International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Deep Learning Based Chatbot Adapted to the Electronic Funds Transfer Process of Turkish Banking

Ahmet Toprak*[1], Metin Turan[2], Feyzanur Sağlam Toprak[3]

Submitted: 29/10/2022 **Revised:** 22/12/2022 **Accepted:** 04/01/2023

Abstract: Advanced applications of Natural Language Processing require understanding the semantic of the language. If traditional machine learning techniques are used, the models built for conversations, called chatbots, are unable to be truly generic. On the other hand, deep learning allows us to extract the complexities within language and makes it easier to model. It can also leverage for building a chatbot which has a real conversation with human. In the study, Electronic Funds Transfer process of Turkish bank operations has been designed. A dictionary of terms used in this process has been created in order to train dialog model. Language descriptor layer first checks the language of command. Named Entity Recognition layer later, classifies the words according to their asset structures, especially the amount and account number information in the Electronic Funds Transfer process. LSTM architecture is used to keep the other stages of the dialog, so that order of dialog is in control. The performance evaluation of the designed model was calculated separately for 3 different EFT processes. According to the results obtained, a success rate of 70% was achieved in EFT with account number, 90% in EFT with IBAN number, and 90% in EFT with credit card number.

Keywords: Chatbot system; intent classification; long short term memory; natural language processing; recurrent neural networks.

1. Introduction

With the rapid development on the big data analytics, obtain and processing data have become decisive for organizations to gain advantage with respect to the competitors. At this point, chatbots which is specific to desired purpose help us. Chatbot is a program that is having a conversation with a real person, and requires both using Expert System (ES) rules and Natural Language Processing (NLP) in harmony, where ES rules applied to produce answers for dialog using NLP.

The chatbot market is estimated to be worth $ 17.17 billion in 2019 and will reach to $ 102.29 billion by 2025.

As shown in Fig. 1 according to Scopus, there was a rapid growth of interest in chatbots especially after the year 2016. Many chatbots were developed for industrial solutions while less famous chatbots relevant to the research and their applications exist [1].

[1] *Department of Computer Engineering, Istanbul Commerce University, Istanbul, Turkey*
ce.ahmet.toprak@gmail.com
[2] *Department of Computer Engineering, Istanbul Commerce University, Istanbul, Turkey*
mturan@ticaret.edu.tr
[3] *Turkey Finans Participation Bank Inc, Information Technologies, Istanbul, Turkey*
feyza-saglam@hotmail.com
* *Corresponding Author Email: ce.ahmet.toprak@gmail.com*

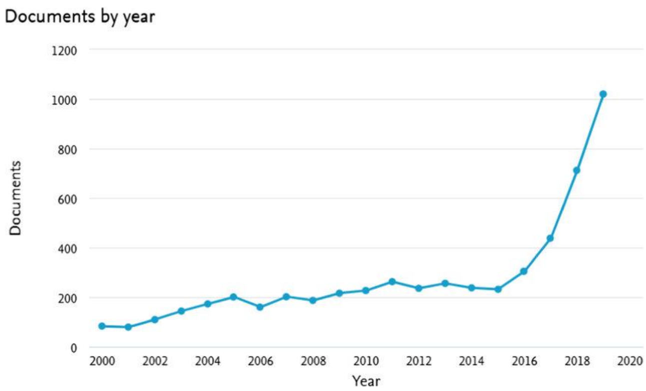

Fig. 1. Search results in Scopus by year chatbot.

In general, chatbots are created in 3 different ways: Word Based, Rule Based and Natural Language Based. Word and Rule based chatbots are static and the cost of continuous maintenance reveals. In order to get rid of this maintenance cost and to obtain more structural chatbots, it is important to turn these processes into chatbots that understand natural language. The methods used by chatbots depending on the creation of different ways are shown in Fig. 2.

