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PAPER

# Comparative Study of Machine Learning Approaches for Detecting Fake News in Arabic Text

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**ABSTRACT**

It is evident that fake news remains a critical global problem, especially in the Arabic language, although there is an absence of vast amounts of annotated datasets required for effective state-of-the-art natural treatment. In this paper, we compare deep neural networks (DNNs), XGBoost, gradient boosting (GB), and long short-term memory (LSTM) networks on the task of distinguishing real and fake Arabic news. When we applied special preprocessing for AFND with specific approaches to tackle the class imbalance problem, we observed that XGBoost was found to be the best method, performing with an accuracy of 72.86% on the test database. The present model performed optimally on relevant parameters related to the absence of capitalized terms, precision (0.83%), recall (0.71%), and F1-score (0.76%), especially for "undecided" cases. XGBoost's performance is revealed in these results, and feature selection and optimization are promoted, leading to improvements in the Arabic natural language processing (NLP) domain.

**KEYWORDS**

Arabic fake news detection, deep learning (DL), fake news, XGBoost, machine learning (ML)

## 1 INTRODUCTION

### 1.1 Background and motivation

Fake news poses a global challenge, eroding public trust and destabilizing the information ecosystem. This issue is especially critical in the Arabic-speaking world due to diverse dialects, cultural factors, and regional conflicts [1]. Arabic's linguistic complexity, with its rich morphology, diverse syntax, and dialectal variations, complicates natural language processing (NLP) tasks [2]. Additionally, the lack of large-scale annotated datasets further hinders the development of robust NLP models for over 400 million Arabic speakers across 22 countries [3]. To address these challenges, researchers are leveraging advancements in AI and NLP, particularly deep learning and multilingual techniques [4]. Innovations such as transformer-based models (e.g., BERT, GPT) and multilingual embeddings have demonstrated

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their potential to enhance NLP for Arabic, providing promising pathways for effective fake news detection [5].

### 1.2 Problem statement

Most of the previous work in this field is performed for English and other languages; therefore, the approaches developed in this field cannot be used directly for Arabic, as it is significantly different from English in terms of syntactical structure, morphological structure, and dialects [6]. This is made difficult by the fact that there are few large, high-quality annotated datasets available for Arabic [7]. This study seeks to improve machine learning (ML) and deep learning (DL)-based Arabic fake news detection by benchmarking DNNs, XGBoost, gradient boosting (GB), Naive Bayes (NB), logistic regression (LR), and LSTM. The study also tackles important challenges such as class imbalance, noisy data, and dialectal variation by customizing the preprocessing and feature extraction steps for the Arabic speech corpus. Besides that, it investigates the feasibility of using text, images, video, and metadata for the purpose of objectivity enhancement in social media fake news using DL models. Possible future work may involve comparing the methods used here to techniques developed in English and searching for methods to address the problems that are particular to every language.

### 1.3 Research objectives

This study proposes the following objectives: To compare the efficiency of traditional ML and DL techniques in detecting fake Arabic text by training several classifiers, including XGBoost, GB, NB, and LR; To classify the fake news, with the best-performing one selected. To investigate the use of advanced DL techniques, especially DNNs and LSTMs, in improving detection precision of fake news in Arabic text analysis by comparing the results of each model on the test dataset.

The paper is structured as follows: Section 2 covers the literature review, Section 3 explains the methodology, Section 4 discusses results and evaluation, and Section 5 concludes with limitations and future directions.

## 2 LITERATURE REVIEW

### 2.1 Overview of fake news detection

Fake news detection has rapidly emerged as a critical research area due to the rise of misinformation on social media and its harmful impact on democratic processes, societal tensions, and crises such as public health emergencies [8] [9]. Early approaches relied on traditional ML models, such as support vector machines (SVM) and NB, using feature extraction techniques such as term frequency-inverse document frequency (TF-IDF) and bag-of-words [10]. However, these methods struggled to capture the subtle patterns often found in fake news. DL models, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have shown superior performance by effectively capturing sequential and contextual nuances in text, which are essential for distinguishing fake from real news [11].

## 2.2 Transformer-based advances

Transformer architectures have significantly improved fake news detection for Arabic. Models such as AraBERT [12], Arabic-BERT [13], and others leverage pre-training on large corpora to handle Arabic's linguistic complexities and outperform traditional methods such as TF-IDF and Word2Vec. For example, Bou Nassif et al. (2022) found that ARBERT and Arabic-BERT achieved F1 scores close to 98% when tested on a large Arabic fake news dataset [16]. Similarly, Al-Yahya et al. (2021) demonstrated that transformer models, especially QARiB, outperformed neural networks, increasing F1 scores from 0.83 to 0.95 [14].

