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Fake News Detection with Machine Learning Algorithms

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Abstract

Nowadays, with the advancement of technology, the use of news sources has also undergone a great evolution. News sources have constantly evolved from past to present, ranging from magazines to radios, from newspapers to televisions. The fact that it has become so easy to access news has caused society to pay more attention to fake news. Fake news has the ability to influence society through news sources such as social media, which can reach wider audiences with the development of technology. The difficulties of users in accessing accurate and reliable sources in this information flow that shapes their daily lives increases the potential for the spread of fake news, and it becomes increasingly difficult to distinguish between real and fake news. In this study, classification models for fake news detection were designed using machine learning algorithms. The dataset, which includes fake and real news examples, contains 42,000 examples. Each class, including fake and real samples, contains 22,000 sample data. In order to increase data quality, accuracy and usability, preprocessing methods were applied to the data set. The removal of numbers, stop words, and html tags was done in the pre-processing step to remove unnecessary information from the text. Models were created for fake news detection with singular and ensemble classification algorithms. Performance evaluation of the models was performed using 5-fold cross-validation. In the performance comparisons of the models, values such as accuracy, sensitivity, specificity, tp rate and fp rate were calculated. The highest performance results were observed in the random forest classification algorithm with an accuracy rate of 76%.

Keywords: Fake News Detection, News on Social Media, Classification.

1. Introduction

Throughout the entire historical process, humanity has needed various means of communication and communication, has constantly improved these tools and these developments have brought societies closer. Since the beginning of the modern era, people have witnessed a lot of development, in the past, these events were spread among the people through rumors and this situation has created the need to convey to the people in a more reliable and comprehensive way. As examples of these communication tools; although communication tools such as smoke communication and homing pigeons were sometimes used for various reasons such as war, these primitive communication tools have evolved into more modern technological devices such as correspondence, newspapers, magazines, as well as telegraph, radio and television. Especially in the modern times of technology, the parallel spread of information has led to the rapid spread of false and manipulated information. Therefore, these tools and requirements have also brought information pollution. Just as it is difficult to access accurate information in today's world, it has also been difficult to detect false information and turn it into correct information in the past [1]. But this challenge is more intense now than in the past. Because one-sided news sources are written from a certain point of view, people have been subjected to great manipulation from the moment they first received the news and imposed this dirty information on people. At times, this situation was consciously used by state officials or institutions to use the public for their evil purposes [2]. For example: Procopius, who lived in Byzantium in the 500s AD, was a historian. After he managed to attract the attention of Emperor Justinianus with his official history writings, he produced dubious information known as "anecdotes" in order to tarnish the reputation of the emperor and kept this secret until his death. Pietro Aretino wrote strange sonnets about the candidates to manipulate the papal elections in 1522. He started singing these sonnets to the public near the statue known as Pasquino in Navona Square in Rome.

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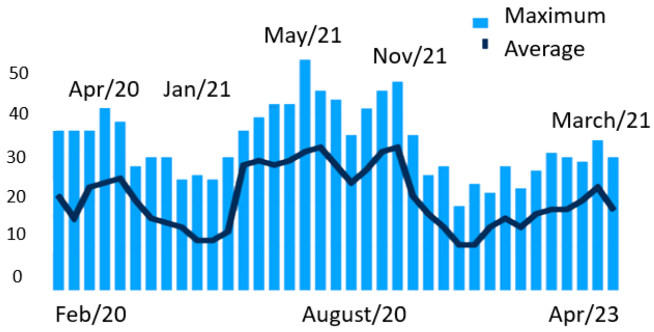

Figure 1. Effects of Fake Trends on the Agenda [3]

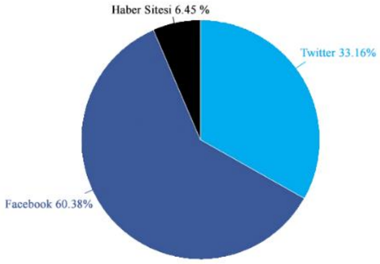

Figure 2. Fake News Distribution on Social Media [4]

The term "pasquinade" later evolved into a general usage for immoral and often false news about public figures [5]. Today, social media platforms play an important role in receiving and sharing news. However, fake trends appearing on these platforms can mislead users and have widespread effects. Twitter is a platform known for its rapid flow of information and provides a striking example of how fake trends form and spread on this network. In Figure 1, it is possible to see the ratios of the effects of fake trends on the agenda to the months. In light of these developments, not only the manipulative effect of misinformation has increased, but also the spread of correct information has increased rapidly. People's interests have expanded further and they have begun to have ideas about the world, not just the region they live in. Thus, as the interest and desire for science increases, over time technology does not stand still as it always does. With the increase in these areas of interest, technological developments have increased exponent tially. These events have begun to spread rapidly around the world. Especially after this interest in the technology sector, new inventions have naturally begun to enter people's lives. Of course, the most important of these inventions are the computer and the mobile phone. With the introduction of these tools into people's lives, of course, information has become more fluid than in the past. People now carry a news machine in their pockets and can access information whenever they want.

Today, a communication platform called digital media has emerged with mobile phones. Therefore, the number of users is also increasing. Access to information has become faster and more comprehensive than ever before. Among these wide-ranging resources, the easy and widespread use of the internet and social media platforms facilitates the sharing of information, but also allows misleading content to spread rapidly. This situation has created an environment that allows fake news to spread much more easily and thus, contrary to popular belief, it has become more difficult for the user to access reliable and accurate information.

Considering this emerging situation, users' difficulties in accessing accurate and reliable sources in this information flow that shapes their daily lives increases the potential for the spread of fake news and it becomes increasingly difficult to distinguish between real and fake news. At the core of this incident, the detection of these fake news is not only an information security issue, but also has a very critical importance for the healthy functioning of a democratic and moral society. Because fake news can influence the way societies think, undermine public trust and even shape political decisions. Following these, detecting fake news and distinguishing it from real information has become a major challenge today. As in the past, today there have been many manipulative movements and political tactics aimed at misleading the public. Although this is sometimes for the good of the public, it can sometimes have bad consequences [6]. Regarding these manipulative events, the fake news post targeting the American president that took place in the USA in 2017 is given as an example. “In the long history of misinformation, recent developments in fake news hold a special place, especially when Kellyanne Conway, special advisor to US President Donald Trump, went to great lengths to invent the Kentucky massacre to defend the travel ban on Muslim countries. The fabrication of alternative facts is also quite rare historically, but the equivalent of today's poisonous, tasteful articles and tweets can be found in different historical periods, even in ancient times. ”

Fake News is gaining widespread popularity by spreading rapidly, especially through social media channels and online news sites. The influence of social media algorithms, the use of emotional content, people's tendency to confirm their own opinions, and the lack of scrutiny of news sources make it easier for fake news to spread. As seen in Figure 2, the distribution of fake news in social media channels is shown. As society uses social media more, it has been observed that the distribution of fake news has increased significantly on Facebook and Twitter. With the proliferation of information brought about by the digital revolution, the rise of social media and the increased availability of online news, the potential for the spread of fake news has naturally increased much more. This situation causes consciously produced misinformation to be shared, sometimes at almost the same speed and interaction as real news [7]. Therefore, detecting and combating fake news has become an important problem faced by modern societies in the information age. Therefore, users need to be more conscious and careful when using social media [8].

