Fake News Detection

by

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Abstract

The term fake news refers to intentionally misleading or fabricated news articles designed to deceive readers by presenting false information as true. This study focuses on the problem of detecting Turkish fake news. Initially, a Turkish dataset consisting of 4,455 training examples, specifically curated for fake news detection, was examined and analyzed. Subsequently, the dataset was tested using five different transformer models, including ConvBERT, BERTurk, mBERT, and DistilBERT, and the results were evaluated. Furthermore, various classification models, such as LR, DT, RF, GBM, SVM, and KNN, were applied, along with techniques like Bag of Words, TF-IDF, FastText, and Word2Vec, to evaluate seven classification models. Performance metrics such as accuracy, precision, recall, and F1 score were calculated to assess the models. Based on the obtained results, an interface was designed to present relevant news articles along with their data streams, informing users about the authenticity of the news. This study aims to highlight the significance of methods for detecting Turkish fake news and to facilitate users in accessing accurate information.

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List of Abbreviations

CNN	Convolutional Neural Network
DT	Decision Tree
GRU	Gated Recurrent Units
GBM	Gradient Boosting Machine
KNN	K-Nearest Neighbours
LSTM	Long Short-Term Memory
LSVM	Linear Support Vector Machine
LR	Logistic Regression
MLP	Multilayer Perceptron
NB	Naive Bayes
NER	Named Entity Recognition
NLP	Natural Language Processing
RF	Random Forest
RNN	Recurrent Neural Network
SLP	Single Layer Perceptron
SVM	Support Vector Machine

1 Introduction

"Fake news" is a term used to refer to false news or propaganda that contains incorrect information, transmitted through traditional media channels such as written and television media, as well as non-traditional media channels such as social media. Many types of disinformation exist, including rumors, internet misinformation, and fake news. Fake news is defined as "deliberately created news that is proven to be false by other sources but is created with the purpose of deceiving or misinforming readers" in various studies.
Social media platforms such as TikTok, Facebook, and Twitter emphasize the sharing, interaction, and collaboration of news. This is used by businesses to advertise their products and attract customers through personal sharing. Therefore, the creation and use of mobile applications make these platforms accessible and user-friendly. However, one of the biggest challenges is to control the fake news or misinformation that spreads on social media, covering a wide range of topics such as the economy, environment, politics, and health. The general purpose of publishing such news is to deceive readers, tarnish the reputation of any organization, or gain sensationalism.
Research on fake news distinguishes between content features and context features. The purpose of these studies is to analyze rumor features and extract rumors from text or user profiles. Language features are characteristics of fake news content. Environmental details such as user features and network-based characteristics are content features of fake news.
For example, COVID-19 is a rapidly spreading epidemic disease that emerged in 2020. During this epidemic, numerous news were published on the internet and social media platforms, raising concerns about their authenticity. Many people who are concerned about the accuracy of COVID-19-related news aim to identify and verify the authenticity of the news through the fake news detection project.
The problems caused by fake news written during the COVID-19 period are significant. For example, an article published in "The Guardian" [1] states that fake news written during the COVID-19 period spreads faster than real news. The spread of this fake news can create false information in society and lead to wrong decisions if this information is trusted. In addition, an article published in "Science" [2] also points out fake cures for COVID-19 published on the internet. The use of these fake cures can become ineffective in the treatment of COVID-19 and can cause serious health problems.

[1] https://www.theguardian.com/world/2020/apr/07/fake-coronavirus-news-spreads-faster-than-disease-itself-research-shows

[2] https://www.sciencemag.org/news/2020/03/fake-coronavirus-cures-are-flooding-internet-experts-warn-against-falling-prey

In our own Fake news detection project, we will identify the authenticity of news published on social media platforms and the internet. Our aim is to also ensure those wrong decisions are not made based on false information in society through the fake news detection project.

2 Releated Works

Ahmed et al.(2017) used the publicly accessible ISOT Fake News dataset to achieve an accuracy of 92 percent with their Linear SVM classifier. Ozbay F.A et al.(2020) also attempted to employ 23 classifiers, including ZeroR, CV Parameter Selection (CVPS), Weighted Instances Handler Wrapper (WIHW), DT, and others, to identify bogus news. However, they only used TF-IDF as their feature extraction technique. By achieving accuracy, precision, recall, and F1-scores of 96.8%, 96.3%, 97.3%, and 96.8%, they stated that their technique beat the findings in.

Similar research was also done by Ahmad et al. (2020) They evaluated the performance of individual learning algorithms and collective learning algorithms. They evaluated the effectiveness of the LSVM, Multilayer Perceptron, KNN, and Logistic Regression methods separately. Following that, they were put up against ensemble learning techniques such as Random Forest, Voting Classifier, Bagging Classifier, and Boosting Classifier. They also contrasted those approaches using a variety of datasets, including the ISOT Fake News Dataset, the Fake News Dataset, the Fake News Detection Dataset, and a dataset created by combining these datasets. The accuracy, precision, recall, and F1-scores achieved from testing on the first dataset surpassed the research findings, with values of respectively 99%, 100%, 100%, and 99% utilizing the RF algorithm.

Even before the work of other researchers, Bahad et al. (2019) did research on false news identification using the Fake News Detection Dataset, and this research also makes use of GloVe pre-trained word embedding. It integrates it with a number of deep learning architectures, including CNN, Recurrent Neural Network, Unidirectional Long Short-Term Memory, and Bidirectional LSTM. The study also tested it using the Fake or Real News Dataset and acquired 91.48% accuracy using Unidirectional LSTM. One of them was superior to Ahmad et al. research results with a value of 98.75% accuracy using the Bidirectional LSTM.

LSTM, LSTMdrop, and the hybrid model of LSTM and CNN were the three deep learning algorithms that Ajao et al. (2018) tested and compared for spotting fake news items posted on Twitter. The results demonstrated that the LSTM had the best prediction performance (%82 accuracy). A different CNN/RNN hybrid model was tested. The hybrid model outperformed the CNN or RNN models in false news prediction, which were both capable of handling fake news datasets well. On a dataset of 10,700 records, the model in this study attained %93.92 using a deep neural network and word embedding representation.

Shim, J.-S et. al.(2021) proposed a new fake news detection model using link2vec to improve automatic fake news detection performance. Two real-world fake news datasets in English and Korean were applied to the Link2vec-based model to evaluate the effectiveness. This model's performance was determined to be higher than comparable models in fake news datasets in both English and Korean. The LOGIT, SVM, and ANN classifiers are the three that are trained in this study. The results showed that the SVM classifier outperformed other classifiers and achieved a classifier accuracy of %93.1 for the dataset used. However, to assess the efficacy of link2vec, deep learning classifiers were not examined in the study. Additionally, this method is based on the URL of the news article. Because there are no connected URLs for news on social media, such a model cannot be used to identify fake news there.

