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ADVANCED TURKISH FAKE NEWS PREDICTION WITH BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS

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ABSTRACT: The increasing usage of social media and internet generates a significant amount of information to be analyzed from various perspectives. In particular, fake news is defined as the false news that is presented as factual news. Fake news are in general fabricated toward a manipulation aim. Fake news identification is in general a natural language analysis problem and machine learning algorithms are emerged as automated predictors. Well-known machine learning algorithms such as Naïve Bayes (NB) and Random Forest (RF) are successfully used for fake-news identification problem. Turkish is a morphologically rich language and it has agglutinative complexity that requires dense language pre-processing steps and feature selection. Recent neural language models such as Bidirectional Encoder Representations from Transformers (BERT) proposes an opportunity for Turkish-like morphologically rich languages a relatively straightforward pipeline in the solution of natural language problems. In this work, we compared NB, RF, Support Vector Machine (SVM), Naïve Bayes Multinomial (NBM) and Logistics Regression (LR) on top of correlation based feature selection and newly proposed Turkish-BERT (BERTurk) to identify Turkish fake news. And we obtained 99.90 % accuracy in fake news identification which is a highly efficient model without substantial language pre-processing tasks.

Keywords: *Machine learning, Text mining, Bidirectional Encoder Representations from Transformers (BERT), Fake news, BERTurk*

Çift Yönlü Transformatör Kodlayıcı Temsilleriyle Gelişmiş Türkçe Sahte Haber Tahmini

ÖZ: Sosyal medya ve internetin artan kullanımı, çeşitli açılardan analiz edilmesi gereken önemli miktarda bilgi üretmektedir. Bu bağlamda yalan haber, gerçek haber olarak sunulan asılsız haber olarak tanımlanmaktadır. Sahte haberler genellikle bir manipülasyon amacına yönelik olarak üretilir. Sahte haber tespiti, genel olarak bir doğal dil analiz problemidir ve otomatik tahmin ediciler olarak makine öğrenmesi algoritmaları kullanılmaktadır. Naïve Bayes ve Rastgele Orman gibi iyi bilinen makine öğrenme algoritmaları, sahte haber tanımlama sorunu için başarıyla kullanılmaktadır. Türkçe morfolojik olarak zengin bir dildir ve yoğun dil ön işleme adımları ve özellik seçimi gerektiren sondan eklemeli karmaşıklığa sahiptir. Transformer olarak bilinen Çift Yönlü Kodlayıcı Temsilleri (BERT) gibi son zamanlardaki sinirsel dil modelleri, Türkçe benzeri morfolojik olarak zengin diller için doğal dil problemlerinin çözümünde nispeten basit bir metot fırsatı sunmaktadır. Bu çalışmada, NB, RF, Destek Vektör Makinesi, Naïve Bayes Multinomial ve Lojistik Regresyon ile korelasyon tabanlı öznitelik seçimi ve yeni önerilen Türkçe-BERT (BERTurk) ile Türkçe yalan haberlerini tespit etmek için karşılaştırdık. Ön işleme adımları olmaksızın BERTurk ile sahte haber tanımlamada %99,90 doğruluk elde ettik.

Anahtar Kelimeler: *Makina öğrenmesi, Metin madenciliği, Çift yönlü transformatör kodlayıcı temsilleri (BERT), Yalan haber, BERTurk,*

1. INTRODUCTION

Fake news identification problem has recently gained an increasing focus among researchers due to the growing circulation of fake news through media platforms (D'Ulizia et al., 2021). Fake news issue is continuously disseminating because of digitalization of information. Fake news is explained as "Fake news is not simply false news. Its nature is determined by fraudulent content in news format as well as by an ability to travel as much as, and in some cases, even more than, authentic news" in European Commission report (Web1, 2018). From this point of view, as social media usage increases, the spread of fake news increases and this becomes a critical problem. Since internet or social media users may trust in digital platforms while accessing or exchanging information, there is a need to automated fake news filtering tools. An interesting example of the influence of fake news on public opinion is the United States presidential election in 2016. There was an intense debate that the public opinion manipulated through social media (particularly Facebook) circulated fake news (Flynn et al., 2017).

