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Automatic Face Detection Uses Deep Learning to Prevent Cheating in General Election

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Abstract—General elections are the cornerstone of a democratic system, where legitimacy and public trust in this phase have been crucial for maintaining political stability and social welfare. In this context, challenges such as systematic fraud and the complexity of voter identification were primary concerns. This study aims to analyze the effectiveness of visual identity detection technology in ensuring electoral integrity and reducing fraud risks. Utilizing Convolutional Neural Networks (CNNs) as part of Deep Learning (DL) was expected to address this issue. This research evaluates the visual identity detection system on a dataset of faces with variations in perspectives and accessories. The test results showed that the model accurately recognizes faces, achieving an accuracy rate of approximately 90%. The analysis concludes that advanced research is needed for further development with more diverse datasets to enhance accuracy in various complex situations. This research provides insights into the application of visual identity detection technology in general elections, aiming to contribute to strengthening public trust and security in the democratic process.

Keywords— *Convolutional Neural Networks, Deep Learning, electoral fraud, electoral integrity, general elections, visual identity detection*

I. INTRODUCTION

“General elections (Pemilu) are the primary means of democracy, functioning to establish a just government [1]”. “Safeguarding the integrity of a nation's democracy through fair, transparent, and free elections is the top priority [2]”. “Therefore, a fair and honest election will be achieved if the law is upheld according to the prevailing legislation [3]”.

“The right to vote as a human right is an essential part of the principle of popular sovereignty reflected in the principles of democracy and serves as a fundamental basis in state governance, as enshrined in the constitution [4]”. In the context of elections, the persistence of the Final Voters List (DPT) by the General Election Commission (KPU) has been a crucial step in ensuring that every citizen has equal and fair access to exercise their right to vote. “Through elections, citizens can express their aspirations by choosing leaders and representatives who will run the government [5]”. “Furthermore, elections also serve as a means for the public to engage directly, or in other words, as an opportunity for public participation in politics [6]”.

“Security guarantees are a necessity to ensure that the integrity of the elections is maintained effectively [7]”. “In reality, violations and electoral fraud are commonplace in every election cycle, manifested in various forms at each stage of the electoral process [8]”. “When voters perceive injustice, they may lose trust in the democratic system and doubt the legitimacy of the government formed from that election [9]”.

Indonesia's diverse geographical, social, and political landscape complicates the maintenance of election security and integrity. The country's rich variety of cultures and languages necessitates a comprehensive approach and advanced technology for effective democratic processes. Despite high citizen participation in periodic elections, challenges remain to ensure the security and integrity of the electoral process.

“In addition to these challenges, recent events surrounding the 2024 Presidential Election highlight the potential for electoral fraud. BBC News Indonesia reported that a study by social media analytics firm Drone Emprit found that conversations about the 2024 Presidential Election, quick counts, and electoral fraud were the most discussed topics by netizens on social media. A viral two-minute video on social media showed many ballots for the 2024 Presidential Election that had already been marked. This information was obtained by DEEP Indonesia, revealing that 24 ballots had already been punched, consisting of 7 ballots for candidate number 02 and 17 ballots for candidate number 03 [10]”.

In the context of these issues, developing a visual identity detection system is a promising solution to mitigate the risk of fraud and enhance the security and integrity of elections in Indonesia. As the election process grows more complex, modern technology offers practical solutions. By using the right technology and careful implementation, these problems are hoped to be effectively addressed, maintaining public trust and producing more representative and accurate election results.

The contribution of our research is the creation of a lightweight and robust deep learning (DL) model capable of performing automatic face recognition. “Deep learning is a subset of machine learning algorithms with high complexity characteristics [11]”. Additionally, we collected our dataset by directly capturing facial images under various lighting

conditions and angles to enrich the diversity of the dataset, aiming to enhance the model's accuracy in identity detection within the context of elections.

By combining a robust democratic tradition with modern technological innovations, Indonesia has great potential to develop a safer, more transparent, and trustworthy electoral system.

II. RELATED WORKS

Some research according to face detection used DL, which some researchers have conducted. "Developed a model DL to recognize image faces that used 560 images as train images and test images. Used two layers of CNNs followed by a flattened layer and a dense layer. The model test's results varied for different datasets, and the performance of the model can be seen in the results of the accuracy which reached 100% for the 16-man dataset, 97% for the 30-man dataset, and 97% for the 2-man dataset [12]". However, this DL model has not yet covered some cases like low-resolution images, pose variations, etc.

