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A study on the Detection of Fake news in Spanish

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Abstract. False information published with the intention of misleading social media users is known as fake news. These are created to appear as credible and genuine information and can manipulate opinions and be disseminated for political or financial purposes (Kaliyar et al., 2021). Fake news is especially propagated on Twitter, today X due to its great capacity for interaction with users, as well as the possibility of retweeting and commenting, which allows for greater dissemination of information.
This study proposes a model for detecting fake news in Spanish, which faces challenges such as linguistic diversity and limited resources available for preprocessing. Using a database of approximately 40,000 news extracted from two acquaintances news accounts in Mexico on Twitter, such as “Reforma” and “El Deforma”, from 2019 to 2024, a model based on Natural Language Processing, Machine Learning, Deep Learning, and transformer models were developed. This model allows distinguishing whether a headline of a news article in Spanish published on Twitter is true or fake. The algorithms used include Logistic Regression, Naïve Bayes, Support Vector Machines, LSTM, Bidirectional LSTM and mBERT and BETO. After comparing their results, the best accuracy of 0.98 was obtained with BETO. Therefore, transformer-based models outperformed the other approaches used in the study in terms of accuracy. This study allowed identifying the words frequently used in the corpus of fake news, concluding that they often use expressions with exaggerated adjectives and words expressing certainty or amazement in a social, political, and entertainment context.

Keywords: Fake News, Twitter, Natural Language, Machine Learning, Deep Learning, Transformers.

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1 Introduction

The use of social media completely revolutionized the way information is shared and consumed, becoming a relevant part for both government agencies and business. These platforms have provided users with the ability to share content and opinions without relying on traditional and centralized media, potentially allowing for a more democratic distribution of opinions, offering users the possibility to reach a large proportion of the population in real time (Prieto et al., 2020). Furthermore, social media allows individuals to disseminate information at no cost, with little research and fewer filters than before, becoming a powerful source of spreading fake news (Aïmeur et al., 2023) (Nasir et al., 2021).

Twitter, recently rebranded as X, is a microblogging and social media platform that owes its name to the original focus on short and concise messages, known as ‘tweets’, which allow users to share brief thoughts and updates with others. Over the years, Twitter doubled the initial 140-character limit and has gradually introduced support for sharing non-textual content, such as images and video (Marta, 2024). According to Twitter, the platform has over 206 million active users in 2022, defined as the number of accounts identified by the platform (Qi, Shabrina, 2023).

On Twitter, immediate communication prevails, and private and public communication are intertwined. The linguistic implications affect different levels of language: ortho typographic, morphological, syntactic, semantic, and pragmatic. In digital, synchronous, and ubiquitous exchange, the narrative is not controlled but rather the interaction, favoring a "conversational ecology". Authorship is shared, as the successive interventions of the interlocutors construct the continuity of the narrative, which tends to be improvised, lightly weighed, with relatively unelaborated syntax, and relaxed orthography in an informal context. The use of ortho typographic alterations, emoticons, or the insertion of audiovisual elements can help convey the communicative intention of the journalist, from parameters different from traditional journalistic media (Vázquez et al., 2016).

The first definition of the term "fake news" was provided by Allcott and Gentzkow, as news that are internationally and verifiably false and could mislead readers (Aïmeur et al., 2023). Fake news is one of the main concerns regarding the spread of internet connectivity, as it has the potential to cause significant political harm to countries. Fake news gained popularity during the U.S. presidential election campaign (Patel et al., 2022). They influenced voters during the 2016 U.S. presidential elections, as out of the 171 million tweets published during the election, 25% of them were false and intended to influence voters (Naredla, Adedoyin, 2022).

Fake news is considered one of the greatest threats to humanity, as it affects all aspects of human society, such as the economy, healthcare, and morality (Bodaghi, Oliveira, 2022). The proliferation of fake news on social media platforms poses significant challenges for society and individuals, leading to negative impacts, thus there is a need to automatically detect fake news. Machine Learning and Deep Learning techniques have emerged as promising approaches to characterize and identify fake news content (Alghamdi et al., 2024).

Mislead is promoted for political, ideological, or financial reasons. However, fake news can also appear and spread to entertain or provoke. (Huyen et al., 2023).

This document describes the process to develop a model that can determine whether the title of a news article is true or false using various Machine Learning, Deep Learning classifiers and Transformer based models. The main objective of this model is to identify if the original title of the news is authentic or fabricated. To achieve this, the model must accurately calculate the difference in the average weight of the words, identify the original title, and estimate the probability that said title is true.

