TELKOMNIKA Telecommunication, Computing, Electronics and Control
Vol. 19, No. 3, June 2021, pp. 886~892
ISSN: 1693-6930, accredited First Grade by Kemenristekdikti, Decree No: 21/E/KPT/2018
DOI: 10.12928/TELKOMNIKA.v19i3.18357

Bigram feature extraction and conditional random fields model to improve text classification clinical trial document

Jasmir Jasmir[1], Siti Nurmaini[2], Reza Firsandaya Malik[3], Bambang Tutuko[4]
[1]Faculty of Engineering, Universitas Sriwijaya, Palembang, Indonesia
[1]Computer Engineering, Universitas Dinamika Bangsa, Jambi, Indonesia
[2,4]Intelligence System Research Group, Universitas Sriwijaya, Palembang, Indonesia
[3]Communication Networks and Information Security Research Lab, Universitas Sriwijaya, Palembang, Indonesia

Article Info

Article history:

Received Jul 25, 2020
Revised Oct 17, 2020
Accepted Oct 29, 2020

Keywords:

Clinical trials
Conditional random fields
Deep learning
Text classification

ABSTRACT

In the field of health and medicine, there is a very important term known as clinical trials. Clinical trials are a type of activity that studies how the safest way to treat patients is. These clinical trials are usually written in unstructured free text which requires translation from a computer. The aim of this paper is to classify the texts of cancer clinical trial documents consisting of unstructured free texts taken from cancer clinical trial protocols. The proposed algorithm is conditional random Fields and bigram features. A new classification model from the cancer clinical trial document text is proposed to compete with other methods in terms of precision, recall, and f-1 score. The results of this study are better than the previous results, namely 88.07 precision, 88.05 recall and f-1 score 88.06.

Corresponding Author:

Reza Firsandaya Malik
Communication Networks and Information Security Research Lab
Universitas Sriwijaya
Palembang, Indonesia
Email: rezafm@unsri.ac.id

1. INTRODUCTION

Text classification is defined as labeling natural language text documents with classes or categories of predetermined sets [1, 2]. Text classification is an important component in many NLP applications, such as sentiment analysis [3], relationship extraction [4] and spam detection [5, 6]. Text classification has also attracted the attention of researchers to continue to develop innovations and testing, including those sourced from cancer clinical texts commonly referred to as cancer clinical trials. Clinical trials are research that implicate people. Through clinical trials, the medical party detect new ways to enhance treatments and the quality of life for people with illness [7].

Classification of clinical trials text has been developed through several approaches such as statistical approaches [8]; eligibility screening approach [9]; machine learning approach [10]; deep neural network [11, 12] clustering [13], convolutional neural network [14] and approaches to fine grained document clustering [12], It appears that the use of deep learning methods in the modeling of clinical trial classification is still limited. Until now, the classification of clinical trial texts is still being developed. The use of deep learning methods has become a great hope in solving clinical trial problems, especially modeling and performance and computational improvement [14]. However, due to the high dimensions and sparse text data, and the complex semantics of natural languages, text classification presents its own challenges [15].

Currently, deep learning technology [16] has achieved extraordinary results in many areas, such as computer vision [17] speech recognition, [18] and text classification [19]. Vincent menger [20] states that in some cases approaches with deep learning techniques applied to the classification of clinical texts can produce conclusions that match expectations, but will be different if tested on other clinical datasets and with different domains and different sizes. One of the studies on clinical trials that attracts attention is research from [21] (Bustos and Pertusa 2018). In this study, there is an explanation of predictions of patients with cancer, whether the patient is eligible or not worthy of being called a cancer sufferer based on medical records from doctors.

The method used in this research is K-Nearest neighbor (KNN), support vector machine (SVM), convolutional neural network (CNN) and FastText. In this study, the results displayed state that the KNN method is better than complex models such as SVM, CNN and FastText. However, the time spent by KNN in assessing the performance of this dataset is still long, and its performance is still very slow, this means that this method is only effective but not efficient.