"Reference [13] conducted research comparing machine learning (ML) methods and DL methods that are implemented in face recognition. Most of the results showed that the DL method was more prominent than the ML method. Besides this, some varying results were found in the ML method when different features were chosen. Therefore, they recommended using the DL method in the future of this research".

"Reference [14] during the global pandemic of COVID-19, the use of a mask was compulsory by health authorities in every country. This was a challenge to conduct automatic recognition while many people were wearing masks. Built the DL model that can recognize the masked face using Inception-ResNet. The model was trained by a dataset that was provided by the National Engineering Research Center for Multimedia Software (NERCMS), School of Computer Science, Wuhan University, named the RWMFD. The lack of the number of images in the RWMFD dataset became an excellent input to conduct advanced research to create a more robust DL model".

III. RESEARCH METHOD

The research process consists of five key stages which are the analysis stage followed by the design stage then the development stage and testing stage, and finally implementation stage:

A. Analysis Phase

During the analysis stage, the current system or application is monitored while data collection is conducted simultaneously. "System analysis is used to understand the stages of input, processing, and output [15]".

1) *Current System Analysis*: The current face recognition system at polling stations relies on manual matching, where officials visually compare ID photos with voters' faces. This method demands high concentration, and any lapse in focus can reduce accuracy and efficiency. Manual verification also slows down the voting process, especially with large voter turnouts, leading to long queues and wait times. Despite its flexibility and low cost, this system's challenges highlight the need for improvements like automated facial recognition technology to enhance accuracy, efficiency, and security, thereby easing the workload on

officials and reducing human error.

2) *Data Collection*: In Data Collection for testing, the process is broken into several items:

- Training Data
- Validation Data
- Testing Data

3) *Preprocessing*: "The detected image undergoes preprocessing first [16]". "This data transformation process involves converting raw data into a more understandable format. The goal of this process is to correct common errors in raw data, such as missing information and irregular formatting [17]".

B. Design Phase

This phase involves designing the program architecture, selecting and implementing algorithms, and developing the face recognition system. Key steps include:

1) *Image Acquisition*: This is the initial step of obtaining digital images using devices like cameras. In this research, mobile phones and laptops capture image data for the face recognition system. The quality of the images significantly affects the effectiveness of the recognition process.

2) *Image Extraction*: This step involves extracting features or information from the images that need to be identified. It includes measuring key facial features such as shape, texture, and distances between elements like the eyes, nose, and mouth.

3) *Classification*: "Based on its definition, classification is a process aimed at describing and distinguishing various classes of data [18]". In this phase, the data is separated and categorized into different groups. In this research, the data is broken into three main groups such as data for training, validation, and testing.

4) *Identification*: This phase determines the identity of an object based on the extracted and classified features. Once the model is trained and validated, it can identify new faces, leading to successful face identification.

C. Development Phase

In this development phase, the first step is to write code using the Python programming language and the CNNs architecture to improve the accuracy of face image identification. The following steps for coding:

- Preprocessing,
- Model,
- Training,
- Identify.

D. Testing Phase

"The testing phase is the stage to evaluate whether the system is functioning properly or not, as well as to identify any shortcomings in the system when errors occur during the testing process [19]". In this phase, testing is conducted by running the application on a laptop. When the application is opened, it automatically connects to the camera. The application then automatically identifies the face in front of it and displays whether the face matches the data stored in the dataset.

E. Implementation Phase

The implementation phase is the final stage where the program results are reviewed and discussed. After evaluating the outcomes, the application can be deployed within the voter list face recognition system. Fig. 1 illustrates the research steps, using colored boxes to clearly represent the workflow sequence.

- 1) *Analysis (Light Blue)*: Data collection is conducted carefully to ensure relevance and sufficiency, forming the foundation for the research.
- 2) *Design (Yellow)*: Key system elements are designed in detail, including system architecture, algorithms, and the face recognition feature, ensuring all components work harmoniously.
- 3) *Development (Purple)*: The coding process is carried out based on the design, requiring attention to detail and programming skills to produce efficient, error-free code.
- 4) *Testing (Green)*: Thorough testing is performed to verify that all features work as intended and that there are no bugs, ensuring program reliability.
- 5) *Implementation (Red)*: The tested system is deployed in the real environment, marking the transition from development to operational use.