Samadi M. et al.(2021) explored different deeply contextualized text representation models. The paper aimed to compare different combinations of neural classifiers and pre-trained models. For this purpose, three different classifiers SLP, MLP, and CNN have been proposed for fake news detection. Using different cutting-edge pre-trained models such as BERT, RoBERTa, GPT2, and Funnel Transformer, they were compared with each other. According to the results, CNN classifier using Funnel Transformer achieved a significant improvement in multiclass classification results in short expressions of LIAR dataset. In addition, a binary classification task was evaluated using the ISOT and COVID-19 datasets to validate the effectiveness of the model. The results from these datasets confirmed the superiority of the embeddings supplied to CNN by RoBERTa and Funnel Transformer.

D. Kar et al.(2020) revealed the textual features of their tweets about COVID-19 along with their network and user characteristics. They suggested mBERT. mBERT is a deep neural network approach. The best levels of performance have been achieved compared to RF, SVM and other traditional machine learning techniques.

Bajaj S. (2017) employed a variety of machine learning and neural network approaches to ascertain which algorithm produced the greatest results., He applies these algorithms to his dataset, which he assembled from two sources: 13,000 fake news stories were purchased from an open Kaggle dataset, and 50,000 real news pieces were taken from the Signal Media News dataset. Divide all of the data into three sets: training (60%) and test (20%) sets. He applied numerous machine learning and neural network techniques, including logistic regression, feedforward networks, RNN (Vanilla, GRU), LSTMs, Bi-LSTMs, CNN with Max-Pooling, and CNN with Max-Pooling and Attention. The results showed that GRU achieved the best overall performance and the best F1 score.

Other research by Natali Ruchansky et. al. (2017) for getting better result more than the previous one; she put forth the CSI model, which is composed of deep neural networks and is capable of extracting data from many domains, capturing temporal relationships in user involvement with articles, and also choosing crucial aspects. They developed this method to address three key issues with fake text: first, how well the article's headlines and body match; second, how readers are affected by an article's emotion; and third, how to identify the article's source by examining the URL's structure and the credibility of the media source. They examined two datasets from Weibo and Twitter, and CSI offers the best overall comparison model and version performance. We can observe that adding user features increases the total percentages from GRU-2 by 4.3%.

3 Design

In this section, we describe the steps we took to apply various methods for detecting fake news. Figure 1 shows the main processes we followed.

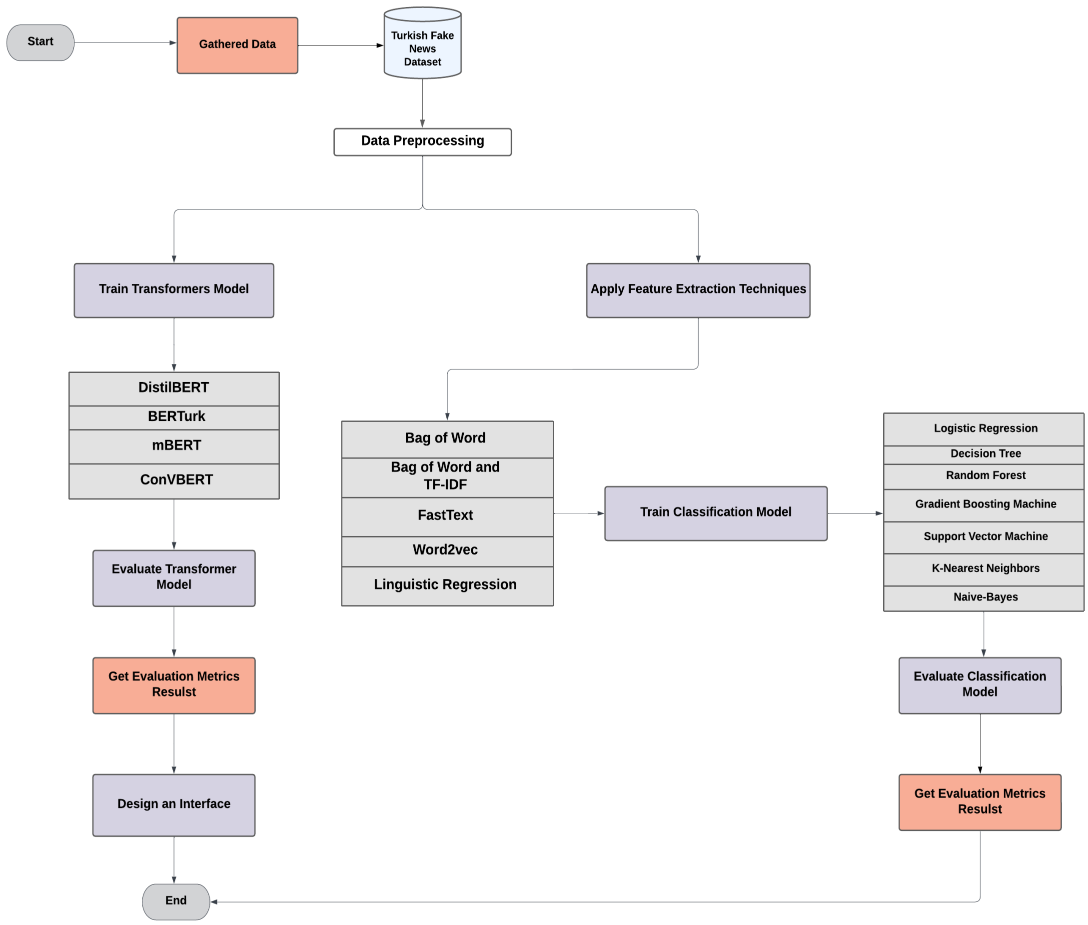

Figure 1: A general overview of the processes followed in the project.

4 Methodology

A study was conducted using five transformer-based language models to analyze and compare their performance on a particular task.

The performance of the models was evaluated using a well-established evaluation metric for the task and a dataset representative of the task at hand. Changing the hyperparameters of the models and comparing the outcomes were used in several tests to identify the top-performing model.

The following parts will show and analyze the analysis' findings as well as go into depth about the models and experimental setup.

4.1 Natural Language Processing

Natural language processing is the study of how computers can comprehend, interpret, and create human language. This branch of artificial intelligence and computer science use methods and models to handle and examine massive volumes of text or audio data and carry out operations including translation, summarization, and information extraction.

4.2 Transformers

4.2.1 ConvBERT

ConvBERT is a variant of the BERT language model that substitutes a CNN architecture for the original BERT model's special interest mechanism. ConvBert aims to improve the efficiency and ease of training on big datasets by lowering the computational complexity and memory requirements of the BERT model. ConvBert may be tailored for a range of natural language processing tasks, including text categorization, sentiment analysis, and question answering, as it is a transformer-based model.

