SHM PUBLISHER
SURYA HIJAU MANFAAT

Journal of Information System Exploration and Research

https://shmpublisher.com/index.php/joiser

p-ISSN 2964-1160 | e-ISSN 2963-6361

Digit and Mark Recognition Using Convolutional Neural Network for Voting Digitization in Indonesia

Mandasari[1*], Bagus Al Qohar[2]
[1,2] *Department of Computer Science, Universitas Negeri Semarang, Indonesia*

DOI: https://doi.org/10.52465/joiser.v2i2.365
Received 08 July 2024; Accepted 30 July 2024; Available online 30 July 2024

Article Info

Keywords:
Convolutional neural network;
Handwriting digit;
Election result

Abstracts

Digitization of voting results in Indonesia is essential to ensure the accuracy and integrity of the election process. This research introduces an innovative approach that uses Convolutional Neural Networks (CNN) for handwritten number recognition and tally mark recognition. This research uses a dataset obtained from Kaggle. The research process is conducted in several stages, namely Data Collection, Preprocessing, Data Sharing, Modelling, and Evaluation. The results showed that the proposed model achieved an accuracy of 98%. This research shows that using the CNN algorithm for handwritten number recognition and tally mark recognition can improve accuracy and efficiency in digitizing voting results. It is expected that this research can make a significant contribution to the development of a more reliable digital voting system. Future research is recommended to use a larger dataset to validate the strength of the model, which has been built on more varied data.

1. Introduction

Elections are a crucial element in a democratic system that allows people to choose their representatives in government [1]. The outcome of these elections affects the direction of public policy and the overall development of the country. As such, the prediction of election results has a significant impact on the political, social, and economic context of a country [2-5].

Along with technological advancements, the digitization of voting results is an important step to ensure transparency, accuracy, and efficiency in the electoral process [6]. In Indonesia, which has a strong democratic tradition, a reliable and fast vote-counting mechanism is crucial. Handwritten number recognition and tally mark recognition are crucial techniques in the process of modernizing election practices [1], [2], [6].

This research aims to develop an election result prediction model using artificial intelligence techniques, specifically by utilizing the Convolutional Neural Network (CNN) algorithm [7]. The purpose of this research is to evaluate the effectiveness of CNN in digitizing voting results and compare it with

* ***Corresponding Author:***

Mandasari,
Department of Computer Science,
Universitas Negeri Semarang
Semarang, Indonesia.
Email : mandasr@students.unnes.ac.id

other existing approaches [8]. Various factors that affect election results, such as historical election data, demographics, political trends, and social variables, will be comprehensively analyzed. In this context, Indonesian election data is chosen as the focus of the research, given its significant scale and complexity in the Southeast Asian region [9].

Some previous studies have used statistical models and other machine learning techniques, but not many have utilized CNN in depth for this application [10-14]. In their studies on the application of CNN to handwritten character recognition, and on improving the accuracy of signature recognition through CNN, show the potential of this technique, but no one has specifically applied it to the digitization of voting results [13].

The main contribution of this research is the application of CNN in the context of election digitization, which is expected to provide significant improvements in accuracy and efficiency compared to existing methods [12]. This research focuses not only on technology, but also on the integrity of the democratic process in Indonesia, to reduce human error, speed up processing time, and ensure the validity of election results [15].

In addition, this research also has broader implications in terms of the synergy between artificial intelligence and governance. The combination of advanced technology with institutional frameworks can bring about major changes in transparency, accountability, and inclusiveness in governance [8], [16-18]. Therefore, this research has the potential to make significant contributions to political analysis, decision-making, and technological development in the context of elections, combining knowledge from political science, statistics, and artificial intelligence [19], [20].

2. Method

In this study, we use Indonesian election data as the main research material taken from Kaggle. This data includes voting results marked with election signs and handwritten numbers. This research material was chosen due to the complexity and large scale of the election process in Indonesia, which reflects the real challenges in digitizing voting results [21].