Automated fake news detection systems are in general rely on machine learning algorithms. More clearly, supervised learning policy is frequently used to develop various detection models on top of numerous language processing techniques. In this context, machine learning algorithms are trained with labeled fake news dataset and then tested on a data split to measure their performance (Alim et al., 2021). For English-like analytical languages this task is relatively straightforward. More clearly, the fake news detection pipeline requires the following steps for English-like analytical languages: First the labeled dataset is encoded with a vector space model to be able to train a classifier and then it is pre-processed with simple tasks such as stop-word removal. After this step, a feature selection mechanism may be preferred or not (Conroy et al., 2015). Then the obtained dataset used to train various machine learning algorithms such as NB, LR, SVM and RF. In case of morphologically rich languages the language processing pipeline is similar. However, Turkish being an agglutinative language, requires heavy pre-processing steps that effects the performance of classifiers (Uysal & Gunal, 2014). In more clear terms, the morphological complexity of agglutinative languages need numerous pre-processing steps such as stemming, lemmatization and feature engineering to obtain an efficient model. The difficulty in computational model generation of agglutinative languages is studied in detail by Oflazer (Oflazer, 2014). In this context, Turkish words take numerous inflectional and derivational suffixes and it is possible to derive a Turkish word that correspond to an English sentence (Oflazer, 2014):

yap+abil+ecek+se+niz -> if you will be able to do (it)

One of the main problem of Turkish morphology arises while obtaining vector space model for machine learning classifiers. More specifically, Turkish words are in general composed of morphemes that may result in data sparsity that may decrease performance of classifiers (Nuzumlalı & Özgür, 2014). The solution to this problem is relatively handled with stemming and lemmatization whose goals are obtaining base forms of words with reducing inflectional forms. These language tasks require specialized software or lexicons. We should emphasize that the mentioned tasks are required for traditional machine learning algorithms such as NB or SVM. On the other hand, recent advances in neural language models such as BERT (Devlin et al., 2019) (particularly BERTurk which is Turkish version of BERT) eliminate the need for the underlined pre-processing tasks while generating successful models for many language tasks for Turkish-like languages.

In this study, we made use of traditional classifiers on top of pre-processing tasks including feature selection and we compared the outcomes with BERTurk (Schweter, 2020) for fake news identification problem. One of the main contributions of this study is the usage of BERTurk model in detection of fake news. The second contribution of this study is the experiments that enlighten comparison of challenging Turkish language pipeline with that of BERTurk's relatively straightforward path.

This study is structured as follows: We present literature survey in Section 2 and the overall workflow is explained in Section 3. In Section 4, we make explanations of experiments and corresponding results. In section 5, we underline results of the experiments and we conclude the paper with Section 6 as conclusion.

2. RELATED WORK

Fake news detection is a frequently studied Natural Language Processing (NLP) problem in machine learning literature. For the sake of convenience, we narrow the literature survey in two aspects: i) Recent Turkish fake news studies and ii) Transformer based fake news literature.

Though Turkish is a widely spoken language, there are limited NLP studies in Turkish fake news detection. In their study, Mertoglu et al. generated a lexicon that may be used for fake news identification studies (Mertoğlu & Genç, 2020). Tocoglu et al. made use of various machine learning algorithms and feature selection engineering to generate an efficient fake news (satire) detection model. They obtained accuracy of 97.72% with the recurrent neural network algorithm (Onan & Tocoglu, 2020). Another recent study in Turkish is a clickbait dataset that is evaluated with Bidirectional Long Short-Term Memory (BiLSTM) and the authors obtained a 97% prediction accuracy (Genç & Surer, 2021). For Twitter fake news detection, the authors used RF algorithm to filter false news and they obtained 0.86 as average F1-score (Taşkın et al., 2021). As it is observed from this survey, Turkish fake news studies are infrequent in the literature.

