory in the proposed system. Their experiments essentially classified tweets as fake or real. In general, their experiments distinguished between actual and fake tweets, according to experimental results, the proposed method exceeded traditional method and was more efficient than the equivalent methods with 86.12% accuracy.

Convolutional neural networks (CNNs) with margin loss and a number of alternative embedding models were developed by Goldani et al. [27] for the purpose of identifying fake news. To evaluate their proposed methods, ISOT and LIAR, two recent and well-known datasets, are used. Results for the best architecture show promise, outperforming cutting-edge methods on ISOT by 7.9% and on the test set for the LIAR dataset by a few percent.

In order to identify fake news, an ensemble classification model was introduced by Hakak et al. [28] and performs better than this state-of-the-art model. The suggested method gathers key features from datasets of “fake news”, are then identified by combining three common machine learning models into an ensemble model: decision trees, random forests, and extra tree classifiers. They achieved training and testing accuracies of 99.8% and 44.15 %, respectively, using the Liar dataset. Additionally, they were prepared to achieve 100% accuracy in both training and testing using the ISOT dataset.

Umer et al. [29] suggested a hybrid neural network design that combines CNN and LSTM with two additional dimensionality reduction algorithms (PCA and chi-square) before presenting the feature vectors to the classifier. The purpose of this study was to determine where a newspaper article stands in relation to its headline. The proposed model enhances the results by 4% and 20%, respectively according to accuracy and F1 score. The experiments demonstrate that PCA outperforms chi-square and other cutting-edge methods by 97.8%.

To create automatic detection systems, Nasir et al [30] used the techniques of machine learning and deep learning that makes them credible for recognizing fake news as well. These techniques are already capable of complicated language processing tasks.

The dataset provided in this work was used by Golbeck et al. [31], who concentrated on satirical and fake news items on US politics that had been published after January 2016. They can be examined manually, with two researchers. In addition, they provide a link to an article that disproves the fake news and factual. We choose 55 websites from this list that are discovered to have published many such articles.

Zhou et al. [32]: The authors compiled a dataset of 140,820 tweets and 2,029 news articles associated with COVID-19. They used News Guard and MBFC to gather information from the news items. Similar to this, we focus on news websites with a poor reputation and at least three fake news articles.

Investigating whether an Arabic news article is humorous or factual is a new classification challenge for Arabic computational linguistics and machine learning that was developed by Hadeel Saadany and Emad Mohamed [33]. According to experimental findings, the proposed architecture can aggregate pre-trained word embeddings with a CNN and achieve better results.

3. Processing and Classification

In this research, we followed a workflow, shown in Fig.1, to develop our proposed fake news detection models. This section introduces the theories employed in this workflow for processing and classification in the proposed models. First, in this section 3.1, we present natural language processing methods that have been used for processing, enhancing, and preparing the data. The classification approaches are then presented, with the traditional machine learning approaches, the deep neural network approaches and ensemble learning techniques are described in Section 3.2.

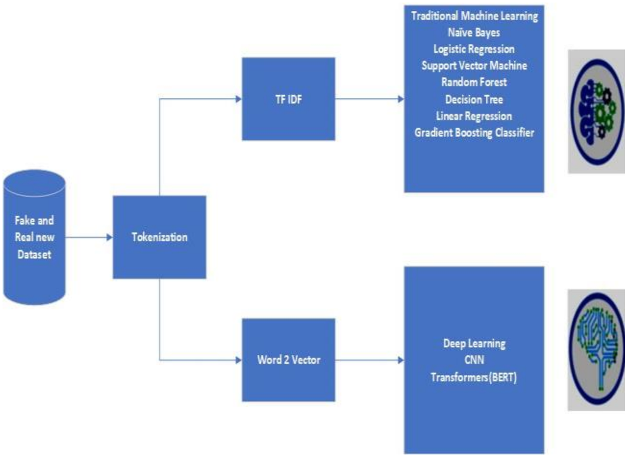

Fig. 1. Workflow of machine generation of manipulated text (Arabic fake news detection)

3.1. Processing and Data Representation

The NLP field has a set of tools and algorithms that make it easier to process and analyze phrases and understand their meanings [34].

3.1.1 **Preprocessing Phases**

There are three major pre-processing stages used in Fig.2. These stages are explained below.

