International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 4, August 2024, pp. 4147~4153
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i4.pp4147-4153

Automatic notes based on video records of online meetings using the latent Dirichlet allocation method

Rakhmat Arianto[1], Rosa Andrie Asmara[2], Usman Nurhasan[1], Anugrah Nur Rahmanto[2]
[1]Information Technology Department, Business Information Systems Study Program, Malang State Polytechnic, East Java, Indonesia
[2]Information Technology Department, Informatics Engineering Study Program, Malang State Polytechnic, East Java, Indonesia

Article Info

Article history:

Received Jul 20, 2023
Revised Oct 3, 2023
Accepted Mar 9, 2024

Keywords:

Automatic note-taking system
Latent Dirichlet allocation method
Meeting minutes
Text summarization
Topic modeling

ABSTRACT

Meeting minutes can also be used as a benchmark for whether the meeting objectives have been achieved or not. Minutes are taken during the meeting until the end of the meeting, which contain essential points from the meeting. Minutes in online meetings are currently still done manually, and generally, every meeting is recorded as documentation that requires more human resources to change the recording of the meeting file. Based on the problems above, a solution to this problem is needed by creating an automatic note-taking system that can assist the note-takers in concluding the meeting, especially in the Information Technology Department. This study uses the latent Dirichlet allocation (LDA) method to determine text summarization and topic modeling. Based on this research, the system calculation using the LDA method produces a pretty good accuracy value for text summarization of 57.91% and topic modeling with a coherence score of 64.56%. Based on this research, the implementation of the latent Dirichlet allocation method for text summarization and topic modeling provides a fairly good level of similarity accuracy when compared to the minutes that are written manually and can be implemented in the Information Technology Department.

Corresponding Author:

Usman Nurhasan
Information Technology Department, Business Information Systems Study Program, Malang State Polytechnic
Soekarno-Hatta Street no. 9, City of Malang, East Java, Indonesia
Email: usmannurhasan@polinema.ac.id

1. INTRODUCTION

The minutes of a meeting serves several goals, including the following: recording the decisions that were taken at the meeting; tracking the progress that has been made on action items; providing a reference for subsequent meetings; and providing documentation in the event of a legal dispute. According to the findings of a study that was conducted and published in 2020 by Kosmin and Robert [1], the most essential components of meeting minutes are the date and time of the meeting, the names of those who attended the meeting, the decisions that were reached, and the action items that were given. The findings of the paper also indicated that it is critical to maintain brevity and focus on the main points being discussed in each meeting's minutes. Meeting minutes have been proven to be an effective technique to enhance the overall quality of meetings, according to the findings of another piece of study that was released in 2021. This piece of research was conducted by Changpueng and Patpong [2]. According to the findings of the paper, keeping minutes of meetings may be a useful tool for ensuring that all participants have the same understanding of the topic at hand, that decisions are reached in a timely way, and that action items are monitored and performed.

Because to the emergence of the coronavirus disease (COVID-19), organization has been compelled to make adjustments and look for ways to continue its operations in order to conform to the circumstances that are now in place. E-conferences have had to take the place of traditionally in-person meetings in order to support measures implemented by the government to assist in containing the spread of the COVID-19 virus, particularly in Indonesia [3]. Organizations that first felt driven to conduct meetings online have seen several advantages as a result of doing so, some of which are as follows: online meetings can save businesses a significant amount of money on travel costs, accommodation, and food, allow people to participate from anywhere with an internet connection, easier for people with disabilities to participate in meetings, can help to improve productivity by reducing the amount of time that is wasted on travel and preparation, and easier for people to collaborate on projects [4].

The realization of the potential advantages of having meetings virtually has resulted in the emergence of several previously unanticipated challenges, one of which is the challenge of accurately recording meeting minutes. Consequently, we want an online meeting minute's system that is both automated and capable of concurrently overcoming some of the issues that are associated with manually recording online meeting minutes. These issues include the following: the practice of holding an increased number of meetings inside a corporation, manually creating meeting minutes can be a time-consuming task, manually created meeting minutes can be inaccurate, and manually created meeting minutes can be inconsistent [5].