2 Related Work

The following papers aimed at detecting fake news on social networks were reviewed: The authors of (Eduri et al., 2024) process documents in a language other than English so they resort to a hybrid multi-scale residual model CNN_B_ILSTM to capture local and global dependencies in the textual data.

In (Kaliyar et al., 2021), it is mentioned that with the revolution in mobile technology has led to the proliferation of fake news, that has the potential to manipulate public opinions and hence, may harm society. Thus, it is necessary to examine the credibility and authenticity of the news being shared on social media. They use the content of the news article and the existence of echo chambers (community of social media-based users sharing the same opinions) in the social network for fake news detection. They used an ensemble machine learning classifier and their proposed model called DeepFakE for the task of classification that outperforms with the existing fake news detection methods by applying deep learning on combined news content and social context-based features as an echo-chamber. They test their method on a real dataset: BuzzFeed. They get a validation accuracy of 0.8649.

The authors (Pimentel, Portugal, 2020) mention that several techniques can currently be used to detect fake news that mainly depend on supervised models that train a corpus of fake and true news in English. But these models are not available to classify news in Spanish, so they present a strategy to create a corpus of news in Spanish for the purposes of detecting fake news, for which they use Twitter as a mediator to find relevant sources of that news.

The authors (Nasir et al., 2021) propose a novel hybrid deep learning model that combines convolutional and recurrent neural networks for fake news classification, successfully on two fake news datasets (ISO and FA-KES), achieving detection results that are significantly better than other non-hybrid reference methods. It was evaluated on a publicly available dataset and compared with another using state-of-the-art approaches on the same dataset to justify its validity. With the help of a total of seven supervised machine learning classification techniques, which allow further validation of the proposed model. They were evaluated on two sets of data: The FAKES dataset consists of 804 news about the war in Syria. The 426 articles are true and the remaining 376 are false, which corresponds to a well-balanced data set (53% true articles versus 47% false). The ISOT dataset consists of 45,000 news articles are politics and world news, and the dates fall between 2016 and 2017. Seven classifiers were tested for benchmarking: Logistic Regression, Random Forest, Multinomial Naĩve Bayes, Stochastic Gradient Decent, K Nearest Neighbors, Decision Tree, Ada Boost, Convolutional Neural Networks Recurrent Neural Networks.

The authors in (Abualigah et al., 2024) mention that, according to estimates, one in 200 social media posts contains spam and one in 21 tweets contains spam. The problem focused on precision when detecting fake news and correcting it or preventing its spread before it spreads online. A new method is given based on improving the fake news detection system; The level of improvement was significant in the pre-processing stage where GloVe is used, which is an unsupervised learning algorithm developed by researchers at Stanford University with the objective of generating word embeddings by adding global co-occurrence matrices of words from a given corpus. The basic idea behind GloVe word embedding is to derive the relationship between words from statistics. The proposed method contains convolutional neural network (CNN), deep neural network (DNN), and long short-term memory (LSTM) deep learning algorithms. The RNN with GloVe in the pre-processing stage using the Corpus fake news dataset to improve the system, due to sequential processes and classification, has the highest accuracy of 98.974%.

The authors of (Maham et al., 2024) use a framework called "ANN: Adversarial News Net" that is evaluated using four publicly available datasets and is found to outperform baseline methods and previous studies after adversarial training. The experiments show that Adversarial Training improved performance by 2.1% over the Random Forest baseline and 2.4% over the BERT baseline method in terms of precision. So the proposed model can detect fake news in real time.

In (Aïmeur et al., 2023), the authors conduct a review of articles to understand the problem of "fake news", its challenges, root causes, and review of automatic methods of detection and mitigation of fake news on social networks by researchers. The articles reviewed were over a ten-year period, two-thirds of the works will be published in 2019 or later. They were chosen according to 10 keywords, then a list of criteria was made for inclusion and exclusion of articles. Considering 61 articles. They categorized the fake news based on its content and its intention. The problems that were detected were the lack of user awareness, the spreaders of social bots, the dynamic nature of online social platforms that makes the spread of fake news rapid. Techniques to detect fake news are classified based on humans, Artificial Intelligence and blockchain.

