Fake News Detection using Advanced Machine Learning Techniques

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This study contains development of fake detection models in two languages, which are English and Azerbaijani. This study is of particular interest for the low-resource Azerbaijani language which has used fewer studies in this area. We created a reasonably balanced dataset containing 20 thousand news, including 50% fake and real news in Azerbaijani for GPT-4 combining with the source data. We repeated the same procedure for English to get similar numbers with GPT-2. Our methodology consisted of multiple ML and DL techniques ranging from the basic as TF-IDF combined with Logistic Regression to Word2Vec, GloVe embeddings and finished off with the language models transformer based such as mBERT and XLM-RoBERTa. Notably, our results show significant performance gains with each of these more sophisticated methods. Stating the obvious, XLM-RoBERTa had the best results with an F1-score for Azerbaijani as 99%, while reaching up to 97% with English. Overall, these findings demonstrate the power of transformer model in multilingual fake news detection and underscore the merit of using advanced models to address misinformation in various languages. This research has something to offer not only for the fight against fake news on a global scale but also raises some important questions about media integrity in languages that are hardly studied at university around the world. All the code, models, and datasets have been published as open-source material at GitHub and Hugging Face. The repositories can be accessed here: GitHub Repository and HuggingFace.

Additional Key Words and Phrases: Fake News Detection, Machine Learning, Deep Learning

1 INTRODUCTION

The digital age has revolutionized the method we consume and come across information, with news now able to travel faster than it was before. Social media and other platforms have become the biggest local content sources, spreading news from person to person that a data is major source of information impacting children's opinion formation as well as opening them up for political and social activities. It also leads to the issue of fake news; it can spread misinformation or disinformation circulating in social platforms, which results in disastrous outcomes for society [11].

The reason the problem is so urgent though, is that fakes news can move facts around ad mislead an unwary public (often with serious political and societal implications). However, the era of advanced language models has brought new challenges and opportunities with which we must contend to combat this misinformation. As such, our study fills a critical gap by covering two different languages (English and Azerbaijani) to offer comparative findings on fake news detection from language-specific points of view.

Although there have been significant advances in fighting fake news at least for English, low-resource languages mainly due to the lack of data and research refurbishment are lagging. The above discrepancy makes speakers of uncommon languages more vulnerable to misinformation, indicating the necessity for a wider technological development and thus for ensuring inclusive and effective detection systems worldwide [6], [1]. We are doing this research because there is an urgent necessity to make news more reliable on one of the most widely used platforms by people and that is social media. Using even more powerful language models such as GPT-4 will help us learn more and circumvent methods in which fake news is created and disseminated. Our goals are thus to assess how well the models perform when detecting fake news and which linguistic features appear to produce varying accuracy results between English and Azerbaijani. Because there has been little study of fake news in Azerbaijani, our paper not only advances the struggle against misinformation around the world but also begins a crucial conversation about media fairness in less-examined languages.

Our paper is organised as to first present related work on the literature surrounding fake news detection and then provide a full description of our methodology, composed not only by where we gathered data from and

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how we created fake news for model training. We will next in turn present, discuss and conclude our results (including a future outline for research and practice).

2 LITERATURE REVIEW

Fake news is a crucial problem in this digital age and there has been considerable research around it to build effective detection methods which involved complex machine learning as well. However, the literature description on this issue shows that different studies have developed several ways which are embedded in both generative models and discriminative frameworks to improve fake detection's accuracy of reliability.

A notable study explores the use of artificial intelligence to create a large high-quality synthetic corpus of fake news. This then can be a training corpus to enhance any fake news detectors using generative model like RoBERTa, LSTM or GPT-2. The first is the process of generating a corpus, where as noted we failed to generate one at the character level using LSTM and generated a second with sentence-level generation using GPT-2, which proved effective. While there are many questions related to such a generative approach, this method suggests that applying adversarial attacks in post-processing can provide an interesting new way to create datasets of difficult examples and thus train more robust systems [15].

There are also those who have gained great importance for the field, which is research that approaches the automatic identification of fake news on different vehicles. In this study, authors present novel datasets covering seven news domains and conduct fine-grained linguistic analysis to determine the differences between real and fake content. The results are promising, with variants reaching accuracies as high as 76% for detection, so we believe it is worth continuing to explore this multi-dimensional approach through machine learning experiments. Therefore, the study calls for a broader scope of fake news detection that also covers meta-features and multimodal aspects alongside using various computational fact-checking techniques [14].