Several previous studies discussing automatic online meeting minutes are as follows: Pandya and Gawande's research in 2022 [6] states that automated minute book creation (AMBOC) model, bidirectional and auto-regressive transformers (BART) summarizer, hierarchical meeting summarization network (HMNet) model, multi sentence compression graph (MSCG) are employed for detecting useful and informative action items from audio files, Khodake *et al*. research in 2023 [7] states that a system to get fluent, concise, and adequate minutes of meeting from a given transcript achieves eval_rouge1 score of 47.39 and *eval_loss* of 1.56 for summarization tasks, research by Koay *et al.* in 2021 [5] states that a neural abstractive summarizer navigates through the raw transcript to find salient content in meeting minutes, research by Shah and Jain in 2023 [8] states that employees often miss crucial points due to the time-consuming and dull task of taking meeting minutes, resulting in wasted resources exceeding 37 billion dollars. To address this, an automated approach using deep learning methods is proposed. It aims to extract key information from discussions, identify speakers with MFCC, convert audio to text using deep neural network (DNN), and summarize meeting transcripts into condensed minutes using Transformers. This method optimizes productivity, improves communication, and utilizes accessible technical advancements, research by Chen *et al.* in 2021 [9] state that Yanji is an automated system for generating meeting minutes based on speech and speaker recognition, research by Shinde *et al.* in 2021 [10] state that a BART model trained on the SAMSum dialogue summarization dataset summarized meeting transcripts, research by Yamaguchi *et al.* in 2021 [11] state that a reference-free approach for automatic minuting achieve the best adequacy score among all submissions, research by Sharma *et al.* in 2021 [12] state that a pipeline-based system can provide a set of sentences from any given transcript that can best describe it based on selected features and heuristic evaluation metrics, research by Liu *et al.* in 2020 [13] state that focus on designing and implementing SmartMeeting, an intelligent system for generating meeting minutes from meeting audio data and by comparing and evaluating different baseline algorithms on real-world audio meeting datasets, experiments have proven that SmartMeeting can accurately summarize meetings and analyze agreed actions. Research by Garg and Singh in 2021 [14] state that automating minuting is considered one of the most challenging tasks in natural language processing and sequence-to-sequence transformation. Research by Miura *et al.* in 2020 [15] state that this research leads to the development of a system that generates minutes by using repeated questions and answers between a user and the system. The aim of the research is to provide the user with an interactive analysis of meeting records, with a specific purpose or viewpoint. Research by Williams and Haddow in 2021 [16] state that developed an English-language minuting system for task a that combines BERT-based extractive summarization with logistic regression-based filtering and rule-based pre- and post-processing steps. In the human evaluation, our system averaged scores of 2.1 on adequacy, 3.9 on grammatical correctness, and 3.3 on fluency. Research by Kosmin and Roberts in 2020 [17] state that Directors of a public listed company should ensure their concerns are recorded in the board minutes if they cannot be resolved. Research by Sheikhi *et al.* in 2022 [18] state that SmartMinutes improves current practices related to the meeting minutes process by providing automation in areas where possible. Research by Doan *et al.* in 2020 [19] state that deep learning, generative adversarial networks (GANs), and transformers were used to build a tool for automatic generation of meeting minutes. Research by Kimura and Ito in 2020 [20] state that this research would like to solve this problem by realizing an automatic cue system to encourage the attendance of a meeting to mention their idea. The result of the experiment of the proposed system shows that the imbalance of the number of the speech was solved, and all attendances of the meeting could present their idea and opinion. Based on several previous studies, in this study we will propose an automatic note taking using the natural language processing technique using the latent Dirichlet allocation method because some of the available programming libraries only provide processing using English word data, so it needs to be tested in Indonesian language data to see if it gets a score optimal accuracy.

