International Journal Software Engineering and Computer Science (IJSECS)
4 (3), 2024, 1039-1055
Published Online December 2024 in IJSECS (http://www.journal.lembagakita.org/index.php/ijsecs)
P-ISSN: 2776-4869, E-ISSN: 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v4i3.3055.

RESEARCH ARTICLE Open Access

Vehicle License Plate Object Detection for Vehicle Registration Using Fuzzy Logic

Fiky Alannuari
Informatics Engineering Study Program, Sekolah Tinggi Ilmu Komputer Cipta Karya Informatika, East Jakarta City, Special Capital Region of Jakarta, Indonesia.
Email: fiky25alannuari@gmail.com.

Frencis Matheos Sarimole *
Informatics Engineering Study Program, Sekolah Tinggi Ilmu Komputer Cipta Karya Informatika, East Jakarta City, Special Capital Region of Jakarta, Indonesia.
Corresponding Email: matheosfrancis.s@gmail.com.

Dadang Iskandar Mulyana
Informatics Engineering Study Program, Sekolah Tinggi Ilmu Komputer Cipta Karya Informatika, East Jakarta City, Special Capital Region of Jakarta, Indonesia.
Email: dadang@stikomcki.ac.id.

Received: August 3, 2024; Accepted: November 1, 2024; Published: December 1, 2024.

Abstract: Object detection of vehicle license plates plays a role in the efficiency of vehicle data collection systems. There are many factors that make the accuracy and speed of detection on vehicle license plates less than optimal, causing errors in the detection process. The factors that affect the accuracy of object detection of vehicle license plates include clarity, lighting, shadows, color, font type, weather, and others. Based on the advantages of the Fuzzy Logic approach in handling various vague factors and uncertain data, it is hoped that this method can help the detection process to be more accurate and faster. This research aims to develop a method for detecting vehicle license plate objects using the Fuzzy Logic approach so that it can be applied in diverse environments to produce data with consistent accuracy. This research involves the development of software integrated with computers and cameras for vehicle license plate recognition, and also takes some data sources and code from libraries already available in the programming language used. The results of the tests conducted, detection using this Fuzzy Logic approach has an accuracy rate of up to 93.33% and the accuracy of reading the text stored in the database reaches 63.66%.

Keywords: Detection System; Fuzzy Logic; Plate Detection; Object Detection; Vehicle Data Collection.

1. Introduction

Vehicle registration systems play a crucial role in managing traffic, enhancing transportation security, and monitoring the development of road infrastructure. The use of technology to detect and monitor vehicles has become increasingly important, as the need to improve operational efficiency in transportation management grows. One of the key components in this system is vehicle license plate detection, which facilitates automatic vehicle identification and tracking. This detection process not only supports traffic management but also holds significant potential to improve security, reduce congestion, and optimize road usage, particularly in densely populated urban areas.

Despite the great potential of vehicle license plate detection systems, several challenges remain, especially in complex and diverse environments. Visual variations on license plates, such as differences in font types, colors, rotation, as well as tilt and orientation of the plates, often present difficulties in the detection process. Additionally, external factors such as changes in lighting, shadows, noise, and other environmental disturbances can affect the accuracy of detection. Furthermore, the quality of the devices used in the detection system, such as the image resolution and the camera’s ability to capture clear images, also plays a significant role in system accuracy. The uncertainty introduced by these factors can lead to reduced detection accuracy and make it difficult to process data consistently, which in turn impacts the overall performance of the system [1].

Several studies have previously explored the use of various methods for vehicle license plate detection. Deep learning models such as VGG16 and VGG19 have demonstrated satisfactory results in vehicle license plate detection, with their ability to handle complex image variations and produce accurate detection results under certain conditions. On the other hand, models like DenseNet121 and NASNetLarge tend to perform suboptimally in license plate detection tasks, although they are known to have significant potential in other image processing applications [2]. Additionally, research on the use of the K-Nearest Neighbor (KNN) method in vehicle license plate detection for vehicle surveillance under an odd-even system has shown a good accuracy rate of around 80%, based on testing with 20 vehicle images. This indicates that, despite being a relatively simple method, KNN can be effectively applied in license plate detection with a limited dataset [3].

Furthermore, other research using Optical Character Recognition (OCR) with Tesseract to detect vehicle license plates has yielded promising results. Based on tests with 30 license plate samples from a company parking area, the average accuracy achieved was 95.95%. This suggests that, despite the inherent challenges in OCR-based Tesseract accuracy, this method remains effective in detecting and converting license plate numbers into text that can be further processed. On the other hand, an automatic vehicle license plate detection system using the YoloV3 algorithm also achieved excellent results. In tests conducted under sufficient lighting with a threshold of 0.5, YoloV3 achieved a 100% accuracy rate. The OCR detection results using Tesseract within this system showed a detection rate of 92.32%, demonstrating the system’s ability to recognize all alphanumeric characters on vehicle plates, whether for cars or motorcycles, with plate numbers consisting of 7-8 characters per plate [4][5]

Based on the findings from previous studies, it can be concluded that vehicle license plate detection can be performed using various approaches, each with its own advantages and limitations. Therefore, this research aims to develop a more effective vehicle license plate detection system by utilizing a fuzzy logic approach. It is expected that this approach will improve detection accuracy by considering important factors such as image clarity, contrast, noise level, and brightness of the detected objects. Furthermore, by implementing fuzzy logic, a more flexible detection system that can adapt to changing environmental conditions is expected to be achieved. This approach will also facilitate the automatic data entry of detected license plate results into a database for further management purposes. By addressing the existing challenges, the vehicle license plate detection system developed through this research is expected to function optimally under various conditions, ranging from poor lighting to variations in the types of license plates found in the field. It is also hoped that this system can contribute significantly to transportation management systems and can be adapted for other purposes such as traffic surveillance, automatic parking, and vehicle-based security systems.

2. Research Method

This research begins with the collection of vehicle and license plate data, which was directly obtained from several locations, primarily on highways, as well as from online sources such as Kaggle. The data collection focuses on conditions where license plates are clearly visible. Once the data is collected, a thorough data cleaning process is conducted. During this phase, any irrelevant data or duplicate entries are removed to ensure the dataset is ready for the next stages of preprocessing. Preprocessing involves normalizing the data by applying grayscaling and resizing techniques to standardize the image format [6]. After the data cleaning and preprocessing, the next step is labeling the dataset. This is done by detecting the license plate area in the images and marking it using a bounding box, which serves as the label for the license plate in the dataset. The labeled data will then be used to identify the coordinates of the license plates in the images, which will be processed by the license plate detection system. In addition, a fuzzy logic classification approach will be applied, using four variables: clarity, contrast, noise level, and brightness, to determine the accuracy of license plate detection. Each of these variables will be treated as input, with membership values categorized as low, medium, and high, represented by triangular membership functions [7].