Fake News challenge is not restricted to English alone, but in almost all the non-Latin script languages such as Korean too. The morpheme ambiguity along with differences in sentence structures poses additional problems In closing, research conducted on the issue suggests that a convolutional neural network-based architecture working with Fasttext word-embedding trained at syllable level can be used. This method successfully models word similarities in Korean, which greatly improves the ability of our model to identify inconsistencies between headlines that appear above body text and such-bodies texts or lead bodies of news articles. Although there are limitations to how well the method captures headline-body discrepancy in determining whether a news article is fake, this signals an important step towards creating language-specific systems [7].

Using ensemble classification models, in order to deal with the complexity and variability of news contents among different digital channels, has also presented good results. One such study is chosen here which considers the above said challenges of most previous models suffer from poor accuracy due to bad selection of features, lack of tuning parameters etc., and imbalanced datasets. In conclusion, this study can be improved in terms of detection accuracy by creating a powerful ensemble model with decision tree classifiers using the random forest and extra tree approach. In terms of the accuracy, study is promising with 99.8% training and 44.15% testing on Liar dataset [4].

This study discusses the challenges comes by sophisticated neural fake news generators, focusing on understanding the linguistic attributes these generators shows. By conducting a feature-based analysis, the research identifies that stylistic features of text prove to be the most robust in differentiating original news from machine-generated misinformation. The findings suggest that focusing on stylistic elements could improve the effectiveness of models designed to detect neural-generated fake news [2].

Yet another paper presents a hybrid neural network for automated fake news detection utilizing CNN and LSTM, performance of model is enhanced with dimensionality reduction techniques such as PCA and Chi-Square, reducing the dimensionality of feature vector prior to classification, model can grasp all complexties in news when it is agree or disagree or discuss and unrelated as well. Once the PCA is included in detection capabilities dramatically improved, shown a significant increase not only in accuracy but also F1-score. "Overall, the combination of CNN and LSTM with different preprocessing methods demonstrated in this work proves to be efficient after a few epochs and reveals space for improvement on large datasets [16].

3 DATA PROCESSING

Since there have been attempts to research fake news detection in the English language, there were a couple of resources for data. We have utilized datasets for English from publicly available sources such as [18], [8], [19]. In terms of Azerbaijani, we are faced with the difficulty of finding fake news. There are different methods for constructing positive cases. One approach would be to identify and use untruthful sources or websites as non-reliable or fake news which would be very time-consuming and challenging. Another method could be to reference original news and alter it manually by introducing fake facts, information, and so on. Lastly, the relatively simpler way to do this is by using LLMs such as GPT-4o (omni) which is the latest flagship model of OpenAI that is decent in generating content in the Azerbaijani language. We have constructed different prompts and seeds to generate fake news. As a negative case (original news) we used BBC and fed the title of that news to create fake but pretty persuasive news with complex prompt engineering. This is essentially using news titles as a seed rather than solely depending on the LLM itself. And second data generation we have done is without using seed but rather providing the LLM with one domain out of 25 such as Election Fraud, Miracle Cures, Scientific Breakthroughs, Climate Change, Crime Waves, Law Enforcement, and so on. Last but not least another technique would be to provide the LLM with the full news and ask it to alter the text to be fully or partly which we have not done in the interest of time and price.

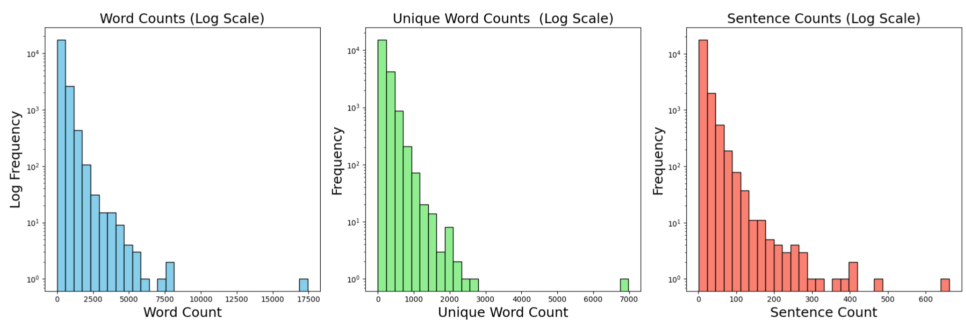

Fig. 1. Histogram of word, sentence and unique words on a log scale.