2. METHOD

In completing the research, the stages of cross industry standard process for data mining (CRISP-DM) were adopted because several previous studies indicated that the CRISP-DM stages were very suitable as a stage of research because they focused on data processing to obtain an optimal model and then carried out prototyping [21]–[25]. The entire stage consists of 6 stages, namely: business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

2.1. Business understanding

This stage focuses on exploring the problems that will be discussed in research by conducting interviews and observations at research sites. We determined the place of research to be the Malang State Polytechnic majoring in information technology. Where, we made observations of the entire implementation of online meetings that had been carried out and we found the fact that the number of stored online meeting video recordings was not accompanied by meeting minutes, so we investigated further by conducting interviews with the person responsible for making minutes for each online meeting activity implemented. From this person, we found the fact that the person was unable to take minutes while attending an ongoing online meeting. If you make minutes outside of carrying out an online meeting, minutes will be taken based on that person's perception. Based on the results of interviews and observations that have been carried out by the Information Technology Department, it is very necessary to make automatic minutes as a solution to fulfill the presence of minutes in every online meeting that is held.

2.2. Data understanding

After knowing the subject matter of the research from the previous stages, a few data samples were taken to serve as examples and descriptions of what data would be processed in the next stage and understanding and confirmation were carried out from the research site. The initial data obtained is in the form of video recordings of online meetings using the zoom application with an average meeting duration of 2 hours with videos in mp4 format. After an in-depth study of the video data, it was discovered that for each video recording of online meetings there is a pattern where the video is divided into 3 parts, opening, holding the meeting, and closing the meeting. In the opening part, meeting participants do not discuss the main issues to be discussed but greet one another. The second part is the core part of the online meeting video recording, and the third is the closing where the participants greet each other and close the online meeting application.

2.3. Data preparation

At this stage, the focus is on preparing the initial data that has been obtained in the previous stage so that it has the same format to be used in the next stage. Video recording data for online meetings is cut so that each video data is part of the contents of the online meeting which is done by opening the video one by one and cutting using existing tools. Because the python library used is the Google Speech-to-Text API which can only process data in the form of voice, then each video that has been cut will be formatted using existing tools to become voice data in the wav format. After each video data has been turned into several voice data, the text is taken from each speech of each online meeting participant by using the online Google Speech-to-Text service and the text that has been obtained is collected.

2.4. Modelling

Furthermore, this stage focuses on implementing several computational algorithms to find which algorithm is the most optimal by using the data prepared in the previous stage. At this stage, two algorithms are used, namely topic modeling and text summarization, both of which use the latent Dirichlet allocation method. The entire framework in the modeling stage is shown in Figure 1.

The text obtained from the previous stage will be processed in the topic modeling and text summarization algorithms. Based on the characteristics of the topic modeling, the text will be carried out in the preprocessing text stage, but in implementing text summarization it does not require the preprocessing text stage. The topic modeling algorithm will get the topic of discussion from online meeting participants which aims to help the note taker to imagine his perceptions. Whereas in text summarization the note taker will receive the summary results of the conversation. Topic modeling calculations are contained in formula (1) where K is the number of topics, D is the document index and α is the Dirichlet parameter. As for the calculation of text summarization contained in formula 2 where $P(S_r|T_k)$ is the probability of the r^{th}

sentence on topic k, $P(W_i \mid T_k)$ is the probability of the i^{th} word on topic k, $P(T_k \mid D_m)$ is the probability of the k^{th} topic in m document and length (S_r) is the number of words in the sentence.

$$\frac{\sum k,d+\alpha_k}{\sum_i^K n_{d,i}+\alpha_i} \tag{1}$$

$$P(S_r|T_k) = \frac{\sum_{W_i \epsilon S_r} P(W_i|T_k) * P(T_k \mid D_m)}{length(S_r)} \tag{2}$$

