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Deep Learning Based Fake News Detection on Social Media

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Abstract—Social media platforms become indispensable channels to discover the latest news by the Internet users. Millions of news is broken first, spread faster, and reach larger communities on these platforms in a very short time compared to traditional media organs. However, in contrast to traditional media, social media platforms lack of security in terms of control mechanisms to verify the reliability and accuracy of the disseminated news. This brings the need for automatic fake news detection systems for these platforms to prevent or reduce spread of false information. In this paper, we study the problem of fake news detection on social media for two languages, both of them having distinct linguistic features: Turkish and English. In this regard, we create the first real-world public dataset of Turkish fake and real news tweets, named SOSYalan, to the best of our knowledge. For English language, we carry out experiments with two benchmark datasets, BuzzFeed and ISOT. We develop deep learning based fake news detection systems for both of Turkish and English languages based on convolutional neural networks (CNN), and recurrent neural networks-long short term memory (RNN-LSTM) approaches with Word2vec embedding model. We evaluate the developed systems in terms of accuracy, precision, recall, F1-score, true-negative rate, false-positive rate, and false-negative rate metrics. The results demonstrate that the developed systems for English language produce accuracy rates ranging from 85.16% to 99.9% which are higher than the most of the existing state-of-the-art studies. Additionally, the accuracy rates of our systems developed for Turkish language ranges from 87.14% to 92.48%, and confirms the superiority of them in comparison to very few studies conducted in this area.

Keywords—fake news detection, social media, deep learning, information security

1. Introduction

With the advent of Internet, the communication patterns of the people have changed. Social media platforms like Facebook, Twitter, and Instagram are started to be used for real-time information sharing and following the latest news about the current events [1]. A recent survey conducted in 2020 shows that more than half of the respondents uses social media to share and follow news [2]. However, due to the increasing popularity of social media users, these platforms have become suitable for spreading of fake news, because there are no verification mechanisms for the shared information on these platforms. Moreover, fake news spread quite fast on these platforms because of the fast information diffusion characteristic of them [3].

Spread of the fake news creates potential information security threats for multiple communities ranging from organizations to the government in a country. For example, misinformation about the

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origin and spreading way of the COVID-19 has caused people to be misled about the protection ways when the virus first appeared. Also, it is known that false claims about the COVID-19 vaccines cause most people to be 'anti-vaxxer' who opposes the government regulations mandating vaccination. Spread of fake news during COVID-19 pandemic has increased around the world so much that a new word 'infodemic' has been defined by WHO (World Health Organization) meaning 'fake news epidemic'[4].

As for the rest of the world, spread of fake news on social media has started to be talked about more in Turkey, especially after COVID-19 pandemic. According to a recent report published by Reuters Institute Turkey ranks first among the countries where disinformation and fake news are most common [5]. This finding highlights the need for automatic systems distinguishing fake news from real ones for Turkish language.

1.1. The novelty and contributions of our study

In the literature, there are many studies proposing FNDSs (fake news detection systems) which are tested for only one specific language, mostly for the English. Therefore, they generally do not compare the performance of their FNDSs on different languages.For Turkish language, unfortunately, there are very few studies. The very first example of a Turkish FNDS is proposed in [6]. However, it is not intended to detect fake news on social media. Instead, it tries to classify long-form of news published in other online platforms, such as websites, as either fake or valid. Nevertheless, the FNDSs presented in that study may not be used for detecting fake news on social media, because linguistic features of the social media posts are considerably different from website articles [7]. In another study, Taşkın et al. developed an FNDS for Turkish posts on social media by using supervised and unsupervised machine learning algorithms [8]. However, they considered only 3 events while developing their FNDS. That is, they collected fake and real news posted about only these certain events, and trained and tested their FNDS for only these topics. In this work, we study the problem of fake news detection on social media for two different languages, both of them having distinct linguistic features: Turkish and English. In this regard, we develop deep-learning based two FNDSs for both Turkish and English languages. This study contributes to the literature regarding the following aspects:

- This is the first attempt, to the best of our knowledge, proposing deep learning based novel FNDSs for both Turkish and English languages, developed and tested for many different topics and contexts posted on social media platforms.
- For Turkish language, we create a real-world public dataset of fake and real news tweets on many different domains for the first time in the literature, to the best of our knowledge. Existing Turkish fake news detection studies either use datasets containing long-form of news published in online platforms other than social media, or they use datasets of social media posts containing fake and real news only on specific topics and events. However, the FNDSs trained on the specific domains would not produce optimal results when they encounter news from different domains. Our dataset named SOSYalan, contains fake and real news tweets on many different topics so that FNDSs trained with it will be applicable to generic domains for Turkish language.
- For both of Turkish and English languages; we develop two different deep learning based FNDSs by implementing CNN and RNN-

LSTM algorithms with Word2vec word embedding model.
- We evaluate performance of the developed FNDSs in terms of accuracy, precision, recall, F1 score, true-negative rate, false-positive rate, and false-negative rate metrics; and compare them with the existing literature and reveal their strengths and important aspects.

The rest of the paper is organized as follows. Section 2 summarizes related works. Section 3 presents proposed deep learning based FNDSs to detect fake news on social media. In Section 4, experimental results are presented, developed FNDSs are evaluated in terms of their performance, and comparisons with the existing literature are given. Finally, in Section 5, the findings are summarized and suggestions for future studies are presented.

2. Related Works

There are many studies in the literature proposing FNDSs developed for English language, while there are very few efforts in the field of Turkish language. In this study, we categorize existing FNDSs developed for social media platforms under two classes: (i) FNDSs for English language, and (ii) FNDSs for Turkish language. In the following subsections, we explain the systems developed for each language in more detail, explain the differences among those systems in terms of linguistic features, and review some examples of state-of-the-art studies, briefly.

2.1. FNDSs for English language

The course of developing a fake news detection system for English language involves classical text mining steps: (i) gathering data, (ii) cleaning data and preprocessing, (iii) feature extraction and vectorization, and (iv) classification, which are followed consecutively. Researchers have focused on different features of fake news while following these steps. These features can be evaluated under three categories as (i) post-based features, (ii) user-based features, and (iii) network-based features. Post based features are mainly the words, hashtags, captions, and memes, etc. in the posts. User-based features concentrate on the features of the social media accounts, such as number of the followers, age groups, genders, and culture of the target audience. Network-based features, on the other hand, deal with connection among the accounts/individuals/groups, and followee-follower relationships to detect the spreading features of fake news on social media [9].