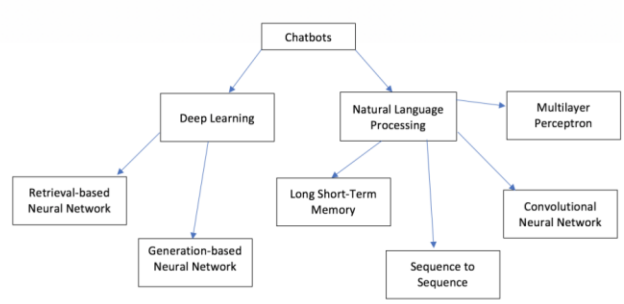

Fig. 2. Conceptual map of chatbot creation methods.

The purpose of the study is to implement Electronic Funds Transfer (EFT) process of Turkish banking that user wants to do through chatbots. First of all, the language descriptor layer to check whether the sentence entered by the user belongs to the Turkish language. Next, the intention recognition stage is introduced. In the intention recognition stage, the sentence given by the user checked for suitability to one of the three different classes, (EFT with account number, EFT with IBAN number or EFT with credit card number). Finally, the relevant sentence is transmitted to the Named Entity Recognition (NER) stage. Thus, the words in the sentence are classified according to their asset structures and information such as the amount and account number that are required in the EFT transaction is obtained. Long short-term memory (LSTM) architecture, is used in order to not losing the flow during the chat.

In the second section, chatbot researches in literature or studies covering methods applied in this study are mentioned. In the third section, used methods in the chatbot study are explained in detail. In the last section, the results are commented on and future studies are discussed.

2. Related Work

The systems we call "chatbot" today dates back to the 1950s. In 1950, Alan Turing [2] wondered if a computer program could talk to a group of people. This question, called the Turing test, is considered by many to be the first idea for the creation of chatbots. Since 1950, studies have been carried out on this Turing's question.

MIT professor Joseph Weizenbaum and his team created a word-based chatbot named ELIZA [3] in 1966. ELIZA simulated the work of a psychotherapist and converted the user's sentences into questions. Eliza is only able to extract keywords from user's answer given to a pre-determined question pattern, such like "…. what do you think about?". Since ELIZA works word and rule basis, it uses pattern matching templates as a response scheme.

In 1972, exactly 6 years after the launch of ELIZA, a chatbot named PARRY [4] was developed by psychiatrist Kenneth Colby to impersonate paranoid schizophrenia. PARRY, who was skeptical, irritable, with thought disorders, behaved like schizophrenia patients. PARRY was brought before five psychiatrist judges in 1979. In the experiment, doctors were asked to decide whether PARRY was a computer program or a real schizophrenic patient. Three of the five physicians did not understand that PARRY is a robot.

In 1988, a chatbot named Jabberwacky [5] was brought to life by British programmer Rollo Carpenter. Jabberwacky could speak with a voice control system instead of a written text, with elements of entertainment and humor in accordance with human nature. Jabberwacky's technology was different from other chatbots in existence. Jabberwacky does not have a specific rule and all conversations with users are stored in the knowledge base. Jabberwacky is considered one of the earliest attempts to create artificial intelligence (AI) through human interaction.

The first breakthrough in chatbot history is the ALICE (Artificial Linguistic Internet Computer Entity) [6], the first on-line chatbot that was inspired by the ELIZA, 30 years after the development of the ELIZA. In 1996, ALICE was developed by Richard Wallace and his team with the ability to discuss any topic on the web. Unlike ELIZA, ALICE allows more complex conversations with support of NLP.

In 2001, a chat-based chatbot named SmarterChild [7] has been created by ActiveBuddy Inc. SmarterChild is considered to be the ancestor of today's programs such as Apple Siri and Samsung S Voice. SmarterChild, which can be added to MSN Messenger and AOL Instant Messenger, has chatted with more than 30 million users in its lifetime. SmarterChild is commonly used in messaging and SMS networks.

In 2006, a chatbot named Watson Assistant [8] was developed by IBM company. Named after Thomas J. Watson, Watson is powered by the latest innovations in machine learning. Watson is an open source, multi-cloud platform that allows you to automate the artificial intelligence (AI) lifecycle. With Watson, you can create powerful models from scratch or take advantage of pre-built enterprise applications.