While there has been some research on the application of CNNs in character and signature recognition, this research focuses on the recognition and digitization of election tally marks using CNNs, which is an area that has not been widely explored [22]. The following Figure 1 is a framework carried out in this study.

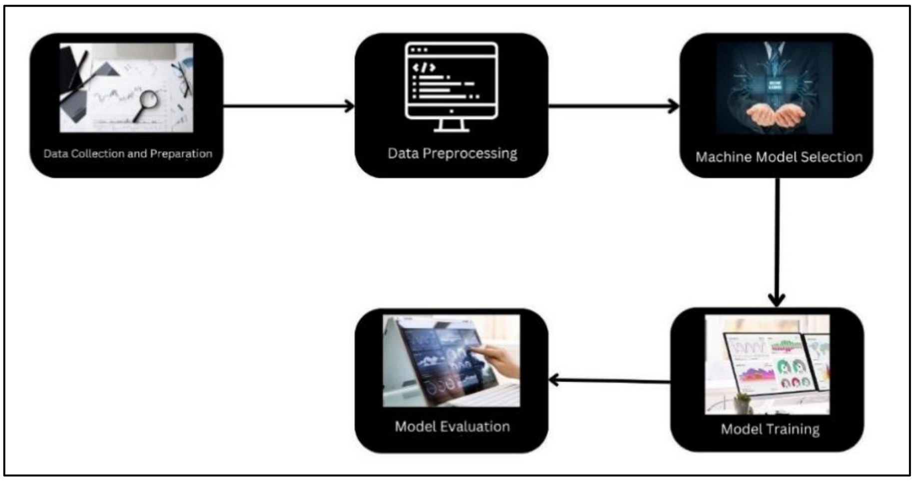

Figure 1. Research framework

Election results can be predicted with the help of artificial intelligence, using a comprehensive range of voting results [1]. Based on Figure 1, the classification method to be used is similar to the method that has been used before, which consists of five stages:

2. 1. Data Collection and Preparation

Data collection is taken through a dataset originating from Kaggle, titled ‘Tally Marks Classify Torch Conv2d’ Tally Marks Dataset (kaggle.com). This dataset consists of images of a subset of photos of voting result forms from the 2020 gubernatorial election publicly available from the general election committee website that will be used for classification. The raw dataset used is about 4000 photos and generated 38,000 images. the dataset is stored in JPG format, due to lossy compression, the background is not very black and some have non-zero but low intensity (<10).

2. 2. Data Pre-Processing

The initial dataset consists of 38,000 images with .jpg format and 22x28 pixel resolution. After the cleaning process, 200 corrupted or unreadable images were removed, leaving 37,800 images. Next, the images were resized to 28x28 pixels and normalized to a range of pixel values [0, 1]. The data augmentation process was performed with rotation, horizontal flip, and brightness change techniques to increase the variety of data. The data is divided into 70% for training, 20% for validation, and 10% for testing.

2. 3. Machine Model Selection

Here, a machine learning algorithm is selected that is suitable for the research objectives and the characteristics of the election data used [23]. After careful review, we decided to use the CNN model [24], [25], which has been proven effective in predicting election results in previous studies. This model can provide a clear interpretation of the contribution of each feature to the prediction results [26]. We developed a CNN model with an architecture consisting of multiple convolution, pooling, and fully connected layers. This architecture is designed to capture important features from images of tally marks and handwritten numbers.

2. 4. Model Training

Based on historical selection data with known outcomes, the model is trained. The model tries to find patterns in the information that can be used to predict election results [11], [13]. CNN models are trained using backpropagation techniques with optimization algorithms such as Adam or SGD. The training process involves repeated iterations to reduce the loss function and improve prediction accuracy.