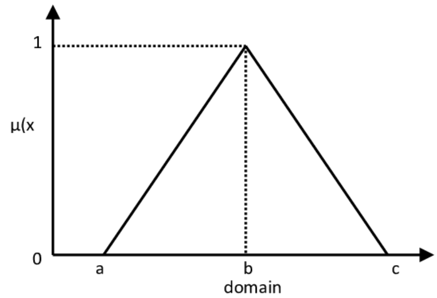


Figure 1. Triangular Curve Membership Function

$$\mu[x,a,b,c] = \begin{cases} 0; & x \leq a \; atau \; x \geq c \\ \dfrac{(x-a)}{(b-a)}; & a \leq x \leq b \\ \dfrac{(c-x)}{(c-b)}; & b \leq x \leq c \end{cases} \tag{1}$$

Once the classification process is complete, fuzzy rules will be established to categorize the accuracy into low, medium, or high levels. These rules will evaluate the classified variables for each image. After the rules are implemented, several images will be tested to check for errors and necessary adjustments will be made.

2.1 Data Collection

Site visits were conducted at various highway locations to observe and analyze vehicle access patterns. Digital images of vehicles and license plates were directly captured from these locations to gather relevant data. Websites hosting journals and books were reviewed to download, read, and study related research that informed the analysis and design of this research. This provided a better understanding of existing methods and helped in shaping the approach for this study.

2.2 Data Cleaning

Once the data was collected, the first step involved inspecting the dataset to ensure its quality and readiness for processing. This inspection was crucial to identify and remove any irrelevant or invalid entries that might have been captured during the data collection phase. For example, images that did not contain clear license plates, or images that were corrupted or incomplete, were excluded from the dataset. In addition, duplicate entries were systematically identified and removed to avoid redundancy, ensuring that each data point was unique and contributed to the overall dataset's integrity. The process also involved checking for any missing or incomplete data, particularly in the images, labels, or metadata associated with each vehicle and its license plate. In cases where data gaps were identified, efforts were made to either retrieve the missing information or flag those entries as incomplete. This step was essential for ensuring that the dataset used for further analysis was accurate, complete, and representative of real-world conditions. After all these corrections were made, the dataset was validated to confirm its readiness for the next phase of preprocessing, making it suitable for building an effective vehicle license plate detection model.

2.3 Preprocessing

Preprocessing is a critical phase in image-based machine learning tasks, as it prepares the data for efficient and effective model training. For this research, the preprocessing phase involved several key techniques to standardize and optimize the input images. The first step was grayscaling, where the images were converted from full color to grayscale. This transformation helps simplify the data by reducing the complexity of the color spectrum, allowing the detection system to focus on the key features of the license plates without being distracted by irrelevant color information. Normalization was also applied to ensure that all the pixel values across the dataset were within a standardized range, typically between 0 and 1. This step is crucial for neural networks, as it helps improve the model's convergence during training by preventing issues caused by varying scales of input data. Furthermore, resizing was performed to ensure that all images had consistent dimensions, which is essential for feeding the data into a detection system that requires uniform input size. This also helps speed up the model training process by ensuring that the computational load remains manageable. Segmentation was another important aspect of preprocessing. This process involved isolating the license plate area from the surrounding background. By applying segmentation techniques, such as thresholding and edge detection, the system could focus specifically on the license plate region, minimizing the influence of irrelevant background features. During segmentation, we extracted relevant features, such as the edges, texture, and shapes that characterize the license plate region. These features were critical for the next steps in training the detection model, as they help the system identify patterns and recognize license plates in varying environments.

2.4 Data Labeling

The next step in preparing the dataset for model training was data labeling, an essential part of supervised machine learning. In this phase, each image in the dataset was analyzed to identify the exact location of the license plate. This was done using bounding boxes, which are rectangular markers that delineate the area of interest—in this case, the license plate on the vehicle. By drawing bounding boxes around the license plates, we could easily locate and extract the region containing the plate for further processing. Each bounding box was then labeled with the corresponding license plate number, which acted as the target label for the system. This labeling process was crucial because the detection system relies on accurate annotations to learn how to detect and recognize plates during the training phase. The labeled dataset serves as the foundation for training the detection model, allowing it to understand which areas of the images correspond to vehicle license plates and how to differentiate them from other parts of the vehicle or background. Data labeling also involved ensuring consistency and accuracy. Any mislabeling or errors in bounding box placement were carefully checked and corrected. This step is important to ensure that the training process is based on high-quality, precise data. Moreover, the dataset was split into training, validation, and test sets to allow for proper model evaluation and to avoid overfitting, ensuring that the model generalizes well to unseen data.

2.5 Fuzzy Classification

Fuzzy logic was employed to classify the accuracy of license plate detection, based on four key variables: clarity, contrast, noise level, and brightness. Each of these variables plays a significant role in determining how well the detection system can identify a license plate under different conditions. Fuzzy logic allows for the creation of rules that can assess the quality of license plate detection in a more flexible, human-like manner, as opposed to relying solely on binary classification. For each of these variables, a set of membership functions was defined. These functions categorized the variables into three levels: low, medium, and high. The membership functions were represented using triangular curves, which are commonly used in fuzzy logic systems due to their simplicity and effectiveness in approximating real-world situations. Each image was evaluated for these four variables, with the fuzzy logic system determining the degree to which each variable fell into the low, medium, or high categories. The fuzzy rules were then designed to combine the values of these variables to assign an overall accuracy rating for the license plate detection. For example, if the clarity was high, the contrast was medium, and the noise level was low, the system would assign a high accuracy score to the detection. Conversely, if the brightness was low and the noise level was high, the detection accuracy would be rated as low. These fuzzy rules helped to create a more nuanced classification system that could handle the variability inherent in real-world license plate detection scenarios. After developing the fuzzy rules, the system underwent a series of evaluations using test images to check the performance of the classification model. The results were carefully analyzed to identify any potential discrepancies or areas for improvement. Based on these evaluations, the fuzzy rules were refined to ensure the system was able to consistently produce accurate results across a range of detection conditions. The iterative nature of this process is essential to developing a robust detection system capable of handling the diverse environments in which license plates may appear.