We now present transformer based fake news detection literature that are conducted last two years. While we present the related literature, we particularly focus on non-English languages. In their BERT-base approach, Jwa et al. identified fake news stories in Korean (Jwa et al., 2019). For Urdu fake news identification, the authors compared machine learning algorithms with BERT and they obtained 0.90 F1 score for BERT outperforming all classifiers (Amjad et al., 2021). In their study, Nagadeh et al. used BERT with contextual speech information to analyze Persian fake news and they obtained promising results (Jahanbakhsh-Nagadeh et al., 2020). For Arabic fake news detection, the authors compared deep neural network models with BERT, and they found transformer model is superior to neural networks to detect Arabic fake news (Al-Yahya et al., 2021). Furthermore, Ozbay and Alatas made use of advanced artificial intelligence algorithm to analyze well-known fake-news datasets and they obtained efficient results in terms of accuracy (Ozbay & Alatas, 2020). In their another study, Ozbay and Alatas used metaheuristic optimization algorithms to identify fake-news automatically (Ozbay & Alatas, 2019). As a last study from recent fake-news research domain, Bozuyla and Ozcift analyzed popular fake-news source, i.e. COVID-19, with the use of neural transformers (Bozuyla & Özçift, 2022). There are many studies in the literature that use transformers in fake news detection. However for the sake of convenience we limit ourselves with a few work from literature. As an overview, we can draw two conclusions from this survey: i) Turkish fake news literature is limited in quantity and there is a research gap for researchers and ii) Transformer based approaches are the new direction particularly in fake news identification domain.

3. METHODOLOGY

In this section, we present the proposed transformer based Turkish fake news detection framework. The whole framework is divided into subsections and they are: data, pre-processing, feature extraction, feature selection, experimental setup. The evaluation metrics is followed the mentioned sub-tasks.

3.1 Data

The data consists of two subsets as fake and real news. For Turkish a rich fake news source is Zaytung web site which is famous in fabricating numerous types of fake data (Github, 2021; Web3, 2021). Fake news subset is generated from Zaytung and real subset is from Hurriyet newspaper. In the dataset, there are 2163 fake labeled samples and 2296 real labeled samples that consists of one or more sentences. The real news were taken from Hürriyet newspaper between dates of January and June 2019. The fake news was collected from the news published on the famous fake news resource, Zaytung, before June 2019. The collected news were in culture, politics, technology, sport, and science etc. domains. The average lengths of fake news and real news sentences are 212, 368 words respectively. Sample sentences from collected data for fake and real news are given in Table 1.

Table 1. Sample sentences from dataset

Turkish	English	Title
Hatay'da fren yerine gaza basan sürücü kızını ezdi. Hatay'da evinin bahçesine aracını park ederken fren yerine gaza basan sürücü, kızını ezdi. Minik kız çocuğu olay yerinde hayatını kaybetti.	In Hatay, the driver, who stepped on the gas instead of the brake, crushed his daughter. While parking his car in the garden of his house in Hatay, the driver, who stepped on the gas instead of the brake, crushed his daughter. The little girl died at the scene of accident.	Real
DİE: "Türk Kadınlarının % 97'si Hep İyi Niyeti Yüzünden Kaybediyor". DİE (Devlet İstatistik Enstitüsü) tarafından açıklanan rakamlara göre "hep iyi niyeti yüzünden kaybeden" Türk kadınlarının sayısı geçen yılın aynı dönemine göre 1 puan artarak %97'ye yükseldi. Yine aynı rapora göre Türk kadınlarının %94'ünün tek kusurları fazla dürüst olmaları ve diğer Türk kadınları gibi rol yapmayı bilmemeleri. Geri kalan %6'lık kısmın ise herhangi bir kusuru bulunmuyor.	TSI: "97% of Turkish Women Always Lose Their Goodwill". According to the figures announced by the TSI (Turkish Statistical Institute), the number of Turkish women who "always lose because of their goodwill" increased by 1 point to 97% compared to the same period of the previous year. they don't know how to act like other Turkish women. The remaining 6% do not have any defects.	Fake

3.2 Pre-processing

The generated dataset is pre-processed with the following steps: i) html tags are removed, ii) special characters such as "*,@" are filtered, iii) noisy characters such as newlines, white-space are discarded, iv) text is encoded in lowercase characters i.e. normalized and finally v) tokenization, i.e. conversion of text strings into words. We provided the sample text before and after preprocessing in Table 2.