2. 5. Model Evaluation

The model performance evaluation is carried out using a confusion matrix. The confusion matrix used in this research is for multi-class classification. Each element of the matrix indicates the number of instances for a specific combination of actual and predicted classes. The confusion matrix includes four primary metrics. True Positive (TP) represents the number of positive cases accurately predicted by the model. True Negative (TN) denotes the negative cases correctly identified by the model. False Positive (FP) refers to the number of negative cases wrongly predicted as positive by the model. False Negative (FN) indicates the number of positive cases incorrectly predicted as negative by the model. The performance evaluation of the classification model is done by calculating the accuracy value, which reflects how well the model can correctly identify the classes as a whole. It is calculated using the following formula:

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

3. Results And Discussion

This research uses datasets retrieved from Kaggle and applies Machine Learning methods, specifically Convolutional Neural Networks (CNN), for the digitization of election results. CNN is an effective technique in pattern and object recognition, which allows models to learn complex features from image data without the need to be explicitly programmed. In this study, CNN is applied to identify and classify tally marks as well as handwritten numbers from election results.

Table 1 shows the architecture of the CNN model used in this study. The model consists of multiple convolution, pooling, and fully connected layers with a total of 250,502 parameters that are all trainable. Each layer has an important role in capturing different features of the image data, with the convolution layer capturing local features and the pooling layer reducing the dimensionality of the data while retaining important information.

Table 1. The architecture of the CNN model

Layer (type)	**Output Shape**	**Param #**
conv2d_4 (Conv2D)	(None, 20, 26, 32)	832
max_pooling2d_4 (MaxPooling2D)	(None, 10, 13, 32)	0
dropout_6 (Dropout)	(None, 10, 13, 32)	0
conv2d_5 (Conv2D)	(None, 6, 9, 64)	51264
max_pooling2d_5 (MaxPooling2D)	(None, 3, 4, 64)	0
dropout_7 (Dropout)	(None, 3, 4, 64)	0
flatten_2 (Flatten)	(None, 768)	0
dense_4 (Dense)	(None, 256)	196864
dropout_8 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 6)	1542

Figure 2 shows the output form of each layer of the model, which underlines the hierarchical structure of CNNs in feature extraction and classification.

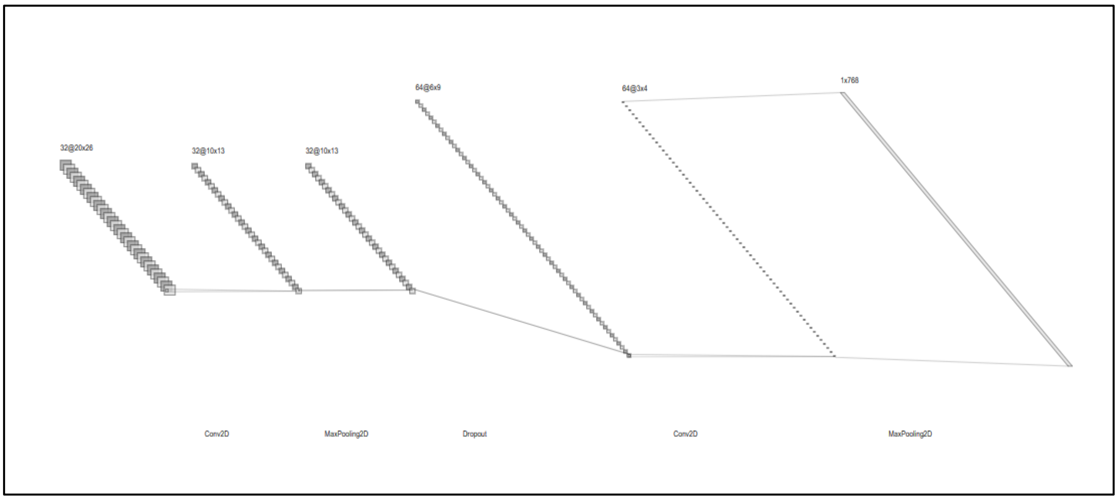

Figure 2. Shape model

Figure 2 shows the shape of the tally marks dataset, which includes vertical lines and X marks for the representation of voice data. This dataset reflects the complexity of recognizing varied tally marks, including image quality issues such as blur and low contrast. This research introduces a dual-modality approach by recognizing not only handwritten numbers but also tally marks, which shows novelty in election digitization methods.

