DISTRIBUTED DYNAMIC MUTUAL IDENTITY AUTHENTICATION FOR REFERRALS IN BLOCKCHAIN BASED HEALTHCARE NETWORKS

[1]N. MANISHA, [2]Ms. S. SURUTHI

[1]MCA, [2]ASSISTANT PROFESSOR,
A.R.J COLLEGE OF ENGINEERING AND TECHNOLOGY, MANNARGUDI.

Abstract-
Multiple healthcare providers for treatment, and their health data is generally distributed among providers. The distributed health data and the decentralized health care system structure make it ideal for block chain-based health information systems. The authors consider the referral use case; for instance, a patient goes to his primary health Centre (PHC) for treatment and is referred to a hospital. Authentication is usually done using certificates or key cryptography, which could become cumbersome when multiple parties are involved in a healthcare interaction. The security requirements were defined, and a novel multi-party, mutual patient identity authentication scheme called ‘‘Distributed Dynamic Mutual Identity Authentication (DDMIA)’’ was proposed for the referral use case in a block chain-based e-health network. The DDMIA enables the PHC to authenticate the patient to the referred hospital. The DDMIA scheme was designed using Elliptic Curve Cryptography. It was proven to be secure by assuming the hardness of the elliptic curve discrete log problem (ECDLP) and Elliptic curve computational Diffie–Hellman problem (ECDH) using CK-Model. The formal security analysis using BAN logic proved that the sessions are secure after authentication. The DDMIA scheme was simulated in the AVISPA tool and proven safe against all active attacks. The scheme allows a patient to be authenticated by multiple parties without registering with all parties. It eliminates the need for multiple registration centers as well as digital certificates. Hence, the DDMIA scheme can be implemented for similar multiparty authentication requirements in block chain-based networks.

I.INTRODUCTION

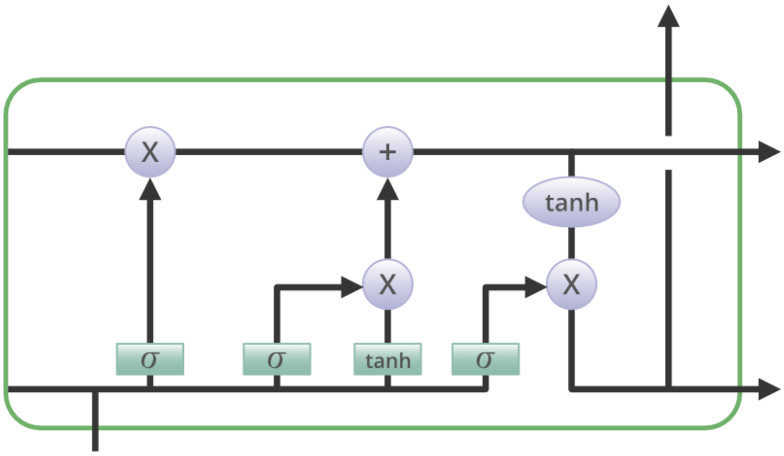
Patients visit various hospitals, private clinics, and public health centers for their health needs. Each of these healthcare providers generate and record health information about the patient. There is a need to share the patient’s health and medical history among healthcare providers, for informed medical decisions, which results in a better quality of healthcare. Technology adoption can improve the quality of healthcare as well as bring down the cost. The national e-health initiatives suggest the adoption of Electronic Health Records to create and maintain a longitudinal electronic record of the patient health information. Policy regulations for aspects like data exchange, data ownership, privacy protection, and security have been set. In general, the adoption of technology for the healthcare sector is low in most countries. Some private hospitals have adopted Hospital Information Systems and electronic medical records, however, seamless data exchange and comprehensive patient health records are not available. Blockchain technology has the potential to transform the healthcare industry. The authors suggest the use of blockchain technology for integrating health data into EHRs as well as seamless data exchange. Various private and public e-health providers can be connected on a network to enable data integration and sharing. The patient’s interactions with e-health care providers can be recorded as transactions in a trusted network without the involvement of third parties. Blockchain technologies will record the distributed health interactions and enable integration of the data into a longitudinal EHR. Blockchain-based data exchange will ensure the completeness as well as the immutability of the patient’s health interactions. Several organizations are using blockchain technology for health records. For instance, the Gem Health Network, OmniPHR deploy blockchain-based technology to share patient records in a seamless environment. MedRec is a decentralized record management system to handle EMRs using blockchain technology. Irrespective of the technology used e-health providers are required to adopt administrative, physical, and technical safeguards to ensure the privacy, confidentiality, integrity, and availability of the e-health Data. E-health providers need to implement access controls, authentication, and nonrepudiation of health records. This article addresses the authentication in blockchain-based health data exchange. There is a need to verify the identity of the person or entity involved in the e-health interaction. Authentication services verify the person or entity seeking data access in the network. Identity confirmation is usually done using public-key cryptography or a DNS based authentication using an existing and widely accepted form of identification such as social security number. In some implementations, the provider nodes and patient nodes are authenticated using consensus methods facilitated by miners using the Ethereum technology stack. An important technical barrier in blockchain-based health data exchange is the need for entity authentication to be robust, it must be repeated for every entity-to-entity relationship. We consider a typical use case in Indian Public Health scenarios, which is the referral.