4.2.2 DistilBERT

DistilBert is a smaller, faster, and cheaper version of BERT, which is a powerful language model developed by Google. It has been extensively utilized for a range of natural language processing applications, including question-answering, text classification, and language translation.DistilBert was developed to make BERT more accessible and easier to use by reducing its size and computational requirements. It does this using the technique of distilling a larger and pre-trained model. This allows DistilBert to achieve similar performance to BERT on many tasks while being significantly faster and cheaper to run.

4.2.3 BERTurk

BERTurk is a language model specific to the Turkish language, designed to help understand the meanings of texts. It processes Turkish texts by considering the specific features, structure, and grammar rules of the Turkish language. As far as I know, there is no solution developed using the BERTurk language model specifically for the purpose of detecting fake news. However, language models like BERTurk can potentially be used for this purpose and may be able to perform the task more accurately due to being specifically designed for understanding the meanings of texts.

4.2.4 mBERT

mBERT is a pre-trained neural network model on large volumes of multilingual text data using transformer architecture. No matter what language the text is written in, it can understand the meaning and context of the content since it is built to operate with text in several languages. It is a useful tool for jobs like text categorization, machine translation, and question-answering because of these capabilities.Unlike the other BERT models, it is trained on a diverse set of 104 languages and is able to support many languages without requiring task-specific fine-tuning.

4.2.5 Training Stage

With the same set of hyperparameters for 5 epochs, we use 4 models (BERTurk[3], DistilBERT[4], mBERT[5], ConvBERT[6]).These models provides a summary of the improved models along with their accuracy ratings.

[3]https://huggingface.co/dbmdz/bert-base-turkish-cased
[4]https://huggingface.co/dbmdz/distilbert-base-turkish-cased
[5]https://huggingface.co/bert-base-multilingual-cased
[6]https://huggingface.co/dbmdz/convbert-base-turkish-mc4-cased

According to the results in Table 1, we can say that the ConvBERT model is more successful than other models based on the Accuracy rates ConvBERT, which has the highest values in terms of Precision and F1 scores, may have made better predictions than other models. However, the DistilBERT model gives the same results with ConvBert in terms of Recall value. Higher values of these models mean that they correctly predicted more samples in the labeled dataset.

	Accuracy	Precision	Recall	F1
BERTurk	0.9831	0.9833	0.9853	0.9843
DistilBERT	0.9618	0.9354	0.9979	0.9656
mBERT	0.9876	0.9834	0.9937	0.9885
ConvBERT	0.9921	0.9876	0.9979	0.9927

Table 1: The outputs of the transformers according to the Fake News Turkish dataset are shown.

4.2.6 Named Entity Recognition

NER is a technique in natural language processing that extracts and identifies named entities from unstructured text data. It can be used as a tool for identifying fake news by detecting entities mentioned in news articles and verifying the accuracy of the information presented. This process of verification can be achieved through various methods such as cross-checking the news source, identifying misleading information and propaganda, and validating the accuracy of claims.

Label	Entity
CARDINAL	24879
DATE	7518
EVENT	714
FAC	2459
GPE	37646
LANGUAGE	159
LAW	419
LOC	2231
MONEY	592
NORP	9866
ORDINAL	421
ORG	60140
PERCENT	307
PERSON	152532
PRODUCT	4909
QUANTITY	776
TIME	387
WORKOFART	3126

Table 2: The Total Number of NER Features in Turkish Fake News Dataset

Table 2 shows that the fake news dataset is divided into two parts: "Label" and "Entity". On the "Label" side, there are 18 features. Each of these features matches the "Entity" values opposite it. The "Entity" values show how many times each feature appears in our dataset of 4455 news articles. This table helps to understand the distribution of features in the fake news dataset. This way we can see which features are more common in the fake news dataset.

Label	Meanings
CARDINAL	Numeric values
DATE	Dates
EVENT	Events
FAC	Structures and facilities
GPE	Countries, cities and regions
LANGUAGE	Languages
LAW	Legal terms
LOC	Geolocations
MONEY	Currencies
NORP	Nationality and ethnic groups
ORDINAL	Rank numbers
ORG	Companies, organizations and institutions
PERCENT	Percentage values
PERSON	Persons
PRODUCT	Products and services
QUANTITY	Units of measure
TIME	Hours, days, etc. time expressions
WORKOFART	Books, movies, etc. artworks

Table 3: The Meanings of The Label Features

Table 3 shows the meanings of the "Label" features. As shown in the table the most detected entity type in this dataset was "PERSON" and there are 152532 "PERSON" entities in total.

5 Datasets

Turkish Fake News Dataset was used in this study.

5.1 Turkish Fake News Dataset

Turkish Fake News Dataset [7] consists of two subsets, fake news, and real news. The Zaytung website, which is renowned for creating a variety of fake data, is a rich source of fake news for Turkish languages (Github, 2021; Web3, 2021). The real news dataset comes from the Hurriyet newspaper, whereas the fake news dataset is derived from Zaytung. The dataset contains a total of 4455 data including 2293 real labeled samples with one or more sentences

[7]https://github.com/sfkcvk/TurkishFakeNewsDataset

and 2162 fake labeled data with one or more sentences. The distribution of fake and real news is shown in Figure 2. The real news was obtained between January and June 2019 from the Hürriyet newspaper. Before June 2019, the fake news was gathered from articles posted on the popular fake news website Zaytung. The news was gathered in the areas of culture, politics, technology, sport, and other topics. Real news sentences often have 368 words, while fake news sentences typically contain 212 words. Table 4 provides sample sentences based on data gathered for both fake and real news.