One of deep learning method that is able to increase the computational value of text classification is conditional random fields [22, 23]. A conditional random field (CRF) is a standard model for predicting the most likely sequence of labels that corresponds to a sequence of inputs. The purpose of this study is to improve the text classification of cancer clinical trials using the conditional random fields method. Conditional random fields (CRF) is a probabilistic model to overcome segmentation and labeling of sequence data. CRF is used to combine features to get a model that will be used to assess the level of importance of sentences [24]. One of the applications of CRF is text classification [25, 26].

Several studies related to the above theme such as the cancer classification [27, 28] and clinical text classification [29, 30]. The other research that discusses the clinical text classification such as Zhang and Fushman [10], which discusses the development of methods for the automatic classification to facilitate the matching of ClinicalTrials.gov dataset patient trials for specific populations such as people living with HIV or woman pregnant. Yao *et al.* [31] produced a clinical text classification on obesity using the rule base feature and CNN methods. Chuan [14] proposes an active deep learning approach to automatically classify clinical trial. Jasmir *et al.* [12] use DNN and fine-grained document to improve classification text of clinical trial.

The conditional random fields method has also been discussed in several themes such as extracting causal relations from emergency [32], named entity recognition [33], and biomedical text [24]. Moharasan and Ho [34] which conduct research on clinis texts with semi-supervised conditional random fields, they proposed and evaluated a two-stage semi-supervised novel for the temporal event extraction, in this work they prove that the influence of undocumented clinical texts helps to significantly increase the accuracy of temporal event extraction. But it still needs to be developed with other additional methods and features. Therefore, to answer of this problem, we built a new model using conditional random fields (CRF) and bigram feature as our methodology to improving computational value.

2. MATERIAL AND METHOD

CRF based model as shown in Figure 1. The dataset is parsed into tags and text, then preprocessing applications such as token creation and bigram feature creation and sentence detection. The next process is conducting training with the CRF and producing a CRF model. At the same time, the tagging process was also carried out. Then the trained model will label it according to its features

2.1. Dataset

Data were taken from clinical reports. Data were extracted from clinical trial protocols about cancer originating from the National Institutes of Health: Bethesda, MD, USA, which can be downloaded from https://clinicaltrials.gov. This data comes from the fields of intervention, conditions, and feasibility written in unstructured free text language. Information in the eligibility criteria is a series of phrases and or sentences that are displayed in free format, such as paragraphs, bulleted lists, and enumeration lists.

2.2. Preprocessing

Preprocessing has a very important role in the technique and application of text mining. This is the first step in the text mining process. In this paper, we discuss three main steps for preprocessing, namely, stopword, stemming and TF/IDF [35]. All eligibility criteria are converted into simple word sequences. Based on this data, the mapping was carried out into the components of the patient's complaints (main complaints, onset, other complaints, information, frequency of attacks, nature of attacks, duration, location, course of disease, previous treatment history, and the consequences of disturbances that arose). All words are lowercase letters. At this stage, information extraction is carried out, in which unnecessary words will be deleted so that the final result required in the classification is obtained. But we don't remove stop words because they are semantically relevant to clinical statements. Next, replace the numbers, arithmetic signs, comparison with the text.

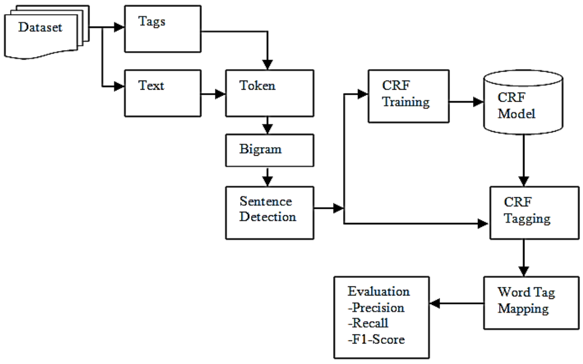

Figure 1. Conceptual model

2.3. Bigram

In general bigram or digram is a sequence of two adjacent elements of a token string, which usually consists of several letters, syllables, or words. Bigram is part of n-gram. The frequency distribution of each bigram in a string (or data type) is usually used for processing simple statistical data [36, 37]. However, in this study, the meant bigram is the phrase most often found in the medical field. bigram which is often found then changed into text form. Bigram can take the form of an expression. Bigrams can also help solve the conditional probability of a token being previously completed, when the conditional probability is applied:

$$P(W_n|W_{n-1}) = \frac{P(W_{n-1},W_n)}{P(W_{n-1})} \tag{1}$$

That is, the probability P() of a token $W_n$given the preceding token W_{n-1} is equal to the probability of their bigram, or the co-occurrence of the two tokens P(W_{n-1}, W_n) , divided by the probability of the preceding token.

