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PREFACE

We would like to present, with great pleasure, the second issue of Matrix: Jurnal Manajemen Teknologi dan Informatika in Volume 15, 2025. This journal is under the management of Scientific Publication, Research and Community Service Center, Politeknik Negeri Bali, and is devoted to covering the field of technology and informatics management including managing the rapid changes in information technology, emerging advances in electrical and electronics and new applications, implications of digital convergence and growth of electronics technology, and project management in electrical, mechanical or civil engineering. The scientific articles published in this edition were written by researchers from Universitas Udayana, Universitas Muhammadiyah Sidoarjo, STMIK Bandung Bali and Politeknik Negeri Jember. Articles in this issue cover topics in the field of Classification of Public Complaint Report Types on Social Crimes Using A Chatbot for Law Enforcement Agencies, Humanoid Object Detection Moving in Open Space Using Yolov8, Prototype Design of Crowdfunding-Based Student Tuition Payment E-Wallet Management Application (Startup) at STMIK Bandung Bali, Android-Based Multi-IoT Fish Feeding System: An End-To-End Information System Approach, Intelligence Attendance Monitoring System Using Real-Time Face Recognition and Raspberry Pi. Finally, we would like to thank the reviewers for their efforts and hard work in conducting a series of review phases thoroughly based on their expertise. We hope that the work of the authors in this issue will be a valuable resource for other researchers and will stimulate further research into the vibrant area of technology and information management in specific, and engineering in general.

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Editor-in-chief

Dewa Ayu Indah Cahya Dewi, S.TI., M.T.

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Classification of public complaint report types on social crimes using a chatbot for law enforcement agencies

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Abstract: Social crime is a complex problem that occurs every day and requires a quick response. The large number of reports with language variations makes the manual classification process difficult. This research aims to develop an AI-based chatbot to classify types of social crime reports automatically using the IndoBERT model. Data was obtained from East Denpasar Police, LAPOR website, and X social media. The initial data set of 250 reports was augmented to 6,250 data using synonym augmentation technique. The data was then divided into 70:20:10 training scenarios to produce the best model. The evaluation showed high performance with accuracy 0.999200, precision 0.999203, recall 0.999200, and F1-score 0.999200. Validation was also done through confusion matrix and accuracy-loss graph. The chatbot is able to receive reports from the public and classify them into five main categories, namely theft, maltreatment, embezzlement, domestic violence, and murder. The results show that IndoBERT is effective in understanding and classifying Indonesian text reports accurately. The system is expected to assist law enforcement agencies in improving efficiency and speed in handling community reports as well as supporting the digitisation of the social crime complaint process.

Keywords: AI, chatbot, complaint report classification, indobert, social crime

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Introduction

Social crimes refer to actions that violate the rules and norms upheld within a society, such as theft, assault, murder, and other forms of social crime [1]. The police institution serves as the primary the initial point of contact within Indonesia's criminal justice process [2]. One of the biggest obstacles encountered by law enforcement institutions is the high number of public complaints related to social crimes, including theft, violence, fraud, and other violations.

Based on statistics gathered by Indonesia's Central Bureau of Statistics (BPS) in 2024, a total of 584,991 criminal cases were recorded nationwide, with crimes such as theft, fraud, assault, and domestic violence dominating the reports received by the police [3]. Currently, the reporting process for public complaints is still frequently conducted manually, requiring individuals to visit police stations in person, which often takes time and necessitates direct interaction with officers. The public often faces difficulties in reporting crimes, and once a report is submitted, the classification and follow-up process can be time-consuming [4]. This situation presents a significant challenge, especially in the digital era, where the public expects faster, easier, and more responsive services. The existing manual process not only hampers efficiency but also complicates the classification of reports due to variations in language, writing structure, and narrative from the complainants, making the system prone to recording errors. Such data irregularities lead to delays in follow-up actions and impose additional workload on officers. Therefore, there is a need for a monitoring system that can assist law enforcement agencies (the police) in classifying public complaints efficiently and accurately. Advancements in information and communication technology present a great opportunity to improve the complaint system. One potential innovation is the use of chatbots. Chatbots can serve as interactive tools that allow the public to report crimes quickly and easily, while also assisting in the classification of complaint reports [5]. Prior studies have explored the application of chatbot systems in legal and governmental service contexts, showing their potential to improve accessibility and efficiency in handling public complaints [6].