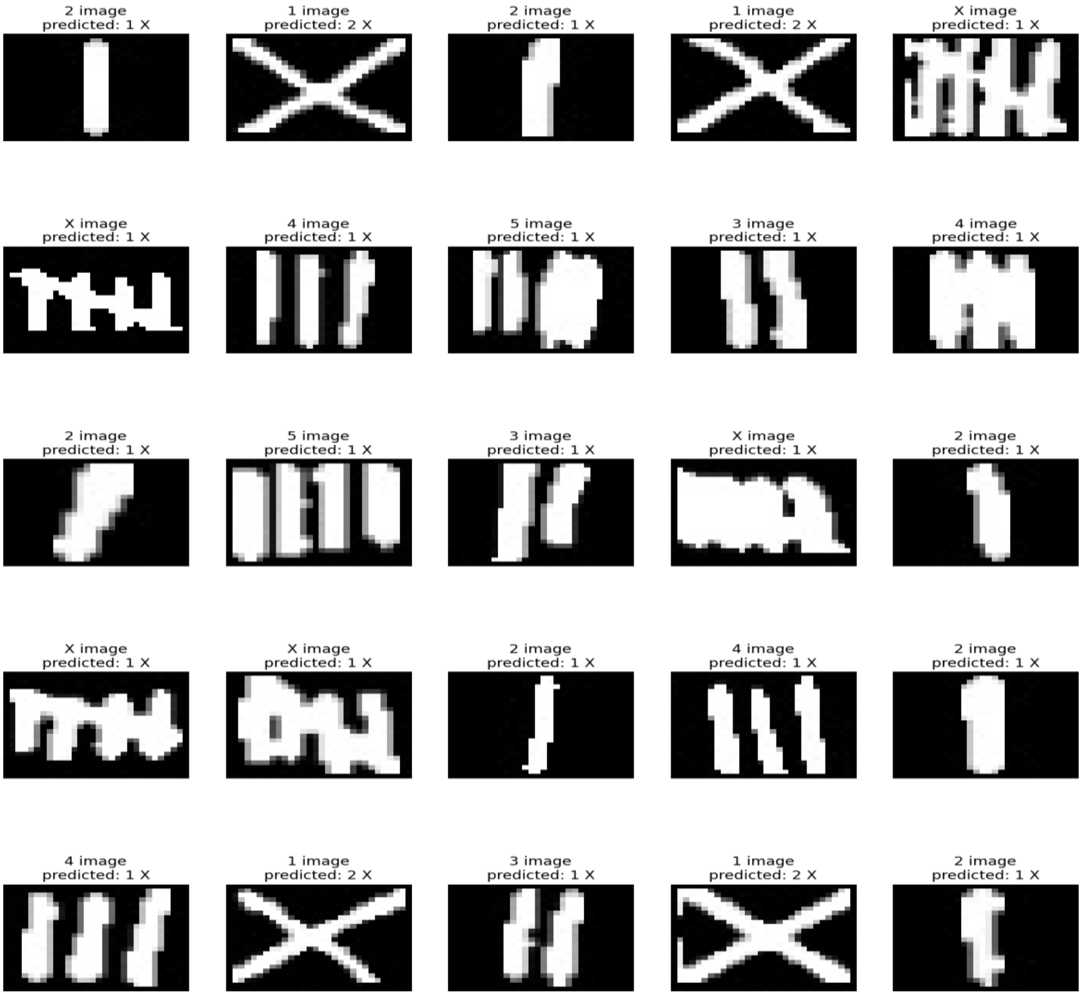

Figure 3. Shape of tally marks dataset

Figure 4 displays a graph of data processing results, including accuracy and loss on training and testing data. This graph shows that the developed CNN model achieves an accuracy of 98.45%, which is higher compared to the traditional model which only achieves 97% accuracy. It also shows that our model has a lower loss performance, signaling an improvement in recognition efficiency.