2.4. Conditional random fields

Conditional random fields (CRF) is a probabilistic model that is widely used in the segmentation and labeling process of a data sequence. CRF is a mixing method between hidden Markov model and maximum entropy Markov model [38] CRF maintains the advantages of supervised and unsupervised methods while avoiding the disadvantages of both methods. By acquiring the advantages of discriminative modeling that the generative model does not have and overcoming the shortcomings of the generative model such as the problem of dependence on high assumptions in the hidden Markov model (HMM) and the usual labeling problems that occur in the maximum entropy Markov model (MEMM).

The set of features used to build the model using CRF based approach include Word and its Context Word, PoS of Word and its Context Words and Prefix and Suffix Information.The conditional random field (CRF) is added to the model in order to add the constraint relationship between the labels, to ensure that the predicted labels are valid and to find an optimal label sequence [39].

$$s(X,Y) = \sum_{i=1}^{n}(T_{yi-1,yi} + T_{i,yi}) \tag{2}$$

$$p(Y|X) = \frac{e^{s(X,Y)}}{\sum e^{s(X,Y)}} \tag{3}$$

$$Y = argmax\ s(X,Y) \tag{4}$$

3. RESULTS AND ANALYSIS

3.1. Precision recall and F-1 score

Measures of classification performance can be defined based on the confusion matrix [40] as seen in Table 1. The confusion matrix provides information on the comparison of the classification results carried out by the system (model) with the actual classification results. The confusion matrix is in the form of a matrix table that describes the performance of the classification model on a series of test data whose true values are known. Precision is a representation of uniformity and repetition of measurements. Precision is the degree of excellence, on the performance of an operation or technique used to get results.

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

Recall is a measure of the success of a system in finding and retrieving information. Furthermore, F-Measure is a process of calculating evaluation by combining precision and recall calculations. recall and precission in a situation can have different weights. The measure that displays the reciprocity between recall and precission is F-Measure which is the average harmonic weight and realization and precision.

$$Recall = \frac{TP}{TP+FP} \tag{6}$$

F-Measure or F1-score is one of the evaluation calculations in information retrieval that combines recall and precission. The recall value and precission in a situation can have different weights. The size that displays reciprocity between recall and precission is F-Measure which is the mean harmonic weight and reall and precission.

$$F1\ Score = \frac{2+(Recall+Precision)}{Recall+Precision} \tag{7}$$

Table 1. Measures of classification performance

		Actual Class	
Predicted Class		Class=Yes	Class=No
	Class=Yes	TruePositive=TP	False Positif=FP
	Class=No	False Negatif=FN	TrueNegative=TN

3.2. Model evaluation and validation

In this study we conducted two experiments, each data from $1x10^5$ to $5x10^5$ data, the first experiments is CRF without bigram and second experiment is CRF with bigram. For small data, it seems that the result is not significant between using bigram and using without bigram, but the results will affect in the larger data. So, by adding the bigram feature combined with conditional random fields, it can increase the computational value, especially for larger data.

3.2.1. CRF without bigram

The initial stage is evaluation using the conditional random field method only. Table 2 and Figure 2 are the CRF results without bigram. Data processing starts from small data which is 100,000 and multiples to the largest data which is 500,000 data. It can be seen that the evaluation value tends to increase with the addition of data. the more data that is processed, the greater the evaluation value will be.

3.2.2. CRF with bigram

The next stage is evaluation using the CRF method with Bigram features as shown in Table 3 and Figure 3. Bigram feature greatly influences the evaluation results. It can be seen that the evaluation value tends to increase with the addition of data. (almost the same as CRF without Bigram), but this result is better than CRF without Bigram, especially on larger data (500,000 data).