2.6 Testing Design

The testing phase focuses on assessing the functional requirements for the system, which includes understanding the operational needs, the resources required for system functionality, and the cost analysis of system development. Data collection during this phase can involve various methods, such as direct observation or literature reviews from relevant sources. This stage is centered around the development of the data structure, internal and external functions, software and hardware architecture, and detailed algorithms.

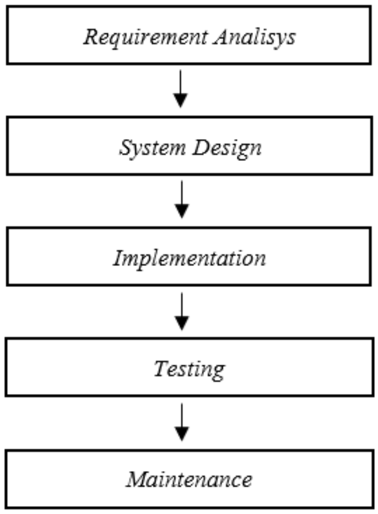


Figure 2. Test Design

The output of this stage will be a document outlining the software and hardware requirements, which will guide the programmers during the implementation phase. During this phase, computer resources will be fully utilized, and once coding is completed, the system will undergo preliminary testing to identify any errors in the system or code. These errors will be corrected before comprehensive system testing begins. If any issues are found during testing, they will be promptly addressed. This testing phase is the final step before the system is ready for use, as all identified errors must be resolved, ensuring the system is fully operational for end-users. The software and hardware used in the system may need updates or adjustments over time. These updates will ensure the system remains functional and adaptable to user needs, and the software and hardware will need to be aligned with the user's requirements and evolving functional demands.

3. Result and Discussion

3.1 Results

3.1.1 Research Tools

The hardware setup plays a vital role in ensuring the smooth operation of the vehicle license plate detection system. The laptop provides sufficient processing power to run the algorithms and store the data, while the camera is responsible for capturing the real-time video feed needed for detection. The 720p camera resolution is chosen to ensure adequate clarity for capturing the license plates, considering the environmental conditions and operational needs of the system.

Table 1. Hardware

Hardware	Description
Laptop (RAM 8GB, ROM 128GB)	Serves as the central processing unit for conducting detection tasks, managing the database, and running the vehicle license plate detection and data collection system.
Camera (720p Resolution)	Used to capture real-time video input while the detection system is active. It records the necessary images and video streams for license plate recognition.

.

Table 2. Software

Software	Description
Operating System	The operating system used is Windows 11, which is compatible with all the software tools and libraries required for this research.
Python 3.11.9	Python is the primary programming language used for writing the code to implement the system's functionality.

OpenCV-Python 4.9	A library used for image processing, enabling manipulation of images and the ability to display real-time video through the camera input for capturing images.
Numpy 1.26	A library that facilitates data manipulation and processing, especially for arrays, with integrated arithmetic functions for efficient data processing.
Scikit-Fuzzy 0.4.2	A library used for fuzzy logic processing, which includes functions for membership and automated computation of fuzzy logic rules based on pre-defined criteria.
PyTesseract 0.3.10 (TesseractOCR)	A library used for extracting text from images, which is crucial for converting detected license plates into readable text.
MySQL-Connector-Python 9.0.0	A library that connects Python programs to web servers like XAMPP, enabling integration with the MySQL database for data storage and retrieval.
XAMPP 8.2.12	A server that can operate independently on various operating systems, containing Apache HTTP Server, MySQL Database, and PHP translators. In this research, it is used solely for managing the MySQL Database connection.

The combination of these hardware and software tools forms the backbone of the detection system. Python, along with its libraries, provides the foundation for image processing, machine learning, and database management. The software stack is tailored to ensure efficient data capture, processing, and storage of the license plate information.

3.1.2 Dataset Collection

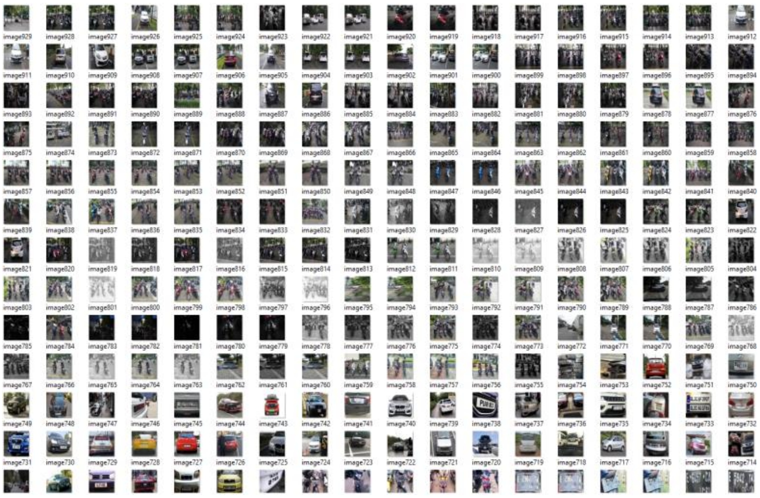


Figure 3. Dataset

The dataset used for training and testing the system was collected from various sources. This included direct collection of vehicle images from highway locations, as well as online resources such as Kaggle, which provided additional sample images. The images were selected based on the clarity and visibility of the license plates to ensure that the system could be trained under optimal conditions. The data collection process focused on acquiring a diverse range of vehicle types, plate styles, and environmental conditions to ensure that the detection system could perform well in varied real-world situations. This diversity is essential for building a robust detection system that can handle different lighting conditions, weather, and vehicle types.

3.1.3 Fuzzy Classification

In this step, four key variables—clarity (Clarity), contrast (Contrast), noise level (Noise Level), and brightness (Brightness)—were used to classify the accuracy of license plate detection. Each of these variables was assessed for their influence on the detection performance, and fuzzy membership functions were applied to categorize each variable into one of three levels: low, medium, or high. The membership values for each variable were defined within a specified range. Specifically, the range for low was between 0 and 50, for medium between 20 and 80, and for high between 50 and 100. These ranges were set to allow the fuzzy logic rules to evaluate the input data effectively. By establishing these ranges, fuzzy logic classification could be applied to generate the corresponding accuracy levels (low, medium, or high).