To prevent the data imbalance we limit the amount of English data to be same as Azerbaijani. In total we gathered 14000 data points where half of them is fake and the rest are original. In terms of language, the number of samples is still the same with 7000 each. 2000 of those are the ones we generated via seed through and 1500 are without seed but with one of the 25 domains we have constructed. The original news used is from BBC with around 2500 data points. We should also note that half of the English dataset is generated via GPT-2 to make a fair comparison just because we have used AI for Azerbaijani counterparts. We have stored the dataset in the HuggingFacen as publicly available which has a useful column to be able to filter as needed such as language, source, and so on (HugginFace Datasets). Data curation included normalization of characters, filtering based on language detection, special character ratio, number of tokens, and character repetition ratio. Samples which has more than 0.055 character repetition have been filtered out to prevent low-quality text that has duplicated substrings. The range for the ratio of special characters and numbers has been set between 0.2 and 0.25. Finally, language detection has been done using FastText [5] to prevent other languages.

Table 1. Distribution of samples per languages and sources

Language	Source	Class	Number of Samples	Number of Words
English	GPT-2	Fake	3,428	
		Original	3,428	600K
	Public Data	Fake	2,000	
		Original	2,000	2,3M
Azerbaijani	GPT-4o with seed	Fake	2,356	
		Original	2,356	1,3M
	GPT-4o without seed	Fake	1,073	
		Original	1,073	1,4M
	Translated	Fake	1,500	
		Original	1,500	
Total Samples - English			10,856	2,9M
Total Samples - Azerbaijani			9,857	2,7M
Total Samples - All			20,713	5,7M

4 METHODOLOGY

There are various Machine Learning and Deep Learning techniques to solve this problem. Our problem statement is that given text we are trying to predict whether given text which is in string format is fake or original. This is essentially binary classification. We represent the label column as 0 (original) and 1 (fake). The main point and challenge is how we represent the given text. In order to feed this information to any ML model we have to represent this text data as numerical data. Some of the techniques include extracting features from the text such as TF-IDF, Count vectorizer, manually engineered features or represent it in a pre-trained embedding which is feature vector that somehow include the information in a n-dimensional space. There are also more advanced BERT-based models that is pre-trained masked language model (MLM) which is encoder only transformer [17]. Since we are dealing with multilingual dataset which includes Azerbaijani the most suitable pre-trained models are mBERT (multilingual BERT) or XLMRoBERTa [3]. We first start with baseline TF-IDF and Logistic Regression on top of that then scaled to more advanced methods such as Word2Vec, GloVe embeddings then finally MLMs (mBERT and XLMRoBERTa). We see almost continues improvements over each architecture. For the Azerbaijani Word2Vec and GloVe we train our own embedding on nearly 130,000 Wikipedia text to get the pre-trained embedding. And for the English embedding we use original pre-trained model from authors that is publicly available.

4.1 Baseline Model: TF-IDF and Logistic Regression

In setting the stage for our multilingual fake news detection project, we initially established a baseline model using TF-IDF (Term Frequency-Inverse Document Frequency) coupled with Logistic Regression. This approach serves as a foundational comparison point for more sophisticated models explored later in the project. TF-IDF is a statistical measure used to evaluate the importance of a word within a document in a collection of documents, effectively distinguishing relevant terms in fake news articles from common vocabulary across the corpus.

The mathematical formulation of TF-IDF is as follows, where TF is the term frequency and IDF is the inverse document frequency:

$$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \text{IDF}(t,D) = \text{TF}(t,d) \times \log\left(\frac{|D|}{|\{d \in D : t \in d\}| + 1}\right)$$

Here, t represents a term, d a document, and D the corpus of documents. The term frequency $TF(t,d)$ is frequency of term t in document d, and the inverse document frequency $IDF(t,D)$ is calculated as the logarithm of the ratio of the total number of documents to the number of documents that contain term t, adjusted by adding 1 to the denominator to avoid division by zero.