Due to the nature of social media platforms, the speed at which news and information shares reach large audiences has reached a considerable level. Since the number of users of these social media platforms has reached millions of people, the spread of fake news has reached lightning speed over time, especially on social media platforms such as Instagram, Twitter, YouTube, Facebook and TikTok. Therefore, these platforms, which everyone has access to, have also increased their user portfolio, and users now include not only adults but also children. According to research done; As people get younger, the time spent on using social platforms increases. As a result of this information, it is observed that social media use is inversely proportional to age. Getting news is the most frequently cited reason for using social media among all age groups except Generation Z [9].

Twitter has now become the new news source. Day by day, people lose their trust in news sources and get almost most of their news from Twitter. With journalists now active on social media, news circulation has become even more intense. This intensity has been abused by some people and institutions and has become manipulative, and over time it has turned into a disadvantageous situation. Fake news made by malicious users affects human activities in every aspect. In this context, identifying fake news is a critical issue in order to protect the individuals or institutions that are the main theme of the news and to ensure that readers obtain reliable information [10]. In addition to accessing information being special, detecting fake news is of great importance. One of the benefits of this is that the reader reaches a single truth and in addition, their trust in the news system increases. For this reason, it is essential to examine fake news in more detail before starting fake news detection studies [11].

In this study, for the modeling created for the detection of fake news, primarily data cleaning (getting rid of noisy and inconsistent data), data integration (bringing together different data sources), data selection (to turn the data sets used into a better categorized data set). It needs to be made suitable for data processing using data mining techniques such as identifying important data to be analyzed) and data transformation. Thus, thanks to these well-categorized data sets, it will be easier to detect fake news [12]. In addition to facilitating communication, social media platforms also face problems such as the spread and interaction of bot accounts. In particular, Twitter constantly takes various measures to distinguish between real and fake accounts [13]. Within the scope of these measures, the number of closed bot accounts is increasing day by day. As seen in Figure 3, the rates of bots closed on Twitter are given by month [14].

Figure 3. Closed Bots

In the study of Shu and other researchers, it can be seen that they examined the psychological and social aspects of fake news in traditional media and social media, as seen in Figure 4. When we look at the first category, there are fake accounts created for propaganda purposes, while the second category includes the "echo chamber" effect, which occurs as a result of users following people with similar thoughts and trusting the news shared by these accounts, where they tend to receive and share news that is close to their interests, even though it is fake news. It has been emphasized that fake news spread by fake accounts created for propaganda purposes on social media is spread through social bots, troll accounts and semi-robot accounts. News frequently shared by troll or bot accounts in similar time periods is perceived as true by real users and shared by many real accounts in a short time. This increases the credibility of fake news shared through real accounts [15].

In the balanced dataset containing equal number of fake and real news samples, relevant preprocessing methods were applied to the dataset in order to improve data quality and increase accuracy and usability. Thus, the effect of unexpected results was minimized and the way was opened for the creation of a more robust model. Different classification models were created with single (Logistic regression, Decision Tree, Gradient Booster, Random Forest, K Nearest Neighbor, Naive Bayes and Support Vector classification) and ensemble classification (ensemble classification) algorithms. Cross-validation was used to objectively ensure the performance of the model. Accuracy, sensitivity, specificity, tp ratio, fp ratio values were calculated to compare the performance techniques of different classifiers. Fake news detection was detected with a higher success rate in the random forest classification algorithm compared to single classification algorithms. The following features were taken into account for an interesting model.

1.1 Features That Make a Pattern Interesting

In our study, an automatic pattern (model) was studied that detects the accuracy of the news in the tweets sent on Turkish texts shared on the Twitter network.

1.1.1 Easily Understandable by People

As in Section II, in the Literature study section, studies and analyzes related to the detection of fake news are given. In Section III, definitions and details of the classification algorithms used in the Method section are given. In Section IV, the results of the classification algorithms used in the previous section were obtained and compared and examined. This study focuses on the detection of fake news and the strategies and solutions used in this process. The comprehensibility factor plays a critical role in ensuring that the information in the article is understandable to a wide audience. This study addresses the issue of fake news detection in a way that everyone can understand, by focusing on methods such as avoiding complex terms, supporting with examples and using visual tools. In the fight against fake news, clear communication plays a vital role in raising public awareness and taking effective measures.

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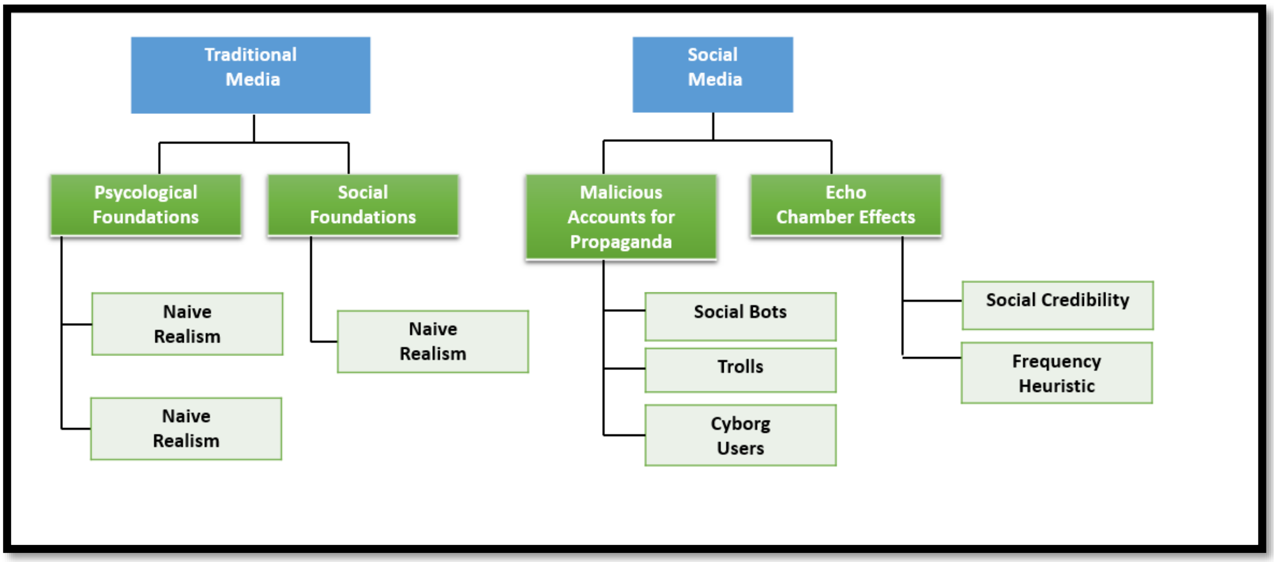

Figure 4. Types of Fake News [4]

1.1.2 Validity of the Pattern

This study focuses on detecting fake news on Twitter. We discuss new strategies for Twitter analysis and fake news detection to combat misleading information that spreads rapidly on social media platforms. The study offers a more reliable approach to combating fake news by addressing issues such as strengthening validation processes and using test data effectively to obtain highly accurate results. These strategies are an important step in increasing society's access to accurate information and reducing misleading content spread on social media.

1.1.3 Potentially Useful Pattern

This study discusses how potentially useful data can be used to detect fake news on Twitter, an important platform of social media. Detection of fake news is of critical importance in ensuring society's access to accurate information and combating misleading content. This study examines in detail the potentially useful features obtained by analyzing Twitter data and how this data can be used effectively in detecting fake news. In order to contribute to fake news detection processes, our study emphasizes the role of potentially useful data in fake news analysis.