Table 2. Sentences before and after preprocessing steps

Text before preprocessing	Text after preprocessing
Ölümünün 14. yılında Barış Manço'yu şarkılarıyla anan sevenleri Kanlıca mezarlğını "haydi kızlar... ayıı" sesleriyle inlettiler. Türk müziğinin unutulmaz seslerinden Barış Manço aramızdan ayrılışının 14. yılında ailesi ve sevenleri tarafından Beykoz Kanlıca'daki kabri başında anıldı. Anma töreninde Manço'nun en sevilen şarkıları her sene olduğu gibi yine hep bir ağızdan seslendirilirken bu yıl repertuara eklenen ayı şarkısı sayesinde Kanlıca mezarlığı renkli görüntülere sahne oldu.	ölümünün 14 yılında barış mançoyu şarkılarıyla anan sevenleri kanlıca mezarlğını haydi kızlar ayıı sesleriyle inlettiler türk müziğinin unutulmaz seslerinden barış manço aramızdan ayrılışının 14 yılında ailesi ve sevenleri tarafından beykoz kanlıcadaki kabri başında anıldı anma töreninde mançonun en sevilen şarkıları her sene olduğu gibi yine hep bir ağızdan seslendirilirken bu yıl repertuara eklenen ayı şarkısı sayesinde kanlıca mezarlığı renkli görüntülere sahne oldu
DİE (Devlet İstatistik Enstitüsü) tarafından açıklanan rakamlara göre "hep iyi niyeti yüzünden kaybeden" Türk kadınlarının sayısı geçen yılın aynı dönemine göre 1 puan artarak %97'ye yükseldi.Yine aynı rapora göre Türk kadınlarının %94'ünün tek kusurları fazla dürüst olmaları ve diğer Türk kadınları gibi rol yapmayı bilmemeleri. Geri kalan %6'lık kısmın ise herhangi bir kusuru bulunmuyor.	die devlet istatistik enstitüsü tarafından açıklanan rakamlara göre hep iyi niyeti yüzünden kaybeden türk kadınlarının sayısı geçen yılın aynı dönemine göre 1 puan artarak 97 ye yükseldi yine aynı rapora göre türk kadınlarının 94 ünün tek kusurları fazla dürüst olmaları ve diğer türk kadınları gibi rol yapmayı bilmemeleri geri kalan 6 lık kısmın ise herhangi bir kusuru bulunmuyor.

The whole preprocessing pipeline is presented in Figure 1.

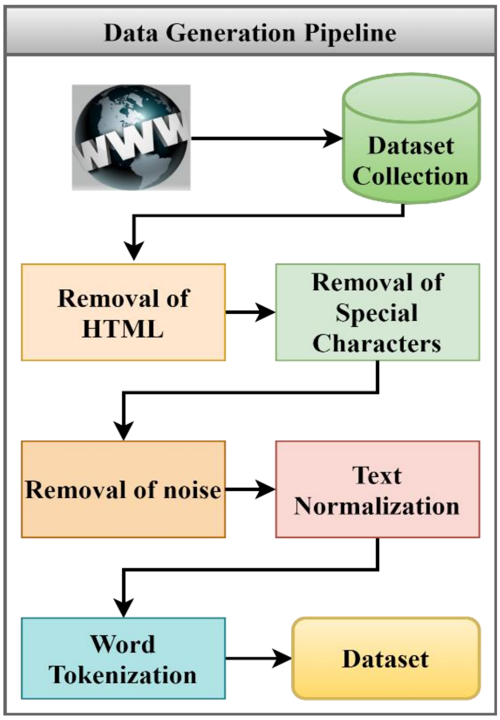

Figure 1. Data pre-processing framework.

3.3 Feature Extraction and Feature Selection

Having tokenized the dataset, we need to obtain the weight of each word in the whole data. This is a well-known concept in computational language processing literature. In this aspect, the frequency of terms, i.e. Term Frequency (TF) and Inverse Document Frequency (IDF) concepts are used to obtain final optimum weights of terms (words) in the dataset and this is calculated with Equation 1.

$$w_{ij} = tf_{ij} * \log\frac{N}{df_i} \qquad (1)$$

In Equation 1, w_{ij} is weight of a term i in the sample j, N is total sample size in the dataset, tf_{ij} corresponds to the frequency of term i in the sample j, and finally df_i corresponds to the number of samples that contain term i (Dadgar et al., 2016).

With this transformation the dataset is now encoded in terms of numerical values that is suitable for machine learning algorithms.

After feature extraction, we obtained 1413 terms for two classes. We used WEKA machine learning package to obtain feature extraction based on TF-IDF. Some example terms having highest TF-IDF score and corresponding weights are given in Table 3.