In 2010, a new breakthrough in technology was made and Siri [9] one of the most known and used voice assistants today, was developed by Apple. Siri, Apple's chat program as a personal assistant, uses voice queries and a natural language user interface to answer questions, make suggestions and perform actions by transferring user requests to the internet service. While Siri makes recommendations and responds to the user requests using various internet services, it adapts to users' language usage, searches and requests with continuous use [10].

In 2012, the world-famous search engine Google took its place in the chatbot market. Google Now aka Google Assistant [11] is a smart personal chatbot assistant developed by Google. Google Assistant was originally used to inform the user based on the time of day, location and preferences. Over time, it has integrated with the natural language user interface to answer questions, make suggestions and perform actions by transferring the user's requests to the web services.

In 2014, Microsoft created its personal assistant named Cortana [12] as a rival to Siri, Apple's voice assistant. The biggest feature of Cortana is that it is a customizable assistant beyond being a voice assistant. Cortana constantly monitors your frequency of use of applications, calendar and agenda programs, e-mails and even your internet history, and then gets the chance to offer solutions by understanding the needs.

In 2014, ALEXA [13], a chatbot that can give voice commands using the NLP, was developed by Amazon. Using ALEXA is as simple as asking a question. You can ask ALEXA to play music, read the news, control your smart home, tell a joke, and more. One of the most important features of ALEXA is that it constantly updates itself (learning).

In 2016, Facebook company launched a chatbot called Messenger [14], which is a messaging service that provides text, audio and video communication. Messenger is a bot built on MQTT, an open source protocol integrated with web-based chat feature. Messenger allows Facebook users to chat with their environment via both the main web page and mobile applications. In March 2015, Facebook announced that the number of users using the application reached 600 million.

In 2019, Xiaoice [15] is an artificial intelligence-based chatbot developed by Microsoft's Asian office based on emotional computing. It can be used in various areas such as chat bot, smart voice assistant, creating content with artificial intelligence, and production platform [16].

In addition to the studies based on the English language, there are examples for the Turkish language. One of these is the chatbot made by Ozyurt and Kose [17] in 2006. Within the scope of this study, in the light of Turkish grammar rules, a program for realizing human-computer dialogue, which is evaluated under dialogue-based processes, was designed and coded.

Another study on the Turkish language is the conversation robot created by Amasyali and his friends [18] in 2012. For the chatbot, daily conversations (meeting, sports, cinema, etc.) have been chosen.

3. Theoretical Background

In this section, methods and processes used for chatbots, especially the adaption of advanced machine learning techniques into chatbots is discussed.

3.1. Long Short Term Memory

Long Short Term Memory (LSTM) networks usually just called "LSTMs" are a special kind of RNN, capable of learning long-term dependencies. They were introduced by Hochreiter and Schmidhuber [19] in 1997, and were refined by the time. They work well on a large variety of problems, such as machine translation [20] and picture captioning [21].

In the Fig. 3, for each instance of training (sentence) we map each word with an output, if the word is name (John, Ellen …) we map it to 1. Otherwise, we map it to 0. So to train LSTM on sentences to recognize names within, the LSTM architecture would be like Fig. 4.

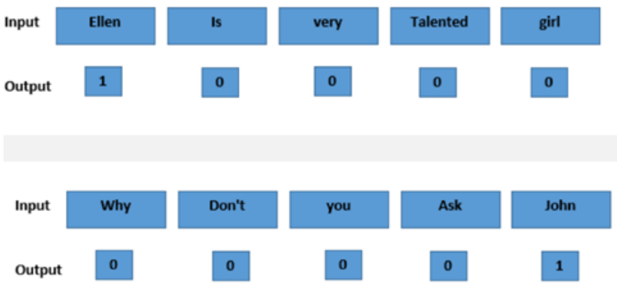

Fig. 3. Detect names in a sentence for LSTM model.