1.1.4 Novality of the Pattern

In this study, a new perspective on the detection of fake news is presented and a model developed on Twitter data is discussed. On social media platforms, where fake news spreads rapidly, it is inevitable to adopt an approach beyond traditional methods. This study explains in detail how a new and innovative model was created and its success in detecting fake news effectively. This novel (innovative) model, developed using Twitter data, manages to stand out in fake news analysis. Additionally, experiences on real and fake test data are presented in detail in the article to concretely prove the features provided by the model.

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2. Literature review

In the literature, it can be seen that many studies have been carried out to detect fake news on social media. For example, in the studies of Mehmet Kayakuş and Fatma Yiğit Acıkgöz (2023), as a first step, they tried to obtain research and information about fake news and in the light of this information, a draft was created and the study started. Then, the semi-supervised artificial intelligence algorithm was applied to the structured fake news dataset. The data is divided into two as training and test data according to the 70 percent - 30 percent random assignment method. When the study results are examined according to the f-measure, it is seen that the Naive Bayes classification algorithm is more successful than the Decision Trees classification algorithm [16].

Taşkın and his team (2021) used machine learning-based methods in their study to detect fake news that could mislead people. Pre-processing was applied to the data set used for this purpose and fake news was detected with machine learning processes. Unsupervised learning algorithms, Non-Negative Matrix Multiplication and Linear Discriminant Analysis; Prediction was made with supervised learning algorithms, K Nearest Neighbor, Support Vector Machines and Random Forest algorithms. Successful results have been obtained in supervised learning algorithms with an f-measure value of 0.86 [17]. In their study on fake news detection with machine learning methods, Zeba and her team [18] achieved 96.8% accuracy with Naive Bayes and 99.6% accuracy with neural network and support vector machines [19]. Aswini and his team offer solutions to fake news detection with deep learning methods. The model outperforms existing architectures by 2.5% and achieves an accuracy of 94.21% on test data [20]. In the study of Fatima and his team on fake news detection, the frequency inverse document frequency (TF-IDF) term consisting of n-grams and the bagging method were used as feature extraction techniques for the dataset consisting of fake and real news. In the study, it was observed that the N gram method gave better results than the bag method and the most successful results (100% accuracy) were achieved with support vector machine algorithms [21]. Sathish and his colleagues used various machine learning algorithms to detect fake and real news. They achieved 99.7% accuracy with the decision tree [22]. In the age we live in today, fake news has become a serious problem. Identifying and stopping the spread of misinformation is of importance. In order to examine the current emotional environment, textual data must first be converted into numerical data. Using TF-IDF, textual data was converted into numerical data. Models for fake news detection were developed using decision trees, support vector machines and logistic regression classification algorithms. The study achieved a maximum accuracy of 98% with machine learning algorithms [23]. People prefer the internet to access news because it is easy and cheap. In this study, they developed models with machine learning methods using the publicly available LIAR dataset for fake news detection [24]. Fake news affects our social life in every field, especially politics and education. Various classification algorithms and machine learning models have been developed to detect fake news. Methods such as Term Frequency-Inverted Document Frequency were used for feature extraction and support vector, naive bayes, passive aggressive classifier were used as classification algorithms. The highest accuracy of 95.00% was obtained with support vector machines [26].

Fake news or unreal news that harms social integrity appears everywhere. The study enabled the detection of fake news using probabilistic latent semantic analysis. In order to detect fake and real news, different machine and deep learning techniques were compared using three different data sets. In the study, it was observed that deep learning techniques gave more successful results than machine learning techniques. In this encounter, it was observed that the Bi-LSTM algorithm gave the most successful results (95% accuracy) in detecting fake news [27]. Fake news has a huge negative impact on the majority of society. In order to detect these news, three different evaluation methods: Count Vectorizer, TF-IDF Vectorizer and N gram were used. Models for fake news detection were developed using Naive Bayes, SVM, Random Forest and Logistic Regression classification methods. The highest success rate was achieved with the SVM classifier (93% accuracy) [28]. Models have been developed with data mining methods to automate the authenticity of news received from various sources such as websites, blogs and e-content. Data mining techniques are applied to collect data, clean and visualize the data. The aim of the study is to develop models to understand misleading information. In order to detect fake news efficiently, models have been created using data mining methods to detect fake news by combining the title and text of the news [29]. In the study, it is classified using the ensemble model, which consists of three popular machine learning models, namely Decision Tree, Random Forest and Extra Tree classifier, for the detection of fake news, which achieves better accuracy compared to the current situation. While 100% accuracy was achieved for the ISOT dataset, 99.8% accuracy was achieved for the Liar dataset [30]. A classification model was developed with machine learning techniques to enable the detection and dissemination of facts. Features were extracted from the dataset using text representation models such as Bag of Words, Term Frequency-Inverse Document Frequency (TF-IDF) and bi-gram frequency. It has been observed that the TF-IDF model gives more successful results than the bag of words and TF-IDF method. Fake news has become quite common in digital media. For this purpose, Z and his colleagues developed models with machine and deep learning algorithms for the detection of fake news. Naive Bayes and Support Vector Machine were used as machine learning algorithms, and Long Short-Term Memory (LSTM), Neural Network with Keras and Neural Network with TensorFlow were used as deep learning algorithms. Accuracy, precision, recall and f-measure values were included in the performance comparison of the models. The results have shown that deep learning algorithms provide more successful results than machine learning algorithms. The highest accuracy rate was obtained with the LSTM model (92.99%) [31]. Khaled and his colleagues developed models using Machine and Deep Learning methods to detect fake news in the Arabic language. LSTM, bidirectional LSTM, CNN+LSTM, and CNN+BiLSTM methods were used as deep learning models. Experiments were carried out using three different data sets. It was observed that the BiLSTM model performed better than other models in terms of accuracy [32]. Fake and Misleading content always misleads people, causing turmoil in public life. In Bengali, models were created with machine learning algorithms to detect fake news. This algorithm uses TF-IDF method for feature extraction. Feature selection was made with Extra Tree Classifier.

Feature selection was made with Extra Tree Classifier. An 87% accuracy rate was achieved with the Gaussian Naive Bayes classification algorithm [33].

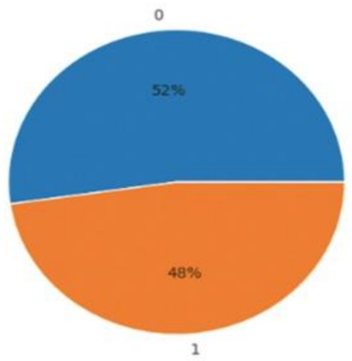

Figure 5. Ratio of Fake News to Real News [4]

In this study, we discuss a creative model developed on Twitter data by bringing a different perspective to this field regarding the detection of fake news. In today's social media platforms, where fake news spreads rapidly, it is very important to adopt an approach other than traditional methods. This study explains in detail how a new, understandable and innovative model was created and highlights the success of this model in effectively detecting fake news. This new model, developed with the use of Twitter data, manages to stand out in fake news analysis. In addition, the article presents in detail the experiences made on real and test data in order to concretely prove the features provided by the model.

3. Method

3.1 Data set

In this study, it is aimed to detect tweets containing real and fake news spread on Twitter on a certain subject with artificial intelligence. Within the scope of this research, a topic that was trending on Twitter and contained fake news was selected. The data set was divided into training and test data using the K Fold Cross Validation (K=2) method. The training data was used to define and learn the parameters of the model. Figure 5 shows the ratio of total fake and real news in this data set. Table 1 shows 5 examples of the first version of our data set.