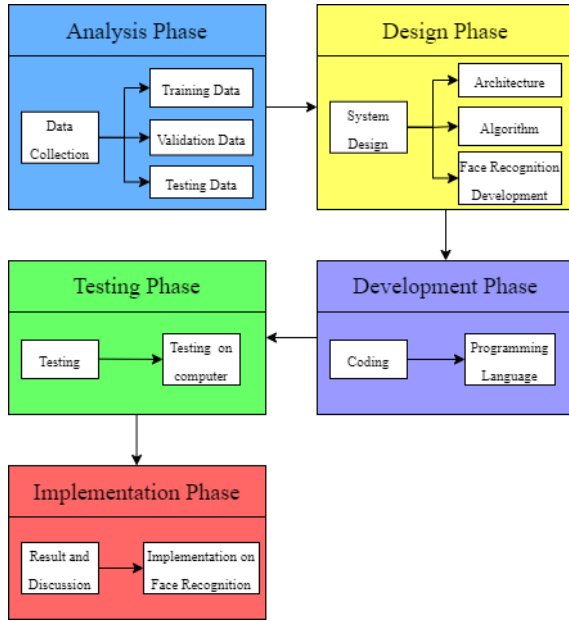


Fig. 1. Research Stages. [20]

IV. RESULTS AND DISCUSSION

A. Data Collection Phase

Face recognition requires substantial training data, categorized into training, testing, and validation data. Training data teaches the model patterns, while testing data evaluates reliability by comparing predictions with known outcomes. Validation data assesses accuracy across training and testing phases, serving as a performance benchmark. A diverse dataset enhances learning and accuracy.

The dataset consists of 680 images from 34 electoral roll members (DPT), with each member having 20 images organized into training, testing, and validation folders. This structure enables intensive training of the face recognition model, improving accuracy.

1) *Training Data*: Out of 20 images for each member of the electoral roll (DPT), 12 images are used during live photo sessions. Each member is photographed in four variations: a front view with no expression, a front view with a smile, a left profile, and a right profile, with each variation captured three times. These variations help the face recognition algorithm accurately identify individuals, even with minor changes in appearance. This diverse training data reduces identification errors and enhances system reliability, making the algorithm more robust against real-world conditions. Thus, the system is expected to effectively recognize the identities of DPT members under various conditions and lighting.

2) *Validation Data*: To ensure accuracy, consistency, and quality, validation data is compared with training data. For each electoral roll (DPT) member, 4 out of 20 images—different from the training data—are used. Once the model's accuracy is validated, the results are saved in a file, typically in the .keras format (e.g., model5.keras), which includes the model's architecture, weights, and configuration, allowing for future use without retraining. This process ensures that the model performs well on both training and unseen data, preventing overfitting and confirming its effectiveness in real-world scenarios.

3) *Testing Data*: Testing data is used to evaluate the model's accuracy with new, unseen data. The test dataset consists of 4 out of 20 images per member that differ from the training and validation data. After testing, the model's performance is assessed based on how well it recognizes identities from these new images. This process ensures the model has good generalization ability and can be reliably applied in real-world scenarios.

B. Face Recognition Development Phase

The development of face recognition involves several key steps, from image capture to identification.

1) *Image Acquisition*: This step involves capturing two-dimensional representations of three-dimensional forms, including black-and-white and colored images. Face recognition starts when the camera captures an image, using multi-face recognition to capture multiple images simultaneously, from which one is selected and stored in the dataset.

2) *Preprocessing*: This critical phase enhances image quality for analysis by applying various techniques to address missing values, smooth out noise, and resolve inconsistencies. It also standardizes different data formats, optimizing storage and ensuring images are ready for efficient analysis.

3) *Feature Extraction*: This step identifies and captures important characteristics from images, particularly facial features like hair, eyes, and mouth. By retaining only significant information, this process enhances the performance of machine learning algorithms, improving accuracy in data identification.

4) *Classification*: Image classification groups images based on extracted features, facilitating the identification process. It involves determining whether the data contains a face and categorizing it accordingly.

5) *Identification*: During this process, images that have been preprocessed, extracted, and classified are matched against a stored dataset. If there is a significant similarity, the image is

identified as corresponding to a specific name in the dataset.

C. Coding Development Phase

At this phase, the algorithm for facial recognition is realized using the Python programming language with TensorFlow and Keras. The process begins with writing the code, which involves the following steps:

1) *Preprocessing*: This process involves obtaining several captured images or pictures. It is the initial step in coding, where these images will be stored as a dataset.