II.EXISTING SYSTEM

There are few existing studies that have applied SVM, KNN, Decision Tree and Ensemble Learning. Some studies use single set features, such as bag of words (BOW), N-grams, LIWC or LDA to identify depression in their posts. Sentiment analysis could be a field dedicated to extracting subjective emotions and feelings from text. One common use of Sentiment Analysis is to work out if a text expresses negative or positive feelings. Written reviews area unit nice datasets for doing Sentiment Analysis as a result of they usually go with a score which will be wont to train a rule. Support Vector Machines also known as support vector networks. It is a non-probabilistic linear binary classifier that analyses data for classification or anomaly detection. It builds a hyper plane into high dimensional feature space and finds a hyper plane that isolates the data into two classes with the biggest separation to the closest training data purpose of any class. Decision tree is a simple and all around used classification based systematic approach that makes the hierarchical tree from the training dataset. The state of decision tree is to divide the data hierarchically that have different characteristics. For instance, of text documents classification, roots are commonly identified in terms and internal individual nodes may be sub-divided to its children in view of the yes or no of a term in the document. Ensemble methods use multiple learning algorithms of decision tree for better predictive performance. **Adaptive Boosting (AdaBoost)** is an ensemble technique that can combine many weak classifiers into one strong classifier. It is widely used for binary class classification problems. MLP is a special case of the artificial neural network often used for modeling complex relationships between the input and output layers. Due to its multiple layers and non-linear activation, it can distinguish the data that is not only non-linearly separable

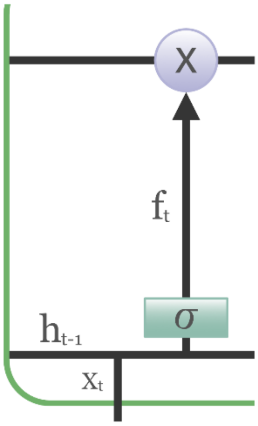
III.PROPOSED SYSTEM

Propose a lexicon-enhanced LSTM model (LE-LSTM) to integrate sentiment lexicon into LSTM to capture more sentiment information of words. First, we use sentiment lexicon as the extra information to pre-train a word sentiment classifier. And then each word can get its sentiment embedding including the words not in sentiment lexicon. During the main training process, we concatenate the word embedding and its sentiment embedding as the input of LSTM and fine-tune the word sentiment classifier network. Long Short-Term Memory is a kind of recurrent neural network. In RNN output from the last step is fed as input in the current step. LSTM was designed by Hochreiter & Schmidhuber. It tackled the problem of long-term dependencies of RNN in which the RNN cannot predict the word stored in the long-term memory but can give more accurate predictions from the recent information. As the gap length increases RNN does not give an efficient performance. LSTM can by default retain the information for a long period of time. It is used for processing, predicting, and classifying on the basis of time-series data.



3a.Structure of LSTM

The information that is no longer useful in the cell state is removed with the forget gate. Two inputs x_t (input at the particular time) and h_t-1 (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias. The resultant is passed through an activation function which gives a binary output. If for a particular cell state the output is 0, the piece of information is forgotten and for output 1, the information is retained for future use. Information is retained by the cells and the memory manipulations are done by the gates.