## 2.3 Emerging multimodal and multilingual approaches

Recent research suggests that incorporating multimodal features, such as combining text with images or videos, enhances fake news detection. For instance, multimodal systems such as BERT-VGG16 and CARMN have improved accuracy by integrating text, visual, and semantic data [15] [16]. Multilingual transformer models, such as mBERT and XLM-R, also show promise for bridging resource gaps by leveraging shared patterns across languages, enabling advancements in under-represented languages such as Arabic [17].

## 2.4 Progress in Arabic fake news detection

Despite significant progress in fake news detection for languages like English, Arabic presents unique challenges due to its rich morphology, diverse dialects, and complex syntax [18]. These factors, coupled with a lack of large annotated datasets, make developing robust Arabic NLP models particularly difficult. The need for automated tools tailored to Arabic has grown with the rise of social media and misinformation in the Arab world [7].

Dialectal variations across Arab countries further complicate the task [19]. Modern Standard Arabic (MSA) is typically used in formal contexts, while informal communication often employs dialects, making it difficult to create models that work consistently across contexts.

Researchers have tackled these issues through various methods. Darwish et al. (2020) improved text classification accuracy with dialect-specific preprocessing [20], while others focused on building Arabic-specific NLP tools such as stemmers and lemmatizers to enhance text processing [21]. Nagoudi, Elmadany, and Abdul-Mageed (2020) developed a model for detecting manipulated Arabic news using POS tagging, achieving a macro F1 score of 70.06 [22]. Studies targeting specific contexts include Khalil et al. (2021), who analyzed over seven million Arabic tweets on COVID-19, leveraging hashtags and fact-checkers for classification [23]. Himdi et al. (2022) introduced a crowdsourced dataset and an ML model achieving over 75% accuracy, identifying linguistic features as key for detection [4]. DL methods have also advanced Arabic fake news detection. Al Harrag and Djahli (2022) developed a CNN-based model with 91% accuracy, outperforming earlier approaches [24]. Wotaifi and Dhannoon (2023) combined Text-CNN and LSTM into a hybrid deep neural network, achieving 91.4% accuracy on the AraNews dataset [25]. Fouad, Sabbeh, and Medhat (2024) found BiLSTM to perform best among several DL models, emphasizing future work on stacking layers and pre-trained embeddings [26].

### 2.5 Methods overview

In this study, we use a wide range of machine learning and deep learning algorithms to detect fake news in Arabic, namely deep neural networks (DNNs) [27], XGBoost [28], GB [29], NB [30], LR [31], and LSTM [32] networks.

Deep neural networks excel in text classification by capturing interactions between words and phrases, which is valuable for detecting deceptive content. Word2Vec and GloVe embeddings enhance DNNs by representing words in continuous vector spaces, improving their ability to understand relationships between words [11]. XGBoost and GB are ensemble methods that use decision trees as weak classifiers. These models are effective for text classification tasks such as fake news detection due to their flexibility in learning non-linear decision boundaries and handling class imbalance [33]. Naive Bayes, a probabilistic classifier, assumes feature independence. While simple and fast, it struggles to model interactions between words, making it useful as a baseline for text classification tasks such as spam detection [34]. LR, known for its simplicity and stability, is widely used in text classification. While it can't model complex non-linear relationships such as more advanced models, it remains a reliable tool for fake news detection studies [35]. LSTMs, a type of recurrent neural network (RNN), excel at processing sequential data, where word order is crucial. LSTMs can capture long-term dependencies in text, making them effective for distinguishing between fake and real news [36]. Recent studies show that LSTMs with attention mechanisms perform well in fake news detection and other NLP tasks [37].