2) *Model*: The next step is to design the neural network model architecture, which will be optimized during training using TensorFlow with the RMSprop optimizer and the categorical cross-entropy loss function. The CNNs architecture is demonstrated in Fig. 2 below:

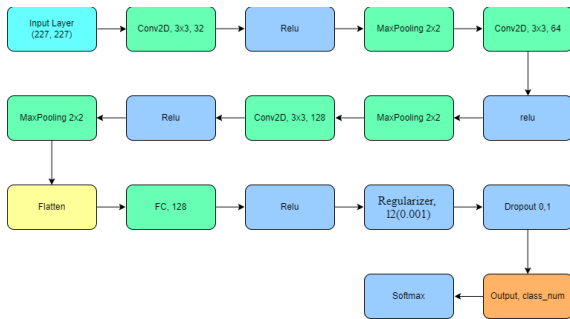


Fig. 2. CNN Architecture Flowchart.

3) *Training*: The training process is conducted using both the training and validation datasets. Several images grouped into different datasets are matched and combined into a single dataset, which is stored as a combined document. In this research, the training process utilizes training and validation data. This involves iterating through several epochs by calling the model's fit method. During training, the model's parameters are updated based on the loss and accuracy values calculated for each batch of data.

The following Fig. 3 and Fig. 4 shows the accuracy and loss graphic during training:

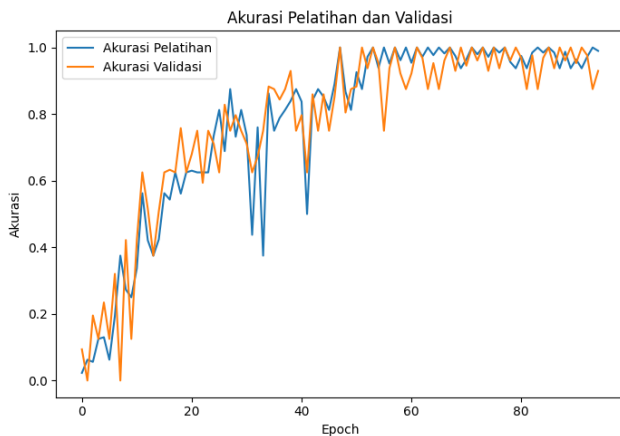


Fig. 3. Accuracy Graphic

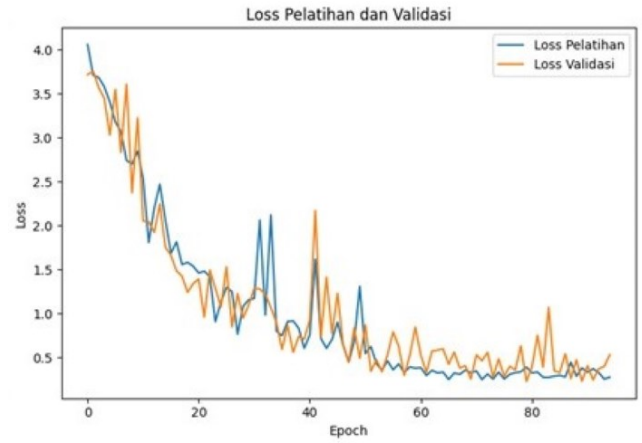


Fig. 4. Loss Graphic

This graph illustrates the model's accuracy and loss changes in accuracy and loss of the model over several epochs, showing the model's performance on the training and validation datasets. The final data can be seen in Table 1 below:

TABLE I. Final Accuracy and Loss Results

Epoch	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy
100	0.25%	0.43%	0.99%	0.95%

4) *Testing*: During the testing phase, we will evaluate the model's performance using a separate testing dataset that has not been used in training or validation. This phase is crucial for assessing the model's ability to recognize new, unseen data, ensuring accurate identification of patterns and predictions beyond the original training datasets.

5) *Identification*: The identification stage is a key phase in the face recognition process where the model's capabilities are applied practically. This stage includes functions such as data management to organize and process input data, logic to accurately identify faces using algorithms, and output display to present results in a user-friendly format. By effectively managing these components, the identification stage ensures reliable and accurate performance of the face recognition system in real-world applications.

D. Testing Phase

After designing and coding the program, the application will be tested using Python. When launched, it activates the device's camera to capture faces. Upon detecting a face, the program displays a box around it and labels the person based on the classification.