In this regard, Gupta et al. used post-based features to detect fake news on Twitter about COVID-19 virus. They developed different FNDSs for English and Hindi languages by using support vector machines (SVM) and Pseudo-Tagged SVM algorithms. The best results are obtained from SVM classifier with 93% accuracy rate [10]. In another study dealing with post-based features researchers aimed to make fake news detection task independent from language and data source [11]. In this direction, they worked on a data set consisting of different language groups (Latin, Germanic, Slavic) and different data sources (web sites, social media platforms). They used traditional machine learning algorithms which are naive bayes (NB), k-nearest neighbor (KNN), SVM and random forest (RF), and achieved 94% accuracy rate. Ahmad et al. focused on detecting fake news about politics by using post-based features. They obtained accuracy rates varying between 91 and 99%, and concluded that using different combinations of machine learning algorithms produces better results than using these algorithms alone [12]. Özbay and Alataş lso considered post-based features, and they used twenty-three different supervised artificial intelligence algorithms to detect fake news on social media for English language. As a result of experiments, they found that the decision tree (DT) algorithm achieved the best results in terms of the performance evaluation metrics among the algorithms they used [13]. Shu et al. presented a new fake news data repository, and they developed FNDSs by using PolitiFact and GossipCop data sets from their repository. They applied several machine learning algorithms which are support vector machines (SVMs), logistic regression (LR), Naive Bayes (NB), CNN, and social article fusion (SAF) whose accuracy results ranging between 49-72% [14].

Tacchini et al. considered user-based features and studied on classifying Facebook posts as spoofed and non-spoofed. They created a dataset from Facebook's public posts and achieved an accuracy rate exceeding 99% with LR and Harmonic BLC algorithms [15]. Kaliyar et al. considered both user-based and post-based features for detecting fake news on social media. In this context, they proposed BERT algorithm based FakeBERT classifier and compared its performance with deep learning and traditional machine learning algorithms. The results show that FakeBERT outperforms compared algorithms with 98.9% accuracy rate [16]. The authors proposed a new approach in their another study, and they developed a new classifier, EchoFakeD, which is based on tensor factorization method and deep learning. They showed that using both user and post-based features produces better results than considering these features separately [17]. Sahoo and Gupta also took user and post based features into account together, and compared the performance of LSTM to several machine learning algorithms on Facebook data. They found that LSTM gave better results by achieving accuracy rate of 99.4% [3].

In another group of study proposing an FNDS for English language, network-based features are taken into account. In this regard, Han et al. used different techniques from continuous learning to incremental training based graph neural network algorithm. They achieved the best performance with EWC technique producing the accuracy rate of 72% [18]. Okoro et al. considered user and network-based features, and they utilized human evaluations as well as artificial intelligence while developing fake news detection system [19]. As different from other studies, Monti et al. used post, user, and network-based features together in their fake news detection system developed for Twitter. They achieved 92% accuracy rate with CNN-based geometric deep learning model [20].

Reis et al. considered all three post-based, user-based, and network-based features; and developed KNN, NB, RF, SVM, and XGBoost (XGB) based FNDSs whose F1 score results ranging between 0.75 and 0.81 [21]. Jiang et al. developed several traditional machine learning deep learning based FNDSs. They used different combinations of vectorization and embedding techniques with the algorithms they used, and achieved 99.94% and 96.05% accuracy rates for the ISOT and KDnugget datasets, respectively [22]. Goldani et al. developed a CNN-based FNDS with margin loss and different word embedding techniques. The results showed that their FNDS outperformed baseline approaches in terms of accuracy by 7.9% and 2.1% for the ISOT and LIAR datasets, respectively [23]. The authors proposed a capsule neural networks based FNDS in their another study, and they reported that this approach outperforms the same baseline approaches in terms of accuracy by 7.8% and 3.1% for the same datasets [24]. Hakak et al. developed ensemble machine learning based FNDSs by applying decision tree, random forest and extra tree classifiers. Experimental results showed that they achieved better accuracy rates compared to the state-of-the-art, and their FNDSs perform 100% accuracy rate for the ISOT dataset [25].

Unlike the studies summarized above, Vishwakarma et al. analyzed fake news in the form of images by exploring and checking credibility of them on the top 15 Google search results. Instead of developing a machine learning based FNDS, they classified an event as real or fake by calculating a reality parameter which is based on Google search index determined according to the reliability rank of the web sites with that image based news [26].

2.2. FNDSs for Turkish language

As mentioned in Section 1, there are very few studies proposing an FNDS for Turkish language.

In [6], which is the very first example of a Turkish FNDS, Mertoğlu created a real dataset containing fake and real news, and developed 5 different traditional machine learning based classifiers which are k-nearest neighbors, multinomial naïve bayes, support vector machines, logistic regression, and decision trees. However, the FNDSs developed in [6] were not intended to detect fake news on social media. Instead, they try to detect long-form of fake news published in other online platforms such as the websites like teyit.org. The FNDSs presented in that study may not be used for detecting fake news on social media, because linguistic features of the social media posts are considerably different from website articles. For example, unlike website articles, social media posts are less topic-focused, contain noise and much less words.

On the contrary, Taşkın et al. [8] developed an FNDS for detecting fake Turkish news on social media. To this end, they used post-based features along with network-based features obtained from social media analysis methods. They developed various supervised and unsupervised classifiers to detect fake news. They achieved the best F1 score of 0.9 with SVM algorithm, and showed that following/follower network characteristics are among the most important features affecting the spread of fake news. Yet, while developing their FNDS, they considered only certain topics related to 3 events in which fake news spread the most in Turkey. That means, they trained and tested their FNDS for only these 3 topics, and generalizability of the obtained results to different topics is not evaluated.

Finally in [27], the authors investigated the reasons behind spreading false news in Turkey. Although this study did not aim to develop a fake news detection system, it tried to determine the actual features and attributes of fake news and their spreading characteristics. The results showed that emoji usage is statistically related to fake news characteristics, while usage of photos and videos is not statistically significant in fake news detection. Additionally, the study concluded that posts in Facebook are more likely to be fake news compared to Twitter and Instagram posts.

Table 1 gives the summary of state-of-the art fake news detection systems for both Turkish and English languages in the literature. In the table, existing systems are summarized according to their language, classification approach (traditional machine learning (ML) or deep learning (DL)), dataset used, accuracy results, contributions and limitations. From the above analysis and Table 1, we can conclude that the most of these efforts propose an FNDS for only one specific language, mostly for the English. Therefore, they generally do not compare the performance of their FNDSs on different languages. The systems proposed for detecting Turkish fake news, on the other hand, do not either developed for social media platforms, or they are use-case based FNDSs tested for certain topics on social media.

Table 1. Summary of existing fake news detection systems and comparison of our study with these systems.

Reference	Language	Approach	Datasets and accuracy rates	Contributions	Limitations
[3]	English	ML, DL	Custom dataset created for the study: 91.1-99.4%	Utilizing DL along with traditional ML algorithms.	Does not tested on benchmark datasets. Tested on a small dataset of 15.328 Facebook posts.
[6]	Turkish	ML	Custom dataset: 89-96%	First example of a Turkish FNDS along with a benchmark dataset containing long form of fake and real news in Turkish. A new features set for agglutinative languages.	Not intended to detect fake news on social media. Only traditional ML algorithms are considered.
[8]	Turkish	ML, DL	Custom dataset: -	First example of Turkish FNDS for social media. Utilizing DL and social network analysis along with ML.	The created dataset contains tweets related to only 3 events. Tested on a small dataset of 1287 tweets.
[10]	English, Hindi	ML	Covid-19 fake news: 91.86-93.45%, Devanagari: 63-97%	FNDS for both Hindi and English languages.	Detecting fake news only related to Covid-19.
[11]	English, Portuguese, Bulgarian	ML	FakeBrCorpus: 60-91%, TwitterBR: 51-81%, Fakenewsdata1: 59-86%, Fakeorrealnews: 61-94%, btvlifestyle: 61-95%	FNDSs for multiple languages from distinct origins. Evaluations for both social media and website news.	Only traditional ML algorithms are considered.
[12]	English	ML, DL	ISOT: 86-99%, DS2:28-94%, DS3: 53-96%, DS4:62-91%	Using data from many different domains.	Very low performance results on DS2 by most of the algorithms.
[13]	English	ML	BuzzFeed:50.1-65.5%, ISOT:50.1-96.8%, Random political news: 50.6-68%	Using data from many different domains.	Very low performance results on DS2 by most of the algorithms.
[14]	English	ML, DL	BuzzFeed:58-69.1%, GossipCop: 49.7-72.3%	A fake news data repository with diverse features in news content, social context, and spatiotemporal info.	Does not achieve high accuracies compared to the existing works.
[15]	English	ML	Custom dataset created for the study: 71.6-99.3%	High classification accuracies.	Does not tested on benchmark datasets. Tested on a small dataset of 15.500 Facebook posts.