After transforming the text data to TF-IDF vectors, we have applied the Logistic Regression model with which is very powerful and common statistically model for binary classification tasks. Logistic Regression estimates the probability whether an observation is a member of class depending on specific distinct input features. That the model uses a logistic function to model something with only two outcomes (in this case whether a news article is fake or not) seems obvious:

$$P(y = 1|x) = \frac{1}{1 + \exp(-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n))}$$

In this equation, y represents the binary outcome (fake or not fake), x are the features derived from TF-IDF, $\beta_0, \beta_1, ..., \beta_n$ are the coefficients of the model, and n denotes the number of features.

4.2 Word2Vec embedding

Word2vec is a natural language processing (NLP) model. It helps us convert words into text so that we can do further process it using machine learning models. It was created by Mikolov and others [12] at Google. There are two architectures one of wihch is Skip-gram that predicts words from their context and another is CBoW. In order to build the Azerbaijani part of our dataset, we employed a Skip-gram model of Word2Vec as it was more appropriate in dealing with low-frequent words within Azerbaijani. This result situation gives us a model setting vector 1024 size, window size is 3 and word inclusion model when the counter is least, keep it at 1. In order to handle these unique Azerbaijani linguistic properties, we applied a custom stopword list of 200 stopwords without stemming.

The mathematical formulation of the Skip-gram model was formulated over following objective function, where log probability of surrounding words is maximized by using target word:

$$\max \sum_{t=1}^{T} \sum_{-m \leq j \leq m, j \neq 0} \log p(w_{t+j}|w_t)$$

Here, w_t represents the target word, w_{t+j} represents context words within a window of size m around w_t, and T is the total length of the text. The probability $p(w_{t+j}|w_t)$ is modeled using a softmax function:

$$p(o|i) = \frac{\exp({v'_o}^T v_i)}{\sum_{w=1}^{W} \exp({v'_w}^T v_i)}$$

where v_i and v'_o are the input and output vector representations of words, and W is the vocabulary size.

In practice, training our Word2Vec model means adjusting these vector representations such that the probability of observing real textual contexts in our data set is as high as possible, effectively placing words into a 1024-dimensional space where their semantic and syntactic similarity are measured by how close together their vectors lie.

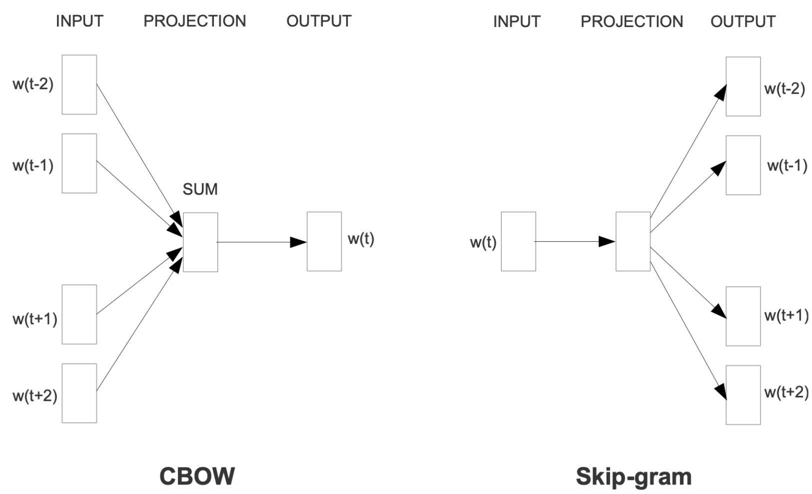

Fig. 2. Different architectures for Word2Vec: Skip-gram and CBOW [12]

On the other hand, for English language segments we used a pre-trained Word2Vec model available from Google to provide us with very powerful and well-optimised set of embeddings that we didn't have to actually go ahead and train. Because of that we have consistency in methodology and however adapted to specific linguistic features for both Azerbaijani and English texts.