3.1.1 Getting Data from Twitter and Topic Selection

The tweets sent regarding this issue were referenced from the Kaggle study called "fake news detection". After text pre-processing and analysis were carried out on the determined tweet messages, two categories were created: real and fake news. These categories are classified as real and fake. There are four attributes in the real category; these are "title", "text", "subject" and "date". Title has approximately 21,000 different values. Text has approximately 21,000 different values. 53% of the tags under the Subject heading are political news, and 47% are news from the rest of the world. Date includes the period from 13-01-2016 to 31-12-2017. In total, there are approximately 42,000 pieces of data in the real and fake.

Data Preprocessing Steps

In this study, KDD (Knowledge Discovery in Databases) steps were applied, KDD refers to the data mining process and consists of several stages [18].

The KDD stages are;

1. Data Cleansing: The data mining process usually starts with real-world data. This data may contain missing, inaccurate or inconsistent information. During the data cleaning phase, such problems are resolved and the data set is prepared.

2. Data Integration: Data from different sources should be integrated. Data integration involves combining, adapting, and bringing together data sets.

3. Data Selection: This is the stage of selecting relevant data features and subsets. This involves selecting data that suits the purpose of analysis.

4. Data Transformation: The data set is transformed through processes such as itemization and normalization. This can help the dataset be more effective in the modeling stages.

5. Data Mining: In the data mining phase, various itemization techniques are used to discover patterns, relationships or information. Algorithms such as decision trees, support vector machines and clustering can be used at this stage.

6. Pattern Evaluation: Where visualization and information presentation techniques are used to mine instant information for users

7. Presentation of Information: Where visualization and information representation techniques are used to present data mined information to users.

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Table 1. Initial State of the Data Set

	Title	Text	Subject	Date
0	Donald Trump Sends..	Donald Trump Just…	News	Dec 31, 2014
1	Drunk Bragging	House Intelligence…	News	Dec 31, 2017
2	Sherif David…	On Friday, it was…	News	Dec 30, 2017
3	Trump Is So…	On Christmas day…	News	Dec 29, 2017
4	Pope Francis…	Pope Francis	News	Dec 29, 2017

In our study, the steps taken to detect a pattern (Fig. 6) are given below.

- Data Cleaning: The data in this study contains missing, incorrect or inconsistent information. During the data cleaning phase, such problems were resolved and the data set was prepared. For example, the missing values were checked with the msno.bar () function and the number with missing values was found with isnull ().sum(). This phase focused on missing data, meaningless characters, or other data integrity issues.

- Data Integration: Data from different sources should be integrated. Data integration involves combining, adapting and bringing together data sets. It accomplishes this stage by combining two separate data sets containing fake and real news (with pd. concat ()).

- Data Selection: This is the phase of selecting relevant data features and subsets. This involves selecting data that suits the purpose of analysis. For example, the columns "title", "text", "subject", "date" can be selected.

- Data Transformation: The data set is transformed through processes such as itemization and normalization. This will help the dataset be more effective in the modeling stages.

- Data Mining: In the data mining phase, various itemization techniques are used to discover patterns, relationships or information. In the data set in this study, various classification methods from data mining methods are applied to create a model for the purpose of distinguishing fake and real news with the "class" column.

- Pattern Evaluation: The results obtained for "pattern evaluation" or model evaluation can be evaluated by looking at the outputs of the models included in the code (Logistic Regression, Decision Tree, Gradient Booster, Random Forest, K-Nearest Neighbors, Naive Bayes, Support Vector Machine) [18]. Model evaluation is usually done using metrics such as accuracy, precision, recall and f-measure.

- Knowledge Presentation: This is the name given to the presentation stage. It is determined whether our data is ready for presentation, and the results of the modeling are shared with the necessary visuals and explanations.

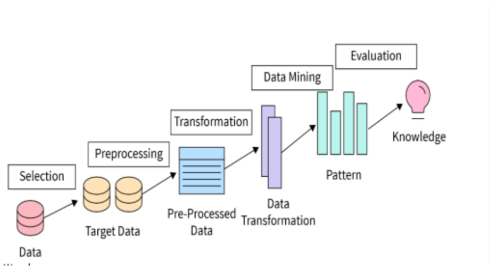

Figure 6. Fake News Detection Methodology

3.2.1 Text Preprocessing

Preprocessing method is a stage of great importance in text mining and application. In the text preprocessing step, crowded data, redundancies and useless data are cleared, thus the success of the study is expected to increase. The processes used for pre-processing are converting letters to lowercase characters, character cleaning, URL cleaning, cleaning HTML tags, cleaning new lines, cleaning numbers and digits [20]. These are different text preprocessing steps that can be done on texts in the preprocessing step. The data in the data set we use must have a common layout in a document where uppercase and lowercase letters are used. This may be caused by typos and possible errors. In text preprocessing, the uppercase or lowercase conversion process aims to change all the letters in a text so that they are all the same. Common words that do not add meaning to the relevant text, such as the use of punctuation marks, web programming codes, URLs, emoji's, frequently used and infrequently used words, are removed. Various stop word features should be extracted by analyzing stop words in the text data, that is, words that are commonly used and generally meaningless, using the list called Stopwords. Then the columns in the data frame are analyzed. cat cols: Lists containing categorical (string or category type) columns are printed one by one in our code. num cols: Lists containing numeric columns are printed as code. cat but car: Lists that are of category type but contain columns whose cardinality (number of unique values) is higher than a certain threshold value are printed as code.

3.2.2 Feature Extraction Methods

The "title", "subject" and "date" columns were extracted from the dataset, usually part of the data preprocessing step. Whether to remove or not use these attributes depends on the analysis purposes and the characteristics of the data set. We can explain the reasons for removing each of the title, title and date columns respectively as follows. The "title" usually contains text data and can contain many different words and characters. Therefore, they may need to be processed before being used directly. Title can be subjected to separate analysis, especially for use in text item modeling or natural language processing applications. However, it is possible to remove this column to focus on your original analysis. Topic titles usually refer to a specific topic or category. However, this information can already be found in the "class" column, which can be used as a target variable, especially if classification models are to be used. In this case, the "subject" column containing similar information may be unnecessary. Date can be important for time series analysis or analysis performed over specific date ranges. However, since this type of analysis is not performed and the "date" column does not affect the model, it may be preferable to remove this column. Removing columns simplifies the dataset and reduces unnecessary noise when training the model [21].

3.3 Classification

3.3.1 Supervised Machine Learning Algorithms

In this study, 7 classification algorithms were used to predict whether the news obtained from tweets on Twitter are fake or real. These; Logistic Regression Classification, Decision Tree Classification, Gradient Boosting Classification, Random Forest Classification, K Nearest Neighbor Classification, Naive Bayes [23].

3.3.2 Logistic Regression Classification (LR)

Logistic Regression is a model generally preferred for two-class (binary) classification problems. The general purpose of classification algorithms is to classify by determining the value of the dependent variable. The relationship between the sigmoid function and the coefficients in LR plays a critical role in the process of estimating the probability of the dependent variable. The results of the LR Classification algorithm's Principal Component Analysis (PCA) and K Fold approach without PCA are given in Table 2.

3.3.3 Decision Tree Classification (DT)

Decision trees are a widely used technique in the field of data mining and machine learning. This method can be applied to both classification and regression problems and is especially preferred because it is understandable and interpretable by humans. In this study, a model was created using decision tree classification and predictions were made on test data. The algorithm works by splitting the dataset and creating a custom classification model for each subset. The success of the model is strictly evaluated and the classification report reveals the results. The results obtained with the K-Fold Approach with PCA. The results of the DT classification algorithm with PCA and the K-Fold approach without PCA are given in Table 2.