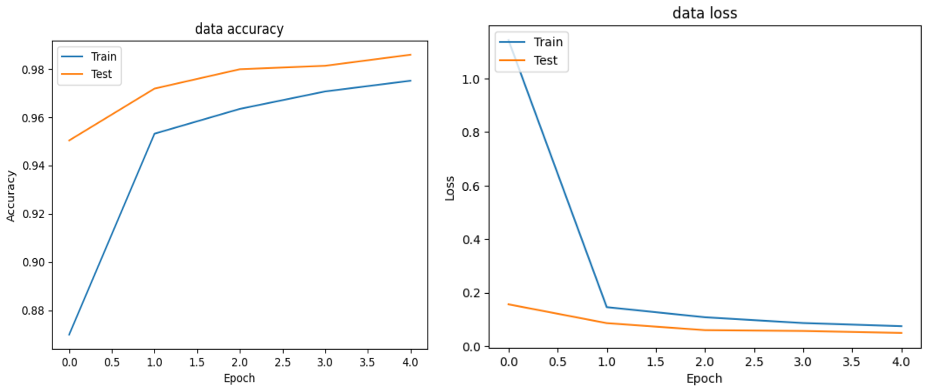

Figure 4. Graph of accuracy and data loss data processing results

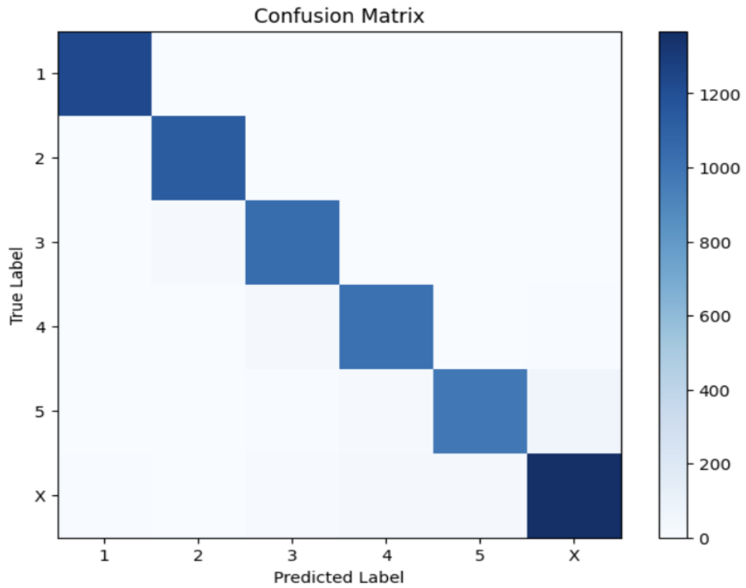

Figure 5 Confusion Matrix Evaluation Results

Figure 5 shows the evaluation results using the confusion matrix for the developed CNN model. A confusion matrix is a very useful tool to analyze the performance of a classification model by comparing the model's predicted results against the actual labels. By using a confusion matrix, we can calculate performance metrics such as accuracy, precision, recall, and F1-score in more detail.

In this study, the CNN model achieved an accuracy of 98.45% on the Tally Mark dataset. This figure shows a significant improvement compared to previous research which only achieved an accuracy of 97% [26]. The Tally Mark dataset used in this study has a better representation of different types of tally marks, including lines and X marks, which allows the model to learn from more varied data. The CNN model used adopts an architecture with more layers and parameters that allow for more in-depth feature processing. These improvements indicate that our model is not only more effective at recognizing and classifying tally marks but also better at handling variations and varying image quality.

4. Conclusion

This study aims to digitize voting results in Indonesia to ensure the accuracy and integrity of the election process using Convolutional Neural Networks (CNN) for handwritten number recognition and tally mark recognition. Utilizing a dataset from Kaggle, the research was conducted in several stages: Data Collection, Preprocessing, Data Sharing, Modelling, and Evaluation. The proposed model achieved an accuracy of 98%, demonstrating that CNN can significantly enhance the accuracy and efficiency of digitizing voting results. These findings suggest that this model could contribute to the development of a more reliable digital voting system. Future research should consider using a larger dataset to validate the model's robustness with more varied data.