4.3 GloVe embedding

GloVe (Global Vectors for Word Representation) uses a unique approach to word embedding which allows the relativeness of words through both global statistics and corpus locality. It was developed by Pennington et al. [13] at Stanford. The word vectors are constructed in this space cause the geometric analogy of the relationship between words to be reflected in semantics:

We generated our custom GloVe model by training it with a Azerbaijani Wikipedia dataset and setting parameters of the embedding to make sure that terms are well represented. In order to achieve this, we built an co-occurrence matrix from the corpus concerning words in a 15-word window from each term as following: This is a record of how often each word appears in the context of every other word. All this boils down to a rich, global aggregate statistical view of connections between words. The settings of our model, specifically a vector size of 128 and that words needed to appear at least three times in our text to be included in the vocabulary combined with 20 iterations performed during the training steps

$$\text{Model Configuration:} \quad \begin{aligned} \text{Vector Size} &= 128 \\ \text{Window Size} &= 15 \\ \text{Min-Count} &= 3 \\ \text{Iterations} &= 20 \\ \text{X-Max} &= 10 \end{aligned}$$

GloVe's embedding process relies on an objective function that minimizes the difference between the logarithm of the actual co-occurrence probability of word pairs and the dot product of their corresponding vector representations, adjusted by bias terms for each word:

$$\min \sum_{i,j=1}^{V} f(X_{ij})(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij})^2$$

Here, X_{ij} denotes the number of times word j occurs in the context of word i, w and $\tilde{w}$ are the word vectors, b and $\tilde{b}$ are bias terms, and f is a weighting function that addresses the varying relevance of word pairs based on their frequency. The function f ensures that rare associations are not overly influential, applying a cutoff at an X_{max} value of 10.

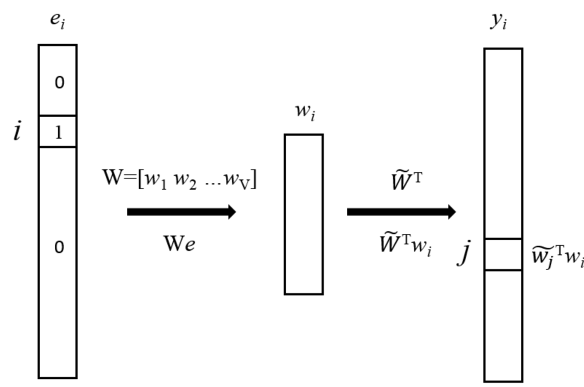

Fig. 3. GloVe embedding model architecute [9]

5 BERT-BASED MODELS: XLM-ROBERTA AND MBERT

We have used two important BERT based models XLM-RoBERTa(Cross-lingual language Model-Roberta)and mBERT(Multilingual BERT) to improve our fake news detection methodologies which play a major role in multilangual datasets and overcome the difficulties. The Transformer models use self-attention mechanisms to create contextualized word embeddings. The heat-end fine-tuned model uses this architecture.

Since XLM-RoBERTa and mBERT are pre-trained on large-scale multilingual corpora covering multiple languages, they can understand the linguistic subtleties among various languages pretrained out of the box with minimal language-specific adaptation. This pre-training follows the masked language modeling (MLM) objective, in which a model is trained to predict a word given both its surrounding context and randomly (15%) replaced tokens.

$$L(\theta) = -\sum_{i=1}^{N} \log p_\theta(w_i | w_{\text{context}_i})$$

Here, w_i represents the masked word, w_{context_i} denotes the words surrounding w_i, N is the number of words, and θ are the model parameters.

Following hyperparameters are carefully chosen to optimize learning and performance:

$$
\text{Training Configuration:} \quad
\begin{aligned}
\text{Per Device Train Batch Size} &= 16 \\
\text{Per Device Eval Batch Size} &= 16 \\
\text{Number of Training Epochs} &= 5 \\
\text{Number of Saved Models} &= 100 \\
\text{Early Stopping Patience} &= 3 \\
\text{Learning Rate} &= 2 \times 10^{-5} \\
\text{Weight Decay} &= 0.01 \\
\text{Warmup Ratio} &= 0.1
\end{aligned}
$$

For fine-tuning BERT-based models, the correct learning rate and a valid weight decay may be 2×10^{-5} and 0.01, respectively, in this way we can carry out gradual learning without overfitting. The warmup ratio of 0.1 gives a period at the beginning of training where the learning rate increases smoothly, this is very important for adjusting the early training phase of model.