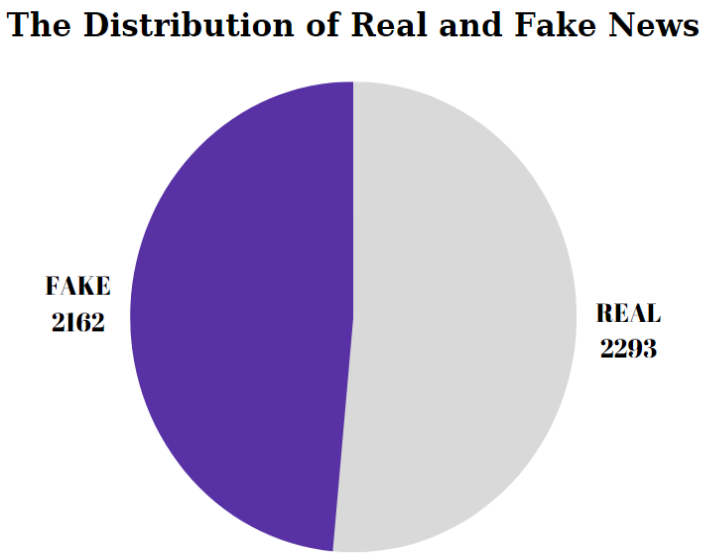

Figure 2: The Distribution of Real and Fake News of Turkish Fake News Dataset

TURKISH	ENGLISH	LABEL
23 Nisan Mağdurlarından Örnek Dayanışma Her 23 Nisan'da bir günlüğüne temsili olarak cumhurbaşkanlığı, başbakanlık, valilik, belediye başkanlığı, kaymakamlık gibi makamlara getirilen ancak hayatlarının ilerleyen bölümlerinde bir baltaya sap olamayan çocuklar bir dernek çatısı altında toplanıyorlar.	Exemplary Solidarity from the Victims of 23 April Every 23 April, children who are brought to the positions of presidency, prime minister, governorship, mayor, district governorship for one day, but who cannot handle an ax later in their lives, gather under the roof of an association.	Yalan
Karşı şeride geçti, faciaya neden oldu Uşak'ta meydana gelen trafik kazasında karşı şeride geçen otomobil faciaya neden olurken kazada 4 kişi hayatını kaybetti.	Passed to the opposite lane, causing a disaster In the traffic accident that occurred in Uşak, the car passing to the opposite lane caused the disaster, while 4 people died in the accident.	Gerçek

Table 4: Sample Sentence From Dataset

5.2 Data Preprocessing

The following procedures are used to pre-process the generated Turkish Fake News Dataset:
As a first step, HTML elements are deleted from the texts. This step aimed to eliminate any HTML tags or formatting that might interfere with the analysis. The special characters like ",@" other than alphabetic letters and specific Turkish characters were removed to clean the text of unnecessary symbols and noise. To improve the readability and uniformity of the text, newlines, and white spaces were eliminated by replacing consecutive spaces with a single space. This step aims to standardize the text and remove any unnecessary whitespace. Subsequently, the text was encoded in lowercase letters to ensure case insensitivity and facilitate text analysis. Furthermore, stop words, which are commonly occurring words with little semantic meaning, were removed from the text. This was achieved by utilizing the Turkish stop words list from the NLTK library. Lastly, extra whitespaces were re-

moved, and the pre-processed text was ready for further analysis. Figure 3 shows the data preprocess steps.

These data preprocessing steps significantly improved the quality and consistency of the textual data, enabling more accurate and meaningful analysis. The resulting pre-processed text provided a cleaner and more standardized representation of the original dataset, thereby facilitating subsequent steps in this study. Pre-processed Turkish fake news dataset was used in all models except Linguistic Regression in this study. Table 5 presents the sample text before and after preprocessing.

Text before preprocessing	Text after preprocessing	LABEL
23 Nisan Mağdurlarından Örnek Dayanışma Her 23 Nisan'da bir günlüğüne temsili olarak cumhurbaşkanlığı, başbakanlık, valilik, belediye başkanlığı, kaymakamlık gibi makamlara getirilen ancak hayatlarının ilerleyen bölümlerinde bir baltaya sap olamayan çocuklar bir dernek çatısı altında toplanıyorlar.	nisan mağdurlarından örnek dayanışma her nisanda bir günlüğüne temsili olarak cumhurbaşkanlığı başbakanlık valilik belediye başkanlığı kaymakamlık gibi makamlara getirilen ancak hayatlarının ilerleyen bölümlerinde bir baltaya sap olamayan çocuklar bir dernek çatısı altında toplanıyorlar	Yalan
Karşı şeride geçti, faciaya neden oldu Uşak'ta meydana gelen trafik kazasında karşı şeride geçen otomobil faciaya neden olurken kazada 4 kişi hayatını kaybetti.	karşı şeride geçti faciaya oldu uşakta meydana gelen trafik kazasında karşı şeride geçen otomobil faciaya olurken kazada kişi hayatını kaybetti	Gerçek

Table 5: Sample Sentence From Dataset

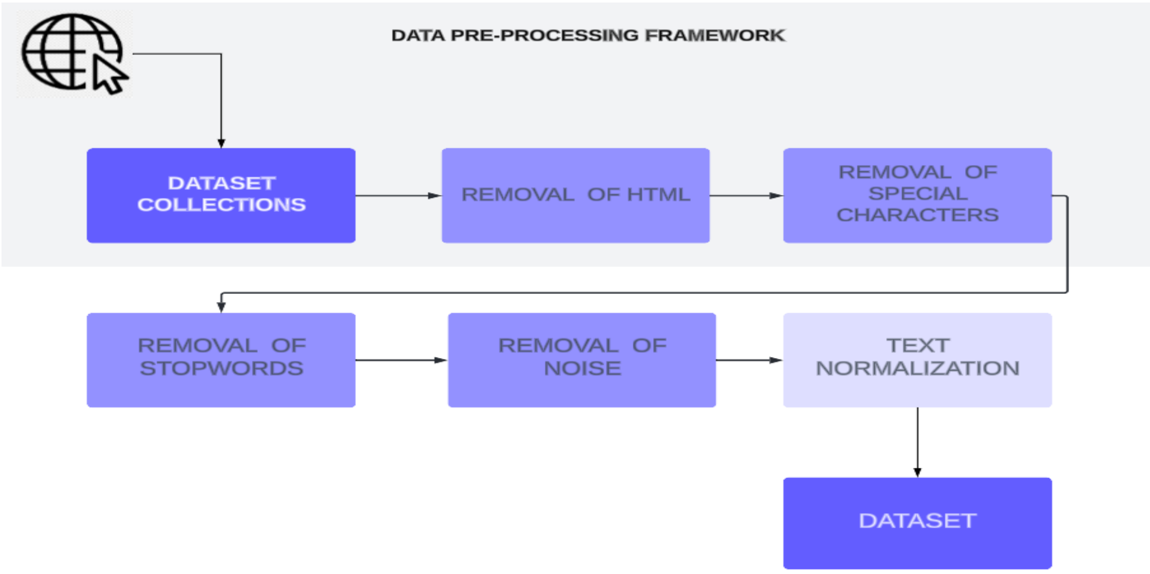

Figure 3: Data Generation Pipeline

5.3 Evaluation Metrics

Accuracy is a measure of how well a model is able to predict the correct outcome. It is calculated by taking the ratio of the number of correct predictions made by the model to the total number of predictions made. To calculate accuracy, you need to determine the number of true positive, false positive, and false negative predictions made by the model.