### 2.6 Gaps in the literature

Although there has been great progress in concerning fake news detection, the majority of the existing work revolves around news articles, not social media. Applying transformer-based models in combination with features engineering can improve Arabic detection because of its dialectal and often casual rich nature. To overcome the resource scarcity in Arabic data, there is multilingual mBERT and cross-lingual embeddings. This study emulates ML algorithms as ML, algorithms such as XGBoost, NB, and contrast it with DL models such as DNNs, and LSTMs, while proposing the integration of multidimensional data in the future. It also shows that there are such preprocessing techniques as TF-IDF most suitable for Arabic, and these could be enhanced by cross-lingual evaluation. Dialects are not well represented in the datasets especially in Arabic and the shortage of Arabic datasets of high quality is still an issue; hence, a wider variety of datasets by incorporating dialects and multimodal data will enhance performance. The preliminary validation of the method involving the evaluation of the positive class, either as "credible" or "undecided" rather than as "negative," demonstrated the usefulness of using more than just accuracy as a measure in evaluating the results of the binary classification into "credibility" and "non-/low-/incredibility." This work lays down the groundwork with XGBoost, scoring 72.86% accuracy, to advance the use of ML and DL in distinguishing between authentic and fake Arabic news; future work includes work on multimodal data and cross-linguistic approach with other languages.

## 3 METHODOLOGY

### 3.1 Dataset description

The Arabic Fake News Dataset (AFND) contains 606,912 articles collected from 134 Arabic news sources and is appropriate for fake news classification. The articles are either fact-checked as credible, non-credible, or undecided using the Misbar fact-checking tool. The data itself is stored in JSON format organized within folders that correspond to the individual sources; each source has its name, title, text of the article, date of publication, and the source itself.

Limitations are as follows: The dataset is imbalanced, with more credible articles than non-credible articles; this can create bias in the model. It is an LAR dataset mostly in Modern Standard Arabic (MSA) and limited by sampled informal dialects found on social media. Some of them provide more articles than others, it is genre imbalanced as well, where political and economic genres dominate the others. There are no such fine-grained categories as satire or propaganda in the presented dataset. Future developments should aim at enhancement of dialectal and genre variations; addition of metadata for more subclasses of fake news, and a proper mix of classes and sources. Hence, Table 1 shows sample articles with features such as title, text, publish date in ISO 8601 format, and source. The Label column is left blank, and its purpose is to classify the given data. All examples are in Arabic, collected in May 2021 from one source only.

As shown in Figure 1, the dataset has an uneven distribution of articles, with “Undecided” having the most (over 200,000 articles), followed by “Credible,” and “Not Credible,” which has the fewest articles.

**Table 1.** Sample news from the Arabic news articles dataset

| Title No. | Text | Published Date | Source | Label |
|---|---|---|---|---|
| 0 | المنتخب الوطني المغربي لأقل من 20 سنة يخوض تجم... | يخوض المنتخب الوطني المغربي لكرة القدم لأقل من… | 2021-05-23T00:00:00 | source_1 |
| 1 | وزير النقل اعمارة:السرعة عامل مسبب لحوادث السي... | ترأس عبد القادر اعمارة، وزير التجهيز و النقل و... | 2021-05-22T00:00:00 | source_1 |
| 2 | ميسي يؤكد أن الفوز بكأس اسبانيا كان ”نقطة تحول“ | أكد النجم الارجنتيني ليونيل ميسي أن فوز فريقه... | 2021-05-22T00:00:00 | source_1 |
| 3 | خطأ مدري... M.ma: دبلوماسي مغربي سابق بإسبانيا لـ2 | أكّد الدبلوماسي المغربي السابق بإسبانيا، عبد ا... | 2021-05-22T00:00:00 | source_1 |
| 4 | شركتان، فرنسية وبريطانية تعلنان عن نتائج إيجاب... | أعلنت شركتا سانوفي الفرنسية العملاقة في تصنيع... | 2021-05-17T00:00:00 | source_1 |