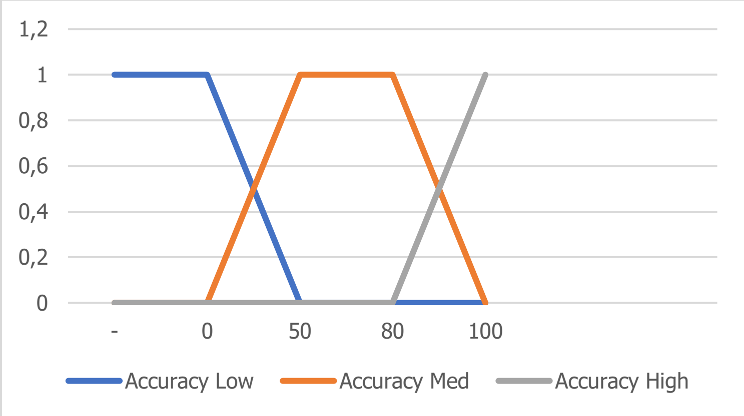


Figure 4. Fuzzy Rule Classification

One of the fuzzy rules used, for example, states: "If clarity = high, contrast = high, noise level = low, and brightness = high, then the accuracy is high." Other rules were created in a similar manner to handle a variety of scenarios. The complete set of rules can be seen in Figure 5.

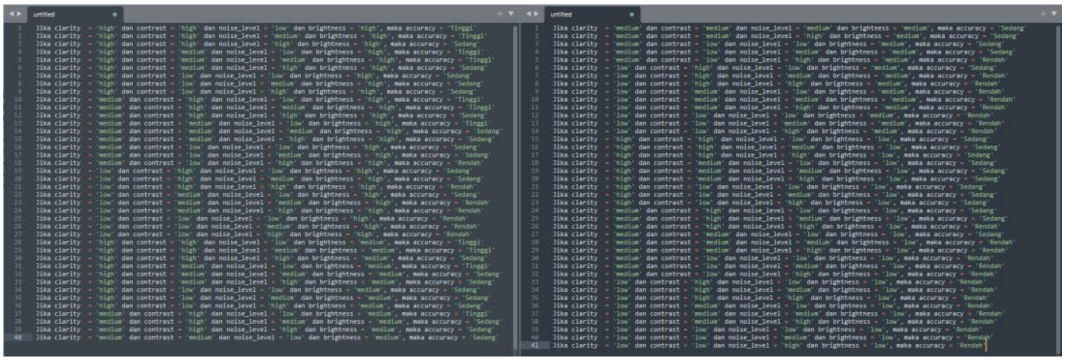


Figure 5. Applied Fuzzy Rules

The fuzzy classification process was essential for assigning an accuracy level based on multiple factors. By considering these variables simultaneously, the system can make nuanced decisions on the quality of the license plate detection and classification.

3.1.4 Test Results

Table 3. Accuracy Evaluation

No.	Subject	Clarity Score	Contrast Score	Noise Score	Brightness Score	Accuracy
1		73.9996	66.9028	51.3484	49.0702	60.2595 [Medium]
2		86.0013	61.5569	50.0721	55.5357	56.6872 [Medium]
3		79.0001	56.8744	35.3224	44.1905	57.9143 [Medium]

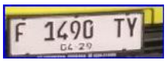
4		70.0025	58.2732	40.9272	40.4069	49.6435 [Low]
5		77.9972	59.076	85.8646	39.4959	47.8365 [Low]
6		81.9998	56.3098	100	48.2885	50 [Medium]
7		84.0004	63.3797	65.0483	44.2431	58.4297 [Medium]
8		71.0011	59.0895	15.3105	41.878	65.3593 [Medium]
9		84.9951	60.1612	100	44.7071	50 [Medium]

As shown in Table 3, the accuracy of license plate detection varied, with most entries falling under the medium accuracy category. A total of seven data points achieved medium accuracy, while two were classified as low. This suggests that the system is effective in detecting plates under normal conditions, though some instances, particularly with lower clarity or contrast, led to lower accuracy results.

Table 4. Overall Test Results

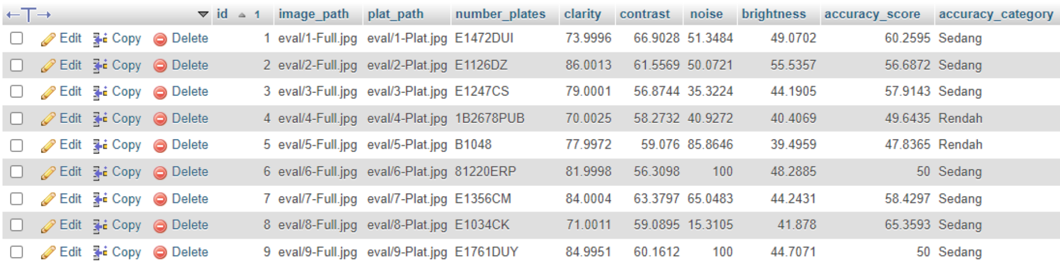
No.	Subject	Detection Result	License Plate Detail	Text Conversion	Conversion Accuracy
1				F1623VM	7/8*100% = 87.5%
2				B1546DKNL	7/8*100% = 87.5%
3				*Invalid*	0%
4				F1420RD	6/7*100% = 85.71%
5				1601JA	5/7*100% = 71.42%
6				B2060KKH	8/8*100 % = 100%
7				B1270ROG	8/8*100 % = 100%
8				F102528D	5/7*100 % = 71.42%
9				B2076TYL	8/8*100 % = 100%
10				TF1421FAZ	8/8*100 % = 100%

11				BF1319FAA	8/8*100 % = 100%
12				*Invalid*	0%
13				82922KIL	6/8*100 % = 75%
14				*Invalid*	0%
15				F1027FBD	8/8*100 % = 100%
16.				OT	0%
17				*Invalid*	0%
18				1562JER	6/7*100 % = 85.71%
19				SS	0%

20				IF1590XXP	7/7*100 % = 100%
21				F1667VOE	7/7*100 % = 100%
22.				ES1105RX	6/7*100 % = 85.71%
23				F1204TI	7/7*100 % = 100%
24				D1457SAY	8/8*100 % = 100%
25		-	Not detected	-	-
26		-	Not detected	-	-
27				TA	0%
28				F18348J	6/7*100 % = 85.71%
29				*Invalid*	0%