[16]	English	ML, DL	Kaggle fake news dataset: 98.9%	Utilizing DL along with traditional ML algorithms.	Tested with data which is only related to U.S. General Presidential Election-2016.
[17]	English	DL	BuzzFeed:82.5-91.8%, PolitiFact: 86.84-92.3%	Utilizing DL along with content and context-based features.	Tested on the small datasets of containing 182 and 240 posts.
[18]	English	DL	PolitiFact: 69.6-81.1%, GossipCop: 84.1-85.3%	A continual learning based method to solve the problem of GNNs trained on a given dataset may perform poorly on the unseen data.	Does not achieve high accuracies compared to the existing works.
[19]	English	ML	-	A hybrid model using both ML based detection and expert evaluations.	Presents only the proposed model, does not contain experimental results.
[20]	English	DL	BuzzFeed:88.3-92.7%	Exploring fake news specific propagation patterns by utilizing geometric DL.	Tested only on a small dataset.
[21]	English	ML	BuzzFeed:72-86%	Presenting important features on fake news detection, and explores the effect of different features on the classification success.	Tested only on a small dataset. Does not achieve high accuracies compared to the existing works.
[22]	English	ML, DL	ISOT:68.65-99.87%, KDnugget: 79.87-92.82%	Utilizing DL along with traditional ML algorithms. Proposing a stacking model to improve the classification performance.	Limited to English language.
[23]	English	DL	ISOT:83-99.1%, LIAR: 40-41.6%	Proposing CNN with margin loss and testing the model with different embedding methods.	Very low performance results on the LIAR dataset.
[24]	English	DL	ISOT:83-99.8%, LIAR: 24-40.9%	Capsule network based approach testing the model with different embedding methods.	Very low performance results on the LIAR dataset.
[25]	English	ML	ISOT:97.59-100%, LIAR: 21.23-44.15%	Utilizing feature extraction. Reducing training time of the ensemble classifiers.	Very low performance results on the LIAR dataset.
Our work	English, Turkish	DL	BuzzFeed: 85.16-93.41%, ISOT: 98.02-99.9%, Proposed SOSYalan: 87.14-92.48%	Among the very first examples of Turkish FNDS for social media. A new benchmark dataset. DL based FNDS for both English and Turkish languages outperforming existing literature.	DL algorithms takes more time to train and test compared to ML.

Therefore, to the best of our knowledge, this is the first attempt proposing deep learning based FNDSs for both Turkish and English languages, developed and tested for many different topics and contexts posted on social media platforms.

3. Fake News Detection on Social Media for Turkish and English Languages

In this section, our deep learning based fake news detection models for Turkish and English languages are presented. The steps of the proposed framework are given in Figure 1, and explained in the following subsections.

3.1. Datasets

In this study, we have used 2 different datasets from English language: (i) BuzzFeed [28] and (ii) ISOT [29] which are mostly preferred datasets in fake news detection studies for English language. In order to detect fake social media news for Turkish language, on the other hand, we have created a real-world public dataset, SOSYalan, since there is no such a public dataset containing fake and real Turkish news on social media platforms. As mentioned before, to the best of our knowledge, SOSYalan is the first dataset in this field. The statistics of each dataset is shown in Table 2, and details about them are given in following subsections.

Table 2. Statistics of the datasets.

Dataset	Fake news	Real news	Total
Buzzfeed	91	91	182
ISOT	23481	21417	44898
Proposed SOSYalan	4196	5165	9361

3.1.1 Buzzfeed dataset

BuzzFeed dataset was created by Potthast et al. in 2016 [28]. It contains 91 news article in total collected from 9 accounts in Facebook in a week before the 2016 US Presidential Election. The columns of the dataset represent news number, news text, and label as 'fake' or 'real', respectively.

3.1.2 ISOT fake news dataset

The ISOT dataset is larger than BuzzFeed, and it contains 44898 news in English, 21417 of which are real, while 23481 of which are fake news. Subjects of the fake news are government-news, middle-east, US news, left-news, right-news and politics, while the subjects of real news are world-news and politics [29].

3.1.3 Proposed SOSYalan dataset

The SOSYalan dataset is created within the scope of this study. It includes a total of 9361 news tweet labelled as 'fake' or 'real'. 4196 of them are fake news tweets collected from Twitter accounts of '@teyitorg', '@dogrulukpayicom', '@zaytung', '@dogrulaorg', '@DeminHaber' via Twitter API. These accounts belong to the official information verification platforms that review news and social media posts. They review news spread through online channels and unverified information originating from social media; and gives information about their correctness. In another saying, they classify unverified information as 'fake' or 'real' manually, and inform people. The columns of SOSYalan represent news number, news text, and news label as 'fake' or 'real', respectively. It is publicly available on https://l24.im/rHNi.

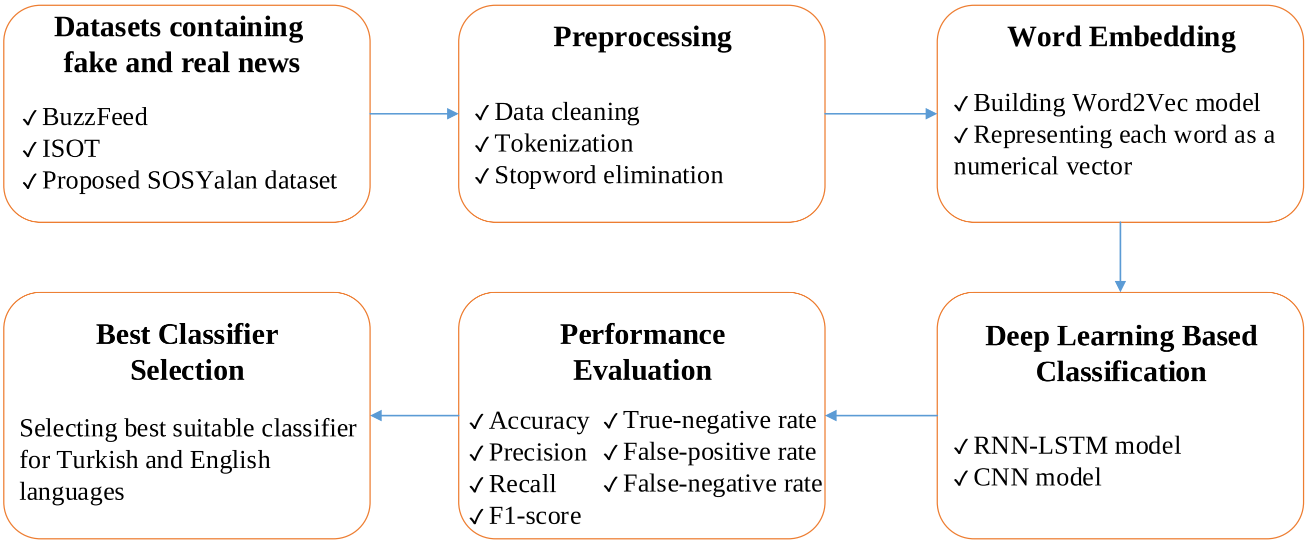

Figure 1 The steps of the proposed framework.