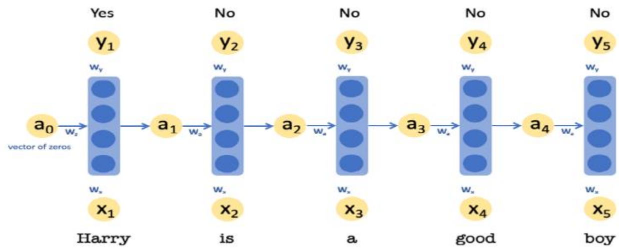

Fig. 4. LSTM structure for example.

3.2. Language Identification

Since chatbot applications are generally used online, users are likely to try to communicate in different languages. Against this possibility, it should be first determining the language and the text should be analysed accordingly [22].

In this study, Azure Text Language Analysis Rest (Representational State Transfer) API service was used for language detection. It evaluates text input for each document and returns language identifiers along with a score that indicates the strength of the analysis. The value is between 0 and 1.

3.3. Intent Classification

Intent is chatbot jargon for the motive of a given chatbot user. It's the intention behind each message that the chatbot receives. Intent is all about what the user wants to get out of the interaction [23]. The major aspect of this chatbot conversation engine is intent classification. Understanding the intention is only possible with prior knowledge analysis. There are various intent classes and the perception of the intention of the user's statement is the first step to continue the conversation. At this point, classifiers using machine learning and deep learning methods are generally preferred. LSTM networks have been previously adapted to work well in this area [24]. They were useful for the development of this study as well.

3.4. Named Entity Recognition

The term “named entity”, now widely used in NLP, was coined for the MUC-6 (Sixth Message Understanding Conference) [25]. Named Entity Recognition (NER) is an information extraction (IE) technique to identify and classify named entities in text. In our study, deep learning based model and multi-lingual Bert word embeddings (bert_multi_cased) library was used in order to extract the named entities in the sentence taken from the user. The bert_multi_cased library is not successful in detecting IBAN (International Bank Account Number) definition. In order to overcome this problem, the IBAN formation scheme was used. An example of the Turkish IBAN format is shown in Fig. 5. The country code for Turkey is TR. The IBAN consists of 33 check digits for validating the routing destination and account number. The BBAN (Basic Bank Account Number) is 0006 1005 1978 6457 8413 26, which contains the country-specific details of the account number. The bank identifier is 00061 and the account number is 0519786457841326.

IBAN	TR33 0006 1005 1978 6457 8413 26
ISO Country Code	TR (Turkey)
IBAN Check Digits	33
BBAN	0006 1005 1978 6457 8413 26
Bank Identifier	00061
Reserved Field	0
Account Number	0519786457841326
SEPA Member	No

Fig. 5. Turkish IBAN format.

4. Designed Model

Python programming language and MS SQL database are used for this chatbot integration.

4.1. Dataset

The training data for a chatbot requires it to have a conversational flow. It needs to have a sentence or a question and a response. Since a special purpose chatbot related to the EFT process was designed in this study, the training data set was created manually, such as greetings, EFT with account number, EFT with IBAN number and EFT with credit card number. Training data and intents pairs were formed in line with general needs.