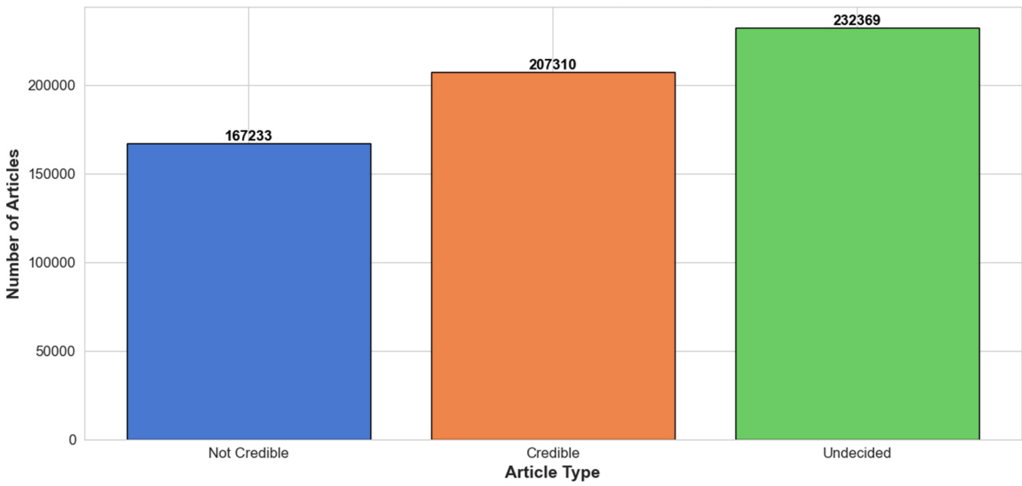


**Fig. 1.** Distribution of articles in the dataset

## 3.2 Data preprocessing

The present study focused on the following issues in developing the training corpus AFND for model training: the problem of the class imbalance, the usage of text noise, and dialectal variety. With regard to class imbalance, where 'credible' generates more articles than 'not credible,' some approaches were used. SMOTE manufactured new examples for the minority classes, while undersampling involved the proportionate elimination of a segment of the majority class. Cost-sensitive learning was also used in such a way that during the training process, weights for each class were modified so that misclassification of classes with fewer instances is penalized. Low-quality text features like background material, HTML tags, and a script that eliminated special characters, non-Arabic punctuation, and excess white space handled formatting. These were removed from the pool if an article contained less quality content or only contained fillers and advertisements. Text pre-processing corrected spelling, realized standard diacriticization, and stripped off elongations as it normalized the text. Stemming and lemmatization were left out for this reason because using these two procedures might strip a number of essential linguistic characteristics of the Arabic language. In future work for better text representation and balancing classes, it may be useful to use dialect-specific embeddings; there are already multilingual pretraining models such as AraBERT and data augmentation methods including back-translation, which could be employed.

### 3.3 Feature engineering

The study employed TF-IDF as well as word embedding for feature selection. Text pre-processing was used to extract the words that carry significant information since TF-IDF was used to transform textual data into numerical vectors. In future work, other approaches, such as Word2Vec or GloVe may be used, but due to the simplicity and effectiveness of TF-IDF in text classification, it was used at this phase.

### 3.4 Model selection

That is why the present study compares the effectiveness of several approaches to fake news detection in Arabic, with reference to the main AI tendencies in the context of multilingual news filtering tasks. DNNs learn features in the text and outperform simpler models in detecting differences between credible and non-credible articles. This task requires a robust, efficient, class-imbalance friendly solution, and among all the discussed algorithms, the ensemble method based on GB or XGBoost, is the most suitable. XGBoosting is a model that shares properties with GB but applies a distinct boosting technique. These two models simply enhance performance by working out learning algorithms for samples with imbalanced data. The text classification model used an NB algorithm because of its simplicity and interpretability given its limitations of feature independence. For LR, since it is simple but effective binary classifier, examples were used based on its stability and easy interpretation. Finally, LSTM networks, which are a subgroup of RNN, were added due to their suitability in capturing sequential characteristics of text, key to distinguish between fake and real news.

These models were carefully chosen to compare classic and modern approaches in Arabic fake news detection and to understand how AI is adapting its strategies for multilingual and low-resource languages.

### 3.5 Training and testing

The dataset was divided into three subsets: 80% for training, 20% for validation, and 20% for testing. Hyperparameters are tuned from the validation set, while overfitting is avoided through 5-fold cross-validation each of which has balanced classes. Offline evaluation of these models is also far better than online evaluation because it guarantees better model generalization and model accuracy.

### 3.6 Hyperparameter tuning

Hyperparameter tuning for shallow models, including LR, and NB, was done using SimpleGrid, while others, such as XGBoost and DNNs, required tuning by random search. Cross-validation was used to prevent the model from memorizing training data and evaluate the model on different partitions and tune parameters such as learning rate, number of estimators, and layers of the model.

### 3.7 Evaluation metrics

When analyzing the results of the models, four parameters have been applied; accuracy, precision, recall, and F1-score, due to the peculiarity of the Arabic language, as well as the imbalance of the classes and dialects used in the experiment. It is an average of the performances, and it is very misleading when the training and testing samples are partitioned. Precision eliminates false positives, which is very important when it comes to trust, while recall will ensure that manipulative fake news is spotted. F1-scores, which take both precision and recall into account, approach the problem of dealing with the class imbalance. For evaluation purposes, these metrics were computed for each class—credible, not credible, and undecided—to measure model performance and identify the areas that might need improvements especially in handling the articles that fall under the undecided category.