Fig. 2. Preprocessing phases

Tokenization:

Tokenization is the initial step in data preprocessing. Tokenization divides a sentence, a phrase, a paragraph, or any entire text into smaller [35].

Removal of Stop Words:

The classifiers perform better when such pronouns and prepositions are removed [36].

Stemming:

Text allows for a variety of word styles for grammatical and semantic reasons [37][38].

3.1.2 Data Representation

To process the data, it has to be represented numerically in a form that captures its main features. Next, we discuss the two main representation approaches we use in our model.

A. Word Embedding

When words have the same meaning and a comparable representation, they are said to have the same word embedding, which is a learned representation for text [39].

B. Term Frequency-Inverse Document Frequency (TF-IDF)

Term Frequency-Inverse Document Frequency (TF-IDF), has been created to describe retrieval. It basically assesses the significance of a tokenization in a widely gathered corpus by taking into account a word's usage frequency across all corpora as well as how many times it appears in a single document [40].

3.2 Classification Approaches

In this work, we use several classifiers. These classifiers, as presented next, may be divided into two main categories: classic machine learning classifiers and deep neural network approaches.

3.2.1 Classical Machine learning classifiers

Machine learning classification is defined as a set of mathematical and statistical models that try to extract patterns from data and associate such patterns with distinct categories of data samples. We present next the classifiers we used in this paper.

A. Binomial Logistic Regression

A dichotomous variable that relies on a combination of either constant independent variables or categorical is used in a binomial logistic regression [42].

B. Naive Bayes (NB)

To solve binary classification issues and challenges, the Naive Bayes classifier involving several classes, and it can make estimating the probability for each potential measurement trace simpler [43].

C. Support Vector Machine (SVM)

Using machine learning theory, SVM is a regression prediction and a classification technique that seeks to improve predictive accuracy while automatically preventing the data from being overfit [44].

D. Random Forest (RF)

In random forests, many classification trees start appearing. In order to categorize a new object from an input vector, the classification algorithm moves the input vector down each tree in the forest. Every tree contributes generously, and we assert that every tree votes for that class. The group with the highest votes is preferred by the forest [45].

E. Decision Tree (DT)

Any path starting from the foundation is defined by an information-separating sequence within a decision tree, which is a tree-based technique, until a Boolean outcome is attained at the leaf node [46]. A succession of the most important tests is quickly and cogently combined into DTs, where each test compares a numeric property to a threshold value [47] [48].

3.2.2 Deep Learning Approaches

Deep learning neural networks use a combination of data inputs, weights, and biases to attempt to simulate the human brain. These components can be combined to precisely identify, categorize, and describe items in the data [49].

A. Convolutional Neural Networks (CNN)

Conventional neural networks (CNNs) are deep learning models used mostly in computer vision, but they can also be applied to natural language processing (NLP). CNNs use a sliding kernel to convolute the original input. The technical term "local invariance of translation for a picture" refers to their sensitivity to the placement of features in the input file [50].

B. Transformers

In Transformers deep learning models, every input and output component have a relationship, and the weights between them are dynamically chosen based on that relationship this is described in Fig.3. Models of a bidirectional encoder Transformers (BERT) are a cutting-edge language transformer models utilized for numerous applications in sequential modelling and natural language processing [51].

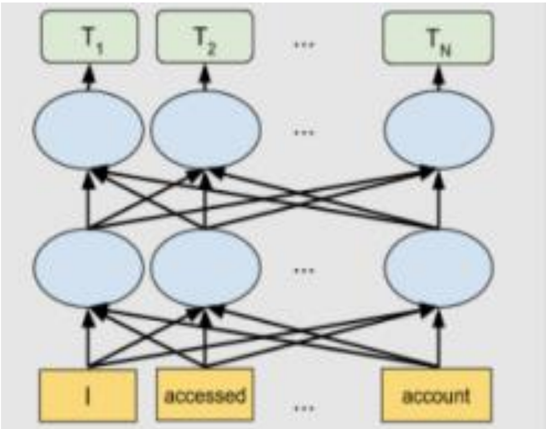

Fig. 3. Bert Architecture

3.2.3 Ensemble learning Approaches

A. Bagging Algorithms

A bagging classifier is an ensemble that aggregates the individual predictions of basic classifiers after fitting them to random parts of the original dataset [53].