JSON format for used intent types are given Fig. 6. As can be seen, greetings, EFT with account number, EFT with IBAN number and EFT with credit card number transactions correspond to an intention class. The inputs given to these classes at the beginning were used in the training phase of the model.


```
{
 "intents": [
  {
   "tag": "SELAMLAMA",
   "patterns": [
    "Merhabalar",
    "Selamlar",
    "Nasılsın",
    "Naber",
    "Selam",
    "Günaydın"
   ],
   "responses": [
    "Merhabalar :)",
    "Seni gördüğüme sevindim",
    "Nasıl yardımcı olabilirim"
   ],
   "context_set": ""
  },
  {
   "tag": "IBAN_EFT",
   "patterns": [
    "IBAN",
    "İBAN",
    "iban",
    "ibana eft",
    "eft iban"
   ],
   "responses": [
    "IBAN numarasını söyler misiniz lütfen",
    "IBAN lütfen",
    "Sisteme kayıtlı 26 haneli IBAN numaranızı girebilir misiniz?"
   ],
   "context_set": ""
  },

  {
   "tag": "ACCOUNT_NUMBER_EFT",
   "patterns": [
    "Hesap no",
    "hesap numarası",
    "hesap no eft",
    "hesap numarasına eft",
    "Hesapno"
   ],
   "responses": [
    "Hesap numarasını söyler misiniz lütfen",
    "Hesap No lütfen",
    "Sisteme kayıtlı 8 haneli hesap numaranızı girebilir misiniz?"
   ],
   "context_set": ""
  },
  {
   "tag": "CREDIT_CARD_EFT",
   "patterns": [
    "kredi kartı no",
    "kredi kartı numarası",
    "kredi kartına eft",
    "kredi kartı numarasına eft",
    "kredi kartı"
   ],
   "responses": [
    "kredi kartı numarasını söyler misiniz lütfen",
    "kredi kartı No lütfen",
    "EFT yapmak istediğiniz kredi kartı numarasını girebilir misiniz?"
   ],
   "context_set": ""
  }
 ]
}
```


Fig. 6. Representation of intent classes for the designed chatbot model.

Explanations of the used parameters in the training data set are given in Table 1.

Table 1. Explanations of the parameters.

Attribute Name	Description
Tags	Tags are keywords assigned to the patterns and responses for training the chatbot.
Patterns	These are the types of queries asked by the user to the chatbot.
Responses	Responses are the answers generated by the chatbot for the respective queries.
Context_Set	Context is given for which the queries require a search and find operation.

4.2. Data Preprocessing for the Model

In order to identify the intention of the sentences given to the system by the user, the sentences are pre-processed initially. The input is first divided into tokens then they are all lemmatized. Strings can now be compared to the chatbot database which contains all of the responses, and an appropriate message in order to give to the user. However, the model does not understand the text, it requires the text to be converted into numbers. The whole process is represented in Fig. 7. Hand- prepared data was split into two categories, training and testing datasets. The split ratios were 80% and 20%, respectively.

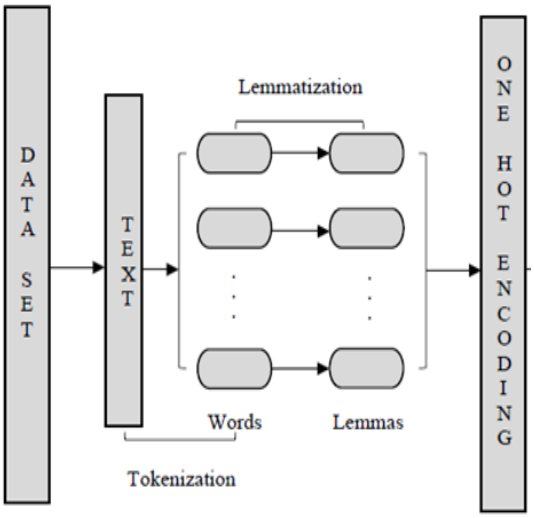

Fig. 7. One hot encoding process for data set.

4.3. Building and Training the Model

The designed model has an end-to-end architecture. During the training process, both questions and answers are given, and the learning of the relationships between them is carried out through the LSTM model, which is a deep learning method. Then, it is expected to generate answers from the message entered into the chat by the user with the LSTM model. Words must be transformed into vectorial dimensions, thanks to the Word2Vec algorithm, it has been used and given as a parameter to the LSTM model.

A deep learning model was trained with a small number of data (approximately 150 messages for a total of 3 EFT transaction type classes). The parameters used in this model are shown in Table 2.

Table 2. Parameters of the deep learning model.