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

Precision is a measure of the accuracy of a model when it predicts positive outcomes. It is calculated by taking the ratio of the number of true positive predictions made by the model to the total number of positive predictions made by the model. Precision is a good metric to use when the goal is to minimize false positives, as it measures the proportion of positive predictions that are actually correct.

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

Recall is a measure of the ability of a model to identify all relevant instances. It is calculated by taking the ratio of the number of true positive predictions made by the model to the total number of actual positive instances in the data. Recall is a good metric to use when the goal is to minimize false negatives, as it measures the proportion of positive instances that were correctly predicted by the model.

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

F1 score is a metric that combines precision and recall, with a higher score indicating better performance. It is useful when you want to balance precision and recall, as it is a single score that represents the overall performance of the model.

$$F1 = \frac{2 * (precision * recall)}{precision + recall} \tag{4}$$

6 Experimental Setup and Results

6.1 Bag of Words and TF-IDF

A text document representation technique based on word frequencies is called "Bag of Words." It ignores word order and structure and considers each word as a separate vector element. BoW is frequently employed in tasks like sentiment analysis and text categorization.

Classifier	Accuracy	Precision	Recall	F1
LR	0.9696	0.9702	0.9692	0.9696
DT	0.9158	0.9158	0.9158	0.9158
RF	0.9281	0.9279	0.9283	0.9280
GBM	0.9551	0.9554	0.9551	0.9550
SVM	0.9607	0.9611	0.9607	0.9606
KNN	0.6060	0.7418	0.5897	0.5228
NB	0.9652	0.9659	0.9665	0.9652

Table 6: Turkish News Classification Results using Bag of Words with %80-%20 Data

Table 6 shows the Bag of Words classification results.%80 of the given dataset was used for training and %20 for testing. The LR model achieves the highest accuracy rate, which is %96.96, and demonstrates excellent performance in terms of precision, recall, and F1 score. As opposed to that, KNN model performs relatively poorly compared to other classifiers, with the lowest accuracy of %60.60 and F1 score of %52.28, indicating its struggle to accurately capture relationships. The SVM model stands out with an accuracy of %96.07 and good precision, recall, and F1 score metrics. The SVM model shows high success in correct positive and correct negative predictions. In conclusion, the LR model exhibits the best performance with the highest accuracy rate, followed closely by the SVM model. The KNN model, on the other hand, performs less satisfactorily compared to the others.

Classifier	Accuracy	Precision	Recall	F1
LR	0.9618	0.9619	0.9614	0.9616
DT	0.9184	0.9185	0.9184	0.9184
RF	0.9207	0.9200	0.9210	0.9204
GBM	0.9521	0.9525	0.9521	0.9520
SVM	0.9626	0.9630	0.9626	0.9625
KNN	0.6278	0.7422	0.5906	0.5306
NB	0.9596	0.9598	0.9620	0.9595

Table 7: Turkish News Classification Results using Bag of Words with %70-%30 Data

According to the BOW classification results using %70 training and %30 testing data, the LR model achieves the highest accuracy rate of %96.18. The LR model also demonstrates good performance in terms of precision, recall, and F1 score. Similarly, the SVM model shows a comparable accuracy rate of %96.26 to the LR model and performs well in terms of precision, recall, and F1 score. On the other hand, the KNN model performs less effectively compared to the other classifiers. It has the lowest accuracy rate of %62.78 and F1 score of %53.06, indicating its struggle to accurately capture the relationships in the dataset. In summary, the LR and SVM models exhibit the best performance in the BOW classification with %70 training and %30 testing data, while the KNN model performs comparatively weaker.

BoW + TF-IDF is a text representation method used in text-based documents. BoW represents word frequencies, while TF-IDF calculates the importance of a word. Each word in the document is considered as a vector element, taking into account both word frequencies and the word's prevalence in the document collection. This combined method reflects the word distribution in the document while emphasizing rare and important words. It is commonly used in tasks such as text classification, information retrieval, and recommendation systems.

Classifier	Accuracy	Precision	Recall	F1
LR	0.9551	0.9554	0.9546	0.9549
DT	0.9124	0.9124	0.9124	0.9124
RF	0.9405	0.9403	0.9404	0.9404
GBM	0.9483	0.9490	0.9483	0.9483
SVM	0.9696	0.9697	0.9696	0.9696
KNN	0.9012	0.9072	0.8988	0.9003
NB	0.9001	0.9137	0.9040	0.8997

Table 8: Turkish News Classification Results using Bag of Words and TF-IDF with %80-%20 Data

Table 8 shows the Bag of Words + TF-IDF classification results. %80 of the given dataset was used for training and %20 for testing. According to this table, the SVM algorithm demonstrates the best performance with an accuracy rate of %96.96. Additionally, SVM has a precision of %96.97 and a recall of %96.96. This indicates that SVM excels in correctly predicting positive examples. The F1 score is also measured at %96.96, indicating high performance in terms of both precision and recall. In conclusion, SVM is the top-performing algorithm for text classification.

Classifier	Accuracy	Precision	Recall	F1
LR	0.9543	0.9546	0.9536	0.9541
DT	0.9109	0.9114	0.9109	0.9110
RF	0.9379	0.9373	0.9380	0.9376
GBM	0.9543	0.9548	0.9543	0.9543
SVM	0.9618	0.9619	0.9618	0.9618
KNN	0.9035	0.9063	0.9006	0.9024
NB	0.8698	0.8907	0.8783	0.8693

Table 9: Turkish News Classification Results using Bag of Words and TF-IDF with %70-%30 Data

Among the classifiers evaluated using a %70 training %30 test split on a text classification task with BOW+TF-IDF features, SVM achieves the highest accuracy of %96.18. Its precision, recall, and F1 score also reach %96.19, %96.18, and %96.18 respectively, indicating its strong performance in accurately classifying positive examples. Other classifiers such as LR, GBM, DT, RF, KNN, and NB perform slightly lower in comparison. Therefore, SVM emerges as the top-performing classifier, delivering excellent results for this specific text classification task.

6.2 FastText

FastText is an open-source natural language processing library developed by Facebook that is designed for use in NLP tasks such as text classification and word embedding. It operates on character n-grams to create word embedding vectors and applies natural language processing algorithms using these vectors. It is faster and more efficient than traditional word embedding methods and produces effective results for low-resource languages. Additionally, it performs well in situations where there is inadequate training data available.