3 Methodology

With the aim of creating a model capable of distinguishing between fake and true news, the methodology shown in Figure 1 was followed. This methodology involved the construction of a dataset with news samples extracted from Twitter at different periods and years, from 2019 to 2024 coming from the Twitter accounts of “Reforma” and “El Deforma”. Subsequently, the news prepared for numerical representation and feature extraction, to use them as input the classification model and evaluate the results.

3.1 Dataset Extraction

To extract news from Twitter, it was necessary to register as a developer to obtain a token and access keys. This allowed the connection to the Twitter API through the Tweepy library in Python.

This methodology was used to obtain headlines from real and parody newspapers, to create a dataset of news headlines in Spanish.

The headlines of “El Deforma”, a parody newspaper, and the “Reforma” newspaper, which publishes news on politics, sports, science, health, economy, security, and entertainment, were used 18,313 tweets were retrieved from each site, during the period from November 2019 to February 2024.

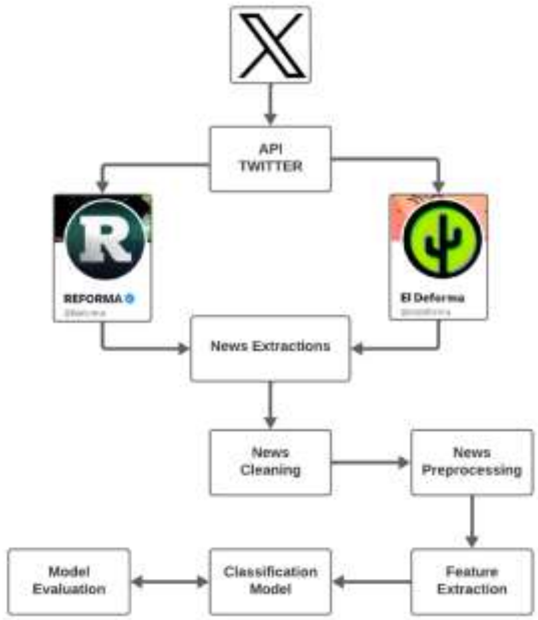


Figure 1. Methodology Overview: Steps from Data Collection to Classification Evaluation.

3.2 Cleaning and Preprocessing

The first step is to clean the text, and the process is detailed below:

- *Lower Tweets*: Text are converted to lowercase.
- *Remove the URLs*: Links starting with “http” or “https” or “www” are replaced by empty string.
- *Remove mentions*, retweet and hashtags: Word starting with “ “, “#”, “RT” are removed.
- *Remove symbols*: Emoticons, symbols and pictographs, transport and map symbols, flags, other language characters are removed.
- *Remove non alphabet characters*: Replacing characters except Digits and Alphabets with a space.
- *Remove consecutive letters three or more*: three or more consecutive letters are replaced by only one. (eg: “oigaaaa” to “oiga”).
- *Remove punctuations*: Punctuations are removed from the sentence since it is not affecting the meaning of the sentence (Alp et al., 2022).

Preprocessing techniques were applied with the aim of ensuring the correct input data for feature engineering and model construction.

- *Removal of common words*: Common words that do not have any relevant meaning compared to other keywords were eliminated. For this purpose, a set of words related to the context of fake news detection was constructed and added to the most common stop words set.
- *Text Standardization*: A custom dictionary was developed in the Spanish language for abbreviations.
- *Spelling correction*: A dictionary was constructed to correct spelling, as many users neglect spelling when writing on social media.
- *Tokenization*: The news was divided into minimal units of meaning, in this case words.
- *Stemming*: The root of the words was extracted.
- *Lemmatization*: The root of the words was extracted considering the vocabulary.

After cleaning and preprocessing the 36,626 news, they were reduced to 34,236, resulting in 17,118 fake news and 17,118 true news which were then processed.

3.3 Text representation and Feature Extraction

The numerical representation of news is necessary for classification. Machine Learning algorithms require news to be converted into numbers, specifically vectors of numbers, which capture linguistic properties of the text.

The TF-IDF method allows quantifying words reflecting their importance in a document within a corpus of documents. This method is based on the idea of assigning a weight to each word based on its occurrence in the document and across all documents. These weights highlight distinctive words that contain useful information in a specific document. Therefore, the IDF of a rare term is high, while the IDF of a frequent term is likely to be low. For each word in a document, the term frequency TF is first calculated, which counts the number of occurrences of the word in a document, and then the inverse document frequency IDF (Alghamdi et al., 2023).

The TF-IDF method was used to extract features that will serve as inputs for the Machine Learning algorithms: Logistic Regression, Naïve Bayes, and SVM, while word embeddings were used for the Deep Learning models, as they could capture semantic relationships and prevalent contextual nuances in the news.