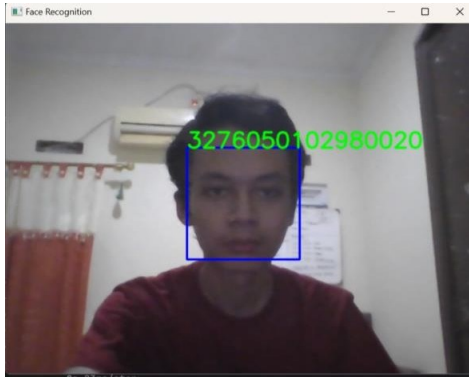


Fig. 5. Face Identification Process

Fig. 5 shows a successful face recognition process where an individual is correctly identified and matched with the class of facial data stored in the dataset.

E. Implementation and Results Phase

In this implementation phase, we tested our system using the prepared testing data. We utilized the model5.keras file, which contains the facial representations from the training and validation datasets:

1) *Testing on the Testing Data:* We began testing using a dataset consisting of facial images captured from various angles, as well as additional photos featuring accessories. During the testing, we loaded these images and matched each detected face with the facial representations encoded in the model5.keras file. Out of 34 people with 4 images per person, only 1 image failed to be predicted, resulting in an accuracy of $135136 \times 100 = 99.26\%$. The results are as follows:

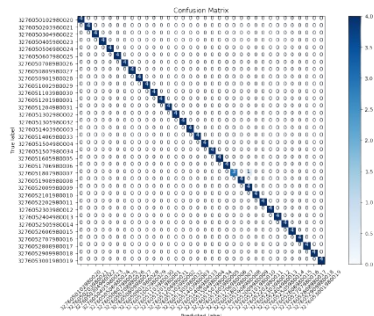


Fig. 6. Confusion Matrix

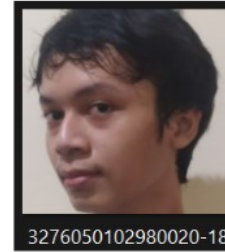
From Fig. 6, we can see that most faces in the testing dataset were correctly predicted. However, one face in a particular class did not match the training and validation datasets.



Name: C:\Users\labib\PycharmProjects\fcproject\dataset\testing\3276051807980007\3276051807980007-17.jpg, Image ID: 23, Label: 3276052009980009, Prosentase: 0.25231659412384033

Fig. 7. Incorrect Prediction

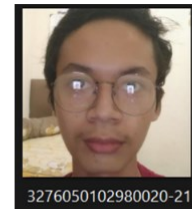
In Fig. 7, the model predicted the image with the label 3276052009980009, whereas it should have been labeled 3276051807980007, with the model showing only 25% confidence. In contrast, Fig. 8 shows the model predicting the image with the correct label and having a confidence level of 99.9%.



Name: C:\Users\labib\PycharmProjects\fcproject\dataset\testing\3276050102980020\3276050102980020-18.jpg, Image ID: 0, Label: 3276050102980020, Prosentase: 0.9997801184654236

Fig. 8. Correct Prediction

In Fig. 9, the author conducted an additional test on the label 3276050102980020 by adding an image with an accessory and a pair of glasses. The model incorrectly predicted it as label 3276050708980026, whereas it should have been labeled 3276050102980020.



Name: C:\Users\labib\PycharmProjects\fcproject\dataset\testing\3276050102980020\3276050102980020-21.jpg, Image ID: 6, Label: 3276050708980026, Prosentase: 0.48957911133766174

Fig. 9. Addition of Accessories

1) *Results Analysis:* The experiment revealed several key findings. Most faces in the testing dataset were accurately predicted by the model, showcasing its effectiveness. However, some incorrect predictions occurred; for instance, the model misidentified an image, labeling it as 3276052009980009 instead of the correct label 3276051807980007, with only 25% confidence. Additionally, accessories impacted prediction accuracy.

An experiment with glasses added to the face labeled 3276050102980020 resulted in the model incorrectly predicting it as label 3276050708980026. This indicates that the model struggles with faces that have additional attributes or differ from the training data. Overall, improvements are needed, and the model should be trained with more diverse data to enhance its recognition capabilities in varied situations.

V. CONCLUSIONS

This study demonstrates that visual identity detection technology enhances electoral integrity by reducing voter fraud risk at polling stations. It enables accurate voter verification, preventing duplicate voting and false identities, thereby improving public trust. However, challenges such as

inadequate image quality, poor lighting, and low camera resolution can hinder face identification. Compared to traditional fraud prevention methods, facial recognition technology is more efficient, providing quick and precise voter verification, reducing queues, and minimizing errors and biases. The findings suggest that with proper strategies to address implementation challenges, facial recognition technology is a viable and sustainable option for future electoral processes, adding significant value to election integrity.

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