Parameter Name	Parameter Value
Input	Takes a user query as an input
Embedding	Generates a 38-d vector embedding for an input sequence
Bidirectional	Bidirectional layer on an LSTM cell of 632 units with ReLU activation
Epoch	32
Batch Size	64
Learning Rate	The learning rate of 0.5 is a suitable value for LSTM
Dropout	Dropout of 0.02
Dense	Fully connected with softmax activation

After model trained, when a message enters to the chatbot system, then the message is given to this deep learning model as a parameter and the model output is one of the 3 intention classes shown in Fig. 8.

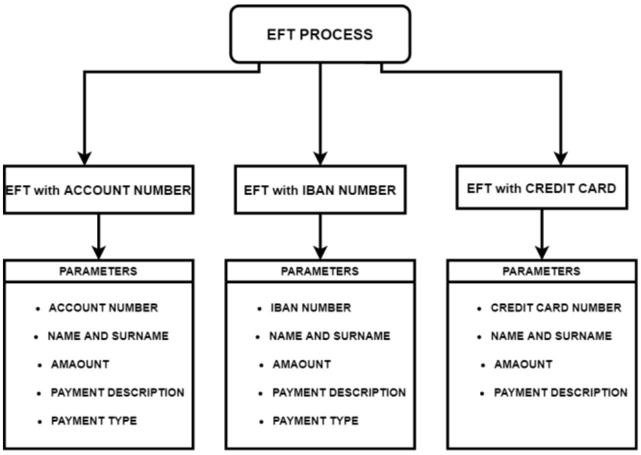

Fig. 8. Intent classes for EFT transaction.

5. Results

The performance of the chatbot trained in the study was evaluated using sample chat flows. Chatbot was very successful in understanding the intention of the transaction that the user wants to do and continuing the conversation within this flow. For each 3 EFT process, 20 chat message templates were used to test the model. According to the results obtained, a success rate of 70% was achieved in EFT with account number, 90% in EFT with IBAN number, and 90% in EFT with credit card number.

Conclusion why the higher success rate in EFT with IBAN number and EFT with credit card number is obtained is due to the more specific IBAN and credit card number formats used. The account number format may differ from bank to bank. Therefore, the intent class is incorrectly assigned in some cases. Furthermore, special solutions produced for some entity types (currency, etc.) that are not supported by NER API made significant contributions to this success of the chatbot.

When compared with the studies on Turkish language [17], [18] mentioned in the literature review section, former studies were created statically. Moreover, they don't check whether the messages entered by the user in the chatbot are in Turkish or not and NER integrations.

6. Future Studies

The study contributes to the literature applied with the following additional features and different approaches in chatbot flow processes.

- A flow related to the EFT process has been formed and the system has been adapted according to this flow. For a different topic, the model can be trained and used in similar manner.
- Additional languages could also be integrated in order to produce an international product.
- LSTM is not the only alternative in deep learning, especially in RNNs. Various LSTM architectures can be tried instead of the GRU LSTM architecture used.
- Comparisons can be achieved for vector representations of words using different Word2Vec algorithms.
- Especially in cases where transactions need to be very fast, it can be integrated into the chatbot MQ (Message Queue) structure to be created in order to return a fast response without waiting the user.

References

[1] Colace, F., M. De Santo, M. Lombardi, F. Pascale, A. Pietrosanto and S. Lemma, Chatbot for e-learning: a case of study. International Journal of Mechanical Engineering and Robotics Research, 2018. 7(5): pp. 528–533.

[2] Turing, A. M., Computing machinery and intelligence. Mind, 1950. 1(236): pp. 433-460.

[3] Weizenbaum, J., ELIZA-a computer program for the study of natural language communication between man and machine. Commun. ACM, 1966. 1(9): pp. 36-45.

[4] Colby, K. M., Human-Computer Conversation in A Cognitive Therapy Program. Boston MA USA, 1999. 511: pp. 9-19.

[5] Angeli, A. D, and S. Brahnam, I hate you! Disinhibition with virtual partners. in Interacting with Computers, 2008. 20(3): pp. 302-310.