One applicable methodological approach is the use of IndoBERT. By utilizing IndoBERT, chatbots can categorize reports based on specific categories, enabling law enforcement agencies to respond and resolve cases more swiftly. IndoBERT is a machine learning model known for its high effectiveness in understanding the context of natural language [7]. Using this model, chatbots can classify reports according to the types of social crimes reported Research on text classification has been widely conducted, particularly in the areas of news, general text, and academic publications. Studies such as Abri et al. [8], Fitrianto and Editya [9], Latifah et al. [10], Khairani et al. [11], Supriyadi and Sibaroni [12], Prabowo and Indra [13] employed fine-tuned IndoBERT models and revealed that IndoBERT achieved high accuracy levels. Additionally, studies by Juarto [14], Nabiilah et al. [15], Rizky and Hidayat [16] explored text classification using IndoBERT combined with other methods and found that IndoBERT consistently outperformed alternative approaches in terms of accuracy. However, previous research using IndoBERT has generally been limited to experimental applications in text classification and has yet to be integrated directly into interactive chatbot systems. One potential innovation is the use of chatbots which could enhance the accessibility and practical benefits of IndoBERT technology by enabling direct interaction with the public [17]. As a result, the public has not had direct access to such technology, and its practical benefits have not yet been fully realized.

This study focuses on developing a chatbot designed to classify public complaint reports related to social crimes. The system is built to identify and categorize reports into five main categories: theft, assault, embezzlement, domestic violence (DV), and murder. The selection of these five classes is based on the most frequently handled case types by local police units *(Polsek)*, as well as on authentic data collected directly from *Polsek* offices as the primary data source for model training and testing. These crime types are considered to represent the most common social problems in communities and require urgent response due to their direct impact on public safety and order. By focusing the classification on these five types of cases, the chatbot system is expected to serve as an interactive tool that streamlines the digital recording and classification of reports. Moreover, the system is also expected to reduce the workload of police officers in sorting reports, thereby allowing time and resources to be allocated more effectively to more complex cases. Through systematic and data-driven classification, law enforcement authorities will also find it easier to identify crime patterns and formulate more targeted countermeasures.

Methodology

This study employs a quantitative approach using an experimental method based on text classification to develop a chatbot system for classifying public complaint reports related to social crimes. The object of this study is public complaint report data collected directly from the East Denpasar Police Sector *(Polsek Denpasar Timur)*, along with secondary data obtained through web scraping techniques from the LAPOR website and social media platform X. The initial dataset consisted of 250 reports, which was expanded to 6,250 reports using synonym-based data augmentation techniques to enrich sentence variation.

The research process involves several key stages: data collection, text cleaning and preprocessing (including normalization, punctuation removal, stopword removal, and case folding), manual labeling based on five crime categories (theft, assault, fraud, domestic violence, and murder), and tokenization using the IndoBERT tokenizer. The data was divided into several training scenarios, namely 60:20:20 and 70:20:10 used in the phases of training, validation, and evaluation respectively. The model used is IndoBERT, fine-tuned using the Hugging Face Transformers library.

IndoBERT is a Transformer-based language model that has undergone a pre-training phase using a large Indonesian text corpus from multiple sources such as news articles, social media, and encyclopedias. During the pre-training stage, IndoBERT was trained in an unsupervised manner with objectives like masked language modeling (MLM) and next sentence prediction (NSP), based on the BERT model architecture introduced by Devlin et al. [18] and utilizing the Transformer mechanism proposed by Vaswani et al. [19]. This approach enables IndoBERT to learn general language representations specific to Indonesian. In this study, the pre-trained

IndoBERT model was then fine-tuned on a labeled dataset consisting of public complaint reports related to social crimes. Fine-tuning involved supervised learning where the model parameters were updated using a smaller, task-specific dataset categorized into theft, assault, embezzlement, domestic violence, and murder. This adaptation process allows IndoBERT to specialize in understanding the linguistic characteristics and context patterns present in community crime reports, improving its performance in the classification task within the chatbot system. The dataset consisted of complaint reports written in Indonesian, each represented as a single paragraph of natural language text. Each report was manually labeled with one or more crime categories depending on its content. The five categories used were theft, assault, embezzlement, domestic violence, and murder. Each record in the dataset includes the report text and a list of target labels, enabling the use of multi-label classification methods. This approach aligns with recent studies that highlight the effectiveness of multi-label classification models, particularly for classifying complaint data involving overlapping categories [20].