30				1260AHC	6/8*100 % = 75%

Based on the results shown in Table 4, out of 30 vehicles with different license plates, two vehicles failed to be detected, resulting in a detection accuracy of 93.33%. However, when considering the text conversion using the TesseractOCR library, 5 out of 28 detected plates did not convert to text. Therefore, 23 plates were successfully converted, giving an overall text conversion accuracy of 64.66%.



	id	image_path	plat_path	number_plates	clarity	contrast	noise	brightness	accuracy_score	accuracy_category
Edit Copy Delete	1	eval/1-Full.jpg	eval/1-Plat.jpg	E1472DUI	73.9996	66.9028	51.3484	49.0702	60.2595	Sedang
Edit Copy Delete	2	eval/2-Full.jpg	eval/2-Plat.jpg	E1126DZ	86.0013	61.5569	50.0721	55.5357	56.6872	Sedang
Edit Copy Delete	3	eval/3-Full.jpg	eval/3-Plat.jpg	E1247CS	79.0001	56.8744	35.3224	44.1905	57.9143	Sedang
Edit Copy Delete	4	eval/4-Full.jpg	eval/4-Plat.jpg	1B2678PUB	70.0025	58.2732	40.9272	40.4069	49.6435	Rendah
Edit Copy Delete	5	eval/5-Full.jpg	eval/5-Plat.jpg	B1048	77.9972	59.076	85.8646	39.4959	47.8365	Rendah
Edit Copy Delete	6	eval/6-Full.jpg	eval/6-Plat.jpg	81220ERP	81.9998	56.3098	100	48.2885	50	Sedang
Edit Copy Delete	7	eval/7-Full.jpg	eval/7-Plat.jpg	E1356CM	84.0004	63.3797	65.0483	44.2431	58.4297	Sedang
Edit Copy Delete	8	eval/8-Full.jpg	eval/8-Plat.jpg	E1034CK	71.0011	59.0895	15.3105	41.878	65.3593	Sedang
Edit Copy Delete	9	eval/9-Full.jpg	eval/9-Plat.jpg	E1761DUY	84.9951	60.1612	100	44.7071	50	Sedang

Figure 6. Data Entry into Database

The final step involved inserting the detected and converted license plate data into a MySQL database, as shown in Figure 6. This allows for efficient storage and retrieval of data, which can be used for further analysis or practical applications in the transportation management system.

3.2 Discussion

The results of this study demonstrate the potential and limitations of the vehicle license plate detection system developed using fuzzy logic and the TesseractOCR library. In terms of detection accuracy, the system performed quite well, identifying the license plates of 28 out of 30 vehicles, resulting in a detection accuracy rate of 93.33%. This indicates that the system is generally capable of recognizing license plates under a variety of real-world conditions. However, there were still a few instances where the license plates were not detected. These failures may have been due to issues such as low-quality images, poor contrast between the plate and the background, or environmental factors like insufficient lighting or obstructions. Addressing these factors could further improve the system's detection capabilities.

When it comes to the conversion of detected plates into text using TesseractOCR, the accuracy was much lower, with an overall conversion rate of only 64.66%. This suggests that while the system can detect license plates fairly reliably, extracting the text from those plates remains a challenge. There are many reasons why OCR accuracy might not reach ideal levels, such as the wide variation in license plate fonts, sizes, and the quality of the captured images. Additionally, factors like noise, skewed angles, or reflections on the plate can make text extraction difficult. While TesseractOCR is a good starting point for text recognition, it may not always perform optimally, especially with the diverse range of plates used in real-world scenarios. This is an area where improvements could have a significant impact on the overall system performance.

The fuzzy logic approach used to evaluate the quality of each license plate detection—based on clarity, contrast, noise, and brightness—proved to be an effective way to classify the accuracy of the system's output. By using fuzzy sets to categorize these variables, the system was able to handle different levels of input quality, providing a more flexible evaluation of the detection accuracy. The majority of plates were classified as medium accuracy, with a smaller number falling into the low accuracy category. This shows that the system can generally handle most images but struggles in certain conditions where plate quality is compromised.

Despite the promising results, there are still several challenges that need to be addressed. One of the main issues is environmental variability—license plates can appear under a variety of conditions, such as low light, glare, or poor contrast, all of which can hinder detection. Additionally, the system may struggle with unusual fonts or layouts, as license plates often differ depending on the country or region. These variations can lead to a mismatch between the system's training data and real-world input, affecting both detection and OCR accuracy. Another challenge lies in the images themselves—plates that are skewed, tilted, or partially obscured can result in errors during both detection and text conversion.

Looking ahead, there are several areas where the system can be improved. Enhanced image preprocessing techniques, such as noise reduction and better contrast adjustment, could help improve both detection and OCR accuracy. In particular, using more advanced OCR methods, like deep learning-based models (e.g., convolutional neural networks), could address the limitations of TesseractOCR, especially in cases where traditional OCR struggles. Additionally, incorporating a more robust license plate detection model that is better at handling varied angles and environmental conditions could further improve the system's performance. Moreover, refining the fuzzy logic rules and adjusting the membership functions to account for a wider range of plate conditions might help improve the classification of accuracy, particularly in more challenging scenarios.

4. Related Work

The field of automated vehicle license plate recognition (LPR) has seen significant advancements with various methodologies employed to improve detection accuracy, classification, and system adaptability. These studies predominantly focus on deep learning models, optical character recognition (OCR), and fuzzy logic. While much of the research in this domain addresses the challenges posed by environmental variations such as lighting, noise, and plate design diversity, this study introduces fuzzy logic into the process to refine the classification of detected plates. Below is a structured comparison of related studies and how they align with or differ from the approach taken in this research. Aida and Hardiyanto (2024) explored the introduction of white vehicle license plates in Indonesia, noting the challenges this change presents for LPR systems. Their research emphasizes the need for LPR systems to adapt to evolving plate designs, which is a concern also addressed by this study. By incorporating fuzzy logic, this research enhances the flexibility and robustness of LPR systems to handle variations in plate designs and environmental conditions such as lighting changes or image noise [7]. Unlike Aida and Hardiyanto's focus on policy and design changes, this study applies fuzzy logic to improve real-time detection and classification accuracy under such dynamic conditions.

Permana Saputra and Latifa (2023) employed Convolutional Neural Networks (CNNs) for vehicle and license plate detection. Their research effectively demonstrated the potential of deep learning for LPR applications. While both studies share the use of CNNs, this study introduces fuzzy logic as an additional post-detection classification layer. This layer accounts for environmental factors such as clarity, contrast, and noise, enabling the system to better perform in less-than-ideal conditions like low lighting or poor image quality, which was not addressed in Permana Saputra and Latifa's work [9].