References

[1] B. Heredia, J. D. Prusa, and T. M. Khoshgoftaar, "Social media for polling and predicting United States election outcome," *Social Network Analysis and Mining*, vol. 8, no. 1, p. 48, Dec. 2018, doi: 10.1007/s13278-018-0525-y.

[2] K. Brito and P. J. L. Adeodato, "Machine learning for predicting elections in Latin America based on social media engagement and polls," *Government Information Quarterly*, vol. 40, no. 1, 2023, doi: 10.1016/j.giq.2022.101782.

[3] D. E. Safitri and A. S. Fitrani, "Implementasi Metode Klasifikasi Dengan Algoritma Support Vector Machine Kernel Gaussian Rbf Untuk Prediksi Partisipasi Pemilu Terhadap Demografi Kota Surabaya," *Indonesian Journal of Business Intelligence (IJUBI)*, vol. 5, no. 1, p. 36, 2022, doi: 10.21927/ijubi.v5i1.2259.

[4] V. JalajaJayalakshmi, V. Geetha, and M. M. Ijaz, “Analysis and Prediction of Stroke using Machine Learning Algorithms,” in *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, 2021, pp. 1–5. doi: 10.1109/ICAECA52838.2021.9675545.
[5] C. A. N. Batubara, H. H. Nuha, and S. Prabowo, “Sistem Akusisi Data Untuk Polling Berbasis Media Sosial Dan Autentikasi User Menggunakan Recaptcha,” *eProceedings of Engineering*, vol. 6, no. 2, 2019.
[6] N. Putu, L. Santiari, and I. G. S. Rahayuda, “Perbandingan Akurasi Algoritma K-Nearest Neighbors (KNN) dan Naive Pattern Search (NPS) dalam Website Handwritten Recognition untuk Latihan Menulis Bentuk,” 2023.
[7] I. P. A. P. Wibawa, I. K. A. Purnawan, D. P. S. Putri, and N. K. D. Rusjayanthi, “Prediksi Partisipasi Pemilih dalam Pemilu Presiden 2014 dengan Metode Support Vector Machine,” *Jurnal Ilmiah Merpati (Menara Penelitian Akademika Teknologi Informasi)*, vol. 7, no. 3, p. 182, 2019, doi: 10.24843/jim.2019.v07.i03.p02.
[8] W. I. Rahayu, A. Anindita, and M. N. Fauzan, “Penentuan validasi data pemilih dan klasifikasi hasil pemilu DPRD Kab. Bone untuk memprediksi partai pemenang menggunakan metode Naive Bayes,” *Jurnal Teknik Informatika*, vol. 14, no. 1, pp. 32–39, 2022.
[9] M. I. R. Biru, “Partisipasi Masyarakat dalam Pemilu 2019 di Kabupaten Kutai Kartanegara,” *EJournal Ilmu Pemerintahan*, vol. 8, no. 2, 2020.
[10] V. M. Safarzadeh and P. Jafarzadeh, “Offline Persian Handwriting Recognition with CNN and RNN-CTC,” in *2020 25th International Computer Conference, Computer Society of Iran (CSICC)*, 2020, pp. 1–10. doi: 10.1109/CSICC49403.2020.9050073.
[11] S. Aqab and M. U. Tariq, “Handwriting recognition using artificial intelligence neural network and image processing,” *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 7, pp. 137–146, 2020, doi: 10.14569/IJACSA.2020.0110719.
[12] P. A. Winata and I. Roysida, “Implementation of a faster R-CNN algorithm for identification of metastatic tissue using lymphoma histopathological images,” 2023.
[13] S. Prihatiningsih, N. S. M, F. Andriani, and N. Nugraha, “Analisa Performa Pengenalan Tulisan Tangan Angka Berdasarkan Jumlah Iterasi Menggunakan Metode Convolutional Neural Network,” *Jurnal Ilmiah Teknologi dan Rekayasa*, vol. 24, no. 1, pp. 58–66, 2019, doi: 10.35760/tr.2019.v24i1.1934.