Evaluation was conducted using including metrics like accuracy, precision, recall, F1-score, and the confusion matrix. An additional evaluation was conducted an evaluation was conducted to measure the model's effectiveness for each individual category and detect potential misclassifications. The most accurate model was subsequently implemented within a Telegram-based chatbot, developed using Python and the python-telegram-bot library, and tested for its ability to classify text-based reports in real time. The research workflow is illustrated in Figure 1.

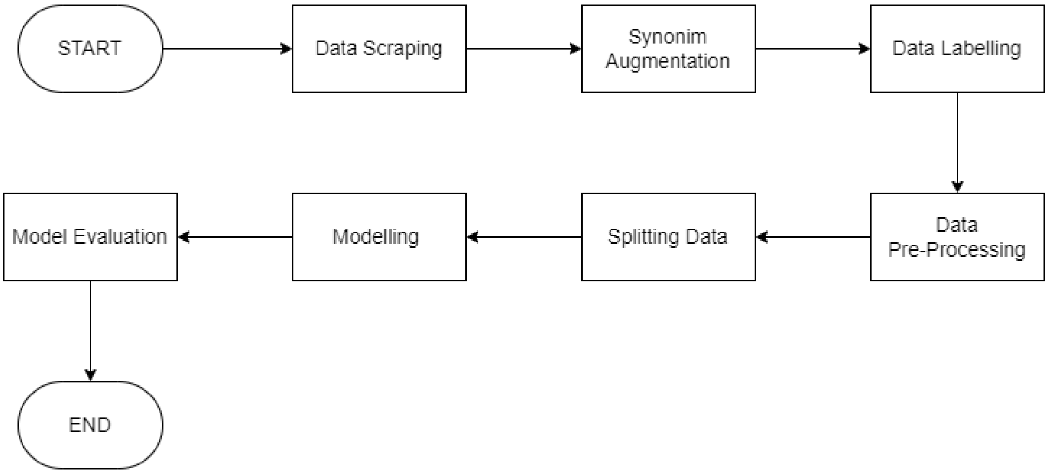


Figure 1. Research Workflow

Data collection is the initial stage carried out to obtain relevant and high-quality information from various sources for the purposes of analysis, decision-making, or research. This is followed by the synonym augmentation process, which increases the number of public report datasets. After the synonym augmentation process, the data is then subjected to labeling. Dataset labeling is the process of assigning labels or categories to each collected report dataset based on specific characteristics, to help the model understand the patterns and relationships between the input data and the corresponding expected outcomes. The labeled data then undergoes data preprocessing was carried out to cleanse, reformat, and ready the data for subsequent analysis. After preprocessing, the dataset was split into training, validation, and testing segments. The model is built and optimized using the training dataset so that it can learn and identify patterns in order to perform classification tasks Validation data serves the purpose of utilized to fine-tune the model and ensure proper learning in the process is valid, clean, and appropriate. The testing dataset serves to measure the model's ability to generalize to new, previously unobserved data, to determine how well it can classify data it has never seen before. Next, modeling is carried out using the IndoBERT algorithm, and finally, the model was assessed using standard evaluation metrics such as accuracy, precision, recall, and the F1-score. The modeling workflow of this study is illustrated Figure 2 below.