3.2.3. Comparison table

The Table 4 and Figure 4 is a comparison of Bustos and Pertusa [21] research (same dataset and different methods) and Moharasan and Ho [34] research (different dataset and same method). The results of this research indicate that precision 88.07, recall 88.05 and f-1 score 88.06. When compared with previous studies Bustos and Pertusa [21] using the same dataset and some deep learning methods like CNN and FastText, the results of this study with the CRF method are quite good and an increase in evaluation values. Then when compared to the Muharasan's study [34] which uses CRF and different dataset, our reseach is better then previous research, especially by using bigram.

The model built works better, this is because the context that is studied specifically from the clinical trial text document faces a lesser amount of ambiguity than the general context in the classification process. Another reason is that the CRF is a statistical-based model, the higher the ratio of causal sentences that appear, the more comprehensive the statistical information will be, and the higher the evaluation score will be.

Table 2. Result of CRF without Bigram

	100,000	200,000	300,000	400,000	500,000
Precision (%)	70.1	75.1	78.02	80.03	84.01
Recall (%)	72.7	74.7	77.35	79.67	84.3
F-1 Score (%)	71.4	74.9	77.68	79.84	84.15

Table 3. Result of CRF with bigram

	100,000	200,000	300,000	400,000	500,000
Precision (%)	68.6	73.6	79.05	83.07	88.07
Recall (%)	71.7	73.6	78.01	82.72	88.05
F-1 Score (%)	70.12	73.60	78.53	82.89	88.06

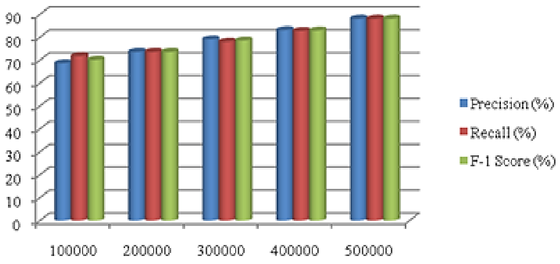

Figure 2. Graph of CRF without bigram

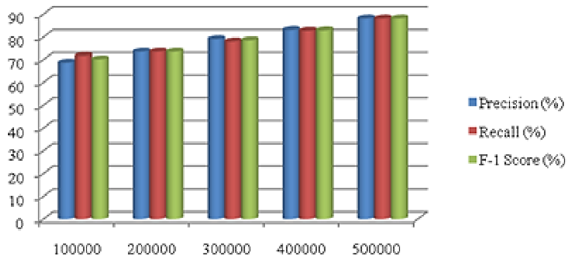

Figure 3. Graph of CRF with bigram

Table 4. Result of comparison with Aurelia Bustos and Moharasan

Event	Precision (%)	Recall (%)	F-1 (%)
FastText[21]	88.00	86.00	87.00
CNN [21]	88.00	88.00	88.00
SVM [21]	79.00	79.00	79.00
BaseLine[34]	79.17	81.12	80.13
CRF + Lexical+Syntactic [34]	85.27	72.53	78.39
CRF + Random Selection [34]	86.42	82.25	84.21
Proposed Method CRF with Bigram	88.07	88.05	88.06

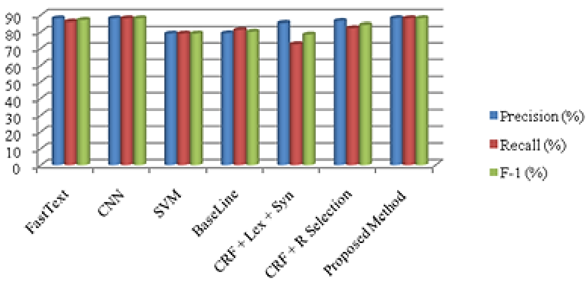

Figure 4. Result of comparison with Bustos [21] and Moharasan [34]

4. CONCLUSION

CRFs are successfully being applied to clinical trials text classification. The evaluation results indicate that clinical trial text document, which are freely available, can be exploited by conditional random fields, thus opening the potential to explore more ambitious goals by making additional efforts needed to build datasets that corresponding. The results of this study are better than the previous results, namely 88.07 precision, 88.05 recall and f-1 score 88.06. The next research is multilabel classification. The problem will be a multilabel classification task, where classes will be "effective" vs. "ineffective" and "learned" vs "not learned", and both can be true or false. This will allow us to classify four types of cases: effective and studied, potentially effective but not studied, ineffective and learned, and potentially ineffective and not learned. The main effort in this case lies in building a dataset, which includes the efficacy results obtained for each study. New models can be developed to produce potential cancer treatments that can be considered for certain patient cases based on the efficacy of complete clinical trials.