Similarly, Setya Budi *et al.* (2024) used YOLOv5-DeepSORT and HyperLPR for vehicle and plate detection. Like this study, their work employs advanced object detection methods; however, the key distinction lies in the incorporation of fuzzy logic in this research. Fuzzy logic is used to refine the accuracy of the detection process by considering image quality factors such as clarity and brightness, providing a more robust solution for plate detection in various environments [12].

Permadi *et al.* (2021) applied fuzzy logic to control an automatic handwashing device, showcasing its broader applicability in dynamic systems. Although their study was not focused on LPR, it provides valuable insights into how fuzzy logic can improve system performance by handling real-time uncertainties. In this study, fuzzy logic is employed specifically to classify plate detection accuracy, enhancing the system's adaptability to different lighting and environmental conditions, which was not addressed in Permadi *et al.*'s work [10]. Romadhon and Novita (2023) used fuzzy logic Tsukamoto for detecting body temperature, emphasizing fuzzy logic's potential to classify uncertain data. Similarly, this study applies fuzzy logic to classify the accuracy of license plate detections, improving adaptability in real-time systems. The key difference, however, is that Romadhon and Novita focused on healthcare, whereas this study specifically targets vehicle recognition using fuzzy logic [11].

Darmawan *et al.* (2016) proposed an automatic gate system using OCR for vehicle license plate recognition. Like this study, OCR is used to extract text from plate images. However, this research extends the application of OCR by incorporating fuzzy logic for post-detection classification. This additional layer allows the system to adapt to varying environmental conditions such as poor image quality or noise, which is not fully addressed in Darmawan's work 0. Similarly, Cahyo (2019) explored OCR for license plate recognition, focusing on converting plate images into readable text. While OCR is used in both studies, this research improves upon Cahyo's work by integrating fuzzy logic to classify detection accuracy based on image quality factors such as contrast and noise. This integration enhances the robustness of the system, especially in real-world applications where plate images may not be ideal [17]. Fauzan and Wahyu (2021) also used YOLOv3 for vehicle detection and Tesseract OCR for text conversion, aligning closely with this study. However, this study differentiates itself by introducing fuzzy logic to classify the detection accuracy, allowing the system to handle challenges such as poor lighting or skewed plates, which were not explicitly addressed in their work [18].

Akhmad *et al*. (2020) applied Hough Transform and Harris Corner methods for license plate recognition using low-cost hardware like Raspberry Pi. Their focus was on making LPR systems affordable and accessible. While their approach works effectively for plate detection, the current study adds value by incorporating fuzzy logic to further classify detection accuracy. This additional layer addresses challenges related to image noise, skewed angles, and varying lighting conditions, which Akhmad's work did not consider [16]. Pustokhina *et al*. (2020) utilized CNNs combined with K-Means clustering for license plate recognition. Their focus was on optimizing clustering methods for plate detection. In contrast, this research integrates fuzzy logic to classify and evaluate the quality of plate detections. This enhances the system's ability to adapt to variations in image quality, such as noise or distortion, providing a more robust and flexible solution for real-world LPR systems [19].

Qin *et al*. (2022) developed a vehicle path tracking system that integrates license plate recognition with traffic network big data. While their system integrates traffic data for traffic management purposes, the current study focuses more on enhancing detection accuracy through the use of fuzzy logic. The incorporation of fuzzy logic in this research helps the system adapt to real-time conditions, such as lighting and plate angle variations, improving the reliability and robustness of the system in dynamic traffic environments [20]. Saif *et al*. (2019) applied CNNs for automatic Bangla license plate recognition, demonstrating the flexibility of CNNs in regional contexts. Similar to their work, this research utilizes CNNs for plate detection but extends the approach by integrating fuzzy logic to classify the accuracy of the detections based on image quality and environmental conditions. This makes the system more adaptable and robust compared to Saif *et al*.'s system, which does not address these aspects [22].

Padmasiri *et al*. (2022) investigated automated license plate recognition in resource-constrained environments, with a focus on optimizing systems for low-power devices. This study complements the current research, which builds on the idea of resource efficiency by introducing fuzzy logic to improve post-detection classification. The addition of fuzzy logic enables the system to be more adaptable to varying environmental conditions, providing more reliable results even in less-than-ideal [23]. Orduna *et al*. (2019) applied fuzzy logic to motion detection in embedded systems. Although their work does not directly focus on vehicle recognition, it demonstrates the adaptability of fuzzy systems in real-time applications. This aligns with the current study, where fuzzy logic is used to classify the accuracy of license plate detection, helping the system to better handle environmental variations [24]. Lestari and Mulyana (2022) explored the use of Tesseract OCR for character recognition in images, a key component in this study for plate text extraction. While both studies utilize OCR, this research builds upon it by incorporating fuzzy logic, allowing the system to classify OCR results based on image quality factors such as contrast and noise. This improves the robustness of the OCR process in real-world applications where the plate images may not be ideal [25].

Setya Aji *et al*. (2023) applied fuzzy logic to monitor eye health using IoT devices. Although their work focuses on healthcare, it demonstrates the broad applicability of fuzzy systems for real-time monitoring. Similarly, this study uses fuzzy logic to evaluate license plate detection accuracy, enhancing the system's adaptability to environmental changes such as lighting and noise [26]. Loce *et al*. (2017) investigated computer vision techniques for intelligent transportation systems (ITS), providing insights into the broader use of LPR in traffic management. While their work integrates traffic data, the current study extends LPR systems by refining detection accuracy through the application of fuzzy logic, offering a more adaptable solution for real-time systems [27].

Lambert-Torres *et al*. (2016) explored the application of fuzzy systems, emphasizing their utility in decision-making under uncertainty. Their work underscores the importance of fuzzy logic in systems where data is ambiguous, which is directly applicable to LPR systems that deal with variable image quality. This research leverages fuzzy logic in a similar manner to classify license plate detection accuracy, making the system more robust in real-world environments [28]. Yu and Jafari (2019) studied the modeling and control of uncertain nonlinear systems using fuzzy equations and Z-numbers. Their work on managing uncertainty through fuzzy logic provides a strong theoretical foundation for real-time applications like LPR. This study applies these principles by using fuzzy logic to enhance vehicle plate detection, improving its adaptability to varying conditions such as lighting, vehicle speed, and image quality [29]. Wahyuni (2023) also contributed to the field of fuzzy logic, applying it to dynamic systems. While focused on system control, her work shares similarities with this research in applying fuzzy logic to real-time license plate detection, managing the uncertainties that arise from varying environmental conditions [30]. While much previous research has focused on specific aspects of LPR—such as vehicle detection, OCR, or resource optimization—this study differs by introducing fuzzy into the core of the detection process. This system enhances the ability to classify and evaluate detection accuracy, making it more reliable and adaptable for real-world applications as well as more robust, efficient, and adaptable to handle the complex and diverse environments in which it operates.