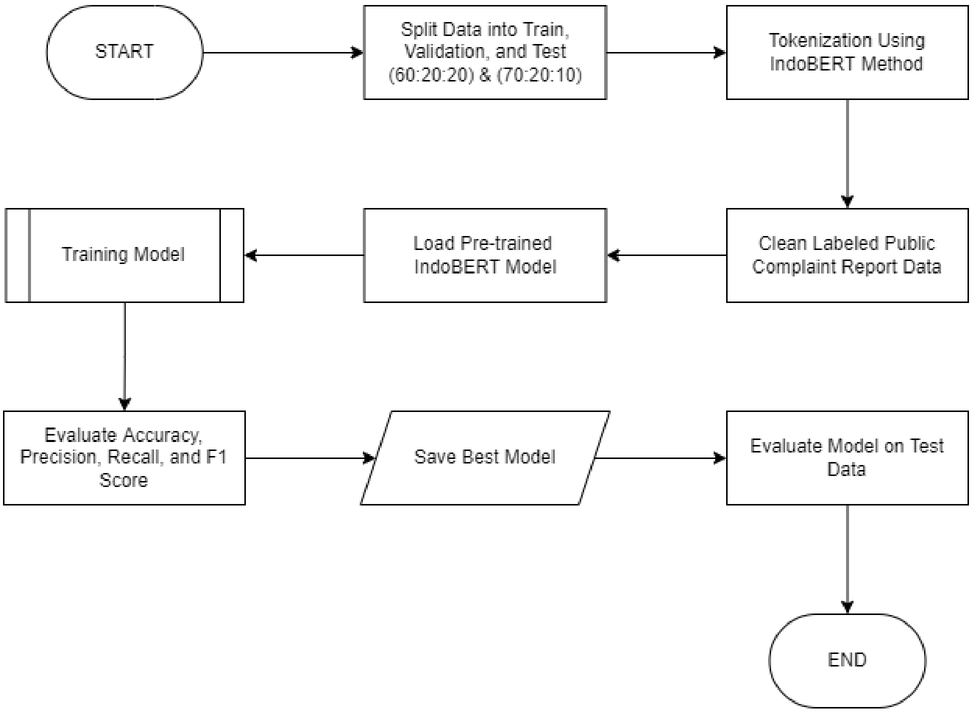


Figure 2. Modeling Workflow

Results and Discussions

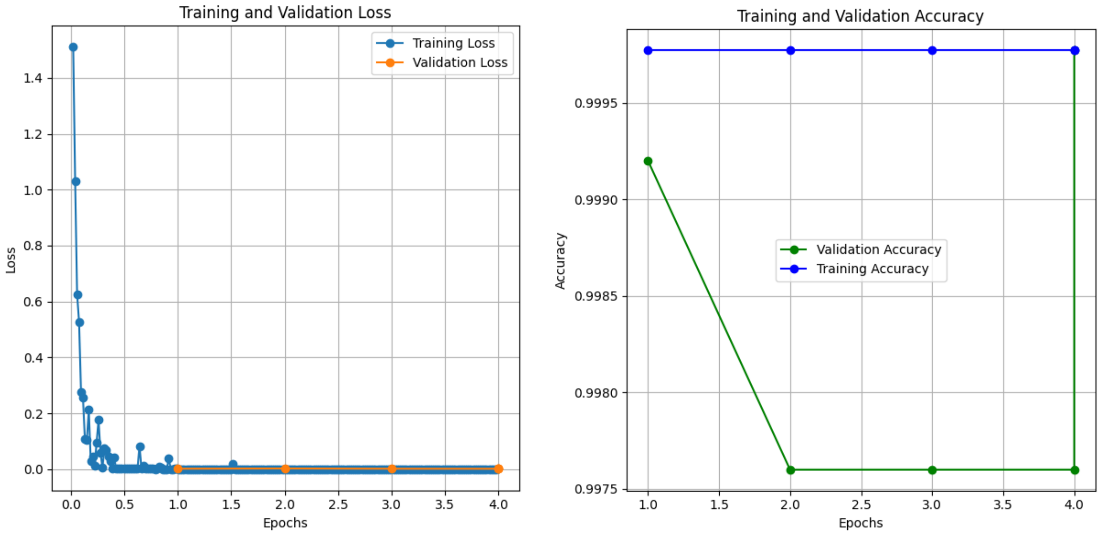
Results

The training outcomes suggest that the best-performing model was obtained through data augmentation techniques, the dataset was partitioned into 70% for training, 20% for validation, and 10% for testing. This proportion combination yielded optimal model performance, allowing the model to efficiently extract patterns from the training data, adjust its parameters through validation, and evaluate its accuracy using previously unseen test data. A summary of the training outcomes can be found in Table 1.

Table 1. Evaluation metrics results of the IndoBERT Model 70:20:10 scenario

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1
1	0.0015	0.001824	0.9992	0.999203	0.9992	0.9992
2	0.0002	0.002654	0.9992	0.999203	0.9992	0.9992
3	0.0001	0.001763	0.9992	0.999203	0.9992	0.9992
4	0.0001	0.001591	0.9992	0.999203	0.9992	0.9992

The results through the adaptation phase of IndoBERT to the specific task using the 70:20:10 scenario demonstrate the best performance. The training results table shows that the training loss remained within two decimal places and consistently decreased, it shows that the model performs well in recognizing and sorting different types of data. Meanwhile, the validation loss also remained stable at a relatively low value. A modest gain was recorded during epoch two, the validation loss continued to decrease consistently afterward. These outcomes demonstrate that the model is effective in differentiating among types of reports namely theft, assault, fraud, domestic violence, and murder with performance metrics as follows: accuracy 0.999200, precision 0.999203, recall 0.999200, and F1-score 0.999200.