Table 3. TF-IDF scores of words with highest weights

Word	TF-IDF weight	Word	TF-IDF weight
tekstil	3.947	meslek	3.427
yapılacaktır	3.821	adaylar	3.422
ödeme	3.682	sanat	3.362
sınav	3.491	sistem	3.321
kayıt	3.444	oruç	3.285

It is also underlined in the literature that high dimensional nature of data may decrease performance of machine learning algorithms. Feature selection is in general used to obtain the most discriminative feature (term or word in text mining literature) that maximizes classifier performance. From this perspective, we experimented Correlation-based Feature Selection (CFS) method with best first search strategy. The feature (term) size before feature selection was 1413 and with the application of Correlation-based Feature Selection (CFS) method with best first search strategy, we obtained feature size of 200. The first twelve words with the highest weight (importance) are given in Table 4. The corresponding experimental results are presented in Section 4.

Table 4. Some of the most important terms obtained with CFS

aslında	arkadaş	adeta	bile
deneyimli	gergin	halen	ifade
itiraf	komple	resmen	zamanında

3.4 Experimental Setup

In this work, we used five machine learning classifiers, NB, LR, RF, SVM, NBM and BERTurk from literature (Sarker, 2021). The experimental setup is realized in three steps.

(1) Full data without feature selection: The dataset is first divided in 80% train and 20% test splits. Then the classifiers are trained with 80% portion of data and then the performance of the models are evaluated with the test-split in detecting fake news. In the literature, there are various data splits such as 70%-30% and 80%-20% for train test scheme. Also, a widely used train-test split is cross validation. However, for BERT-like transformers cross-validation split requires huge computational load and we

therefore selected 80%-20% for all the experiments carried in the study. This pipeline is shown in Figure 2.

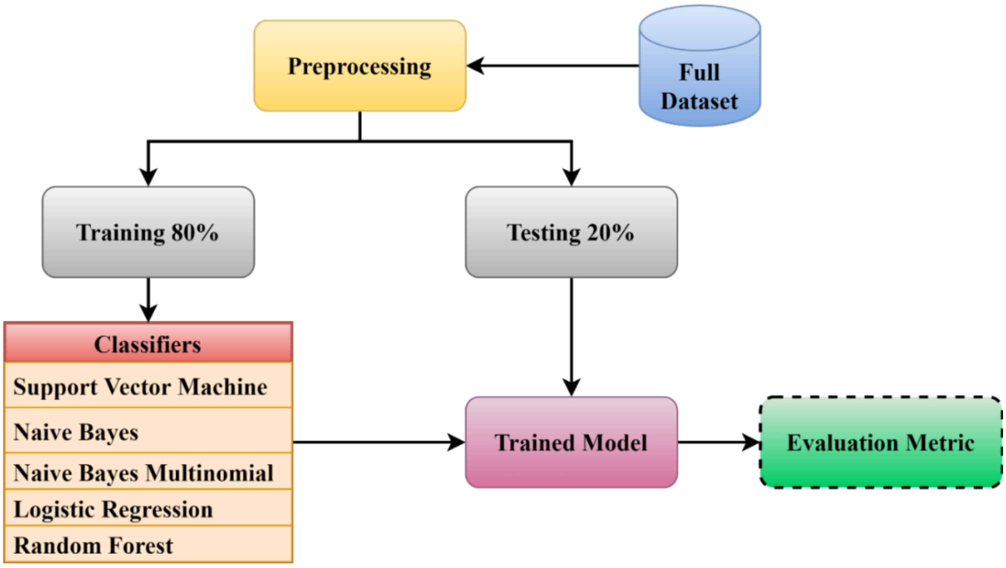

Figure 2. Fake news model generation without feature selection

(2) In this experimental setup, the data is first processed with CFS and then the reduced dataset is then divided into 80-20 train test splits. Then the classifiers are trained and tested as shown in the Figure 3.