B. Boosting Algorithms

Boosting methods increase the weights of training samples that were incorrectly recognized and calculated in a subsequent iteration to turn weak learners into strong learners. Examples of boosting ensemble approaches include adaptive boosting (AdaBoost), gradient boosting machine (GBM), extreme gradient boosting (XGBoost), LightGBM, and categorical boosting (CatBoost) [54].

C. Voting

A voting is a machine learning technique that predicts an output based on the class with the highest probability. The output class is predicted based on the class with the biggest majority of votes after combining the output from all classifiers that were passed into the voting classifier [55].

4. Proposed Model Architecture

We discuss in this section the proposed model's workflow, introduce the dataset, and describe how it was collected and processed, with a focus on the suggested model and its improvements compared to traditional models.

4.1 Data Preprocessing

We represent the configuration of the dataset, the preprocessing of the data, and how that data will be ready to be used in the model.

4.1.1 Data collection

In this study, several steps were taken during the data collection phase. The dataset in Fig.4 was collected from two Arabic news websites, Al-Hudood [56] and Al-Ahram Al-Mexici [57]. The website has 1 million unique visitors on average each month, of which 1732 are bogus news items (55.5%). The real news dataset, which is a component of the Arabic Computational Linguistics project, consists of 1453 (45.5%) items gathered from two official news websites: "BBC-Arabic" and "CNN-Arabic"[58] The two datasets are concerned with political topics relating to the Middle East.

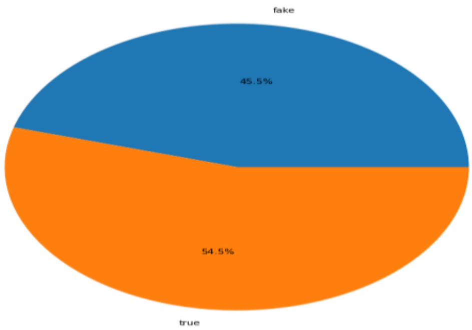

Fig. 4. Dataset Distribution of real and fake news

4.1.2 Data Compiling and Preprocessing

Each dataset was combined into a single file and frequency dictionaries of unigrams, bigrams, and trigrams were made for each file in order to capture these stylistic norms. We cleaned our dataset, deleting the specific formatting Special characters, English characters, and punctuations are used for each source as well as non-informative textual features. In Arabic NLP research, we find the segmentation of words into their constituent tokens [59]. After some preprocessing steps, we find the volume of the dataset and the number of words in this dataset, Fig.5 illustrates these findings.

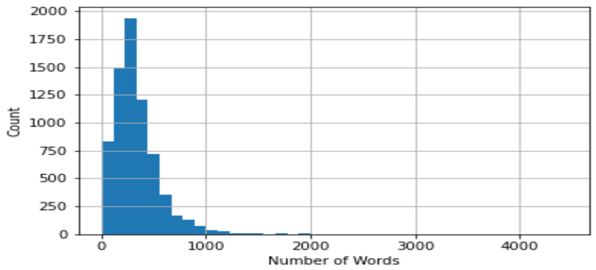

Fig.5. Distribution of word counts per text of fake news data

4.2 The Proposed Model

Voting ensemble model

In the proposed model, ensemble learning was used to combine multiple learners to get an accurate result. We use an ensemble stacking method to combine various different weak learners by using the many predictions produced by these weak models to train a meta-model that generates predictions. This ensemble classifier gives us better performance than the individual classifiers. We combine the preceding machine learning techniques to develop this ensemble model. We choose, as weak learners, a Nave Bayes classifier and a logistic regression. The outputs of these two weak learners are used as inputs by our proposed model, which then learns to make final predictions based on them.

In the ensemble voting method, predictions are weighted according to the significance of the classifier before being combined to provide the final weighted prediction probability. The averaging ensemble model is extended to apply the weight average ensemble technique, and the target label with the highest sum of weighted probabilities is selected (see Fig.6).