(a) (b)

Figure 3. (a) Training and validation loss (b) Training and validation accuracy

Figure 3 (a) illustrates the changes in training loss and validation loss throughout the refinement phase of the model IndoBERT model using the 70:20:10 data split scenario. The visualization reveals a notable decrease in loss during the early stages of training, followed by a gradual stabilization at a lower value. This indicates that the model successfully Was able to extract meaningful features from the data and did not experience excessive overfitting.

Figure 3 (b) presents the graph of changes in training accuracy and as well as performance on validation samples during the increasing number of epochs. This graph depicts the improvement in model performance during training, where the accuracy values gradually increased and eventually stabilized. The stability of the high accuracy values demonstrates that the fine-tuned model using the 70:20:10 split scenario is capable of demonstrating effectiveness in handling data not seen during training.

The model's effectiveness was assessed using several evaluation indicators, including commonly used metrics like accuracy, precision, recall, and the F1-score. Accuracy is not sufficient to test the classification accuracy. Therefore, precision, recall, and F1-score offer more comprehensive insights additional information for classifying report types. Precision refers to The proportion of correctly predicted positives relative to all instances predicted as positive within a specific class, recall measures how well the model detects the correct class, and the F1-score serves as a harmonic mean that balances both precision and recall. Table 2 summarizes the results derived from these performance indicators.

Table 2. Evaluation metrics results of the IndoBERT Model for the 70:20:10 scenario

Class	Precision	Recall	F1-score
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
4	1.00	1.00	1.00

Through the Confusion Matrix, it is possible to observe how the model classifies each category in the dataset, including the number of correct predictions and classification errors that occur. The high performance of IndoBERT in classifying community crime reports is attributed to several factors. First, IndoBERT is a Transformer model that has been specifically trained using a large and diverse Indonesian-language text corpus, making it more contextual in understanding local sentence structures. Second, the fine-tuning technique used in this study was tailored to the specific context of crime reports, including the selection of an appropriate tokenizer. Third, The use of synonym-based augmentation contributes to enhancing the variety within the training dataset without altering its meaning, thus improving the model's capability to generalize when processing unseen or novel reports.