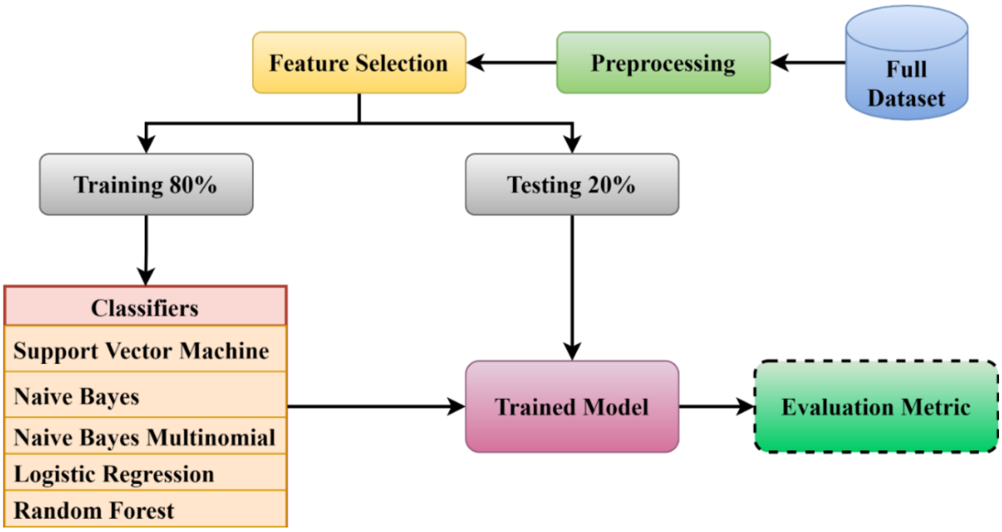

Figure 3. Fake news model generation with Correlation-Based feature selection

(3) BERTurk makes use of full feature set and it does not require dense pre-processing steps. The train and test splits for BERTurk are the same and the framework is summarized in Figure 4.

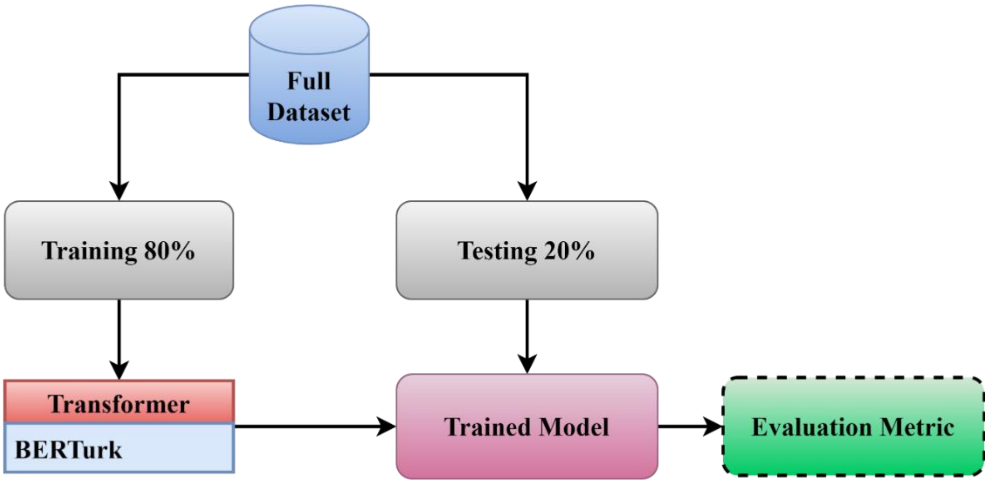

Figure 4. BERTurk fake detection generation model pipeline

3.5 Evaluation Metrics

Comparing real-world performances of classifiers are realized on the basis of numerical metrics such as accuracy. For balanced problems, i.e. number of samples in classes are distributed evenly, Accuracy (Acc) is a preferred evaluation metric (Wardhani et al., 2019)(Sasikala et al., 2017). Acc is based on confusion matrix and it is calculated as in Equation 2.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

In Equation 2, True Positives (TP) and True Negatives (TN) are the correct predictions. False Negatives (FN) and False Positives (FP) are the incorrect predictions in the equation.

Though Acc is efficiently used to compare classifier performances, statistical validation of models require another metric such as Kappa (K_p) [23]. Kappa is calculated with Equation 3 and it generates values between [0,1].

$$K_p = \frac{p_0 - p_e}{1 - p_e} \quad (3)$$

Where p_0 and p_e

$$p_0 = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$p_e = \frac{(TP + FN).(TP + FP) + (FN + TN).(FN + TN)}{(TP + TN + FP + FN)^2} \quad (5)$$

If the generated K_p value of a classifier is above 0.8 then it is statistically validated. The K_p and Acc values of all classifiers are evaluated and discussed in Section 4.