3.3.4 Random Forest Classification (RF)

Random Forest Classification Method is an ensemble learning technique in which many decision trees are brought together. This methodology adopts an approach where each tree is trained independently and the overall model is obtained by taking the average or mode of the predictions of these trees. The main purpose of Random Forest is to obtain a more general and reliable model by reducing the tendency of a single decision tree to overfit. The exact success of the model is evaluated and the classification report is displayed as a result. The K Fold

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approach results of the RF classification algorithm with PCA and without PCA are given in Table 2.

3.3.5 Gradient Boosting Classification (GBT)

Gradient Boosting is known as an ensemble learning technique and aims to create a strong model by combining weak decision trees. This method improves the success of the model by sequentially adding weak decision trees using an error reduction strategy. A frequently used application of Gradient Boosting is decision trees called Gradient Boosted Trees (GBT), which are especially preferred for classification and regression problems. The accuracy of the model is evaluated and presented as a classification report. The PCA and K Fold approach results of the GBT classification algorithm without PCA are given in Table 2.

3.3.6 K Nearest Neighbor Algorithm (KNN)

K-Nearest Neighbors (KNN) is a machine learning algorithm used for classification and regression problems. KNN is a simple and effective algorithm and performs especially well on small-sized datasets. The success of the model is evaluated with precision and the classification report is printed as a result. The PCA and K Fold approach results of the GBT classification algorithm without PCA are given in Table 2.

3.3.7 Naive Bayes Classification (NB)

Naive Bayes classifier is based on Bayes Theorem. Bayes' Theorem is a theorem that updates the probability of an event occurring with information from another context. Naive Bayes Lemma: The "naive" statement assumes independence between each feature of the model. That is, the presence or absence of one feature does not affect the presence or absence of other features. Text Data and Feature Extraction: While working on text data, it is first necessary to convert the text data into features. This is usually done using methods such as "TF-IDF" (Term Frequency-Inverse Document Frequency). Classification: Naive Bayes classifier creates a model using feature vectors and class labels. Feature vectors on text documents can be word frequencies or TF-IDF values. When a test data arrives, the Naive Bayes model calculates the probability that this data belongs to each class. Then, it classifies this data into the class with the highest probability. The success of the model is evaluated with precision and the classification report is printed as a result. The results of the NB classification algorithm's PCA and K Fold approach without PCA are given in Table 2.

3.3.8 Binary Classification Using Support Vector Machines (SVM)

Support Vector Machines (SVM) is a machine learning algorithm used especially for classification and regression problems. Essentially, it tries to create a hyperplane to separate classes in a given data set. The goal of SVM in the binary classification task is to find a hyperplane that best separates two classes in the dataset. A hyperplane is a plane in feature space that divides a subspace into two classes. The success of SVM in classifying data points belonging to a particular class depends on the distance of these points from the hyperplane. The success of the model is evaluated with precision and the classification report is printed as a result. The results of the NB classification algorithm's PCA and K Fold approach without PCA are given in Table 2.

3.4 Performance Metrics

The confusion matrix (Fig.7), also known as the error matrix, is a special tabular layout that allows visualizing the performance of a classification model. Various performance measures are used to determine the classification ability of machine learning algorithms. Statistical values such as accuracy, precision, sensitivity, recall and f-measure provide detailed information about prediction in classification performance measurements. The definitions and formulas of these statistical criteria are given below, respectively.

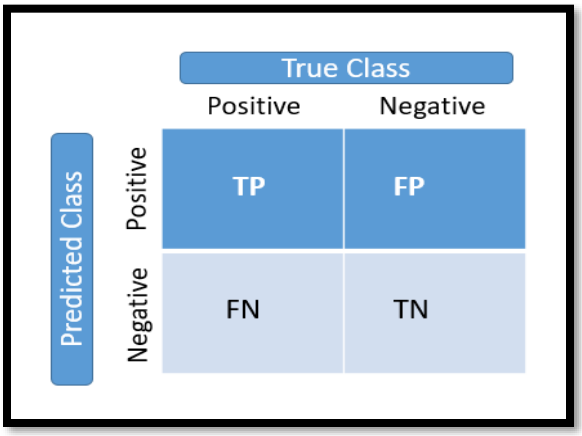

Figure 7. The Basic Structure of a Confusion Matrix

True Positive: A classification model correctly predicts the positive class.

True Negative: A classification model correctly predicts the negative class.

False Positive: This is when a classification model predicts a negative class as positive.

False Negative: This is when a classification model predicts a positive class as negative.

True Positive rate: The proportion of all negatives that yield positive test results.

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

Accuracy: It refers to the rate at which a classification model correctly predicts a positive and negative class, in other words, the proportion of data that is correctly predicted among all data.

$$Accuracy = \frac{\text{TP} + \text{TN}}{TP + TN + FP + FN} \tag{2}$$

Sensitivity: It is the rate at which a classification model finds positive examples among all positive examples.

$$Sensitivity = \frac{\text{TP}}{TP + FN} \tag{3}$$

Specificity: It is the rate at which a classification model finds negative examples among all negative examples.

$$Specificty = \frac{\text{TN}}{TN + FP} \tag{4}$$

Recall: Total positive samples are the rate at which they are predicted as positive.

$$Recall = \frac{\text{TP}}{TP + FN} \tag{5}$$

Precision: The rate at which all predicted positive samples are actually positive.

$$Precision = \frac{\text{TP}}{TP + FP} \tag{6}$$

F- Measure: It is the harmonic mean of Precision and Recall values. Since it takes into account False Positive and False Negative results, it is an effective parameter in showing the classification performance of an unbalanced data set.

$$F - Measure = 2 * \frac{\text{Precision} * \text{Recall}}{Precision + Recall} \tag{7}$$

3.4.1 Validation Method

To best evaluate the model performance, the data is divided into two sections: training and testing. While the model is trained with training data, the performance of the model is measured with test data. In this study, k-fold cross-validation (Fig.8) was used to ensure accurate classification performance. This method divides the data into k parts. Each piece is taken as test data in turn and the other pieces are used as training data. After K stages, an average overall performance measure is obtained by taking into account the performances calculated at each stage.

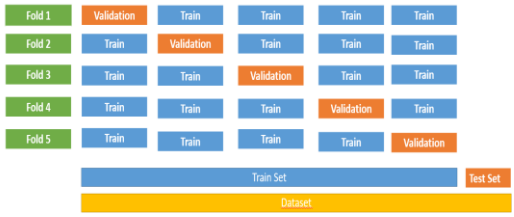

Figure 8. The Basic Structure of a Cross Validation

4. Experimental Results

In this study, the tweets sent on Twitter were recompiled with reference to the Kaggle study called fake news detection, re-examined with new codes and the results of the data set were examined by using classification methods from a different perspective. After the data pre-processing steps on the dataset were carried out on the determined tweet messages, two categories were created under the name of real and fake news. These are categorized as real and fake. There are 4 attributes in the real category, these are; title, text, subject, date. Title has approximately 21,000 unique values. Text has approximately 21,000 unique values. 53% of the tags under the Subject heading are political news and 47% are news from the rest of the world. Date includes the period from 13-01-2016 to 31-12-2017. In total, there are approximately 42,000 pieces of data in the real and fake categories. By applying KDD steps to these data, the data is made more compact, for example; After examining the data set, some preliminary processing was carried out on news headlines and text contents. Special characters, websites, HTML tags, etc. has been cleared. Then, TF-IDF vectorization was used to divide the data into training and test sets and convert the text data into numbers. Next, we train a Logistic Regression model with these vectors. This makes it easier to handle. Later, 7 different classification algorithms were used in this study. These classification algorithms used were Logistic Regression Classification, Random Forest Classification, Decision Tree Classification, Gradient Boosting Classification, K Nearest Neighbor Classification, Naive Bayes, Support Vector Classification algorithms. Training and test data are separated for machine learning, texts are converted into vectors and classification algorithm codes are written. Precision value expresses the proportion of predictions made by an algorithm that are actually correct. Especially in the fake and real news detection problem, it shows how much of the fake news in the data set is correctly identified. A high precision value indicates that the algorithm is successful in correctly classifying fake news.