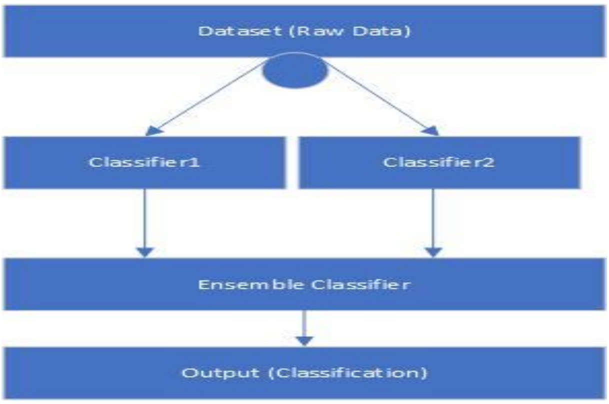

Fig. 6. Ensemble Classifier

Optimization Classifier Model Architecture

A. Algorithms for Enhancement and Boosting

We are using gradient boosting, Catbsoost, and XGB boost algorithms; we find that XGBoost techniques can be used to reduce overfitting. CatBoost is a decision tree (GBRT) improvement gradient boosting technique.

CatBoost can be used in handling machine learning tasks using categorical variables in the data to manage heterogeneous and categorical data. We implement three boosting techniques—gradient boosting, XGB, and CatBoost classifiers—and find the results for each other's and compare them according to high performance and low complexity.

We make some enhancements to the XGBoost algorithm and make the hyperparameter as follows: max_depth: 9, n_estimators: 1000, learning rate: 0.3, seed: 20. These hyperparameters lead to better performance, low execution time, and improved algorithms with low complexity.

B. Bert Model Improvement

We use Bert transformer to get high performance because it is one of the least appreciated techniques and because it was the first work in NLP to show that scaling the parameter budget (from small to large model sizes) leads to large improvements on tasks with very small datasets.

We used the Bert model in our dataset to get high performance with little epoch because when generating word embeddings, BERT is capable of accounting for word order. This enables dynamic and adaptive embeddings that are adapted to the words' content and related sentences. The model parameters are as follows: Model Name: BERT Base, Attention Heads: 12, Hidden Units: 768, and Encoder Layers: 12. The number of distinct encoders used in the model is referred to as the number of encoder layers. The number of weights in a single layer is shown by hidden units. The number of attention heads indicates how frequently the multi-head self-attention is used.

We make some improvements to the model as we use KeyphraseVectorizers package, which can be used to extract enhanced key phrases from text documents. This eliminates the need for user-defined word n-gram ranges and extracts grammatically correct key phrases and word n-gram ranges (1, 3).

5. Results: Analysis and Discussion

We will explain the model evaluation process, each model's output and detail the results of the proposed model.

5.1 Evaluation Metrics

The precision [60], recall [61], accuracy [60], and F1 score of a model [62] can be used to measure its performance is this section. On the other hand, we use confusion matrix [63-65] and execution time performance [66].

5.2 Experiments Results

The outcomes of the results carried out in Python contexts with various setups of the suggested framework are shown in this section. We assess the precision, recall, and accuracy of both fake and true news. Both conventional machine learning methods and deep learning are applied. We will explain the precision, recall, F1, accuracy, and execution time for each technique. The results are described in Table [1] details.

nave bayes with F1 70% and time execution of 0.298 sec.
In the machine learning results, the different confusion

Table1: Comparison of results of different classifiers (recall, precision, f1 and support)

Classifier	Fake precision	Fake Recall	Fake F1	Fake Support	Real F1	Real Support	Accuracy	Execution Time
Naïve Bayes	0.540	1.000	0.700	763	0.534	637	0.544	0.297
Naïve Bayes on count vectors	0.998	0.944	0.970	1403	0.963	1046	0.967	0.037
Naïve Bayes on Word Level TF-IDF	0.992	0.949	0.972	1388	0.963	1061	0.966	0.015
Naïve Bayes on N-Gram Vectors	0.999	0.857	0.923	1546	0.890	903	0.909	0.015
Naïve Bayes on Char Level Vectors	1.000	0.971	0.985	1367	0.982	1082	0.983	0.031
Linear Classifier on Count Vectors	1.000	1.000	1.000	1327	1.000	1122	1.000	2.524
Linear Classifier on Word Level TF-IDF	0.997	0.997	0.997	1327	0.996	1122	0.996	0.069
Linear Classifier on N-Gram Vectors	0.998	1.000	0.999	1325	0.999	1124	0.999	0.031
Linear Classifier on Char Level Vectors	1.000	0.998	0.999	1329	0.999	1120	0.999	0.253
SVM on count Vectors	0.999	0.999	0.999	1327	0.999	1122	0.999	3.282
RF on count Vectors	1.000	1.000	1.000	1327	1.000	1122	1.000	5.224
RF on word level	1.000	1.000	1.000	1327	1.000	1122	1.000	0.878
Logistic Regression	0.990	1.000	1.000	822	1.000	563	0.996	0.136
Decision Tree	1.000	1.000	1.000	793	1.000	956	1.000	0.910
Gradient Boosting Classifier	1.000	1.000	1.000	822	1.000	563	1.000	32.46
XGB Classifier	1.000	1.000	1.000	763	1.000	637	1.000	0.084
CatBoost Classifier	1.000	1.000	1.000	763	1.000	637	1.000	64.85
Ensemble Model	1.000	1.000	1.000	763	1.000	637	0.996	0.136
Bert Transformers	1.000	1.000	1.000	159	1.000	191	1.000	1936
TensorFlow CNN	1.000	1.000	1.000	145	1.000	190	1.000	950.9