4. RESULT AND DISCUSSION

In this section, we summarize the experimental results of used algorithms in terms of Acc, K_p and confusion matrix. The Acc and K_p metrics of all classifiers are given in Table 5 and confusion matrices (Dağli & Öztürk, 2021; Khorram & Baykan, 2021) of algorithms given in Table 6, Table 7 and Table 8 .

Table 5. Experimental results of fake news classification models

Classifier	Full Dataset		Dataset with Feature Selection	
	Acc	Kp	Acc	Kp
NB	.891	.838	.919	.783
NBM	.967	.850	.925	.935
LR	.869	.737	.942	.883
SVM	.985	.894	.947	.971
RF	.937	.881	.941	.874
BERTurk	.999	.995	-	-

Table 6. The confusion matrices of machine learning algorithms

	Confusion Matrix for NB+FS		Confusion Matrix for NBM+FS		Confusion Matrix for LR+FS		Confusion Matrix for SVM+FS		Confusion Matrix for RF+FS	
	Actual		Actual		Actual		Actual		Actual	
	Real	Fake	Real	Fake	Real	Fake	Real	Fake	Real	Fake
Predicted	389	35	438	16	428	29	447	9	429	34
	62	406	13	425	23	412	4	432	22	407

Table 7. The confusion matrices of machine learning algorithms with FS

	Confusion Matrix for NB+FS		Confusion Matrix for NBM+FS		Confusion Matrix for LR+FS		Confusion Matrix for SVM+FS		Confusion Matrix for RF+FS	
	Actual		Actual		Actual		Actual		Actual	
	Real	Fake	Real	Fake	Real	Fake	Real	Fake	Real	Fake
Predicted	418	39	425	41	428	29	438	34	437	39
	33	402	26	400	23	412	13	407	14	402

Table 8. The confusion matrix of BERT

	Confusion Matrix for BERT	
	Actual	
	Real	Fake
Predicted	451	1
	0	440

From confusion matrix evaluation point of view, we observe from Table 6, Table 7 and Table 8 that most of the algorithms are more capable to identify real news compared to fake news. Furthermore, SVM is able to determine real and fake news with only 13 mistakes in terms of FP and FN. The best performance to discriminate real and fake news is achieved by BERTurk with only one mistake.

We can easily observe from Table 5 that BERTurk model generates an outstanding fake detection performance in terms of accuracy. While BERTurk is able to identify fake news with 99.90 % accuracy, the fake news identification value of SVM is 98.50 %. Another point drawn from Table 5 is that CFS feature selection may increase performance of some classifiers such as NB, LR, and RF, the *Acc* values of NBM and SVM are decreased. As we underlined in the article, for Turkish an efficient model requires to optimize various parameters (pre-processing, feature filtering etc.) at the same time to obtain an acceptable model. For the sake of simplicity, we compare the performances of the algorithms in Figure 5.