BERT extracts features from text by splitting it into tokens, adding special tokens like [CLS] and [SEP], and converting them into embedding vectors that include positional and segment information. These embeddings are processed through multiple layers of bidirectional transformers, which use attention mechanisms to consider the context of all tokens in the sequence. The result is contextualized feature vectors for each token, with the vector of the [CLS] token used to represent the entire sequence in classification tasks (Paaß, G., Giesselbach, S. 2023).

3.4 Classification Model

The objective of this study is to investigate the possibility of improving fake news prediction using Machine Learning, Deep Learning and Transformers by evaluating the differences between classification algorithms. Consequently, several algorithms were selected for testing: Logistic Regression, Naïve Bayes, and Support Vector Machine, in addition to applying LSTM and Bidirectional LSTM, and the transformer-based models: mBERT and BETO.

Long short-Term Memory (LSTM) neural networks, and especially Bidirectional LSTM, understand temporal dependencies in sequential data by leveraging information from past and future contexts. (Eduri et al., 2024) Therefore, they were chosen to be applied in this study.

BERT (Bidirectional Encoder Representations from Transformers) was proposed by Devlin and is the most important approach for generating contextual embeddings. BERT is based on the concept of attention and on prior words by Vaswani. The notion of attention is inspired by a brain mechanism that tends to focus on distinctive parts of memory when processing large amounts of information. BETO is the BERT-based that was trained in Spanish (Paaß, G., Giesselbach, S. 2023).

3.5 Evaluation metrics

In this work, detecting fake news is considered as a binary classification problem, and evaluating Machine and Deep learning algorithms is an essential part of proposed model. In this case, five metrics are used for performance evaluation, which include Accuracy, Precision, F1-Score, ROC- AUC, and Cross validation.

Accuracy gives the ratio of correct predictions to the total number of input samples, where TP, TN, FP, and FN represent True Positive, True Negative, False Positive and False Negative, respectively,

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision represents the ratio of all predicted correctly as fake news to those annotated as fake news.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall indicates the ratio of fake news to all fake news.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F1-score, the harmonic mean of precision and recall, gives overall.

$$F1 - score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} = 2\frac{Precision * Recall}{Precision + Recall} \tag{4}$$

The ROC curve compares the performance of classifiers by looking at the trade-off in the False Positive Rate (FPR) and the Positive Rate (TPR), where.

$$TPR = \frac{TP}{TP + FN} \tag{5}$$

$$FPR = \frac{FP}{FP + TN} \tag{6}$$

From the ROC curve, the Area Under the Curve (AUC) shows the classifier overall performance (G, S.K., 2021).

4 Results

The total number of words in the news, as well as in each group of fake and true news, are shown in the results of Table 1. We can conclude that there is the same amount of news in each group; however, fake news has approximately 60 % fewer words than true news.

Table 1. Total Words per Twitter account

	News	Words
El Deforma	17118	88495
Reforma	17118	219623
Total	34236	308119

With the TF term frequency methods, it was possible to identify the most frequent words used in fake news, as shown in Table 2. After reviewing some of the fake news in the “El Deforma” corpus, it is observed that the word “real” is frequently used in this news to affirm the authenticity of certain misleading claims or stories. The word “increible” is used to present information that seems surprising or difficult to believe, increasing the emotional impact on readers. On the other hand, the word “nivel” is associated with a certain degree or height, which could generate sensationalism in fake news.

The other words provide context to the news, as many of the stories occur in Mexico and may be influenced by various social or political factors. Given the relevance of the COVID-19 pandemic recently, it is not surprising to see the word "cuarentena", as it is a health measure, and everything related to this topic is easy to propagate and susceptible to belief. "AMLO" is an important political figure, around whom fake news can be centered. Lastly, the words "internet" and "persona" were found to indicate people's interest in everything happening on the internet, and finally, everything related to the weather, hence the words "años" and "días" have a prominent frequency.

For true news, the most common words include "presidente", "COVID", "ciudad", "nacional" and "país", indicating a political focus, the COVID-19 pandemic, and national interest topics. It is political, social, economic, and health context that fake and true news have in common, indicating that these are the chosen topics for the construction of fake news, sometimes with a touch of humor and entertainment.

The most relevant bigrams were also detected, among which stand out: "increible cierto", "quieres sentir", "Lopez Gatell", "momento exacto", "triste cierto". "dias felices".