REFERENCES

[1] M. Z. A. G. Sorkhi, “Improving Text Classification Performance Using PCA and Recall-Precision Criteria,” *Arab J Sci Eng*, vol. 38, pp. 2095-2102, 2013.

[2] D. Toruno, E. Çak, M. C. Ganiz, S. Akyoku, and M. Z. Gürbüz, “Analysis of Preprocessing Methods on Classification of Turkish Texts,” *2011 International Symposium on Innovations in Intelligent Systems and Applications,* 2011, pp. 112-117.

[3] A. Y. N. and C. P. Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang, Christopher D. Manning, "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank," *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing,* 2013, pp. 1631-1642.
[4] D. Zeng, K. Liu, Y. Chen, and J. Zhao, "Distant Supervision for Relation Extraction via Piecewise Convolutional Neural Networks," *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing,* 2015, pp. 1753-1762.
[5] A. H. Wang, "Don 't follow me Spam Detection in Twitter," *Conference: SECRYPT 2010 - Proceedings of the International Conference on Security and Cryptography,* Athens, Greece, July 26-28,2010.
[6] S. Xie, G. Wang, S. Lin, and P. S. Yu, "Review Spam Detection via Temporal Pattern Discovery," *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining,* 2012, pp. 823-831.
[7] B. Melinda, "Clinical Trials," *Bill Melinda Gates Found.*
[8] J. J. Hardesty and N. F. Kanarek, "Barriers to non-small cell lung cancer trial eligibility," *Contemp. Clin. Trials Commun.*, vol. 9, pp. 45–49, 2018.
[9] Y. Ni *et al.*, "Increasing the efficiency of trial-patient matching: Automated clinical trial eligibility Pre-screening for pediatric oncology patients Clinical decision-making, knowledge support systems, and theory," *BMC Med. Inform. Decis. Mak.*, vol. 15, no. 1, pp. 1-10, 2015.
[10] K. Zhang and D. Demner-Fushman, "Automated classification of eligibility criteria in clinical trials to facilitate patient-trial matching for specific patient populations," *J. Am. Med. Informatics Assoc.*, vol. 24, no. 4, pp. 781-787, 2017.
[11] Y. Wu, M. Jiang, J. Lei, and H. Xu, "Named Entity Recognition in Chinese Clinical Text Using Deep Neural Network," *Stud. Health Technol. Inform.*, vol. 216, pp. 624–628, 2015.
[12] J. Jasmir, S. Nurmaini, R. F. Malik, and D. Zaenal, "Text Classification of Cancer Clinical Trials Documents Using Deep Neural Network and Fine Grained Document Clustering," *Proceedings of the Sriwijaya International Conference on Information Technology and Its Applications (SICONIAN 2019)*, 2019.
[13] T. Hao, A. Rusanov, M. R. Boland, and C. Weng, "Clustering clinical trials with similar eligibility criteria features," *J. Biomed. Inform.*, vol. 52, pp. 112–120, 2014.
[14] C. H. Chuan, "Classifying Eligibility Criteria in Clinical Trials Using Active Deep Learning," *Proc. - 17th IEEE Int. Conf. Mach. Learn. Appl. ICMLA 2018*, 2019, pp. 305-310.
[15] G. Liu and J. Guo, "Bidirectional LSTM with attention mechanism and convolutional layer for text classification," *Neurocomputing*, vol. 337, pp. 325-338, 2019.
[16] J. Schmidhuber, "Deep learning in neural networks : An overview," *Neural Networks*, vol. 61, pp. 85-117, 2015.