3.2. Preprocessing

For data cleaning purpose, following steps are applied [13], [30]:

- All tweet contents are converted to lowercase.
- Punctuations are removed.
- Links in the tweets are eliminated since they do not contain meaningful words in terms of news content.
- Then, remaining content is tokenized in order to get the words in each tweet.
- Among the tokenized words, stop-words which do not have meaning on their own are eliminated.

3.3. Word Embedding

In this step, words are assigned to corresponding vectors of numbers so that the classification algorithm can understand. Word embedding models calculate geometrical distance between the words and represent them in vector space by putting the words with close meanings to the close positions. Since the geometrical distance between two words is highly related to their meanings in a language, word embedding models can capture the syntactic or semantic relationships among words in a natural language. In this study, Word2vec embedding model is used for each of the BuzzFeed, ISOT, and proposed SOSYalan datasets. Word2vec is a commonly used computationally effective model trained with a neural network with an input, a hidden and an output layer [31]. It uses two different methods for producing semantic relationships: (i) Skip-Gram, and (ii) Continuous Bag of Words (CBoW). While Skip-Gram tries to predict neighbor words of the word in the center, CBoW tries to predict the word in the center by using its neighbors [11], [32]. In this study, we use pre-trained Word2vec model of the Google news corpus for English language, in order to reduce time consumption when training the model and improve the classification performance. For Turkish language, on the other hand, we utilize pre-trained Word2vec model of Turkish

CoNLL17 corpus consisting of 3633786 words in Turkish language which is in NLPL word embeddings repository by Language Technology Group at the University of Oslo [33].

3.4. Deep Learning Based Classification

Deep learning is a subset of machine learning that uses more powerful and flexible learning techniques to imitate the human brain. A deep neural network is a type of artificial neural network consisting of more hidden layers and nodes. Deep learning performs promising results in natural language processing problems such as sentiment analysis, text classification, text summarization and text production. In this section, we provide an overview of the deep learning methods used in this study, and present the architectures of the developed models using these methods.

3.4.1 Convolutional Neural Networks (CNN)

CNN is among deep learning algorithms known to give the best results in text classification [34]. It is a feed forward neural network using a variation of multilayer perceptron designed to require minimal preprocessing [35]. CNN learns from the data which is represented in vector form in the word embedding step. In text classification task, the text is first split into words. Obtained words are converted to word embedding matrix (input embedding layer) of size D. An input embedding layer can be represented as $y = f(x)$ where both input x and output y are tensors. Convolutional filters of different window sizes are applied to the input embedding layer to create a new feature. The pooling method is applied to new features and the pooled features from different filters are combined with each other to create the hidden layer. These are then followed by one or more fully connected layers so that the classification can be made [36].

In Figure 2, the layered architecture of our CNN model is shown. In the model, we use the Adam optimizer and Relu activation function. The epoch size is 10 and batch size is 128. The input embedding vector is 1000, and there is a max pooling layer after each convolution layer to decrease dimension of the input vector. The first convolution layer holds 64 filters with kernel size 1 and ReLU activation function. The subsequent max pooling layer further minimizes embedding vector with $pool\_size = 2$. The second convolution layer holds 8 filters with kernel size 1 and ReLU activation function. Subsequently, there is a max pooling layer with $pool\_size = 2$. The flatten layer coming after these layers converts two dimensional data into a 1 dimensional array in order to input it to the next layers. The next layer is the fully connected layer with ReLU function. The output of the model is compiled by this fully connected layer, 0.25 dropout is applied after these layers, and then it is passed through sigmoid function to form the final output.

3.4.2 Recurrent neural networks-long short term memory (RNN-LSTM)

RNN is one of the mostly preferred deep learning algorithms in text classification problems [37]. Like CNN, it is a feed forward neural network. RNNs process variable-length text input via a repetitive hidden layer whose activation depends on the previous process each time. RNN has a different structure compared to other artificial neural networks. It has a temporary memory, and thus it can make inferences and predictions for the future by using the past knowledge stored in the memory. However, since its memory is short-term, it is not able to store the data for long time. It begins to forget previous inputs as

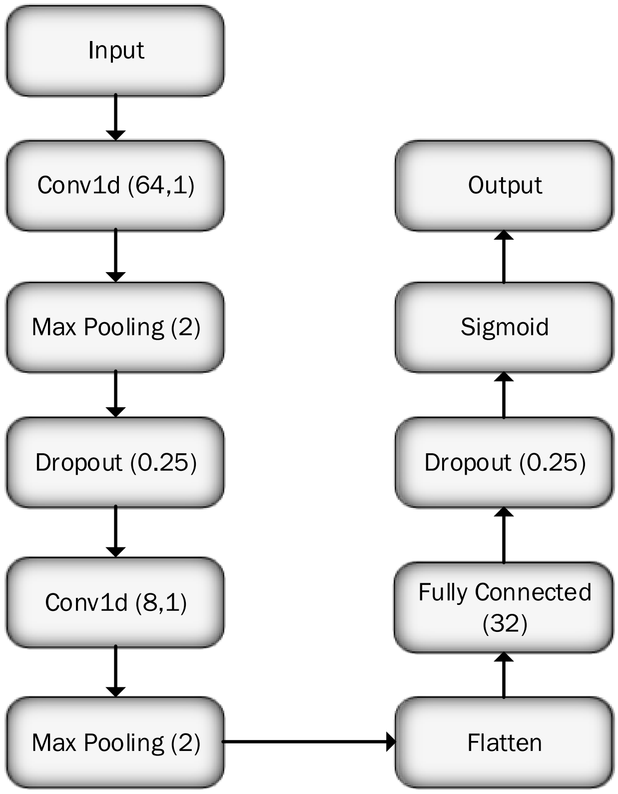

Figure 2 Developed CNN model.

the number of inputs increases. Therefore, the long-short term memory (LSTM) structure is created. LSTM networks are special types of RNNs learning long-term dependencies. In LSTM-RNN the hidden layer of basic RNN is replaced by an LSTM cell, meaning that the recurring module has four different layers interacting with each other, instead of a single layer as in basic RNN [38]. In text classification, a bi-directional LSTM network steps through the input string in both directions simultaneously. This bi-directional processing is an effective approach to predict and classify text data [39]. In Figure 3, the layered architecture of our RNN-LSTM model is shown. In this model, there are two bidirectional LSTMs with 64 and 8 units after the embedding layer. The next layer is the fully connected layer with ReLU function. This layer compiles the model output with 0.25 dropout and then passes it to sigmoid function to form the final output. Adam optimizer and Relu activation function is used. The epoch size is 20 and batch size is 64.