We used 5 training epochs while still implementing early stopping with a patience of 3 to ensure we trained long enough to learn the complexities of the sequence, but not so long as to induce overfitting. Saving 100 models remains best model based on validation performance, rather than using model that comes from the final epoch.

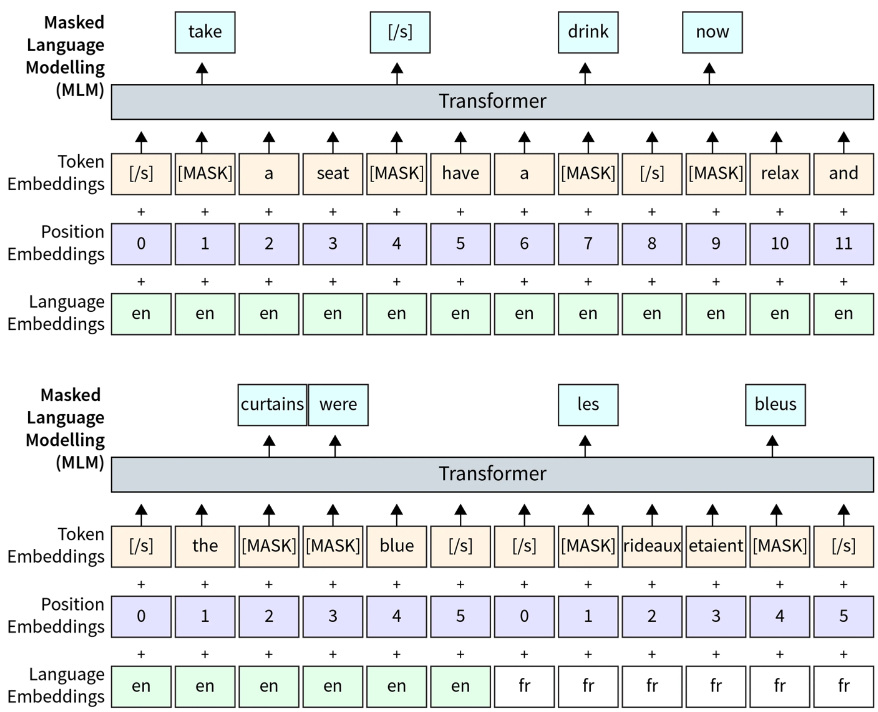

Fig. 4. XLM-RoBERTa model architecture [10]

6 RESULTS

Since we are doing binary classification on pretty balanced dataset we use classic metrics, such as precision, recall, f1 observing loss function for neural network based models and inspect errors in confusion metrics. Precision is defined as the ratio of true positive predictions to the total predicted positives, indicating the model's accuracy in identifying only relevant instances as positive. Recall, or sensitivity, measures the model's ability to identify all relevant instances, calculated as the ratio of true positives to the actual total positives. The F1-score is the harmonic mean of precision and recall, providing a balance between the two by penalizing extreme values.

$$\text{Precision} : \frac{TP}{FP + TP} \qquad \text{Recall} : \frac{TP}{FN + TP} \qquad \text{F1-score} : \frac{2TP^2}{(FN + TP)\,(FP + TP)\,\left(\frac{TP}{FP+TP} + \frac{TP}{FN+TP}\right)}$$

Throughout our explorations on detection of fake news across languages, we have observed multiple models with different performance metrics shown in Table 2. the outcomes confirm that differences exist in the capacity of these approaches to predict gendered word categories for Azerbaijani and English texts, as well as over a corpus comprised of both languages

With the baseline model, using TF-IDF and Logistic Regression on top of that gave an F1-score of 94% for Azerbaijani and 80% in English resulting in an overall metric score of 85%. This shows that the model is doing well with Azerbaijani, but it could definitely improve in the English language. Wor2Vec gave the same results as TF-IDF for Azerbaijani 94% and even for English, it outperformed with a small gap based on score of 84%. We did not build an overall performance score for this model as we are using standalone and not combined embedding. For Azerbaijani GloVe showed a bit lower performance, 90% f1-score but for English outperforms baseline with the 82% f1 score. This deviation highlights that there are model-dependent aspects to fine-tuning regarding the inference of semantic differences of various languages.