[6] AbuShawar, B., and E. Atwell, ALICE chatbot: Trials and outputs. Computación y Sistemas, 2015. 19(4): pp. 625–632.

[7] G. Molnár and Z. Szüts, "The Role of Chatbots in Formal Education," 2018 IEEE 16th International Symposium on Intelligent Systems and Informatics (SISY), 2018. pp. 000197-000202.

[8] Ferrucci, D. A., Introduction to "This is Watson". Ibm Journal of Research and Development, 2012. 56(4): pp. 1-15.

[9] V. Këpuska and G. Bohouta, "Next-generation of virtual personal assistants (Microsoft Cortana, Apple Siri, Amazon Alexa and Google Home)," 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), 2018. pp. 99-103.

[10] Tulshan, A., and S. Dhage, Survey on Virtual Assistant: Google Assistant, Siri, Cortana, Alexa. 4th International Symposium SIRS, 2019. pp.190-201.

[11] A. Lazić, M. Z. Bjelica, D. Nad and B. M. Todorović, "Google Assistant Integration in TV Application for Android OS," 2018 26th Telecommunications Forum (TELFOR), 2018. pp. 420-425.

[12] Y. Zhao, J. Li, S. Zhang, L. Chen and Y. Gong, "Domain and Speaker Adaptation for Cortana Speech Recognition," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018. pp. 5984-5988.

[13] Y. Gao, Z. Pan, H. Wang and G. Chen, "Alexa, My Love: Analyzing Reviews of Amazon Echo," 2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), 2018. pp. 372-380.

[14] D. R. Vukovic and I. M. Dujlovic, "Facebook messenger bots and their application for business," 2016 24th Telecommunications Forum (TELFOR), 2016. pp. 1-4.

[15] Zhou, L., J. Gao, D. Li and H. Shum, The Design and Implementation of XiaoIce, an Empathetic Social Chatbot. Computational Linguistics, 2018. pp. 1-62.

[16] Shum, H., X. He and D. Li, From Eliza to XiaoIce: challenges and opportunities with social chatbots. Frontiers of Information Technology and Electronic Engineering, 2018. 19: pp. 10-26.

[17] Ozyurt, O., C. Kose, Turkce tabanli diyalog sistemi tasarimi ve kodlanmasi. Elektrik, Elektronik ve Bilgisayar Muhendisliği Sempozyumu ve Fuari (ELECO 2006), 2006. pp. 364-368.

[18] Topcu, S., C. Şen and M. F. Amasyalı, Türkçe Sohbet Robotu. Akıllı Sistemlerde Yenilikler ve Uygulamaları Sempozyumu (ASYU), 2012.

[19] Hochreiter, S., and J. Schmidhuber, Long Short-Term Memory. In: Neural Comput, 1997. 9(8): pp. 1735–1780.

[20] Sutskever, I., O. Vinyals and Q. V. Le, Sequence to Sequence Learning with Neural Networks. In: CoRR, 2014. 3: pp. 1-9.

[21] O. Vinyals, A. Toshev, S. Bengio and D. Erhan, "Show and tell: A neural image caption generator," 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015. pp. 3156-3164.

[22] Adamopoulou, E., and L. Moussiades, An Overview of Chatbot Technology. Artificial Intelligence Applications and Innovations (AIAI), 2020. 584: pp. 373–383.

[23] Meng, L., and M. Huang, Dialogue intent classification with long short-term memory networks. Proc. of the National CCF Conf. on Natural Language Processing and Chinese Computing (NLPCC-19), 2019. pp 42-50.

[24] J. Schuurmans and F. Frasincar, "Intent Classification for

Dialogue Utterances," in IEEE Intelligent Systems, 2020. 35(1): pp. 82-88.

[25] Nadeau, D., and S. Sekine, A survey of named entity recognition and classification. in J. Lingvisticae Investigationes, John Benjamins Pub. Co, 2007. 30(1): pp. 3-26.