### 3.8 Future considerations for transformer models

Future work can adapt transformer-based models such as AraBERT for improved context awareness in Arabic NLP applications. Other related scores, such as **Perplexity** and specific assessments on specific tasks such as **ROUGE** and **BLEU** can further improve the performance of the model in the diverse features of Arabic language data for fake news detection.

## 4 RESULTS

### 4.1 Model performance overview

Models were evaluated based on accuracy, precision, recall, and F1-score, with key findings as follows: The DNN evaluated to 34.03% accuracy, with challenges in handling classes labeled “not credible” and “undecided” with F1-scores of 0 while recording better performance in the “credible” class due to a lack of proper feature interactions and imbalanced classes. XGBoost led with 72.86% accuracy, showing balanced performance across categories (F1-scores: 0. Hence, an accurate classifier with respect to "credible" and "undecided" of 0.76 and "not credible" of 0.62 is realized due to the feature selection, hyperparameter tuning, and class imbalance handling, thus suitable for Arabic text. GB scored 65.67% accuracy, performing well with "credible" and "undecided" articles (F1-scores of 0.69 and 0.70) but underperforming for "not credible" (F1-score: 0. However, other differences in boosting methods and possibly in handling of imbalance class played a role in achieving the score of 0.51. NB achieved 57.92% accuracy, struggling with the "not credible" category (F1-score: 0.45), which proved to be less efficient given that it relied on the assumption that features are independent and thus could not handle sophisticated Arabic data sets efficiently. The LR model took 69.09% of accuracy and demonstrated high confinement with the "credible articles classification," having the precision value of 0.75 and the recall of 0.70; however, due to its linear separation capability, it was outperformed by two other models: XGBoost and LSTM. LSTM achieved 70.35% accuracy, with strong performance on sequential data (F1-scores: 0.0.74 of credible, 0.61 of not credible, and 0.73 of undecided), while XGBoost effectively handled the structured data and the imbalance of the classes.

In terms of class imbalance, feature selection, and hyperparameter tuning, the XGBoost model yielded better results than other models for respective categories, namely "undecided" and "not credible." Whenever possible, DNNs require improvement to their tuning, and LSTMs could benefit more from attention or transformer-based embeddings. Performance comparison across accuracy, precision, recall, and F1-score is provided in Table 2, which gives a comparison of all the models.

**Table 2.** Performance comparison of machine learning models

| Metric | DNN | XGBoost | Gradient Boosting | Naive Bayes | Logistic Regression | LSTM |
|---|---|---|---|---|---|---|
| Accuracy | 34.03% | 72.86% | 65.67% | 57.92% | 69.09% | 70.35% |
| Precision | 0.34 | 0.83 | 0.80 | 0.58 | 0.75 | 0.73 |
| Recall | 1.00 | 0.71 | 0.61 | 0.62 | 0.70 | 0.74 |
| F1-Score | 0.51 | 0.76 | 0.69 | 0.60 | 0.72 | 0.74 |
| Precision | 0.00 | 0.76 | 0.77 | 0.56 | 0.59 | 0.68 |
| Recall | 0.00 | 0.53 | 0.38 | 0.38 | 0.63 | 0.56 |
| F1-Score | 0.00 | 0.62 | 0.51 | 0.45 | 0.61 | 0.61 |
| Precision | 0.00 | 0.66 | 0.57 | 0.59 | 0.72 | 0.70 |
| Recall | 0.00 | 0.89 | 0.90 | 0.69 | 0.73 | 0.77 |
| F1-Score | 0.00 | 0.76 | 0.70 | 0.63 | 0.73 | 0.73 |

## 4.2 Comparison and interpretation

The XGBoost yielded the highest prediction accuracy and F1-scores in credibility and undecided classes of voters. Indeed, the high performance is attributed to its effectiveness in dealing with the complexities of Arabic text as well as excellent ability in handling class imbalance, particularly the 'marginally positive' category that makes it conducive for Arabic fake news detection. But, there was an issue with the 'credibility' and 'not credible' classification where the XGBoost model misclassified some of the samples (see Figure 2).