Classifier	Accuracy	Precision	Recall	F1
LR	0.8035	0.8420	0.8104	0.8000
DT	0.9023	0.9023	0.9019	0.9021
RF	0.9315	0.9312	0.9317	0.9314
GBM	0.9483	0.9494	0.9475	0.9481
SVM	0.9629	0.9629	0.9628	0.9628
KNN	0.6083	0.7479	0.5919	0.5256
NB	0.9607	0.9618	0.9621	0.9607

Table 10: Turkish News Classification Results using FastText with %80-%20 Data

Table 10 shows the FastText classification results. %80 of the given dataset was used for training and %20 for testing. According to the table, the SVM algorithm has the highest accuracy (%96.29), precision (0.9629), recall (0.9628), and F1 score (0.9628). SVM performs the best among the algorithms. While DT shows good performance with an accuracy of %90.23 and an F1 score of 0.9021, RF achieves an accuracy of %93.15 and an F1 score of 0.9314, and GBM has an accuracy of %94.83 and an F1 score of 0.9481. On the other hand, LR (%80.35 accuracy, 0.8000 F1 score), KNN (%60.83 accuracy, 0.5256 F1 score), and NB (%96.07 accuracy, 0.9607 F1 score) have lower performance. In summary, the SVM algorithm performs the best, but other algorithms also achieve competitive results.

Classifier	Accuracy	Precision	Recall	F1
LR	0.7382	0.8084	0.7541	0.7297
DT	0.9102	0.9095	0.9103	0.9098
RF	0.9259	0.9252	0.9262	0.9256
GBM	0.9483	0.9492	0.9471	0.9480
SVM	0.9543	0.9539	0.9545	0.9541
KNN	0.6178	0.9450	0.5905	0.5299
NB	0.9551	0.9557	0.9578	0.9550

Table 11: Turkish News Classification Results using FastText with %70-%30 Data

According to Table 11, the NB classifier achieves the highest accuracy (%95.51), precision (0.9557), recall (0.9578), and F1 score (0.9550) among all the classifiers. This indicates that NB performs the best in the FastText classification task with a %70 train and %30 test split. Other classifiers, such as DT (%91.02 accuracy, 0.9098 F1 score), RF (%92.59 accuracy, 0.9256 F1 score), and GBM (%94.83 accuracy, 0.9480 F1 score), also show competitive performance. However, LR (%73.82 accuracy, 0.7297 F1 score), KNN (%61.78 accuracy, 0.5299 F1 score), and SVM (%95.43 accuracy, 0.9541 F1 score) exhibit lower performance compared to NB. Therefore, NB stands out as the top-performing classifier in this FastText classification task.

6.3 Word2Vec

Word2Vec is a natural language processing (NLP) method that generates word representations as vectors. It associates the meaning of a word with its surrounding words. These vectors capture word similarities and relationships, and they are commonly used in various NLP tasks to measure word similarity, perform word classification, and conduct sentiment analysis, among others.

Classifier	Accuracy	Precision	Recall	F1
LR	0.9292	0.9293	0.9292	0.9292
DT	0.8799	0.8801	0.8799	0.8797
RF	0.9281	0.9282	0.9281	0.9281
GBM	0.9371	0.9373	0.9371	0.9371
SVM	0.9191	0.9194	0.9191	0.9192
KNN	0.9090	0.9108	0.9090	0.9091
NB	0.8776	0.8813	0.8776	0.8776

Table 12: Turkish News Classification Results using Word2Vec with %80-%20 Data

According to Table 12, the GBM algorithm achieves the highest accuracy (%93.71) and F1 score (0.9371) among all classifiers in the Word2Vec classification model with an %80 training and %20 testing split. GBM also exhibits high precision (0.9373) and recall (0.9371) values. LR (%92.92 accuracy, 0.9292 F1 score) and RF (%92.81 accuracy, 0.9281 F1 score) perform well. DT achieves an accuracy of %87.99 and an F1 score of 0.8797, while SVM (%91.91 accuracy, 0.9192 F1 score), KNN (%90.90 accuracy, 0.9091 F1 score), and NB (%87.76 accuracy, 0.8776 F1 score) demonstrate lower performance. In summary, GBM stands out as the best-performing algorithm for the Word2Vec classification problem.

Classifier	Accuracy	Precision	Recall	F1
LR	0.9199	0.9206	0.9199	0.9200
DT	0.8713	0.8729	0.8713	0.8715
RF	0.9184	0.9186	0.9184	0.9185
GBM	0.9207	0.9211	0.9207	0.9207
SVM	0.9057	0.9079	0.9057	0.9058
KNN	0.9035	0.9077	0.9035	0.9036
NB	0.8586	0.8680	0.8586	0.8585

Table 13: Turkish News Classification Results using Word2Vec with %70-%30 Data

According to Table 13, the GBM algorithm achieves the highest accuracy (%92.07) and F1 score (0.9207) among all the classifiers in the Word2Vec classification task with a %70 train and %30 test split. GBM also demonstrates high precision (0.9211) and recall (0.9207). Hence, GBM performs the best in this classification task. LR (%91.99 accuracy, 0.9200 F1 score) and RF (%91.84 accuracy, 0.9185 F1 score) show competitive performance. DT (%87.13 accuracy, 0.8715 F1 score), SVM (%90.57 accuracy, 0.9058 F1 score), KNN (%90.35 accuracy, 0.9036 F1 score), and NB (%85.86 accuracy, 0.8585 F1 score) exhibit lower performance compared to GBM. In summary, GBM stands out as the top-performing classifier in the Word2Vec classification task.

6.4 Linguistic Regression

Regression and linguistics seem to be combined in the idea of linguistic regression. Language and its structure are the subjects of linguistics, whereas regression is a statistical method for simulating correlations between variables. The term "linguistic regression" refers to the use of regression analysis in the study of language, which involves using statistical techniques to look into linguistic events and discover connections between linguistic variables.

Language and style have an impact on text features, reflecting the text's substance. The number of characters, words, and letters in the text serves as a measure of its length and complexity, while the use of capital and lowercase letters conveys the formality of the text. Short and lengthy words signify simplicity or complexity in the text, whereas special letters lend emphasis or an emotional tone. The variety of the text is reflected in the number of various words and word kinds, while the quantity of verbs, adjectives, and adverbs influences the expression style. The prepositions, conjunctions, and pronouns that are used to compose the text establish its structure. Quantitative information and the text's emotional tone are expressed through numbers and feelings. In order to gain a deeper understanding of the text's content, these aspects are used in the linguistic analysis of the text.