comparison between different techniques according to precision, recall, F1, and accuracy is shown in Fig.7, which shows that the nave Bayes algorithm has the lowest F1 at 70%, but when we applied the nave Bayes algorithm to count vectors, the precision became 100%, but Fig.8 describes the comparison between different classifiers according to F1 only.

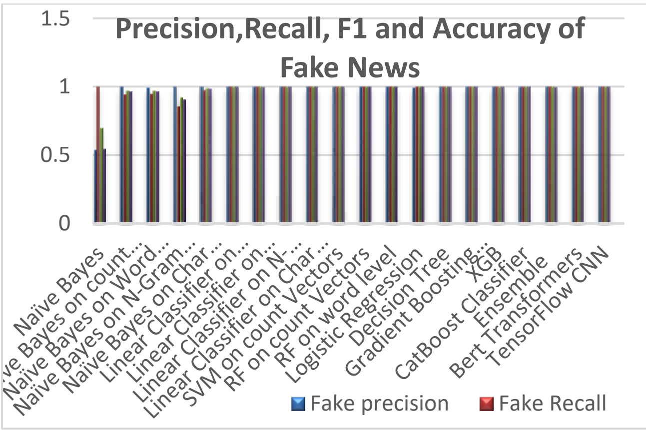

Fig. 7. graph of precision, recall, F1 and accuracy of different classifiers

There are varieties in the results; the linear regression algorithm has good precision where it is applied to count vectors and character levels rather than word levels or n-gramme levels. We noticed that some of the machine learning classifiers have good precision, such as random forest, decision tree, gradient boosting, catboost, and XGB boost, but less precision in logistic regression.

We notice that the **ensample classifier of the combination of both nave bayes and logistic regression has F1 100% with time execution of 0.137 sec, which is preferred to**

matrices of the learning classifiers can be represented in Fig.10**.**

We combine the lowest results of both nave bayes and logistic regression, and the ensample model has F1 of 100%, which has a better result than nave bayes with F1 of 70% or logistic regression with F1 of 99.6%.

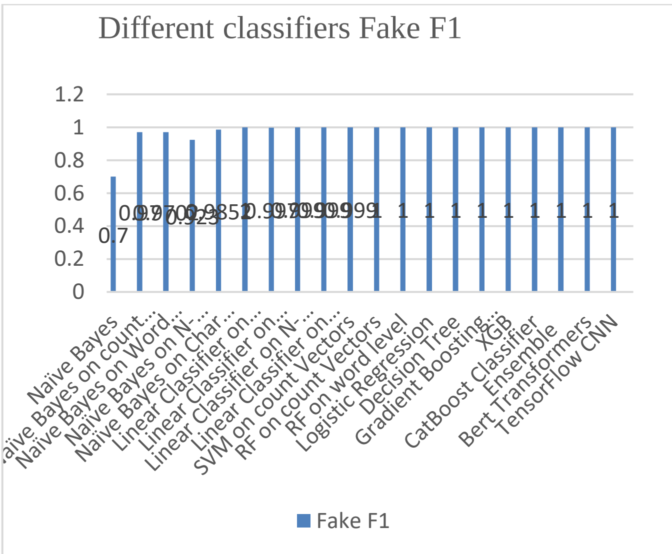

Fig. 8. graph of F1 for different classifiers

According to the classifiers and F1 in Fig. 8, the best F1 is Bert, CNN, gradient boosting, decision trees, XGB, Catboost, a linear classifier on count vectors, a random forest in count vectors, a random forest on word levels, and

When using TensorFlow CNN, we found that F1 was 100% after 10 epochs of iterations; we used Bert transformers and got a good result with F1 being 100% after 3 epochs of iterations. the ensample algorithm (a combination of both Nave Bayes and Logistic Regression). While the lowest accuracy is in nave bayes only and nave bayes on the n-gramme vector.