[17] B. Jou and B. Jou, "From Pixels to Sentiment : Fine-tuning CNNs for Visual Sentiment Prediction NU," *arXiv:1604.03489,* 2017.
[18] Ł. Brocki and K. Marasek, "Deep Belief Neural Networks and Bidirectional Long-Short Term Memory Hybrid for Speech Recognition," vol. 40, no. 2, pp. 191-195, 2015.
[19] K. S. Tai, R. Socher, and C. D. Manning, "Improved Semantic Representations From Tree-Structured Long Short-Term Memory Networks" *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing*, 2015.
[20] V. Menger, F. Scheepers, and M. Spruit, "Comparing deep learning and classical machine learning approaches for predicting inpatient violence incidents from clinical text," *Appl. Sci.*, vol. 8, no. 6, 2018.
[21] A. Bustos and A. Pertusa, "Learning eligibility in cancer clinical trials using deep neural networks," *Appl. Sci.*, vol. 8, no. 7, pp. 1-19, 2018.
[22] S. Lin, J.-P. Ng, S. Pradhan, J. Shah, R. Pietrobon, and M.-Y. Kan, "Extracting Formulaic and Free Text Clinical Research Articles Metadata using Conditional Random Fields," *Proc. NAACL HLT 2010 Second Louhi Work. Text Data Min. Heal. Doc.*, 2010, pp. 90-95.
[23] Z. Liu, B. Tang, X. Wang, and Q. Chen, "De-identification of clinical notes via recurrent neural network and conditional random field," *J. Biomed. Inform.*, vol. 75, pp. S34–S42, 2017.
[24] R. Tiwari, C. Zhang, and W. B. Chen, "Extraction of coexpression relationship among genes from biomedical text using dynamic conditional random fields," *Proc. - IEEE Symp. Comput. Med. Syst.*, 2009, pp. 9-12.
[25] E. Tutubalina and S. Nikolenko, "Combination of Deep Recurrent Neural Networks and Conditional Random Fields for Extracting Adverse Drug Reactions from User Reviews," *J. Healthc. Eng.*, vol. 2017, no. 1, pp. 1-9, 2017.
[26] C. Gu, X. P. Tian, and J. De Yu, "Automatic Recognition of Chinese Personal Name Using Conditional Random Fields and Knowledge Base," *Math. Probl. Eng.*, vol. 2015, no. 7, pp. 1-6, 2015.
[27] Jasmir *et al.*, "Breast Cancer Classification Using Deep Learning," *Proc. 2018 Int. Conf. Electr. Eng. Comput. Sci. ICECOS 2018*, vol. 17, 2019, pp. 237-242.
[28] A. M. Abdel-Zaher and A. M. Eldeib, "Breast cancer classification using deep belief networks," *Expert Syst. Appl.*, vol. 46, pp. 139-144, 2016.
[29] R. Figueroa, Q. Zeng-Treitler, L. H. Ngo, S. Goryachev, and E. Wiechmann, "Active learning for clinical text classification: Is it better than random sampling?," *J. Am. Med. Informatics Assoc.*, vol. 19, no. 5, pp. 809-816, 2012.
[30] V. Garla, C. Taylor, and C. Brandt, "Semi-supervised clinical text classification with Laplacian SVMs: An application to cancer case management," *J. Biomed. Inform.*, vol. 46, no. 5, pp. 869-875, 2013.
[31] L. Yao, C. Mao, and Y. Luo, "Clinical text classification with rule-based features and knowledge-guided convolutional neural networks," *BMC Med. Inform. Decis. Mak.*, vol. 19, no. Suppl 3, 2019.
[32] J. Qiu, L. Xu, J. Zhai, and L. Luo, "Extracting Causal Relations from Emergency Cases Based on Conditional Random Fields," *Procedia Comput. Sci.*, vol. 112, pp. 1623-1632, 2017.