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Table 2. Performance Results of Classification Algorithms

Logistic Regression Classification (PCA ON)

	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.54	0.53	0.53	0.55	0.72	0.37	0.72	0.62
Fold2	0.54	0.52	0.52	0.56	0.74	0.36	0.74	0.63
Fold3	0.56	0.55	0.55	0.57	0.74	0.39	0.74	0.60
Fold4	0.55	0.54	0.54	0.55	0.69	0.41	0.69	0.58
Fold5	0.54	0.52	0.56	0.54	0.70	0.37	0.70	0.62
Average	0.55	0.55	0.56	0.56	0.72	0.38	0.72	0.62

Logistic Regression Classification (PCA OFF)

	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.62	0.62	0.62	0.64	0.75	0.75	0.75	0.79
Fold2	0.63	0.62	0.62	0.63	0.77	0.77	0.77	0.49
Fold3	0.61	0.61	0.61	0.61	0.74	0.74	0.74	0.51
Fold4	0.62	0.62	0.62	0.62	0.72	0.72	0.72	0.47
Fold5	0.63	0.62	0.62	0.63	0.73	0.73	0.73	0.47
Average	0.63	0.64	0.63	0.62	0.75	0.51	0.75	0.49

Decision Tree Classification (PCA OFF)

	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.69	0.69	0.69	0.69	0.65	0.65	0.65	0.26
Fold2	0.67	0.67	0.68	0.63	0.63	0.63	0.63	0.28
Fold3	0.68	0.68	0.68	0.67	0.67	0.67	0.67	0.30
Fold4	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.30
Fold5	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.32
Average	0.69	0.69	0.69	0.69	0.67	0.70	0.67	0.30

Decision Tree Classificatiob (PCA ON)

	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.71	0.71	0.71	0.71	0.70	0.73	0.70	0.26
Fold2	0.70	0.70	0.70	0.70	0.67	0.73	0.67	0.26
Fold3	0.69	0.69	0.69	0.69	0.68	0.71	0.68	0.28
Fold4	0.69	0.69	0.69	0.70	0.65	0.74	0.65	0.25
Fold5	0.69	0.69	0.69	0.69	0.65	0.72	0.65	0.27
Average	0.70	0.70	0.70	0.70	0.67	0.73	0.67	0.27

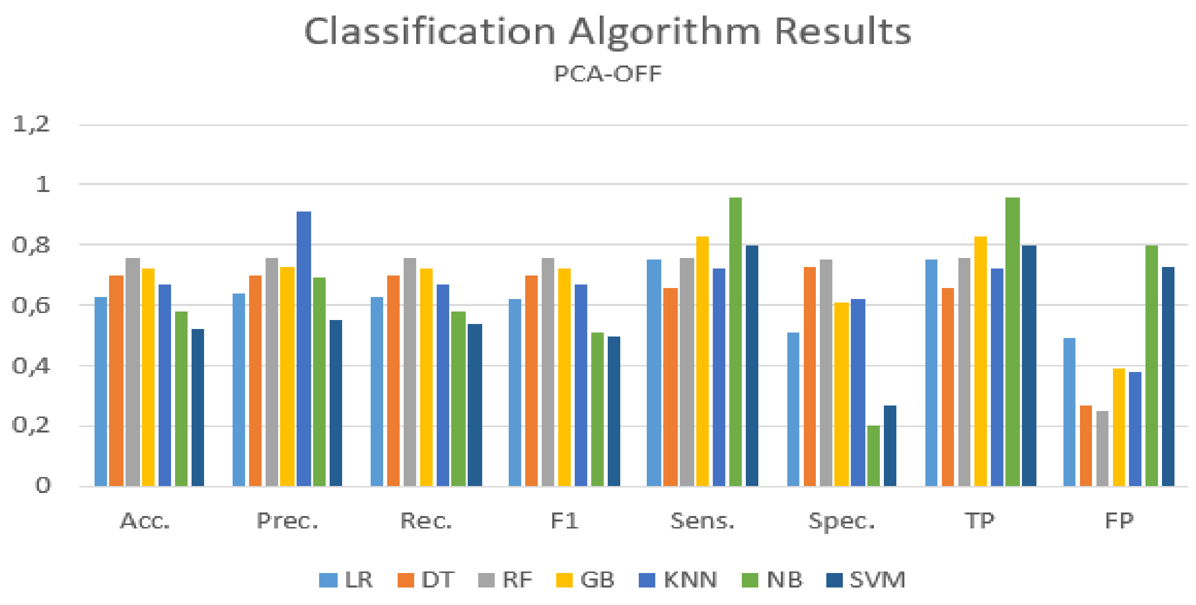
Random Forest Classification (PCA ON)

	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	**0.75**	**0.75**	**0.75**	**0.75**	**0.79**	**0.72**	**0.79**	**0.27**
Fold2	**0.72**	**0.71**	**0.72**	**0.72**	**0.72**	**0.71**	**0.72**	**0.28**
Fold3	**0.75**	**0.75**	**0.75**	**0.75**	**0.79**	**0.71**	**0.79**	**0.28**