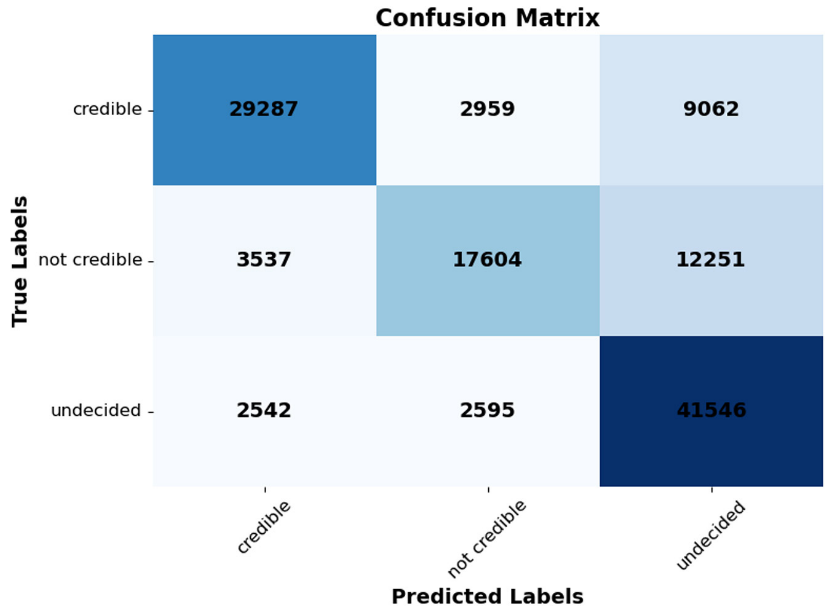


**Fig. 2.** Confusion matrix result of the XGBoost method

Gradient boosting performed slightly worse than XGBoost because of less powerful boosting algorithms and possible problems with parameters. Classification for 'not credible' was particularly challenging for NB while LR which was more balanced could not compare to XGBoost or LSTM. From the results, LSTM had demonstrated high capabilities of context recognition, while XGBoost performed much better in handling structured data. The bar chart (see Figure 3) reveals that XGBoost had the highest accuracy rate for classifying news articles.