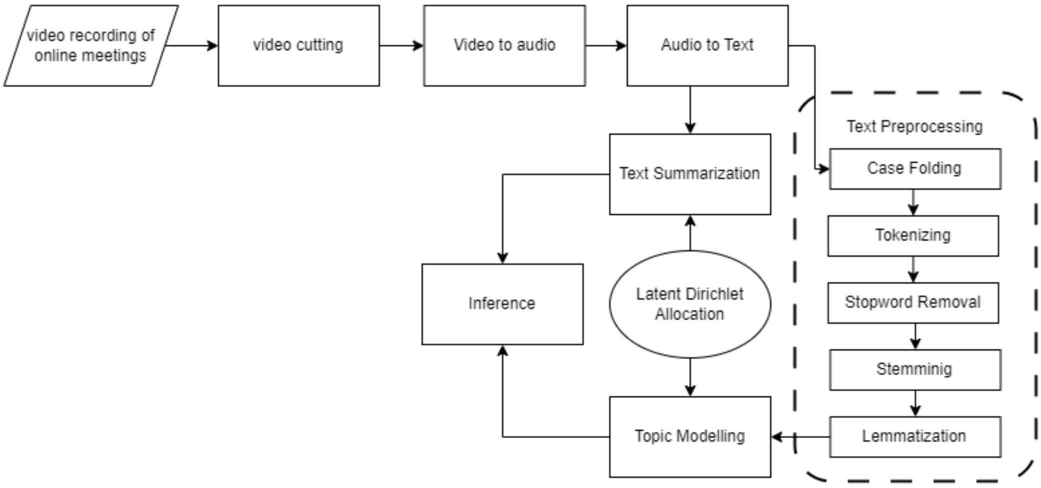

Figure 1. Framework in the modeling stage

2.5. Evaluation

At this stage the focus is on measuring the accuracy of each algorithm used so that the most optimal algorithm is obtained so that it is used for the deployment stage. In topic modeling, accuracy measurement will be carried out using the coherence score which refers to the relationship between one text and another text to form a coherent whole. Whereas in text summarization, the results of implementing text summarization will be calculated for its similarity with existing minutes using the vector space model so that it is known whether the resulting summary results still have a high level of similarity with the existing minutes. If you get a high similarity value, it will be better or vice versa.

2.6. Deployment

Furthermore, this stage aims to build a prototype of the proposed solution by building a simple application that is equipped with a text data input feature, the process of using a more optimal comparison results algorithm, and the expected output display can be formatted according to the rules for making predetermined meeting minutes by the Department of Information Technology. Later, on the prototype that has been formed, system functionality testing will be carried out to find out that each feature that is made functions properly and can be used by users.

3. RESULTS AND DISCUSSION

Testing the accuracy of the system is the testing phase carried out to find out the similarities of the results of the minutes that are generated automatically and the minutes manually. The process of calculating the accuracy of the similarity between the two documents is calculated using cosine similarity. The results of the calculation of cosine similarity can be seen in the Table 1.

In the experiment carried out, 4 video recording data of online meetings were used with file names as shown in Table 1 as well as minutes that have been previously prepared by the maker of the minutes of the meeting. Each video is 2 hours long and the audio to text conversion results produces more than 1,000 words. Words from the results of text summarization and minutes that are made manually will be processed using the vector space model which contains the term frequency-inverse document frequency (TF-IDF) algorithm and cosine similarity so that the degree of similarity between the two documents will be obtained with an average of 57.91% which is not a good similarity value. The weakness of the experiment that has been carried out is that the use of words in manual meeting minutes is the result of the perception of the meeting minutes maker so that many words are not similar the words issued by online meeting participants but still have the same meaning and the number of words produced by text summarization is more than the words in manual meeting minutes because they are written in a short point to point way instead of in paragraph form.

Table 1. Similarity score text summarization result and manual minute of meeting

No	File name	Similarity score
1	Automatic: minutes of 26 oct Curriculum FGD with Pak Salies and Pak Go Frendi Manual: DuDi Curriculum FGD Minutes 26102020	63.44%
2	Automatic: DuDi Curriculum FGD Minutes – 23102020 Manual: DuDi Curriculum FGD Minutes – 23102020	59.18%
3	Automatic: FGD Minutes with DuDi – 19112020 Manual: FGD Minutes with DuDi – 19112020	58.07%
4	Automatic: DuDi Curriculum Evaluation FGD 21 Oct _ 30 Nov Manual: DuDi Curriculum Evaluation FGD 21 Oct _ 30 Nov	50.95%
	Average of Similarity Score	57.91%

Meanwhile, Table 2 shows the results of the coherence score from the use of the topic modeling algorithm with an average of 64.56%. With these results, it can be concluded that the topic modeling algorithm also gets a bad value because during the modeling process of topics from other sources are not much contained in conversations between online meeting participants so that the results obtained from each video are only 5 topics but the words in it have loops such as the results of calculating the frequency of occurrence of words in sentences.