Fold4	**0.74**	**0.74**	**0.74**	**0.74**	**0.78**	**0.70**	**0.78**	**0.29**
Fold5	**0.75**	**0.75**	**0.75**	**0.75**	**0.79**	**0.71**	**0.79**	**0.28**
Average	**0.75**	**0.75**	**0.75**	**0.75**	**0.78**	**0.71**	**0.78**	**0.29**
Random Forest Classification (PCA OFF)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	**0.75**	**0.75**	**0.75**	**0.75**	**0.79**	**0.72**	**0.79**	**0.27**
Fold2	**0.75**	**0.75**	**0.72**	**0.72**	**0.72**	**0.71**	**0.72**	**0.28**
Fold3	**0.76**	**0.76**	**0.75**	**0.75**	**0.79**	**0.71**	**0.79**	**0.28**
Fold4	**0.76**	**0.76**	**0.74**	**0.74**	**0.78**	**0.70**	**0.78**	**0.29**
Fold5	**0.74**	**0.74**	**0.75**	**0.75**	**0.79**	**0.71**	**0.79**	**0.28**
Average	**0.76**	**0.76**	**0.76**	**0.76**	**0.76**	**0.75**	**0.76**	**0.25**
Gradient Boosting Classification (PCA ON)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.73	0.72	0.73	0.73	0.82	0.63	0.82	0.36
Fold2	0.70	0.70	0.70	0.71	0.79	0.61	0.79	0.38
Fold3	0.72	0.71	0.72	0.73	0.84	0.60	0.84	0.39
Fold4	0.72	0.72	0.72	0.73	0.83	0.60	0.83	0.39
Fold5	0.73	0.73	0.73	0.75	0.85	0.62	0.85	0.37
Average	0.71	0.72	0.72	0.74	0.83	0.62	0.83	0.38
Gradient Boosting Classification (PCA OFF)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.71	0.71	0.71	0.72	0.81	0.81	0.81	0.38
Fold2	0.69	0.69	0.69	0.70	0.78	0.78	0.78	0.39
Fold3	0.71	0.71	0.71	0.73	0.84	0.84	0.84	0.39
Fold4	0.73	0.73	0.73	0.74	0.85	0.85	0.85	0.38
Fold5	0.73	0.72	0.73	0.74	0.85	0.85	0.85	0.39
Average	0.72	0.72	0.72	0.73	0.83	0.61	0.83	0.39
K Nearest Neighbor Classification (PCA ON)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.68	0.67	0.68	0.68	0.73	0.63	0.73	0.36
Fold2	0.65	0.65	0.50	0.65	0.70	0.60	0.70	0.39
Fold3	0.67	0.67	0.67	0.67	0.73	0.62	0.73	0.37
Fold4	0.65	0.65	0.65	0.65	0.70	0.60	0.70	0.39
Fold5	0.68	0.68	0.68	0.68	0.72	0.63	0.72	0.36
Average	0.67	0.67	0.67	0.67	0.72	0.62	0.72	0.38
K Nearest Neighbor Classification (PCA OFF)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.68	0.68	0.68	0.68	0.73	0.63	0.73	0.36

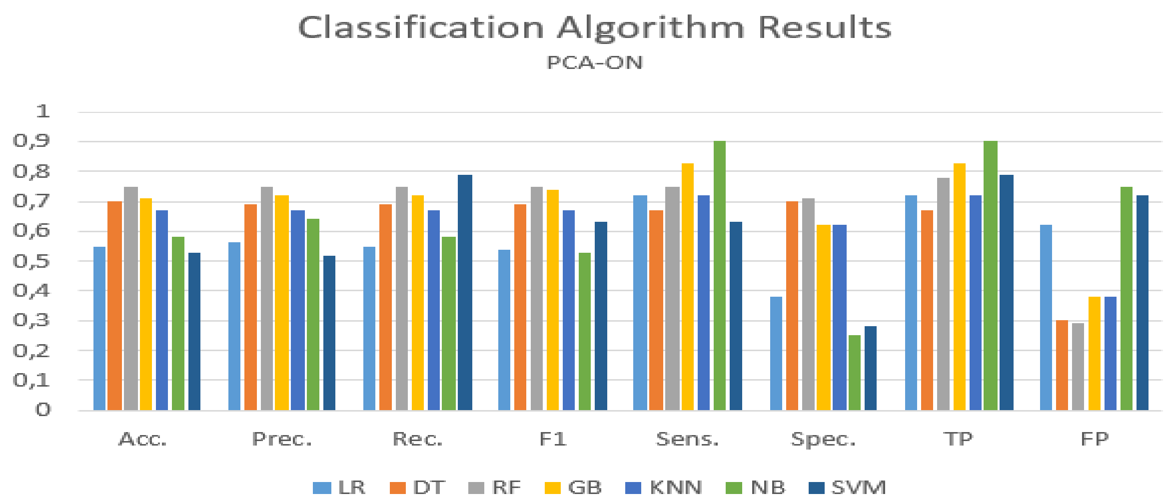
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold2	0.65	0.65	0.50	0.65	0.70	0.60	0.70	0.39
Fold3	0.67	0.67	0.67	0.67	0.73	0.62	0.73	0.37
Fold4	0.65	0.65	0.65	0.65	0.70	0.60	0.70	0.39
Fold5	0.68	0.68	0.68	0.68	0.72	0.63	0.72	0.36
Average	0.67	0.67	0.67	0.67	0.72	0.62	0.72	0.38
Naive Bayes Classification (PCA ON)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.58	0.53	0.58	0.65	0.91	0.25	0.91	0.74
Fold2	0.57	0.52	0.57	0.62	0.89	0.24	0.89	0.75
Fold3	0.56	0.51	0.56	0.62	0.90	0.24	0.90	0.75
Fold4	0.58	0.52	0.58	0.63	0.91	0.22	0.91	0.77
Fold5	0.58	0.54	0.58	0.64	0.90	0.27	0.90	0.72
Average	0.58	0.53	0.58	0.64	0.90	0.25	0.90	0.75
Naive Bayes Classification (PCA OFF)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.57	0.49	0.57	0.68	0.96	0.18	0.96	0.81
Fold2	0.57	0.50	0.57	0.68	0.95	0.20	0.95	0.79
Fold3	0.56	0.48	0.56	0.67	0.95	0.18	0.95	0.81
Fold4	0.60	0.53	0.60	0.70	0.96	0.21	0.96	0.81
Fold5	0.58	0.51	0.58	0.70	0.96	0.20	0.96	0.78
Average	0.58	0.51	0.58	0.69	0.96	0.20	0.96	0.79
Support Vector Machines (PCA ON)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.52	0.62	0.80	0.51	0.80	0.80	0.80	0.75
Fold2	0.52	0.62	0.81	0.50	0.81	0.81	0.81	0.74
Fold3	0.52	0.62	0.79	0.50	0.79	0.79	0.79	0.74
Fold4	0.55	0.63	0.74	0.55	0.74	0.74	0.74	0.66
Fold5	0.54	0.63	0.77	0.53	0.77	0.77	0.77	0.70
Average	0.53	0.63	0.79	0.52	0.79	0.28	0.79	0.72
Support Vector Machines (PCA OFF)								
	Accuracy	F-measure	Recall	Precision	Sensivity	Specificty	TP Rate	FP Rate
Fold1	0.53	0.50	0.53	0.55	0.81	0.26	0.81	0.73
Fold2	0.54	0.50	0.54	0.55	0.80	0.27	0.80	0.72
Fold3	0.50	0.47	0.50	0.51	0.75	0.26	0.75	0.73
Fold4	0.56	0.53	0.56	0.57	0.82	0.28	0.82	0.71
Fold5	0.52	0.49	0.52	0.53	0.78	0.27	0.78	0.72
Average	0.54	0.50	0.54	0.55	0.80	0.27	0.80	0.73

Figure 9. Classication Algorithm Results (PCA-OFF)



Classification Algorithm Results

Figure 10. Classification Algorithm Results (PCA-ON)



Classification Algorithm Results

The higher this metric is, the higher the success of the algorithm in correct labeling, and in our algorithm, the Random Forest Classifier gave the highest precision value. Its value is 0.76. In fact, in this study, a system that enables automatic detection of fake news was used. This system attracts attention with its ability to identify fake news in a short time. In this way, it is possible to quickly detect fake news and prevent its spread. While the accuracy score of the model obtained without using PCA of Random Forest Classification was 0.76, the accuracy rate after applying PCA was determined as 0.75. These results indicate higher precision values than the other six algorithms included in the study.

The purpose of PCA is to preserve the data and transform the data set into a subspace that can be expressed with fewer variables. For this purpose, observations were made to see whether there was a performance difference in the classification algorithms of PCA, one of the widely used dimension reduction methods. The classification performance results obtained without using PCA-OFF and using PCA-ON are given in the graphs. It has been observed that PCA classification algorithms do not have a performance-enhancing effect. The highest success results were observed with the random forest classification algorithm, which includes more than one classification algorithm.