Features	Instance1	Instance2	Instance3
Character-count	127	106	683
Word-count	17	14	80
Letter-count	101	88	590
Total-number-of-upper-characters	2	7	22
Total-number-of-lower-characters	99	81	568
Number-of-special-character	10	4	12
Short-words	3	3	15
Long-words	14	11	65
Number-of-different-words	17	14	72
Unique-word-types-count	6	5	9
Verb-count	4	3	19
Adjective-count	3	2	9
Determiners-count	0	0	4
Conjunction-count	1	0	1
Noun-count	4	4	34
Adverb-count	4	0	4
Preposition-count	0	1	3
Pronoun-count	0	0	0
Number-count	0	0	1
Sentiment	Negative	Positive	Negative
Instance 1	Apple'ın yeni telefonu 'fena' geliyor... Satışa sunulmasına henüz aylar var; ancak nasıl görüneceği şimdiden belli oldu 'gibi'!		
Instance 2	LeBron'un dönüşü muhteşem oldu! Sakatlığını atlatan LeBron James, Clippers maçı ile parkelere geri döndü.		
Instance 3	Tekel Skandalı Büyüyor: İşçilere Yıllarca Her Ay Düzenli Olarak Para Ödendiği Ortaya Çıktı! Maliye Bakanı Mehmet Şimşek'in "72 milyonun hakkını düşünmeliyiz" açıklamalarının ardından gözlerin çevrildiği Tekel'de yeni bir skandal daha patlak verdi. Maliye müfettişlerinin titiz çalışması sonucu ortaya çıkan ürkütücü tablo, Tekel işçilerinin hesabına devletin kasasından yıllardır her ay düzenli olarak para aktarıldığını gösteriyor.Toplantının sonunda basın mensuplarının sorularını yanıtlayan Doğan, devletin diğer kurumlarında çalışanlara da her ay düzenli olarak para aktarıldığı yönünde bazı ihbarlar aldıklarını belirterek, soruşturmanın genişletilerek sürdürüleceğini açıkladı.		

Table 14: Researched and added linguistic features

NER	Instance1	Instance2	Instance3
CARDINAL	0	0	0
DATE	0	0	0
EVENT	0	0	0
FAC	0	0	0
GPE	0	0	1
LANGUAGE	0	0	0
LAW	0	0	0
LOC	0	0	0
MONEY	0	0	0
NORP	0	0	2
ORDINAL	0	0	0
ORG	1	1	4
PERCENT	0	0	0
PERSON	2	1	12
PRODUCT	0	0	0
QUANTITY	0	0	1
TIME	0	0	0
WORK-OF-ART	0	0	0
Instance 1	Apple'ın yeni telefonu 'fena' geliyor... Satışa sunulmasına henüz aylar var; ancak nasıl görüneceği şimdiden belli oldu 'gibi'!		
Instance 2	LeBron'un dönüşü muhteşem oldu! Sakatlığını atlatan LeBron James, Clippers maçı ile parkelere geri döndü.		
Instance 3	Tekel Skandalı Büyüyor: İşçilere Yıllarca Her Ay Düzenli Olarak Para Ödendiği Ortaya Çıktı! Maliye Bakanı Mehmet Şimşek'in "72 milyonun hakkını düşünmeliyiz" açıklamalarının ardından gözlerin çevrildiği Tekel'de yeni bir skandal daha patlak verdi. Maliye müfettişlerinin titiz çalışması sonucu ortaya çıkan ürkütücü tablo, Tekel işçilerinin hesabına devletin kasasından yıllardır her ay düzenli olarak para aktarıldığını gösteriyor.Toplantının sonunda basın mensuplarının sorularını yanıtlayan Doğan, devletin diğer kurumlarında çalışanlara da her ay düzenli olarak para aktarıldığı yönünde bazı ihbarlar aldıklarını belirterek, soruşturmanın genişletilerek sürdürüleceğini açıkladı.		

Table 15: Added NER features

6.5 Feature Selection

Feature selection is the process of choosing a subset of relevant features from a larger set of available features.The main goals of feature selection are to simplify models, improve interpretability, reduce overfitting, enhance computational efficiency, and potentially increase prediction accuracy.

Classifier	Accuracy	Precision	Recall	F1	Old shape	New shape
LR	0.9326	0.9329	0.9326	0.9326	38	11
DT	0.8585	0.8597	0.8585	0.8587	38	5
RF	0.9057	0.9060	0.9057	0.9055	38	15
GBM	0.8776	0.8776	0.8776	0.8776	38	6
LinearSVC	0.8754	0.8877	0.8754	0.8749	38	14

Table 16: Turkish News Classification Results using Feature Selection with %80-%20 Data

"Old Shape" and "New Shape" are terms used to express the dimensions of a dataset. "Old Shape" refers to the original size of the dataset, while "New Shape" shows how these dimensions have been changed. Calculations are made using these new dimensions. Table 16 shows the best features selection results. %80 of the given dataset was used for training and %20 for testing. Among the classifiers in the table, the LR classifier has the highest accuracy, precision, recall and F1 score. Therefore, using the LR classifier for this dataset would yield better results.

Classifier	Accuracy	Precision	Recall	F1	Old shape	New shape
LR	0.9237	0.9243	0.9237	0.9236	38	11
DT	0.8354	0.8354	0.8354	0.8354	38	5
RF	0.8982	0.8984	0.8982	0.8981	38	15
GBM	0.8885	0.8885	0.8885	0.8885	38	6
LinearSVC	0.9237	0.9243	0.9237	0.9236	38	14

Table 17: Turkish News Classification Results using Feature Selection with %70-%30 Data

Table 17 shows the best features selection results. %70 of the given dataset was used for training and %30 for testing. Among the classifiers in the table, the LR and the LinearSVC classifiers have the highest accuracy, precision, recall and F1 score. Therefore, using the LR classifier and LinearSVC for this dataset would yield better results.

7 Results and Discussion

According to our study, various classifiers and feature extraction techniques were used in this study to detect Turkish fake news. Transformer-based models including BERTurk, DistilBERT, mBERT, and ConvBERT were employed firstly. High accuracy scores ranging from 0.9618 to 0.9921 were achieved by these models, with the highest accuracy of 0.9921 exhibited by ConvBERT.
In another study published in Bozuyuk et al.(2022) compared Naïve Bayes (NB), Random Forest (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. They obtained %99.90 accuracy in fake news identification which is a highly efficient model without substantial language pre-processing tasks.

According to our study, LR, DT, RF, GBM, SVM, KNN, and NB classifiers were trained on an 80-20 data split using the Bag of Words technique. The highest accuracy scores was achieved by LR, with scores of 0.9696 ,respectively.
In another study published in IEEE Conference Publication et al.(2021) used term frequency-inverse document frequency (TF-IDF) of bag of words and n-grams as feature extraction technique and Support Vector Machine (SVM) as a classifier for fake news detection. They proposed a dataset of fake and true news to train their system and obtained results that showed the efficiency of their system.

According to our study, we investigated the combination of Bag of Words and TF-IDF with both 80-20 and 70-30 data splits. It was found that SVM achieved the highest accuracy score of 0.9696 for the 80-20 data split, while LR, RF, and GBM also performed well with accuracy scores above 0.94.
In another study by A. Stan et al. (2018), a machine-learning model was trained using a dataset of fake and real news, utilizing the Scikit-learn library in Python. They extracted features from the dataset using text representation models such as Bag of Words, TF-IDF, and Bi-gram frequency. They tested two classification approaches, probabilistic classification and linear classification, on the title and content to distinguish between clickbait/non clickbait and fake/real news. The results of their experiments indicated that linear classification with the TF-IDF model worked best for content classification.