Table 2. Coherence score result of topic modelling

No	File meeting	Coherence score
1	Minutes of 26 oct curriculum FGD with Pak Salies and Pak Go Frendi	56.38%
2	DuDi Curriculum FGD Minutes – 23102020	68.51%
3	Minutes of FGD with DuDi – 19112020	71.93%
4	DuDi Curriculum Evaluation FGD 21 Oct _ 30 Nov	61.43%
	Average coherence score *topic modelling*	**64.56%**

4. CONCLUSION

The use of online meeting applications that started from the implementation due to the spread of the corona virus but with many benefits obtained by the organization, it became the main choice in carrying out meetings so that it had an impact with the number of online meetings that increased but was not followed by an increase in the number of meeting minutes that could be arranged in a short time so that an application was needed that could make meeting minutes faster than taking minutes meeting manually by meeting minutes maker. The solution offered in this article has been experimented using two different algorithms with the results on the text summarization algorithm having an accuracy of 57.91% while the topic modeling algorithm gets a coherence value of 64.56%

ACKNOWLEDGEMENTS

The research team from the Department of Information Technology, State Polytechnic of Malang, compiled this journal article based on the report (automatic notes based on video records of online meetings using the latent Dirichlet allocation method). This work was funded by the Badan Riset dan Inovasi Nasional (BRIN) in the 2022 National Research Priority Grant program. The opinions expressed here are those of the author and do not necessarily reflect the views of the funding agency.

REFERENCES

[1] L. Kosmin and C. Roberts, “Minutes of general meetings and decisions of members,” in *Company Meetings and Resolutions*, Oxford University Press, 2020, doi: 10.1093/oso/9780198832744.003.0020.

[2] P. Changpueng and P. Patpong, “Genre analysis of minutes of meetings conducted in English by Thai engineers,” *Indonesian Journal of Applied Linguistics*, vol. 11, no. 1, pp. 134–145, Jun. 2021, doi: 10.17509/ijal.v11i1.34584.

[3] A. Demir, L. Maroof, N. U. Sabbah Khan, and B. J. Ali, “The role of E-service quality in shaping online meeting platforms: a case study from higher education sector,” *Journal of Applied Research in Higher Education*, vol. 13, no. 5, pp. 1436–1463, Nov. 2020, doi: 10.1108/JARHE-08-2020-0253.

[4] B. Adriel Aseniero, M. Constantinides, S. Joglekar, K. Zhou, and D. Quercia, "MeetCues: Supporting online meetings experience," in *Proceedings - 2020 IEEE Visualization Conference, VIS 2020*, Oct. 2020, pp. 236–240, doi: 10.1109/VIS47514.2020.00054.

[5] J. J. Koay, A. Roustai, X. Dai, and F. Liu, "A sliding-window approach to automatic creation of meeting minutes," in *NAACL-HLT 2021 - 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Student Research Workshop*, 2021, pp. 68–75, doi: 10.18653/v1/2021.naacl-srw.10.

[6] A. Pandya and N. Gawande, "Automatic generation of minutes of meetings," *International Journal of Scientific Research in Science, Engineering and Technology*, pp. 93–99, Mar. 2022, doi: 10.32628/ijsrset22928.

[7] N. Khodake, S. Kondewar, S. Bhandare, and C. Haridas, "Automatic generation of meeting minutes using NLP," *International Journal for Research in Applied Science and Engineering Technology*, vol. 11, no. 5, pp. 7015–7019, May 2023, doi: 10.22214/ijraset.2023.53353.

[8] J. Shah and N. Jain, "Advances in automatic meeting minute generation: A survey," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 503–510, Feb. 2023, doi: 10.48175/ijarsct-8328.

[9] X. Chen *et al.*, "Yanji: An automated mobile meeting minutes system," in *Proceedings - 2021 2nd International Symposium on Computer Engineering and Intelligent Communications, ISCEIC 2021*, Aug. 2021, pp. 425–428, doi: 10.1109/ISCEIC53685.2021.00095.