Finally, advanced bert-based models (mBERT and XLM-RoBERTa) significantly outperformed all other models. when trained, mBERT achieved the scores of 96% for Azerbaijani questions. meanwhile in English mBERT demonstrated a performance close to perfect with accuracy of 98%. Summing up all models' accuracies results in safe value 97%. Furthermore, XLM-RoBERTa architectural showed the highest score among all others with a percentage of 99% for Azerbaijani and 97% in English language so it reaches the largest result (98%). The results of this performance proved how these models are powerful in, using the deep embeddings power to comprehend context that crucial in fake news detection.

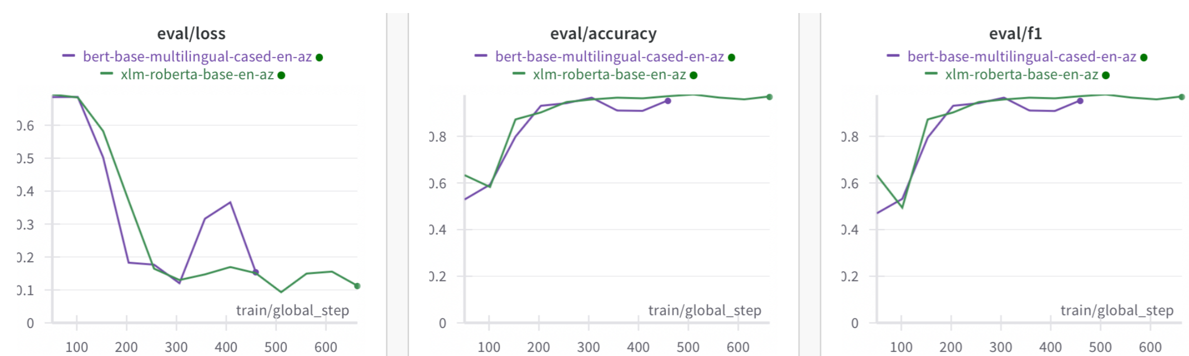

Fig. 5. Loss, Accuracy and F1 values for the mBERT and XLM-RoBERTa models

To conclude, the transformer-based models performed well but among them mBERT and XLM-RoBERTa showed better performance especially their multi lingual usage. Thus, the observed utility of more complex and effective neural network architectures in discriminative language understanding tasks across varying linguistic contexts extends to fake news detection.

Table 2. Performance of Models across Different Languages

Model	Azerbaijani	English	Total
TF-IDF + Logistic Regression	94	80	85
Word2Vec	94	84	-
GloVe	90	82	-
mBERT	96	**98**	97
XLM-RoBERTa	**99**	97	**98**

7 CONCLUSION

In this paper, we tried to study the problem of fake news detection in both English and Azerbaijani languages. We used various machine learning and deep learning approaches for this purpose. We had started with fairly basic models like TF-IDF + Logistic Regression to much more complicated transformer based models (mBERT, XLM-RoBERTa) According to the findings, these state-of-the-art models performed much better when compared with the traditional approaches in general, especially for multilingual datasets. The higher accuracy score achieved by XLM-RoBERTa showed it is better in understanding the subtlety of the languages where there model came from and perform well in some other detection process.

Hereby, our results highlight the desperate necessity of advanced neural architectures which should be used while tackling with fake news detection and specifically contributed for low-resource languages such as Azerbaijani. This research helps to advance the overall fight against misinformation, while focusing on developing inclusive technologies that maintain media integrity across a wide range of linguistic situations.

There are however, many directions for further research that are open to explore. One possible extension is to increase the scale of the dataset by considering additional languages, which can make a more balanced understanding on how our model detects fake news within a truly multilingual environment. Finally, adding more advanced data augmentation methods and/or implementing generative adversial networks (GANs), may provide better generalization capabilities for existing detectors. Future works could elaborate on the real-time detection of fake news, whereby models need to be developed in order to detect rapidly spreading misinformation accurately. Another could be to focus on slightly different topic to detect the clickbaits from news, videos, social medis posts. We can continue to research and improve model, data to fight fake news in this digital age.

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