4. Experimental Results

4.1. Evaluation Metrics

In this study, (i) accuracy, (ii) precision, (iii) recall, (iv) F1-score, (v) true-negative rate (TNR), (vi) false-positive rate (FPR), and (vii) false-negative rate (FNR) metrics are used to compare the performance of deep learning-based models developed for fake news detection on social media. These metrics are calculated by using true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values in the complexity matrix, via Equations (1-7):

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

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

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

$$F1 = \frac{2xPrecisionxRecall}{Precision + Recall} \tag{4}$$

$$TNR = \frac{TN}{TN + FP} \tag{5}$$

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$$FPR = \frac{FP}{TN + FP} \tag{6}$$

$$FNR = \frac{FN}{FN + TP} \tag{7}$$

Accuracy represents the rate of correctly classified instances on a dataset. While precision in fake news detection problem expresses how much of the posts determined as 'fake news' are actually fake news, recall refers to how much of fake news are correctly detected by the classifiers. F1 score is calculated as the harmonic mean of the precision and recall values, and is used to eliminate the trade-off between precision and recall metrics. TNR gives the rate of actual fake news that are correctly identified as such by our models. FPR is the proportion of actual real news that are wrongly identified as fake. Finally, FNR is the proportion of actual fake news that are wrongly identified as real.

4.2. Results

In order to evaluate the performance of the developed models, the datasets are arranged by 10-fold cross-validation method so as 90% of the data is used for training and 10% is used for testing each time. The validation rate is 10%.

4.2.1 Results on the BuzzFeed Dataset

The accuracy results of the developed FNDSs combined with the Word2vec embedding model are shown in Table 3 for the BuzzFeed dataset. The confusion matrices for RNN-LSTM and CNN models are also presented in Table 4 and Table 5,

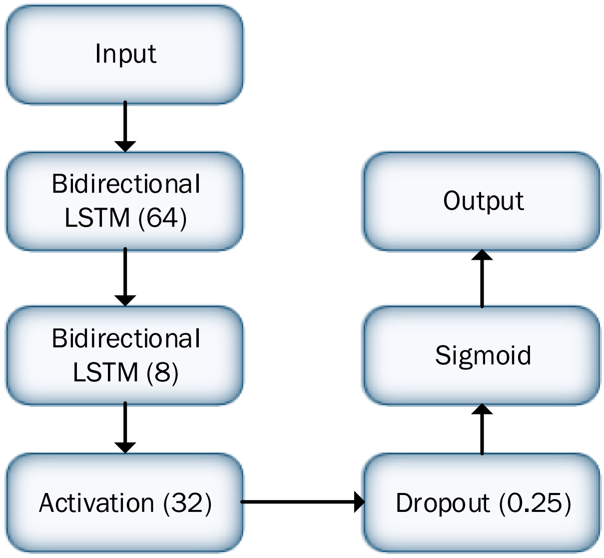

Figure 3 Developed RNN-LSTM model.

respectively. While Figure 4 and Figure 5 show the ROC curves, Figure 6 and Figure 7 presents the evaluation results in terms of each fold for RNN-LSTM and CNN models, respectively.

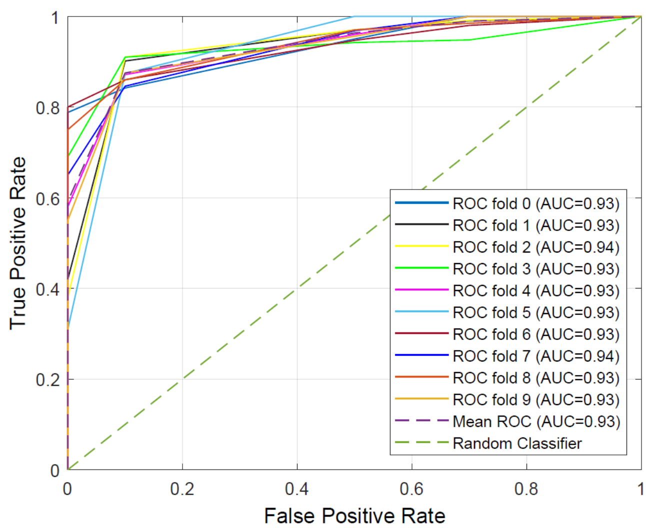

Figure 4 ROC curves of RNN-LSTM for each fold on BuzzFeed.

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Table 3. Results of the developed FNDSs on BuzzFeed.

Model	Accuracy	Precision	Recall	F1-score	TNR	FPR	FNR
RNN-LSTM	**93.41**	**89.9**	**97.8**	**93.68**	**89.01**	**10.99**	**2.2**
CNN	85.16	79.09	95.6	86.57	74.73	25.27	4.4

Table 4. Confusion matrix for RNN-LSTM on BuzzFeed.

	Predicted as fake	Predicted as real
Fake in actual	8.9 (TP)	0.2 (FN)
Real in actual	1 (FP)	8.1 (TN)

Table 5. Confusion matrix for CNN on BuzzFeed.

	Predicted as fake	Predicted as real
Fake in actual	8.7 (TP)	0.4 (FN)
Real in actual	2.3 (FP)	6.8 (TN)

As it can be seen from Table 3, the average accuracy rates of the developed CNN and RNN-LSTM based FNDSs are 85.16% to 93.41%, respectively. RNN-LSTM has performed best result with the accuracy rate of 93.41. It is also the the best classifier in terms of precision, recall, and F1-score metrics. In addition, it is seen that the developed models produce better results in recall metric compared to precision. That means, the probability of missing fake news is less than the probability of missing real news for FNDSs. This is the desired result; because if a news is real in actual, it can be easily verified through several news sources. However, predicting a fake news as real can lead negative consequences considering the rapid spread of news on social media. Therefore, lower precision is more tolerable than lower recall for our problem. In order

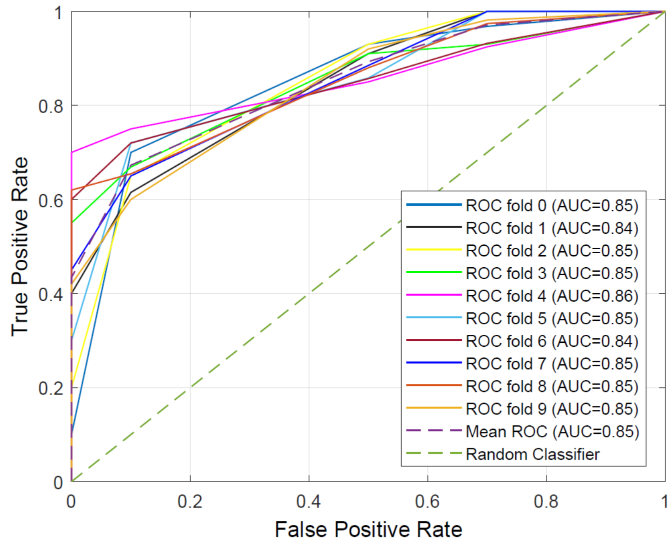

Figure 5 ROC curves of CNN for each fold on BuzzFeed.