[10] K. Shinde, N. Bhavsar, A. Bhatnagar, and T. Ghosal, "Team ABC @ AutoMin 2021: Generating readable minutes with a BART-based automatic minuting approach," in *First Shared Task on Automatic Minuting at Interspeech 2021*, Sep. 2022, pp. 26–33, doi: 10.21437/automin.2021-2.

[11] A. Yamaguchi, G. Morio, H. Ozaki, K. Yokote, and K. Nagamatsu, "Team Hitachi @ AutoMin 2021: Reference-free automatic minuting pipeline with argument structure construction over topic-based summarization," in *First Shared Task on Automatic Minuting at Interspeech 2021*, Sep. 2022, pp. 41–48, doi: 10.21437/automin.2021-4.

[12] U. Sharma, M. Singh, and H. Singh, "Team the turing TESTament @ AutoMin 2021: A pipeline based approach to generate meeting minutes using TOPSIS," in *First Shared Task on Automatic Minuting at Interspeech 2021*, Sep. 2022, pp. 71–77, doi: 10.21437/automin.2021-9.

[13] H. Liu *et al.*, "SmartMeeting: An novel mobile voice meeting minutes generation and analysis system," *Mobile Networks and Applications*, vol. 25, no. 2, pp. 521–536, Jul. 2020, doi: 10.1007/s11036-019-01310-x.

[14] A. Garg and M. Singh, "Team Symantlytical @ AutoMin 2021: Generating readable minutes with GPT-2 and BERT-based automatic minuting approach," in *First Shared Task on Automatic Minuting at Interspeech 2021*, Sep. 2022, pp. 65–70. doi: 10.21437/automin.2021-8.

[15] H. Miura, Y. Takegawa, A. Terai, and K. Hirata, "Interactive minutes generation system based on hierarchical discussion structure," *Web Intelligence*, vol. 18, no. 1, pp. 85–95, Mar. 2020, doi: 10.3233/WEB-200430.

[16] P. Williams and B. Haddow, "Team UEDIN @ AutoMin 2021: Creating minutes by learning to filter an extracted summary," in *First Shared Task on Automatic Minuting at Interspeech 2021*, Sep. 2022, pp. 78–81. doi: 10.21437/automin.2021-10.

[17] L. Kosmin and C. Roberts, "Minutes of meetings of directors," in *Company Meetings and Resolutions*, Oxford University Press, 2020. doi: 10.1093/oso/9780198832744.003.0027.

[18] A. S. H. Sheikhi, E. Iosif, O. Basov, and I. Dionysiou, "SmartMinutes—A blockchain-based framework for automated, reliable, and transparent meeting minutes management," *Big Data and Cognitive Computing*, vol. 6, no. 4, p. 133, Nov. 2022, doi: 10.3390/bdcc6040133.

[19] T. M. Doan, F. Jacquenet, C. Largeron, and M. Bernard, "A study of text summarization techniques for generating meeting minutes," in *Lecture Notes in Business Information Processing*, vol. 385 LNBIP, Springer International Publishing, 2020, pp. 522–528. doi: 10.1007/978-3-030-50316-1_33.

[20] A. Kimura and A. Ito, "An automatic cue to activate a meeting," in *11th IEEE International Conference on Cognitive Infocommunications, CogInfoCom 2020 - Proceedings*, Sep. 2020, pp. 67–72. doi: 10.1109/CogInfoCom50765.2020.9237842.

[21] B. Matthies, "CRISP-DM: das Vorgehensmodell für data mining," *WiSt - Wirtschaftswissenschaftliches Studium*, vol. 51, no. 5, pp. 42–44, 2022, doi: 10.15358/0340-1650-2022-5-42.

[22] M. J. Nodeh, M. H. Calp, and İ. Şahin, "Analyzing and processing of supplier database based on the cross-industry standard process for data mining (CRISP-DM) algorithm," in *Lecture Notes on Data Engineering and Communications Technologies*, vol. 43, Springer International Publishing, 2020, pp. 544–558. doi: 10.1007/978-3-030-36178-5_44.