According to our study, the FastText technique was integrated into the classification process, and accuracy scores above 0.92 were achieved for both the 80-20 and 70-30 data splits with NB, RF, GBM, and SVM classifiers.
Another study published by Uluyol et al. (2022) analyzed the classification success of Turkish fake news pulled from Twitter with different parameters by using word embedding with fastText and using scikit-learn libraries in their fastText language model. With this model, they tested the classification of Turkish news tweets according to two predefined classes (fake, real) and obtained a classification success of %88. In addition, they compared and interpreted the performances of multnomialNB, Stochastic Gradient Descent (SGD), Random Forest, Logistic Regression, K-NN, XGBoost, and Support Vector Machines (SVM) algorithms on Turkish news tweets. At the end of the study, the technique with the best classification accomplishment was the SVM algorithm with a classification success of about %84.

According to our study, Word2Vec was used for feature extraction, and accuracy scores above 0.87 were achieved for both the 80-20 and 70-30 data splits with LR, RF, GBM, and SVM classifiers.
In another study published in Topal et al. (2022) used Natural Language Processing methods to detect fake news for Turkish-language posts on certain topics on Twitter. They tested various supervised and unsupervised learning algorithms with different parameters. The most successful F1 score of fake news detection was obtained with the support vector machines algorithm with 0.9.

Finally, according to our study, linguistic regression and feature selection were applied to the dataset, and accuracy scores of 0.932 for the 80-20 data split and 0.9237 for the 30-70 data split were achieved with LR.
In another study published in Choudhary et al. (2021) proposed a linguistic model that extracts syntactic, grammatical, sentimental, and readability features of particular news for fake news detection and classification. They used a neural-based sequential learning model to achieve superior results for fake news detection. The combined linguistic feature-driven model was able to achieve an average accuracy of &86 for fake news detection and classification.

Overall, the results highlight the effectiveness of transformer-based models, particularly ConvBERT, for Turkish fake news detection. Additionally, LR and SVM consistently performed well across different feature extraction techniques. The choice of feature extraction technique, such as Bag of Words, TF-IDF, FastText, or Word2Vec, influenced the classifier's performance to some extent. Further research is necessary to optimize the classifiers and feature extraction techniques for more accurate Turkish fake news detection.

8 Fake News Detection Web Interface

In an effort to identify Turkish fake news, this interface was created. It was made with Flask, a well-liked Python online application framework that makes it simple and quick to design web apps.

The interface was designed using HTML and CSS. A markup language called HTML is used to specify the structural elements of web pages. Users may enter the news text in a text box on the interface, and a "Evaluate" button launches the assessment. The layout and look of web pages are determined by the style sheet language CSS. The interface's background color, text, and button style were all defined using CSS.

In the Flask application, the user interface uses two separate URL routes. Users are prompted to input fresh text on the home page. The entered news text is retrieved and submitted to the fake news detection feature when the "Evaluate" button is selected. A ConvBERT model is employed for the identification of bogus news. ConvBERT is a transformer model that has been trained exclusively to recognize Turkish false news. The accuracy rate of the interface is greatly increased by the use of the ConvBERT model. The model analyzes the text entered in the "Text" box and outputs factual information to people who read the news. Whether the news is true or false is shown on the page via a notice. False news is displayed in red, while the actual news is displayed in green. The identification of false information is facilitated by this approach. Python and HTML code work together to create the interface's aesthetically pleasing look.

To run the interface, the Flask application is run on an HTTP server. Additionally, a tool called ngrok is used to expose the local server, allowing others to view the interface.

With this interface, consumers will have access to a simple tool for identifying Fake Turkish news. More trustworthy outcomes in the identification of fake news are made possible by the ConvBERT model's high accuracy rate.

Figure 4 shows the interface's home page, which includes a text box for users to add their news content and a button labeled "Evaluate" that starts the assessment procedure.

The interface's result page is displayed in Figures 5 and 6, with a message indicating whether the news is true or fake. Green highlights denote true news, while red highlights denote fake news. The goal of this color scheme is to make it easier to spot bogus news.

Figure 4: Fake News Detection Web Interface Homepage

Figure 5: Fake News Detection Web Interface True Example Result

Figure 6: Fake News Detection Web Interface Fake Example Result

9 Conclusion and Future Work

In this study, a Turkish fake news detection project was conducted. A comprehensive investigation was carried out by applying various models (Transformers: Bertürk, DistilBert, Convbert, mBert), word2vec, fasttext, and bag of words, along with different classifiers (Logistic Regression, Decision Tree, KNN, Naive Bayes, SVM, Random Forest, and Gradient Boosting). Based on the obtained results, the ConvBert model exhibited the best performance, and it was integrated into the API.

The results demonstrate that the ConvBert model outperformed other approaches in Turkish fake news detection. It proved to be an effective tool for distinguishing between fake and real news, achieving high accuracy rates across various news types and language usages. Moreover, the project's API showcased its versatility by being capable of classifying news articles as fake or true, even when they were not present in the dataset.

The findings of this study contribute significantly to the field of Turkish fake news detection. The ConvBert model, along with the integrated API, offers valuable insights and practical applications. Future work should focus on expanding the dataset, exploring advanced language processing techniques, and conducting further optimization to enhance the model's performance.

The detection of Turkish fake news has become a crucial concern in the face of widespread social media and online news sources. The outcomes of this project represent a significant step towards developing algorithms that aid in the identification and prevention of the dissemination of fake news. It is imperative to prioritize such endeavors to promote access to accurate and reliable information, inform the public, and combat the spread of manipulative information.

Several potential areas for future work in the Turkish fake news detection project can be identified based on our findings. In this study, multiple models were experimented with, and a common classifier was applied to determine the most effective one. ConvBert was ultimately selected and integrated into an API. It is suggested that the dataset be expanded by incorporating additional reliable and fake news samples from diverse sources. Furthermore, the feature set can be augmented to include not only the text but also other attributes such as headlines, news sources, and social media posts, which may enhance the accuracy of classifying fake and true news. The utilization of advanced language processing techniques, such as sentiment analysis or key-word analysis, can provide a deeper understanding of the text and potentially lead to more accurate results. Analyzing misclassifications and investigating the reasons behind them would be valuable in identifying areas for model enhancement. Lastly, conducting further performance optimizations and implementing software engineering principles for efficient project management and deployment would contribute to the overall success of the project.

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