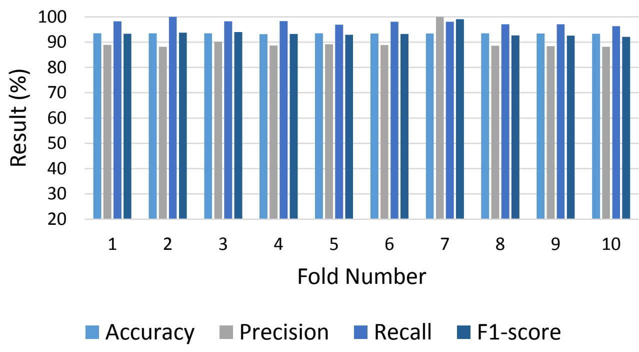

Figure 6 Results of RNN-LSTM for each fold on BuzzFeed.

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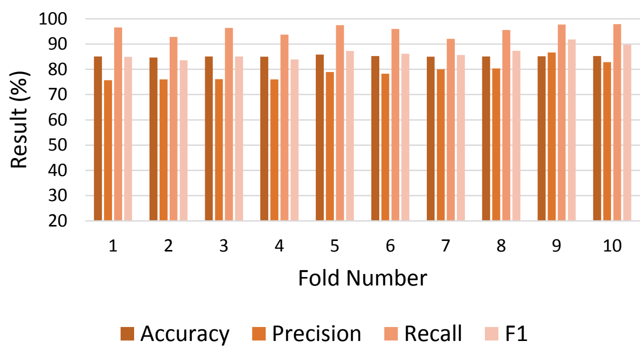

Figure 7 Results of CNN for each fold on BuzzFeed.

to better explain this, TNR, FPR, and FNR results on the BuzzFeed dataset are also given in Table 3. As shown, the false positive rate of our best model is 10.99%, and the false negative rate of it is 2.2%. That means, while our FNDS identifies 10.99 out of 100 actual real news as fake, it identifies only 2.2 out of 100 actual fake news as real. This shows the effectiveness of our FNDS in detecting fake news. Additionally, in order to see the effect of a different optimizer on our model success, we have tested Ada-delta optimizer in our CNN model, to compare it with Adam that we obtained the best results. The results on the BuzzFeed dataset show that we have achieved 80.87% accuracy with Ada-delta optimizer, while this rate is 85.16% for the Adam.

The results obtained for BuzzFeed are compared with the existing studies using the same dataset, and presented in Table 6.

For comparison purposes, existing studies in Table 6 are evaluated according to their classification approaches (traditional machine learning (ML) or deep learning (DL)), word embedding models, and accuracy results. As it can be seen, accuracy rates of the existing FNDSs using ML based methods range from 50-86% for the BuzzFeed dataset. On the other hand, the existing DL-based FNDSs reaches up to 92.7% of accuracy rate showing the superiority of deep learning over traditional machine learning in text classification tasks. According to Table 6, in terms of accuracy, the FNDSs developed in this study outperforms existing studies in the literature by reaching up to 93.41% accuracy on BuzzFeed.

4.2.2 Results on the ISOT Dataset

In order to measure the performance of developed FNDSs on a bigger dataset, the ISOT dataset which is hundreds of times larger than BuzzFeed is used. The evaluation results of the developed FNDSs on ISOT are shown in Table 7. The confusion matrices for RNN-LSTM and CNN models are also presented in Table 8 and Table 9, respectively. While Figure 8 and Figure 9 show the ROC curves, Figure 10 and Figure 11 presents the evaluation results in terms of each fold for RNN-LSTM and CNN models, respectively.

From Table 7 it is seen that the average accuracy rates of the developed CNN and RNN-LSTM based FNDSs are 98.02% to 99.90%, respectively. For ISOT, RNN-LSTM outperforms CNN model as in the BuzzFeed dataset. Compared to BuzzFeed, the accuracy rates of the developed classifiers have increased between 6% to 12% in the ISOT dataset. This increase clearly shows that deep learning models produce better results for large data sets. From Table 7, it is also evident that RNN-LSTM model outperforms CNN in terms of macro-averaged precision, recall and F1 score results. As in the BuzzFeed, it is seen that the developed models produce better results in recall metric compared to precision which is a desired result for the fake news detection problem. In addition, it is seen that the rate

Table 6. Comparison of the developed FNDSs with existing studies using the BuzzFeed dataset.

Reference	Approach	Classifier	Word representation	Test rate (%)	Accuracy (%)
[13]	ML	23 traditional ML algorithms	TF-IDF	30	50.1-65.5
[14]	ML, DL	SVM, LR, NB, CNN, SAF	-	-	58-69.1
[17]	DL	Proposed deep neural network	-	20	82.5-91.8
[20]	DL	Geometric deep learning	GloVe	20	88.3-92.7
[21]	ML	KNN, NB, RF, SVM, XGB	N-gram, POS tagging	5 fold cross validation	72-86
This study	**DL**	**RNN-LSTM, CNN**	**Word2vec**	10 fold cross validation	**85.16, 93.41**

Table 7. Results of the developed FNDSs on ISOT.

Model	Accuracy	Precision	Recall	F1-score	TNR	FPR	FNR
RNN-LSTM	**99.9**	**99.87**	**99.94**	**99.91**	**99.86**	**0.14**	**0.06**
CNN	98.02	97.5	98.74	98.11	97.23	2.77	1.26

Table 8. Confusion matrix for RNN-LSTM on ISOT.

	Predicted as fake	Predicted as real
Fake in actual	2346.8 (TP)	1.3 (FN)
Real in actual	3 (FP)	2138.7 (TN)

Table 9. Confusion matrix for CNN on ISOT.

	Predicted as fake	Predicted as real
Fake in actual	2318.4 (TP)	29.7 (FN)
Real in actual	59.4 (FP)	2082.3 (TN)

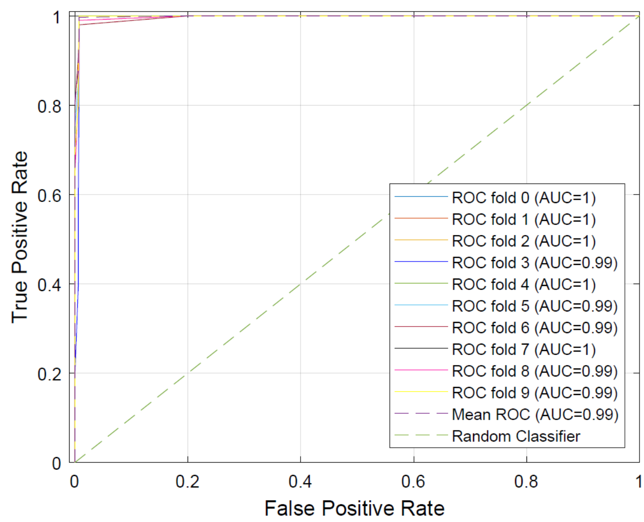

Figure 8 ROC curves of RNN-LSTM for each fold on ISOT.

of correctly identified actual fake news produced by the best-resulting model is 99.86, and the FPR and FNR results are quite low, as desired.