5. Conclusion and Recommendations

The vehicle license plate detection system utilizing Fuzzy Logic achieved a detection accuracy of 93.33% in the final experiment. However, the accuracy of text recognition from images (using TesseractOCR) remains relatively low, with a performance rate of 64.66%. This limitation in OCR accuracy leads to inconsistencies in the database entries, as the data being automatically populated is often incorrect. The integration of fuzzy logic into the detection system allowed for a high accuracy of plate detection, but the OCR component still requires improvement to ensure reliable text conversion. Regarding the implementation of the system into the database, the conversion of images into text is still limited by the capabilities of TesseractOCR, which results in a relatively low success rate of 64.66%. While the data records of detected license plates are efficiently stored in the MySQL database with adequate input speed, the system still suffers from issues related to text conversion. This reflects the need for better OCR performance to achieve more accurate and reliable database records. Another notable issue is the lack of vehicle object detection, which resulted in duplicate license plate readings within the same camera frame. Without distinguishing between consecutive frames or detecting the vehicle object itself, the system detects the same license plate multiple times in quick succession. However, the system does not record duplicate entries in the database if the detection results (including accuracy) remain the same, minimizing redundant data. Furthermore, the testing revealed that the detected area often exceeds the size of the license plate itself. As a result, the area surrounding the plate is also included in the detection, which causes discrepancies in text recognition. These misclassifications occur due to the detection algorithm reading extra characters from the surrounding area, leading to incorrect text conversion from the license plate images.

Based on the conclusions drawn from the testing, several improvements are recommended to further develop the license plate detection and image-to-text conversion system. It is important to introduce additional variables to better assess image quality during detection. These variables should include specific characteristics of the license plate as well as environmental factors that may affect the quality of the captured image, beyond the four variables tested in this study. Improving the camera specifications will significantly improve the quality of the captured images. Higher resolution images will improve license plate detection and text recognition accuracy, resulting in more reliable results. It is also recommended to expand the dataset used to train the model. A larger and more diverse dataset will improve the system's ability to recognize different types and formats of license plates, thereby improving detection accuracy in a variety of conditions. Including a vehicle object detection system is another key recommendation. By detecting vehicles first and focusing the license plate recognition process only on the area where the vehicle is located, the system will avoid unnecessary detections and reduce duplication. For example, once a vehicle is detected, the system should focus only on detecting license plates in the area of that vehicle, thereby increasing efficiency. Exploring other OCR algorithms, such as EasyOCR, may improve text recognition performance. In addition, using GPU instead of CPU to process OCR tasks will improve the speed and efficiency of the system, resulting in faster and more accurate results. Although the integration of fuzzy logic has significantly improved the robustness of the vehicle license plate detection system, the current limitations in OCR performance must be overcome to achieve optimal system performance. By implementing the suggested improvements, the accuracy, adaptability, and efficiency of the system can be further optimized, making it more reliable for real-world applications.

References

[1] Rohan, A., Rabah, M., & Kim, S. H. (2019). Convolutional neural network-based real-time object detection and tracking for parrot AR drone 2. *IEEE access*, *7*, 69575-69584. https://doi.org/10.1109/ACCESS.2019.2919332

[2] Hindarto, D., & Santoso, H. (2021). Plat Nomor Kendaraan dengan Convolution Neural Network. *Jurnal Inovasi Informatika*, *6*(2), 1-12.

[3] Muchyi, Y. A., & Siswono, H. (2022). Deteksi Ganjil Genap Pada Plat Nomor Kendaraan Menggunakan Metode K-Nearest Neighbor (KNN): Array. *Jurnal Ilmiah Komputasi*. https://doi.org/10.32409/jikstik.21.2.3060

[4] Kusnantoro, K., Rohana, T., & Kusumaningrum, D. (2022). Implementasi Metode Tesseract OCR (Optical Character Recognition) untuk Deteksi Plat Nomor Kendaraan Pada Sistem Parkir. *Scientific Student Journal for Information, Technology and Science*, *3*(1), 59-67.

[5] Aprilino, A. (2022). Implementasi Algoritma Yolo Dan Tesseract Ocr Pada Sistem Deteksi Plat Nomor Otomatis. *Jurnal Teknoinfo*, *16*(1), 54-59. https://doi.org/10.33365/jti.v16i1.1522.

[6] Jonathan, M., Hafidz, M. T., Apriyanti, N. A., Husaini, Z., & Rosyani, P. (2023). MENDETEKSI PLAT NOMOR KENDARAAN DENGAN METODE YOLO (You Only Look Once) DAN SINGLE SHOT DETECTOR (SSD). *AI dan SPK: Jurnal Artificial Intelligent dan Sistem Penunjang Keputusan*, *1*(1), 105-111.

[7] Li, H., Qiu, J., Li, T., Xie, G., Wang, D., & Wang, W. (2021). Multiple-criteria evaluation of thin-walled energy-absorbing structures of train under fuzzy environment: modeling and algorithm. *IEEE Access*, *9*, 150393-150402. https://doi.org/10.1109/ACCESS.2021.3125397

[8] Aida, N. R., & Hardiyanto, S. (2024). Ganti warna pelat nomor kendaraan warna putih dimulai 2022, ini penjelasan Korlantas Polri. *Kompas.com.* Retrieved July 10, 2024, from https://www.kompas.com/tren/read/2022/01/24/083000865/ganti-warna-pelat-nomor-kendaraan-warna-putih-dimulai-2022-ini-penjelasan?page=all#google_vignette

[9] Saputra, V. P., Latifa, U., & Ibrahim, I. (2023). Simulasi Detection Counter Pada Objek Kendaraan Motor Dan Mobil Menggunakan Metode Convolutional Neural Network Berbasis Python. *Jurnal Ilmiah Wahana Pendidikan*, *9*(16), 760-766. https://doi.org/10.5281/zenodo.8265040

[10] Permadi, H. S., Ridwan, M., & Rismaningsih, F. (2021). Implementasi logika fuzzy pada alat cuci tangan otomatis portabel dengan sistem monitoring berbasis Android. *Jurnal Buana Informatika, 12*(2), 106–115. https://doi.org/10.24002/jbi.v12i2.4768

[11] Romadhon, M., Indra, J., & Novita, H. (2023). Implementasi Fuzzy Logic Tsukamoto pada Deteksi Kondisi Badan Berdasarkan Suhu Tubuh. *Scientific Student Journal for Information, Technology and Science*, *4*(1), 57-65.