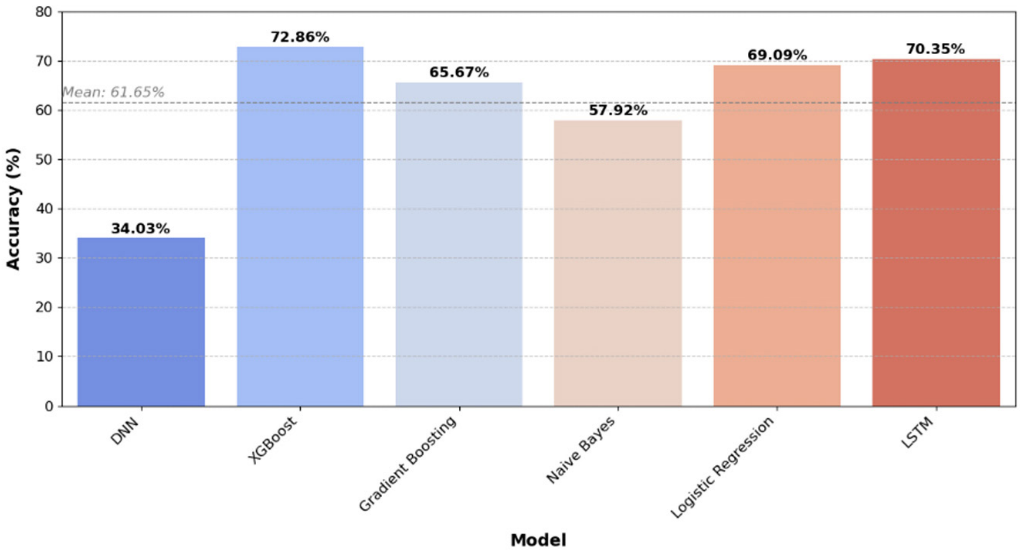


**Fig. 3.** Comparison of accuracy results between the six methods

### 4.3 Error analysis

- **DNN:** As it can be seen in Table 2, the DNN model performed poorly, especially with 'not credible' and 'undecided' categories, resulting in zero recall and F1-scores because the DNN model overfits with the 'credible' class. Better balancing techniques such as SMOTE are proposed to improve performance.
- **XGBoost and GB:** As the experiment showed, both models worked effectively yet failed to recognize 'not credible' content, most probably due to the similarity of textual characteristics. Indeed, since XGBoost has adaptive learning rates and better at handling imbalanced datasets as well as the hyperparameter's fine-tuning led to the superiority compared to GB. As for the future work it is seen that improvement can be made to GB to eliminate this gap.
- **NB:** Complained with 'not credible' categorization since the algorithm assumed independence of features, which made their model less fit in handling large data sets.
- **LSTM:** Overall, it provided a good performance but failed to detect sarcasm, different dialects, and ambiguous information in Arabic fake news detection.
- **Confusion Matrix Insights:** XGBoost performed well with 'credible' and 'undecided' but was not so good with 'not credible' and 'credible.' In the case of GB, misclassifications were also similar to before. P2, NB approach tended to misclassify the documents as 'Uncertain' documents/'Not Credible' documents. It was highly accurate, but its results on ambiguity or sarcasm were worst.

### 4.4 Implications of findings

These findings provide important findings on employing artificial intelligent models in Arabic language for fake news detection especially given the fact that Arabic is a rich language in terms of morphology and yet few annotated datasets are available for it. In general, the XGBoost model accountable for attaining 72.86% of the test accuracy beneficial for solving the issues such as Arabic complex morphology, dialects, and imbalance data set. This is due to the multiple learning model approach, GB, and strong anti-overfitting performance for complex nonlinear relationship and severe class imbalance problems.

XGBoost was found to do a better job of classifying between the "credible" and the "undecided" buckets with less confusion. Therefore, GB was less accurate because of the improper adjustment of its parameters, while LSTM was somewhat effective but highly sensitive to different dialects. Both models struggled to discern between so-called 'credible' and 'non credible' articles because they were very close in the kind of language they used. Possible enhancements in the future could be a higher feature engineering capability via semantic embeddings or DL using transformer models including AraBERT, which is more suitable to capture contextual information.

Using other modalities such as text and images and videos could even improve the detection since fake news is typically a combination of text and images. XGBoost final classification and transformer models for feature extraction may prove ideal as they try to accommodate both structure and deep contextual understanding.

### 4.5 Practical applications

There are implications for preventing misinformation for users of the Arabic language in this study. This information can be used in media monitoring tools and includes XGBoost and LSTM that can be used for real-time identification of fraudulent content. Using transformer-based models such AraBERT could improve effectiveness particularly in multilingual and cross-dialect discussions. It is suggested that news credibility could be better understood using the multimodal analysis of the text, images, and metadata. Integrating these models supports the development of PMC and media literate citizens able to evaluate the news and demand accurate information.

### 4.6 Limitations

Several limitations should be considered: MSA dominates the dataset, which may not represent real-life communication where dialects are frequently used; it is recommended that future studies incorporate more of dialects and more forms of fake news; besides text data, the inclusion of both image and video may further boost model performance. Besides, the results of this study are not the comparison of XGBoost with the most recent transformer models such as AraBERT or any model that is superior in capturing context relations; Therefore, it can be fairly good to support the hybrid method by pointing out its drawbacks. Finally, this study found that while class imbalance was managed through oversampling, there were instances of misclassification that occurred within the not credible and undecided classification, and thus the future studies should investigate other methods of data augmentation and introduce new loss functions.

## 5 CONCLUSION

Evaluation of different ML models used for fake news detection in Arabic was done; these are DNNs, XGBoost, GB, NB, LR, and LSTM networks. It is also important to note that XGBoost achieved the highest accuracy of 72.86% establishing the model's ability to navigate the intricacies of Arabic word forms and dialects. LR and LSTM also afforded high accuracies of 69.09% and 70.35% therefore proving capable to extract related elements within Arabic news articles.

The work helps to advance Arabic NLP by considering the specific difficulties the language entails. Some of the insights are related to stemming and lemmatization that is detrimental for Arabic due to its morphology; oversampling and cost-sensitive learning to address the problem of imbalanced datasets. These approaches thus form the basis for designing and implementing sound NLP solutions in Arabic and similar languages.

Further studies can embark on using other advanced transformer models such as AraBERT, MARBERT, or opt for mBERT or XLM-R to increase accuracy and reliability. Furthermore, challenges with dialect in specific domains could be solved by using domain-specific models besides adding multivariate data such as text, images, and videos would improve fake news detection for fake news that involve the use of images and videos.

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