Table 10 presents the comparative analysis of this work with the existing works using the ISOT dataset. It can be observed that the FNDSs developed in this study outperforms most of the studies in the literature.

4.2.3 Results on the Proposed SOSYalan Dataset

As mentioned before, the most important contributions of our study are (i) developing FNDSs for Turkish language to detect fake news on social

Table 10. Comparison of the developed FNDSs with existing studies using the ISOT dataset.

Reference	Approach	Classifier	Word representation	Test rate (%)	Accuracy (%)
[12]	ML, DL	LR, SVM, Multilayer percept., KNN, RF, Ensb.learners, CNN, LSTM	-	30	86-99
[13]	ML	23 traditional ML algorithms	TF-IDF	-	50.1-96.8
[22]	ML, DL	LR, DT, KNN, RF, SVM, CNN, LSTM, GRU	TF-IDF and GloVe	20	68.65-99.87
[23]	DL	CNN	Word2vec	10	83-99.1
[24]	DL	Proposed deep neural network	Word2vec	10	83-99.8
[25]	ML	DT, RF, Extra tree classifier	-	30	97.59-100
This study	**DL**	**RNN-LSTM, CNN**	**Word2vec**	10 fold cross validation	**98.02, 99.9**

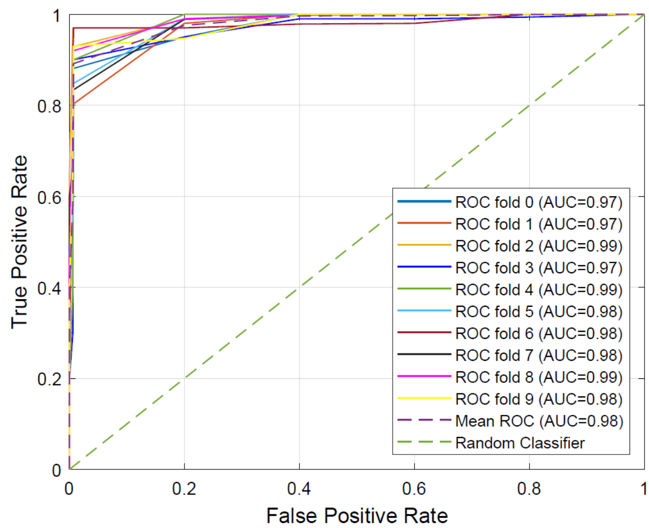

Figure 9 ROC curves of CNN for each fold on ISOT.

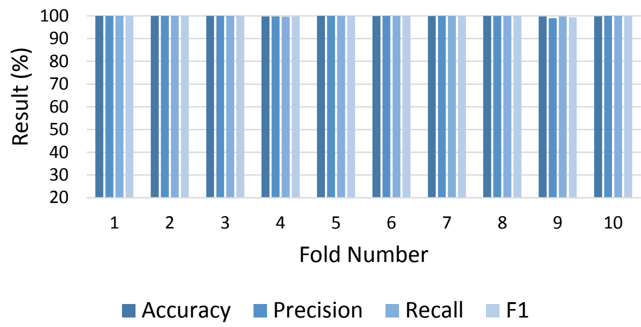

Figure 10 Results of RNN-LSTM for each fold on ISOT.

media, which is a field with very few studies, and to this end, (ii) creating a novel and real-world public dataset of fake and real news tweets on many different domains for Turkish language, named SOSYalan, for the first time in the literature. In this sub-section, we discuss the performance results of the developed FNDSs on the proposed SOSYalan dataset.

The evaluation results of the developed FNDSs on the proposed SOSYalan dataset are shown in Table 11. The confusion matrices for CNN and RNN-LSTM models are also presented in Table 12 and Table 13, respectively. While Figure 12 and Figure 13 show the ROC curves, Figure 14 and Figure 15 presents the evaluation results in terms of each fold for RNN-LSTM and CNN models, respectively.

From Table 11, it is seen that the average accuracy rates of the developed RNN-LSTM and CNN based FNDSs are 87.14% to 92.48%, respectively. Although RNN-LSTM model produces the best results

Table 11. Results of the developed FNDSs on the proposed SOSYalan dataset.

Model	Accuracy	Precision	Recall	F1-score	TNR	FPR	FNR
RNN-LSTM	87.14	87.26	89.8	88.51	83.87	16.13	10.2
CNN	**92.48**	**92.77**	**93.67**	**93.22**	**91.02**	**8.98**	**6.33**

Table 12. Confusion matrix for CNN on the proposed SOSYalan.

	Predicted as fake	Predicted as real
Fake in actual	483.8 (TP)	32.7 (FN)
Real in actual	37.7 (FP)	381.9 (TN)

Table 13. Confusion matrix for RNN-LSTM on the proposed SOSYalan.

	Predicted as fake	Predicted as real
Fake in actual	463.8 (TP)	52.7 (FN)
Real in actual	67.7 (FP)	351.9 (TN)

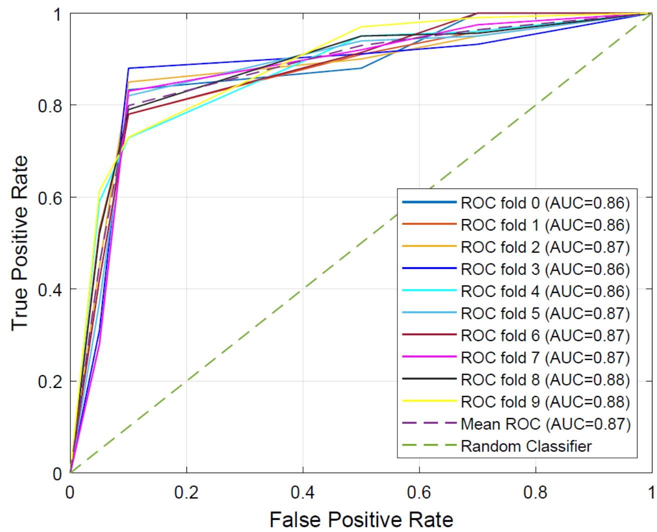

Figure 12 ROC curves of RNN-LSTM for each fold on SOSYalan.