[14] R. Rosita, D. A. A. Pertiwi, and O. G. Khoirunnisa, “Prediction of hospital intensive patients using neural network algorithm,” *Journal of Soft Computing Exploration*, vol. 3, no. 1, pp. 8–11, 2022.
[15] L. H. Husin *et al.*, “Malpraktik Pemilu dan Korupsi: Analisis terhadap Proses Penghitungan dan Rekapitulasi pada Pemilu Indonesia 2019,” *Integritas*, vol. 7, no. 1, pp. 57–78, 2021, doi: 10.32697/integritas.v7i1.720.
[16] R. Pradita, “Aplikasi Quick Count dalam Pemilihan Bupati di Kabupaten Nganjuk,” *Generation Journal*, vol. 6, no. 1, pp. 22–30, 2022.
[17] S. N. J. Fitriyyah, N. Safriadi, and E. E. Pratama, “Analisis Sentimen Calon Presiden Indonesia 2019 dari Media Sosial Twitter Menggunakan Metode Naive Bayes,” *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 5, no. 3, pp. 279–285, 2019.
[18] S. Otjes, “The EU Elephant: Europe in the 2021 Dutch General Elections,” *Intereconomics*, vol. 56, no. 2, pp. 70–75, 2021, doi: 10.1007/s10272-021-0956-y.
[19] A. S. Fitriani, “Penerapan Data Mining Menggunakan Metode Klasifikasi Naïve Bayes untuk Memprediksi Partisipasi Pemilihan Gubernur,” *JTAM (Jurnal Teori dan Aplikasi Matematika)*, vol. 3, no. 2, pp. 98–104, 2019.
[20] A. Subroto and A. Apriyana, “Cyber risk prediction through social media big data analytics and statistical machine learning,” *Journal of Big Data*, vol. 6, no. 1, p. 50, 2019, doi: 10.1186/s40537-019-0216-1.
[21] K. K. Mohbey, “Multi-class approach for user behavior prediction using deep learning framework on twitter election dataset,” *Journal of Data, Information and Management*, vol. 2, no. 1, pp. 1–14, 2020, doi: 10.1007/s42488-019-00013-y.
[22] A. A. SG. Mas Karunia Maharani, Komang Oka Saputra, and Ni Made Ary Esta Dewi Wirastuti, “Komparasi Metode Backpropagation Neural Network dan Convolutional Neural Network Pada Pengenalan Pola Tulisan Tangan,” *Journal of Computer Science and Informatics Engineering (J-Cosine)*, vol. 6, no. 1, pp. 56–63, 2022, doi: 10.29303/jcosine.v6i1.431.
[23] M. D. Kamalesh and B. B, “Personality prediction model for social media using machine learning Technique,” *Computers and Electrical Engineering*, vol. 100, p. 107852, 2022, doi: https://doi.org/10.1016/j.compeleceng.2022.107852.

[24] L. Wang, X. Qian, Y. Zhang, J. Shen, and X. Cao, “Enhancing Sketch-Based Image Retrieval by CNN Semantic Re-ranking,” *IEEE Transactions on Cybernetics*, vol. 50, no. 7, pp. 3330–3342, 2020, doi: 10.1109/TCYB.2019.2894498.

[25] M. I. WICAKSONO, “Pendeteksian Api Berbasis Pengolahan Citra Digital Menggunakan Metode Convolutional Neural Network,” *Etd.Repository.Ugm.Ac.Id*, 2020.

[26] A. S. Talita and A. Wiguna, “Implementasi algoritma long short-term memory (LSTM) untuk mendeteksi ujaran kebencian (Hate Speech) pada kasus pilpres 2019,” *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 19, no. 1, pp. 37–44, 2019.