We notice that transformers take longer to execute, which is 1936 seconds, and this can consume more time and energy, causing the CPU to be more exhausted. This can be described in Fig.9.

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We discovered a relationship between F1 for each algorithm and the time it takes the classifier to execute. Bert transformers take longer to execute, which is 1936 seconds, and this can consume more time and energy, causing the CPU to be more exhausted. This can be described in Fig.9.

We find the **XGB classifier to have accuracy of 100% and a low execution time of 0.084 sec**; we consider it the best classifier that has low power and accurate results.

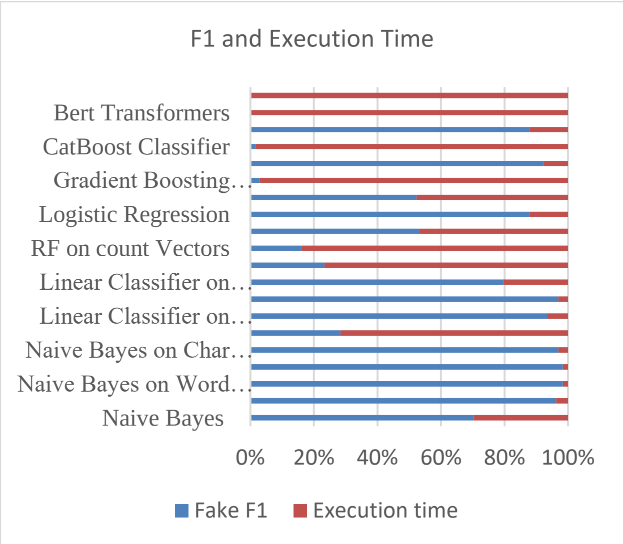

Fig.9. graph of F1 and execution time of different classifiers

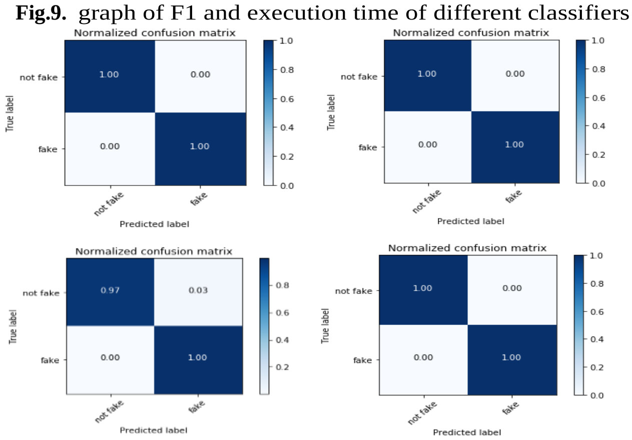

Fig.10. Confusion Matrix of Machine learning Classifiers

6. Conclusion and future work

This paper's main objective is to investigate and detect fake news in order to limit the growth of these false reports that prevail on social media and cause disturbance and confusion for the people. We use different techniques and a constructed example model to detect fake news or real news. This dataset was initially preprocessed using many techniques of NLP. We used the traditional techniques at first, but we enhanced the data processing techniques and then made some enhancements to these approaches to get better results using both machine learning and deep learning techniques. We utilized deep learning BERT transformers, which gave us the best and most accurate results. We develop a proposed model as a combination of naive Bayes and logistic regression that outperforms either algorithm on its own. We do a great job when we calculate the CPU execution time for every classifier. In comparison to other algorithms, the best algorithm is Algorithm XGB Classifier, which has F1 100% and a time execution of 0.084 sec. Our proposed model (Example Nave Bayes+ Logistic Regression) achieved better results with an F1 of 100% and a time of 0.136 sec. Finally, Arabic fake news detection using machine learning and deep learning is a relatively new field and has a great challenge.

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Author contributions

Mohammed E.Almandouh: preparing the original draft, investigation and writing.
Mohammed F. Alrahmawy : conceptualization, data curation and writing.
Mohamed Eisa: resources: editing and reviewing.
A. S. Tolba: supervision, editing and reviewing.

Conflicts of interest

The authors declare no conflicts of interest.

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