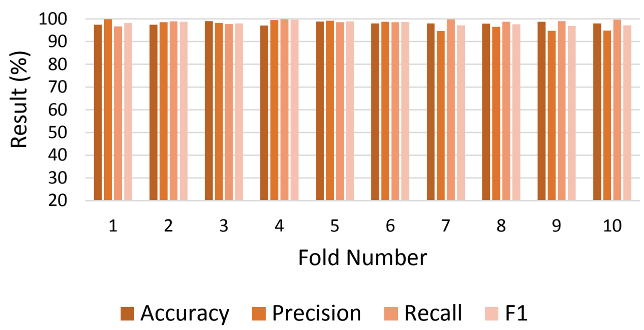

Figure 11 Results of CNN for each fold on ISOT.

for BuzzFeed and ISOT datasets containing news in English, it does not show the best performance with the SOSYalan dataset which contains news in Turkish language. This result supports the need for different deep learning models for languages having different linguistic features. In this case, CNN model performed the best result on SOSYalan with the accuracy rate of 92.48%. However, RNN-LSTM based model still gives very satisfactory results with the accuracy rate of 87.14%. The macro-averaged precision, recall and F1 score results obtained from 10-fold cross validation process for the SOSYalan dataset are also shown in Table 11. It is evident from the table that CNN model outperforms RNN-LSTM with 92.77%, 93.67% and 93.22% for precision, re-

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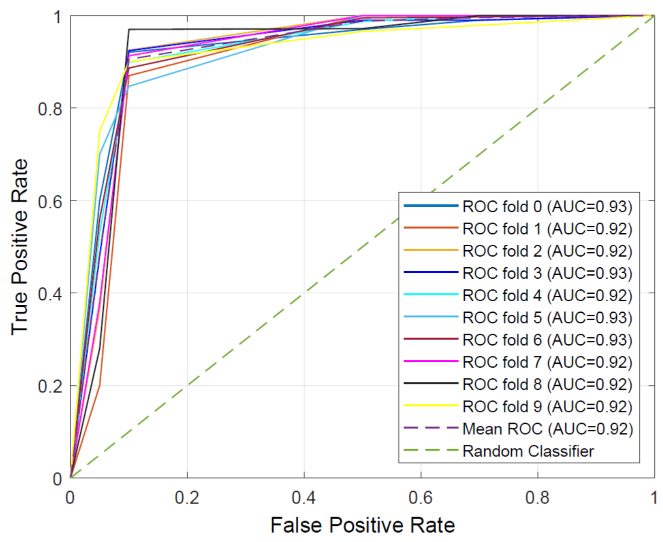

Figure 13 ROC curves of CNN for each fold on SOSYalan.

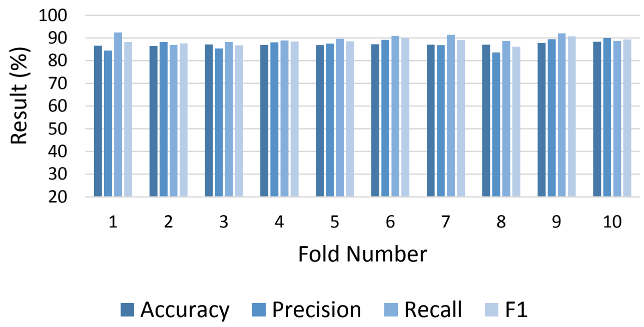

Figure 14 Results of RNN-LSTM for each fold on SOSYalan.

call and F1-score metrics, respectively. In addition, the FNDSs developed for Turkish language produce better results in recall metric compared to precision, as in the FNDSs developed for English language in this study, which is a desired result for the fake news detection problem. Table 11 also shows that the FPR and FNR results for the best model are

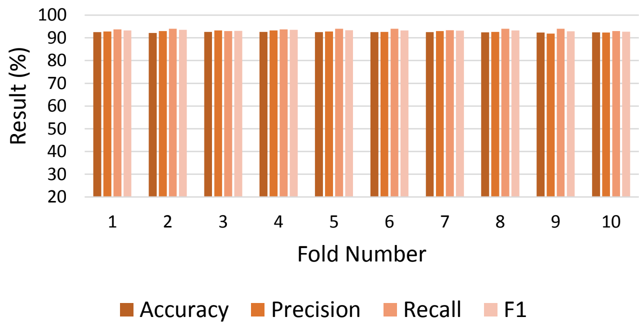

Figure 15 Results of CNN for each fold on SOSYalan.

only 8.98% and 6.33%, while TNR is 91.02%. All these results show that the perfromance results obtained on proposed SOSYalan dataset is very high and acceptable compared to the datasets containing English news post, despite the challenge of working with Turkish language which is an agglutinative language. Table 14 presents the comparative analysis of this work with the existing FNDSs developed for Turkish language.

Unfortunately, there are very few studies in the field of Turkish language, and this is one of the first studies proposing FNDSs for social media for Turkish language, as explained in Section 1 and Section 2. The very first example of a Turkish FNDS [6] is not intended to detect fake news on social media. As shown in Table 14, the authors create a custom dataset for the study containing long-form of news published in other online platforms, such as websites. Although it would not be fair to compare our results with the results of FNDSs developed in [6] due to the text lengths, the accuracy results obtained in this study are reasonably high and acceptable. Despite the challenge of classifying short text, developed CNN classifier with the accuracy

Table 14. Comparison of the developed FNDSs with existing studies using the ISOT dataset.

Reference	Data	Approach	Classifier	Word representation	Test rate (%)	Accuracy (%)
[6]	Custom dataset containing long-form of news published in websites.	ML	KNN, NB, SVM, LR, DT	BOW, N-gram	10 fold cross validation	89-96
[8]	Custom dataset created for the study containing tweets based on 3 topics.	ML, DL	KNN, RF, SVM, RNN, GRU, LSTM	TF-IDF, Word2vec	30	-
This study	**Proposed SOSYalan dataset**	**DL**	**RNN-LSTM, CNN**	**Word2vec**	10 fold cross validation	**87.14, 92.48**

rate of 92.48% has produced slightly lower results than the study classifying longer news articles.

As shown in Table 14, the other study proposing an FNDS for Turkish language uses a custom dataset created for the study containing 3 topics based tweets [8]. Although the dataset is different, it would be a more reasonable comparison since social media data is used, as in our study. Since the authors give only F1-score results among the performance metrics, we cannot compare the accuracy rates of our FNDSs with this study. However, when we compare the F1-score results, we see that the F1-score results of the models presented in [8] range from 57% to 89%. This shows that our CNN-based FNDSs developed for Turkish language outperforms this study by reaching up to 93.22% F1-score.

5. Conclusions and Future Work

The detection of fake news on social media has recently become an emerging research area, because spread of fake news has significant negative effects on information security. Detecting false information spread on these platforms manually is a very difficult task since countless posts are shared on these platforms every day. Therefore, developing automatic fake news detection systems is attracting significant attention from both academia and industry. In this study, we focus on the problem of automatic fake news detection for social media platforms for Turkish and English languages, both of them having distinct linguistic features. To this end, we create a real-world public dataset of Turkish fake and real news tweets on many different topics for the first time in the literature, to the best of our knowledge. We use BuzzFeed and ISOT datasets which are commonly preferred benchmarks on fake news detection studies for English language. For both of Turkish and English languages; we develop two different deep learning based FNDSs by implementing CNN and RNN-LSTM algorithms with Word2vec word embedding model.

The results show that the developed FNDSs for English language produce higher accuracy rates when compared to the existing literature considering social media news in English. In addition, the results confirm the superiority of our systems developed for Turkish language in comparison to very few studies conducted in this area.

Expanding our proposed SOSYalan dataset and testing the developed models with bigger datasets are among the most important future goals of this study. Additionally, adapting the developed FNDSs to different social media platforms allowing for longer posts like Facebook can be the subject of new studies. Finally, we plan to transform developed FNDSs into a real-time and a web-based platform to make them serve as a public and free application.

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