[33] N. Patil, A. Patil, and B. V. Pawar, "Named Entity Recognition using Conditional Random Fields," *Procedia Comput. Sci.*, vol. 167, no. 2019, pp. 1181-1188, 2020.
[34] G. Moharasan and T. B. Ho, "Extraction of temporal events from clinical text using semi-supervised conditional random fields," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10387 LNCS, pp. 409-421, 2017.
[35] H. Fan and Y. Qin, "Research on Text Classification Based on Improved TF-IDF Algorithm," vol. 147, no. Ncce, pp. 501-506, 2018.
[36] R. Pavitra and P. C. D. Kalaivaani, "Weakly supervised sentiment analysis using joint sentiment topic detection with bigrams," *2nd Int. Conf. Electron. Commun. Syst. ICECS 2015*, 2015, pp. 889-893.
[37] B. Mohammed Badr and S. Sameen Fatima, "Using Skipgrams, Bigrams, and Part of Speech Features for Sentiment Classification of Twitter Messages," *Proc. 12th Int. Conf. Nat. Lang. Process.*, 2015, pp. 268-275.
[38] H. Gandhi and V. Attar, "Extracting Aspect Terms using CRF and Bi-LSTM Models," *Procedia Comput. Sci.*, vol. 167, no. 2019, pp. 2486–2495, 2020.
[39] Z. Wan, J. Xie, W. Zhang, and Z. Huang, "BiLSTM-CRF Chinese Named Entity Recognition Model with Attention Mechanism," *J. Phys. Conf. Ser.*, vol. 1302, no. 3, 2019.
[40] A. Darmawahyuni, S. Nurmaini, and F. Firdaus, "Coronary Heart Disease Interpretation Based on Deep Neural Network," *Comput. Eng. Appl. J.*, vol. 8, no. 1, pp. 1-12, 2019.

BIOGRAPHIES OF AUTHORS

Jasmir is senior lecture at Universitas Dinamika Bangsa Jambi, Indonesia. He received his Bachelor in Computer Engineering in 1995 and Master degree in Information Technology in 2006 from Universitas Putra Indonesia YPTK Padang, Indonesia. He is currently pursuing Doctor's degree of Engineering Science, majoring in Informatics Engineering, from Universitas Sriwijaya Palembang, Indonesia. His research interest is data mining, machine learning and deep learning for natural language processing and its application

Siti Nurmaini is a Professor in the Faculty of Computer Science University of Sriwijaya, Indonesia. She is a senior researcher and a founder of The Intelligent Systems Research Group (ISRG) Computer Engineering Department, Faculty of Computer Science, Universitas Sriwijaya. She received the bachelor degree in Electrical Engineering from Universitas Sriwijaya 1992, and master degree in Control System from Institut Teknologi Bandung, Indonesia, in 1998, and Doctor's Degree in Computer Science from Universiti Teknologi Malaysia in 2011. Her work focused on the application of machine learning and deep learning in signal and image analysis techniques to medical diagnosis, especially in cancer, cardiac disease, and Covid 19. She is affiliated with IEEE and has served as an invited reviewer in MDPI journal, ComengApp journal and other scientific publications

Reza Firsandaya Malik is a senior lecturer at Faculty of Computer Science, Universitas Sriwijaya since December 2010. He received the S.T. (Bachelor of Engineering) degree from the Institut Sains dan Teknologi Nasional (ISTN), South Jakarta, in 2000, the M.T. (Master of Technique) degree from the Institut Teknologi Bandung, in 2003, and the Ph.D. degree from Universiti Teknologi Malaysia (UTM), in 2011, where he investigated the Routing Optimization Scheme in wireless mesh networks using particle swarm optimization. He is also appointed as a member of the communication Networks and Information Security (COMNETS) Research Laboratory, Faculty of Computer Science, Universitas Sriwijaya. His current research interests include pervasive computing and artificial intelligence.

Bambang Tutuko is a senior lecturer at Department of Computer Engineering, Faculty of Computer Science, Universitas Sriwijaya Palembang Indonesia since 1995. He received the bachelor degree in Electrical Engineering from Universitas Sriwijaya, Indonesia in 1987, and master degree in Control System from Institut Teknologi Bandung, Indonesia, in 1998. He obtained a Doctor's Degree in Informatic Engineering, Universitas Sriwijaya Indonesia in 2019. His current research interest includes; robotic, control system, and artificial intelligence.