3b.Forget gate

To merge the lexical features obtained from datasets into the LSTM Model, we first perform a linear transformation to the lexical features in order to preserve the original sentiment distribution and have compatible dimensions for further computations. Later, the attention vector learned as in the baseline is applied to the transformed lexical features. In the end, all information is added together to perform the final prediction.Build a social networking service is an online platform which people use to build social networks or social relationships with other people who share similar personal or career interests, activities, backgrounds or real-life connections. Social networking services vary in format and the number of features. The classification model has been exposed as a REST API which was consumed by a Web application built using Python's Flask framework. The main features include an Admin dashboard for visualization of Depression activities, an option to search tweets, and automatic generation and emailing of reports of Depression activity. In this module we developed the API for Depression analytics on chat or post user data. It focuses on keywords and analyzes chat or post according to a two-pole scale positive and negative. Datasets contain unnecessary data in raw form that can be unstructured or semi-structured. Such unnecessary data increases training time of the model and might degrades its performance. Pre-processing plays a vital role in improving the efficiency of DL models and saving computational resources. Text pre-processing boosts the prediction accuracy of the model. The preprocessing step is essential in Depression detection. It consists of both cleaning of texts (e.g., removal of stop words and punctuation marks), as well as spam content removal. In the proposed model, it has been applied to remove and clean unwanted noise in text detection. For example, stop words, special characters, and repeated words were removed. Then, the stemming for the remaining words to their original roots has been applied as a result of this preprocessing, and the dataset containing clean tweets is produced for the proposed model to be run and predicted. In this project, we executed various data preprocessing steps such as tokenization, spelling correction, stop words removing, punctuation removing, digit removing, removing a non-Bangla character, removing Emoticons, word normalization, and lemmatization and data splitting.

IV.CONCLUSION

The detection of spam emails can be evaluated by different performance measures. Confusion Matrix is being used to visualize the detection of the emails for models Several measurements are used for performance evaluation of classifiers like accuracy, precision, recall, and f-score. The results and comparisons of different classifiers after data training and testing are presented in this section. We gathered 49799 tweets from the online resource ‘kaggle’ and translated them into English using the python library Googletrans, which uses the Google Translate Ajax API. 42797 tweets were used to train various ML and DL models. One seven thousand tweets were used for testing in order to quantify accuracy and assessment metrics. As explained about evaluation measures in chapter 9, we have evaluated accuracy, precision, recall, and f-measures that are evaluation measures measured using LR, XGBM and Naive Bayes, LSTM-CNN and BiLSTM. Finally, using various graphs, a comparison of models is presented below. The findings in Table 4 show that the deep learning algorithm (BiLSTM) is a stronger method for detecting Depression tweet classification, with high accuracy of 98.4%.The algorithms are designed to analyze the tweet for emotion detection as well as for detection of suicidal thoughts among people on social media. We validated the performance of our method by conducting extensive experiments on a standard dataset and outperformed the other alternatives for polarity estimation.

REFERENCES:

1. B. A. Primack, A. Shensa, J. E. Sidani, C. G. Escobar-Viera, and M. J. Fine, ``Temporal associations between social media use and depression," Amer. J. Preventive Med., vol. 60, no. 2, pp. 179-188, Feb. 2021.
2. S. Maxim, N. Ignatiev, and I. Smirnov, ``Predicting depression with social media images," in Proc. 9th Int. Conf. Pattern Recognit. Appl. Methods, vol. 2, 2020, pp. 128-138.
3. J. A. Diaz-Garcia, M. D. Ruiz, and M. J. Martin-Bautista, ``Non-query based pattern mining and sentiment analysis for massive microblogging online texts," IEEE Access, vol. 8, pp. 78166-78182, 2020.
4. G. Xu, Y. Meng, X. Qiu, Z. Yu, and X. Wu, ``Sentiment analysis of comment texts based on BiLSTM," *IEEE Access*, vol. 7, pp. 51522_51532, 2019.
5. Y. Li and H. B. Dong, ``Text emotion analysis based on CNN and BiLSTM network feature fusion," Comput. Appl, vol. 38, no. 11, pp. 29-34, 2018.
6. A.Yadav and D. K.Vishwakarma, ``Sentiment analysis using deep learning architectures: A review," Artif. Intell. Rev., vol. 53, no. 6, pp. 4335-4385, Aug. 2020, doi: 10.1007/s10462-019-09794-5.
7. W. Meng, Y. Wei, P. Liu, Z. Zhu, and H. Yin, ``Aspect based sentiment analysis with feature enhanced attention CNN-BiLSTM," IEEE Access, vol. 7, pp. 167240-167249, 2019.
8. F. Hao, G. Pang, Y. Wu, Z. Pi, L. Xia, and G. Min, “Providing appropriate social support to prevention of depression for highly anxious sufferers,” IEEE Trans. Comput. Social Syst., vol. 6, no. 5, pp. 879–887, Oct. 2019.
9. G. Shen et al., “Depression detection via harvesting social media: A multimodal dictionary learning solution,” in Proc. 27th Int. Joint Conf. Artif. Intell., Aug. 2017, pp. 3838–3844.
10. T. Shen et al., “Cross-domain depression detection via harvesting social media,” in Proc. 27th Int. Joint Conf. Artif. Intell., Jul. 2018, pp. 1611–1617.
11. R. Xu and Q. Zhang, “Understanding online health groups for depression: Social network and linguistic perspectives,” J. Med. Internet Res., vol. 18, no. 3, p. e63, Mar. 2016.