Table 2. Top 10 Most Frequent Words on Twitter account

	El Deforma	Reforma
1	real	mexico
2	increible	amlo
3	mexico	presidente
4	nivel	gobierno
5	cuarentena	covid
6	amlo	mil
7	dia	ciudad
8	personas	años
9	internet	nacional
10	años	pais

In the Figure 2 shows the frequency of words in fake news corpus.

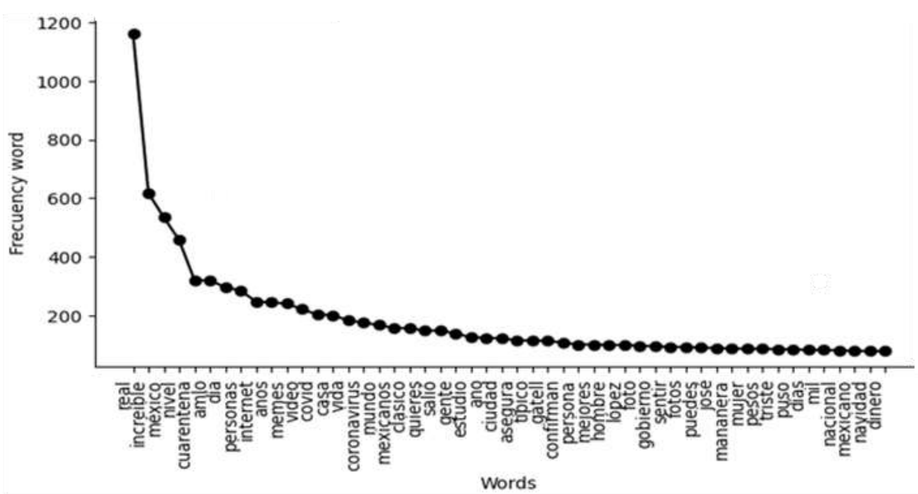
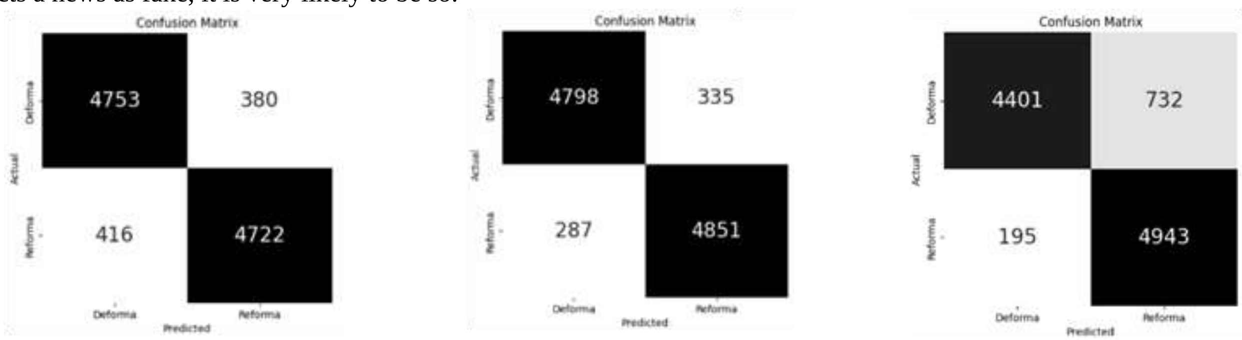


Figure 2. Graphics of Most Frequent Words on El Deforma's Twitter account

The confusion matrices of the Logistic Regression, SVM and Naive Bayes algorithms are shown in Fig.3 are used for calculating the Precision, Recall, F1-Score and the accuracy of the algorithms and they allow appreciate the number of false positives, false negatives, true positives, and true negatives.

The results of applying Machine Learning, Deep Learning and Transformer based models are shown in Table 3, where the algorithms of logistic regression, SVM, Naïve Bayes, LSTM, Bidirectional LSTM, mBERT and BETO are compared. We found that the best accuracy is achieved by BETO, with 0.98 and the algorithm with the best precision, which means that when it predicts a news as fake, it is very likely to be so.