As stated in Table 2, Figure 9 and Figure 10 and , the average performance results of the classification algorithms are as follows.

- By applying PCA of the Logistic Regression classification algorithm, the average performance results obtained are as follows, respectively. Accuracy is 55%, f-measure is 55%, recall is 56%, precision is 56%, sensitivity is 72%, True Positive is 72%, False Positive is 62%. Average performance without PCA the results are as follows. Accuracy 63%, f-measure 64%, recall 63%, precision 62%, sensitivity 75%, specificity 51%, True Positive 75%, False Positive 49%.

- The performance results of the Decision tree classification algorithm without applying PCA are as follows: Accuracy 69%, f-measure 69%, recall 69%, precision 69%, sensitivity is 67%, specificity is 70%, True Positive is 67%, False Positive is 30%. Average performance with PCA are results are as follows. Accuracy 70%, f-measure 70%, recall 70%, precision 70%, sensitivity 67%, specificity 73%, True Positive 67%, False Positive 27%.

- The average performance results obtained with applying the Random Forest classification algorithms are as follows, respectively. Accuracy 75%, f-measure 75%, recall 75%, precision 75%, sensitivity is 78%, specificity is 71%, True Positive is 78%, False Positive is 29%. Average performance without PCA are as follows, respectively. Accuracy 76%, f-measure 76%, recall 76%, precision 76%, sensitivity 76%, specificity 75%, True Positive 76%, False Positive 25%.

- Average performance results obtained applying the Random Forest classification algorithm principal component analysis are as follows, respectively. Accuracy 75%, f-measure 75%, recall 75%, precision 75%, sensitivity is 78%, specificity is 71%, True Positive is 78%, False Positive is 29%. Average performance obtained by applying principal component analysis The results are as follows. Accuracy 76%, f-measure 76%, recall 76%, precision 76%, sensitivity 76%, specificity 75%, True Positive 76%, False Positive 25%.

- The average performance results obtained with the Gradient Boosting classification algorithm with PCA are as follows, respectively. Accuracy 71%, f-measure 72%, recall 72%, precision 74%, sensitivity is 83%, specificity is 62%, True Positive is 83%, False Positive is 38%. The average results of gradient classification algorithm without PCA are as follows. Accuracy 72%, f-measure 72%, recall 72%, precision 73%, sensitivity 83%, specificity 61%, True Positive 83%, False Positive 39%.

- Average performance of KNN with PCA are as follows, repectively. Accuracy 67%, f-measure 67%, recall 67%, precision 67%, sensitivity is 72%, specificity is 62%, True Positive is 72%, False Positive is 38%. Average performance without PCA analysis are as follows. Accuracy 67%, f-measure 67%, recall 67%, precision 67%, sensitivity 72%, specificity 62%, True Positive 72%, False Positive 38%.

- The average performance results of Naive Bayes classification algorithm with PCA are as follows, respectively. Accuracy 58%, f-measure 53%, recall 58%, precision 64%, sensitivity is 90%, specificity is 25%, True Positive is 90%, False Positive is 75%. Average performance without PCA are as follows. Accuracy 58%, f-measure 51%, recall 58%, precision 69%, sensitivity 96%, specificity 20%, True Positive 96%, False Positive 79%.

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- Average performance results of Support Vector Machine classification algorithm with PCA, obtained are as follows, respectively. Accuracy is 53%, f-measure is 63%, recall is 79%, precision is 52%, sensitivity is 79%, specificity is 28%, True Positive is 79%, False Positive is 72%. Average performance without PCA are as follows. Accuracy 54%, f-measure 50%, recall 54%, precision 55%, sensitivity 80%, specificity 27%, True Positive 80%, False Positive 73%.

5. Discussion

As seen in Table 3, many studies have been conducted to detect fake news. Although the performance results obtained are high, the models are not reliable and robust. The models are not robust due to reasons such as the unbalanced creation of data sets, not applying the cross-validation method and the inability to apply pre-processing methods throughout the study. In this study, the number of fake and real news data samples was selected equally, pre-processing methods were applied, and models were created with individual and ensemble classification algorithms. Cross-validation was used. Many performance metrics such as accuracy, sensitivity, specificity, tp rate, fp rate and f-measure were extracted and the models were compared. An original and reliable model has been created with follow-up steps to detect fake news.

Table 3. Classification Algorithm Results of Other Studies

Referans Study	Classificiation Algorithms	Result
Taşkın et al.	Non-Negative Matrix Multiplication, Linear Discriminant Analysis, K Nearest Neighbor Support Vector Machine Random Forest	f-measure 0.86
Zeba et al.	Naive Bayes Support Vector Machine	Accuracy 99.6%
Satish et al.	Decision Tree	Accuracy 99.7%
Nagaraji et al.	Support Vector Machine	Accuracy 95.00%
Asaad et al.	Bi-LSTM	Accuracy 95.00%
Alameri et al.	Naive Bayes, SVM, Random Forest, Losgistic Regression	Accuracy 93.00%
Akdeniz et al.	Naive Bayes, Support Vector Machine, LSTM, Neural Network,	Accuracy 92.99
Our method	Individual classifier (Logistic regression, decision tree, gradient boosting, random forest, k nearest neighbor, naïve bayes and support vector machine) and ensemble classification algorithm	Accuracy 76%

6. Conclusion

According to research, the rate of exposure of people in Türkiye and around the world to fake news is quite high. In addition, it has been observed that the ability to distinguish fake news is low. Additionally, considering that fake news spreads rapidly, especially within the first 2 hours after it is shared, it is of great importance to use automatic detection systems to detect fake news. Supervised learning algorithms perform clustering based on labeled data sets. In this study, the task of finding 2 clusters (real, fake) categorized in each subject was given to supervised learning algorithms. A method of 5-fold cross validation was adopted for conducting random sampling of the training and test data sets. Real and fake news clusters were determined by 7 different supervised learning algorithms using the training set. The resulting clusters were determined to be real or fake news by the clustering purity method. According to the model results obtained by classification methods without using PCA, Random Forest classification algorithm; It has a higher precision value than LR, DT, GB, KNN, NB and SVM algorithms and its value is 0.75. According to the model results obtained by classification methods using PCA, Support vector classification algorithm; According to classification results such as LR, DT, GB, KNN and NB, it has the lowest precision value and its value is 0.53. It is observed that the different supervised classification algorithms used in this study show superior performance compared to the referenced articles by separating the data from different numbers of test data. It is unique in terms of the methods applied in pattern formation. For example; Careful analyzes were made at every stage of the formation of the pattern and appropriate methods were determined. In summary, the use of labeled data in this study appears to make supervised learning algorithms advantageous in terms of the ability to more effectively resolve similarities between data with the same labels. In order to optimize f-measure values, it may be necessary to examine in detail the people followed by users on social media platforms and the accounts followed by these people. During this review, it may be taken into consideration whether the accounts are bots, fake or accounts opened for propaganda purposes. For this reason, friendship graph will be used in future studies and this graph will be given as input to the automatic detection system, aiming to further increase the success of the algorithm.

Author's Contributions

Gülay ÇİÇEK: She served as article consultant. A road map was drawn to solve the problem. Revision has been carried out. Updates have been provided to the article.

Başar YILDIRIM: Participated in data preparation, coding and writing.

Batuhan BATTAL: Participated in data preparation, and writing.

Ömer Faruk DİNÇASLAN: Participated in data preparation and writing.

Ethics

There are no ethical issues after the publication of this manuscript.

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