[12] Setya Budi, A. H., Baiquni, M. A., Mulyanti, B., & Nasution, M. F. (2024). Sistem deteksi laju dan plat nomor kendaraan berbasis video rekaman menggunakan YOLOv5-DeepSORT dan HyperLPR. *Telekontran: Jurnal Ilmiah Telekomunikasi, Kendali dan Elektronika Terapan, 11*(2), 140–149. https://doi.org/10.34010/telekontran.v11i2.10900

[13] Rochmah, A. U., Junus, M., & Imammuddin, A. M. (2021). Sistem Kendali dan Monitoring Garasi Menggunakan Metode Fuzzy Logic Berdasarkan Jarak dan Kecepatan User. *Journal of Telecommunication Network (Jurnal Jaringan Telekomunikasi)*, *11*(4), 208-213.

[14] Darmawan, R., Taqwa, A., & Endri, J. (2016). Rancang bangun sistem palang otomatis dengan pengenalan plat kendaraan. Retrieved from http://ojs.uho.ac.id/index.php/jfe/36

[15] Nasron, N., Suroso, S., & Putri, A. R. (2019). perancangan logika FUZZY untuk sistem pengendali kelembaban tanah dan suhu tanaman. *Jurnal Media Informatika Budidarma*, *3*(4), 307-312.

[16] Romadhon, N. A. G., Usman, K., & Patmasari, R. (2020). Deteksi Plat Nomor Kendaraan dengan Hough Transform dan Harris Corner Menggunakan Akuisisi Melalui Raspberry Pi. *TELKA-Jurnal Telekomunikasi, Elektronika, Komputasi dan Kontrol*, *6*(2), 93-103. https://doi.org/10.15575/telka.v6n2.93-103.

[17] Cahyo, N. D. (2019). Pengenalan Nomor Plat Kendaraan Dengan Metode Optical Character Recognition. *Ubiquitous: Computers and its Applications Journal*, *2*(1), 75-84.

[18] Fauzan, M. R., & Wibowo, A. P. W. (2021). Pendeteksian Plat Nomor Kendaraan Menggunakan Algoritma You Only Look Once V3 Dan Tesseract. *Jurnal Ilmiah Teknologi Infomasi Terapan*, *8*(1), 57-62. https://doi.org/10.33197/jitter.vol8.iss1.2021.718.

[19] Pustokhina, I. V., Pustokhin, D. A., Rodrigues, J. J., Gupta, D., Khanna, A., Shankar, K., ... & Joshi, G. P. (2020). Automatic vehicle license plate recognition using optimal K-means with convolutional neural network for intelligent transportation systems. *Ieee Access*, *8*, 92907-92917. https://doi.org/10.1109/ACCESS.2020.2993008

[20] Qin, G., Yang, S., & Li, S. (2022). A vehicle path tracking system with cooperative recognition of license plates and traffic network big data. *IEEE Transactions on Network and Service Management, 9*(3), 1033–1043. https://doi.org/10.1109/TNSE.2020.3048167

[21] Zaimuddin, M. A., Winardi, S., Mudjanarko, S. W., & Anindito, B. (2019). Sistem booking parkir mall dengan identifikasi plat nomor kendaraan berbasis android. *Jurnal TAM (Technology Acceptance Model)*, *10*(2), 93-99.

[22] Saif, N., et al. (2019). Automatic license plate recognition system for Bangla license plates using Convolutional Neural Network. In *TENCON 2019 - IEEE Region 10 Conference* (pp. 925–930). IEEE. https://doi.org/10.1109/TENCON.2019.8929280

[23] Padmasiri, H., Shashirangana, J., Meedeniya, D., Rana, O., & Perera, C. (2022). Automated license plate recognition for resource-constrained environments. *Sensors*, *22*(4), 1434. https://doi.org/10.3390/s22041434

[24] Orduna, I., Medina Vazquez, A. S., Navarro, M. A. G., & Barragan, C. A. B. (2019). Virtual motion detection method using fuzzy logic for an embedded system. In *2019 IEEE International Conference on Engineering Veracruz (ICEV)* (pp. 1–7). IEEE. https://doi.org/10.1109/ICEV.2019.8920710

[25] Lestari, I. N. T., & Mulyana, D. I. (2022). Implementation of OCR (Optical Character Recognition) using Tesseract in detecting character in quotes text images. *Journal of Applied Engineering and Technological Science (JAETS), 4*(1), 58–63. https://doi.org/10.37385/jaets.v4i1.905

[26] Aji, M. I. S., Mulyana, D. I., & Akbar, Y. (2023). Penerapan IoT Dengan Algoritma Fuzzy Dalam Monitoring Kesehatan Mata Dengan Sensor Berbasis Android. *Jurnal Teknologi Sistem Informasi dan Sistem Komputer TGD*, *6*(1), 42-52. https://doi.org/10.53513/jsk.v6i1.7346

[27] Loce, R. P., Bala, R., Trivedi, M., & Wiley, J. (Eds.). (2017). Computer vision and imaging in intelligent transportation systems. https://doi.org/10.1002/9781118971666

[28] Lambert-Torres, G., da Silva, L. E. B., de Moraes, C. H. V., & Masselli, Y. M. C. (2016). Fuzzy Systems. *Advanced Solutions in Power Systems: HVDC, FACTS, and Artificial Intelligence: HVDC, FACTS, and Artificial Intelligence*, 785-818. https://doi.org/10.1002/9781119175391.ch17.

[29] Yu, W., & Jafari, R. (2019). *Modeling and control of uncertain nonlinear systems with fuzzy equations and Z-number*. John Wiley & Sons.

[30] Wahyuni, I. (2023). *Logika fuzzy tahani*. In *Logika Fuzzy Tahani* (pp. 1–48). Komojoyopress.