[23] J. S. Saltz, "CRISP-DM for data science: Strengths, weaknesses and potential next steps," in *Proceedings - 2021 IEEE International Conference on Big Data, Big Data 2021*, Dec. 2021, pp. 2337–2344. doi: 10.1109/BigData52589.2021.9671634.

[24] C. Schröer, F. Kruse, and J. M. Gómez, "A systematic literature review on applying CRISP-DM process model," *Procedia Computer Science*, vol. 181, pp. 526–534, 2021, doi: 10.1016/j.procs.2021.01.199.

[25] F. Martinez-Plumed *et al.*, "CRISP-DM twenty years later: From data mining processes to data science trajectories," *IEEE Transactions on Knowledge and Data Engineering*, vol. 33, no. 8, pp. 3048–3061, Aug. 2021, doi: 10.1109/TKDE.2019.2962680.

BIOGRAPHIES OF AUTHORS

Rakhmat Arianto obtained a bachelor of applied science (S.ST) degree in the informatics engineering study program, Surabaya State Electronics Polytechnic, Surabaya in 2009. Obtained a master of computer (M.Kom.) degree in the informatics engineering study program, Informatics Engineering Department, Institute of Technology Ten November, Surabaya in 2013. Subsequently, he received the title of Doctor of Computer Science (DCS), Bina Nusantara University, Jakarta since 2021. His career as a lecturer in the Department of Information Technology, State Polytechnic of Malang from 2019 until now. With a research focus on natural language processing, text mining, and data science, he has published "The architecture social media and online newspaper credibility measurement for fake news detection" for the last 5 years at TELKOMNIKA 2019 and a "Fake news detection model based on credibility measurement for Indonesian online news" at JATIT April 2021. He can be contacted at email: arianto@polinema.ac.id.

Rosa Andrie Asmara obtained a bachelor of engineering (ST) degree in the Electronics Engineering Study Program, Brawijaya University Malang, in 2004. Obtained a master of engineering (MT) degree in the Electronics Engineering Study Program, Department of Engineering, Sepuluh Nopember Institute of Technology, Surabaya in 2009 Next, he obtained his doctor of engineering (Dr. Eng), Saga University, Japan since 2013. His career as a lecturer in the Department of Information Technology, State Polytechnic of Malang since 2005 until now. With a research focus on image processing and data science, he has published many international articles in the field of image processing and computer vision. He can be contacted at email: rosa.andrie@polinema.ac.id.

Usman Nurhasan is a lecturer at Malang State Polytechnic, a vocational higher education institution in Indonesia. He holds a bachelor of computer degree from Malang State Islamic University and a master of engineering degree from Brawijaya University in Indonesia. Usman Nurhasan has expertise in several fields, including intelligent systems, text mining, web development, and the internet of things. He has published research papers in various national conferences and journals on topics such as data mining, machine learning, multimedia programming, internet of things and text mining. As a lecturer, Usman Nurhasan is dedicated to providing his students with a high-quality education that combines theory and practical skills. He is also actively involved in research activities and has collaborated with both local and international researchers to conduct research in his area of expertise. He has been a teaching staff at the Department of Information Technology, State Polytechnic of Malang since 2015. He can be contacted at email: usmannurhasan@polinema.ac.id.

Anugrah Nur Rahmanto is a lecturer at Politeknik Negeri Malang (State Polytechnic of Malang), a vocational higher education institution in Indonesia. He received his bachelor’s degree in visual design and communication from Bina Nusantara University Jakarta and his master's degree in product design from the Trisakti University in Indonesia. Anugrah Nur Rahmanto has expertise in several fields, including multimedia and design, UI/UX, web development, and database systems. He has published research papers in various national conferences and journals on topics such as data mining, machine learning, multimedia design and UI/UX. As a lecturer, Anugrah Nur Rahmanto is dedicated to providing his students with a high-quality education that combines theory and practical skills. He is also actively involved in research activities and has collaborated with both local and international researchers to conduct research in his areas of expertise. Anugrah Nur Rahmanto has been a faculty member of Information Technology Department, Politeknik Negeri Malang since 2016. He can be contacted at email: anugrahnur@polinema.ac.id.