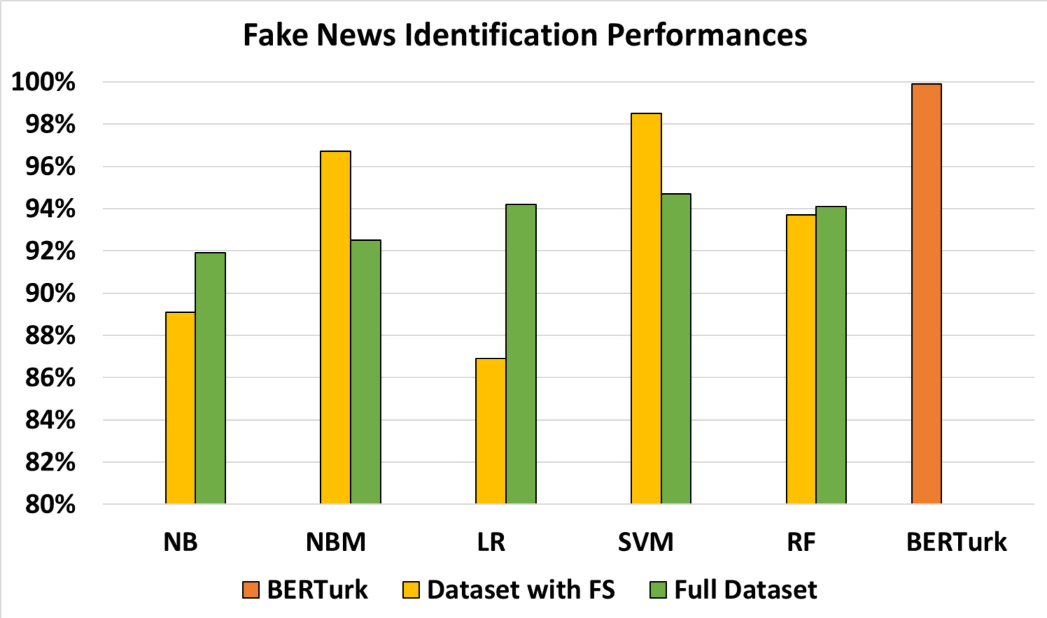

Figure 5. Comparison of performances of classifiers in terms of fake news identification accuracies.

As we obtained the best fake news identifier to be BERTurk, we now need to statistically validate the classifiers. In order to visualize K_p values from Table 5, we draw Figure 6 as follows:

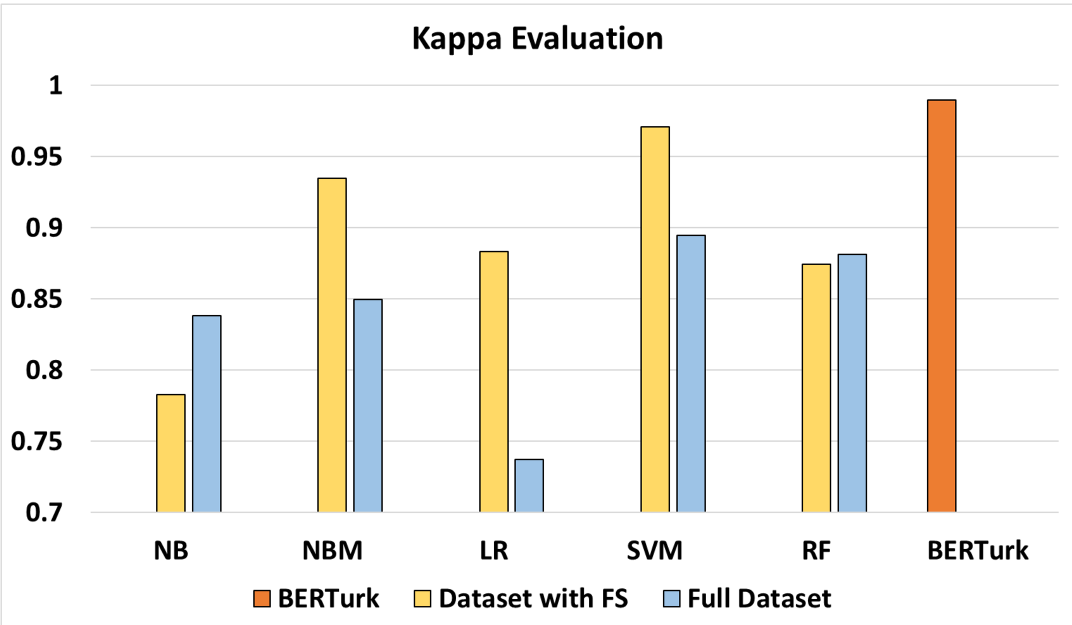

Figure 6. Statistical evaluation of classifiers with Kp values.

From Figure 6, we may first conclude that most of the models have K_p values higher than 0.8 and they are statistically validated. And finally, we also observe from Figure 6 that BERTurk has a K_p value about 1 that is well acceptable.

5. CONCLUSION

In general, Turkish computational language studies require language pre-processing steps and feature selection mechanisms to obtain a relevant model. One of the main drawbacks of this approach is that the mentioned tasks cannot be assembled into a well-defined pipeline and it requires lots of trial-error approaches while obtaining an efficient model. On the other hand, BERTurk-like transformers do not require mentioned processing tasks and they can process relatively raw data without feature selection. In this study, we use two types of classifiers as traditional algorithms such as NB, RF and a recently developed transformer, i.e. BERTurk, to detect Turkish fake news. And the experimental results show that transformer based approach is relatively straightforward method with outperforming fake news identification performance compared to the rest of the classifiers. As a research direction, we recommend transformers to be a better choice for Turkish language processing tasks.

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