(a) (b) (c)

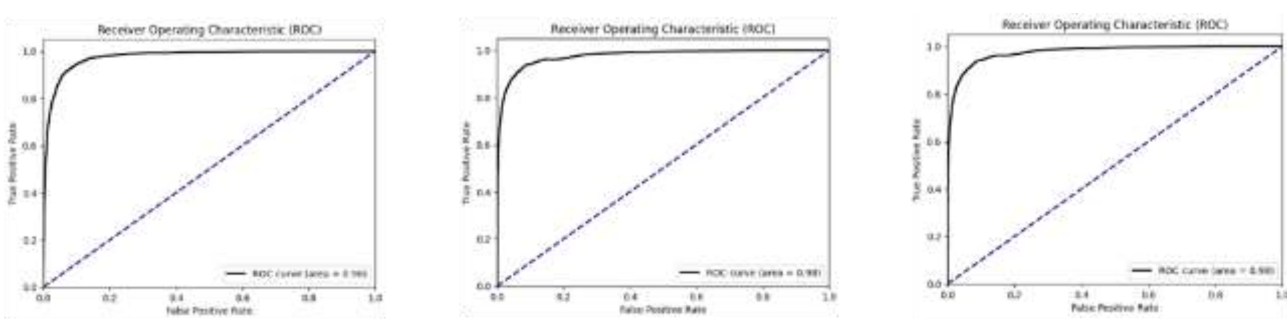
Figure 3. Confusion Matrices for news Classification by (**a**) Logistic Regression, (**b**) SVM and (**c**) Naive Bayes Algorithms.

Support Vector Machines, LSTM, and Bidirectional LSTM have the same value as F1-Score, which surpasses the other algorithms, indicating a balance between recall and precision. The highest Recall value is achieved by the Bidirectional LSTM network, which means that it is very effective in correctly identifying fake news in the test data. This is because the networks can capture contextual relationships both forward and backward in a text sequence.

Table 3. Performance Comparison of Classification Algorithms

	Accuracy	Precision	Recall	F1-Score	Support
mBERT	0.97	0.97	0.97	0.98	6912
BETO	0.98	0.98	0.97	0.98	6912
SVM	0.94	0.94	0.93	0.94	5133
LSTM	0.93	0.93	0.94	0.94	5146
Bidirectional LSTM	0.94	0.92	0.95	0.94	5146
Logistic Regression	0.92	0.92	0.93	0.92	5133
Naive Bayes	0.91	0.96	0.86	0.90	5133

The ROC curve of the Logistic Regression, Naive Bayes and SVM algorithms are very stable, as can be seen in Figure 4. The difference is very small because the AUC value of 0.98 is the same for all three algorithms.



(a) (b) (c)

Figure 4. ROC Curves: (**a**) Logistic Regression, (**b**) SVM and (**c**) Naive Bayes.

To confirm the accuracy of the method, 5-fold cross-validation was applied to all news data, as summarized in Table 4, which shows the mean accuracy of the k-folds cross- validation for each algorithm, finding very little variation.

Table 4. K-Folds

	1-Fold	2-Fold	3-Fold	4-Fold	5-Fold	Mean
Logistic Regression	0.915	0.922	0.921	0.915	0.907	0.916
Naïve Bayes	0.910	0.909	0.916	0.910	0.902	0.910
SVM	0.938	0.940	0.941	0.934	0.928	0.936

5 Conclusions

Since the invention of the printing press there has been fake news, however, with social networks the spread is very fast and in real time, fake news severely affects political, economic, and social fields, fake news has great impacts on health, in democracy and in the financial field.

This study allowed us to train a model that automatically identifies fake news in Spanish, using Machine Learning and Deep Learning techniques with good results using a corpus of fake and true news from Twitter accounts. The characteristics of the words that are frequently used in fake news with a corpus in Spanish are also highlighted.

In our findings, transformers outperformed traditional machine learning and deep learning models in terms of accuracy. This suggests that transformer-based models are more effective for the task of fake news classification in Spanish, because the ability of transformer-based models to capture global context, their pre-training on large datasets, and their capacity to learn richer semantic representations make them more effective for classifying fake news compared to traditional machine learning and deep learning approaches.

Both the multilingual BERT (mBERT) model and the Spanish-specific BETO model were applied for the classification of fake news in Spanish. The results obtained with both models were almost similar in terms of accuracy, recall, precision, and f1-score. This observation suggests that for the specific task of fake news classification in Spanish, both mBERT and BETO are equally effective. The similarity in the performance of both models reinforces the validity of our findings and suggests that multilingual models, such as mBERT, can be as effective as language-specific models, such as BETO, for certain applications in Spanish.

As future work, it is necessary to test this model with different new corpora to strengthen the proposal.

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