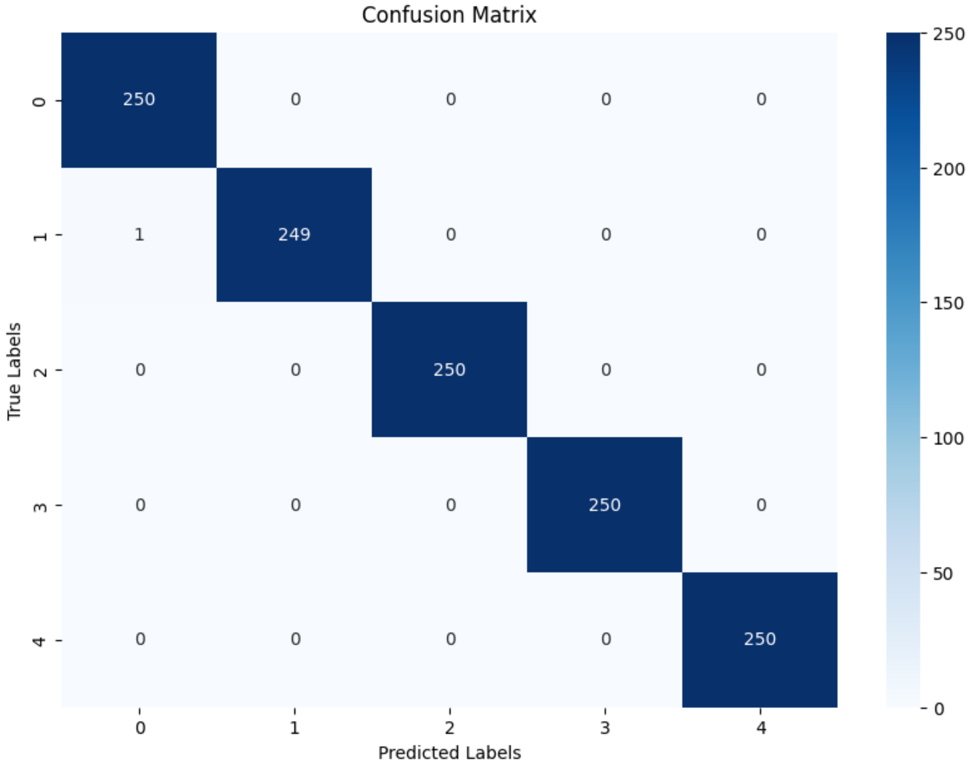


Figure 4. Confusion matrix

The Confusion Matrix derived from the fine-tuning evaluation stage IndoBERT model using a data partitioning scheme consisting of 70% for training purposes, 20% for validation, and the remaining 10% for testing. The distribution of predicted versus actual classes is visualized through the Confusion Matrix, where the True Labels axis represents the true classes of the data, and the Predicted Labels axis shows the predictions made by the model. Elevated values along the matrix diagonal signify that the model achieved reliable classification performance, while values outside the diagonal show the number of classification errors that occurred.

Based on the Confusion Matrix displayed in Figure 4, the model demonstrates a very accurate prediction distribution with perfect diagonal values, indicating no classification errors in the test data. However, when tested with new, more varied data (such as reports written in informal language styles or reports that do not explicitly mention the crime object), there were some cases where the model could only recognize one class, even though the report should belong to two classes. This suggests that the model is still sensitive to sentence structures or certain terms that are dominantly present in the training data. For example, reports containing words like "attacked" and "lost wallet" were sometimes classified only as abuse, without detecting the theft component. This highlights the importance of further training with multi-label reports and more diverse language variations. However, the dataset used in this study has limitations in covering the complexity of sentence structures and more diverse report contexts, which impacts classification accuracy in certain cases involving more than one type of crime. Table 3 below provides two examples of the public complaint reports used in this study, along with their corresponding crime category labels.

Table 3. Examples of the public complaint reports used in this study

Epoch	Training Loss
I was attacked and my phone was taken while walking home.	Theft, Assault
My neighbor secretly took the TV when I wasn't home.	Theft, Embezzlement

These samples illustrate the type of natural language input typically processed by the chatbot, consisting of narrative complaint reports submitted by the public. The classification system utilizes a multi-label approach to account for the possibility of overlapping or co-occurring crime categories within a single report. This allows the model to accurately reflect the complexity of real-world complaints, where one incident may involve more than one type of crime.

(a) (b)

Figure 5. (a) Complete report (b) Incomplete report

Figure 5 (a) above shows the interface of the crime complaint chatbot developed in this study. The user starts the interaction with the chatbot by pressing the 'Start Bot' or 'Help' button. After that, the chatbot provides instructions to the user to submit a complaint related to the crime they experienced. The user then sends a report in the form of a narrative that includes important information such as the time of the incident, location, perpetrator's identity (if known), and the modus operandi of the crime. After receiving the report, the chatbot asks for confirmation from the user regarding the completeness of the information provided, with options 'Complete' or 'Incomplete.' If the user confirms that the report is complete, the chatbot will process the report and classify it into the appropriate category based on natural language processing (NLP) analysis. In this example, the chatbot successfully identified the report as a 'Theft' case. After the classification process, the chatbot displays a confirmation message that the report has been successfully recorded and provides the contact information of the police officer responsible for the case.

Figure 5 (b) above shows the interface of the crime complaint chatbot developed in this study. The user starts the interaction with the chatbot by greeting or directly submitting a complaint related to the crime they experienced. In this example, the user reports a theft case that occurred at an electronics store on March 11, 2024, providing a detailed chronology of the incident, including the identity of the perpetrator and the modus operandi used. After receiving the report, the chatbot asks the user if the information provided is complete or if there is additional information that needs to be submitted. The user is given the option to select 'Complete' or 'Incomplete.' If the user selects the incomplete option, they are prompted to add additional information, and the chatbot will record it to improve the accuracy of the report. Once the report is confirmed to be complete, the chatbot classifies the reported crime type using natural language processing (NLP) technology. In this example, the chatbot identifies the report as both a 'Theft' and 'Embezzlement' case.

The figure illustrates that the model is able to classifies based on the text input by the user. The model performs classification using the previously trained IndoBERT model, as shown in the first report. For example, words like 'secretly,' 'without permission,' and 'checked' become strong indicators for classifying the report into the 'Embezzlement' class. The report also contains terms such as 'lost' and 'took the phone' which help the model identify that the input report should be classified under the 'Theft' class. Therefore, in this case, the report is classified into two classes: theft and embezzlement. The report is classified into two classes because the probability values generated from the classification process show that these two classes have the highest probability values, while the next class has a 10% probability difference from the highest class, thus the report is classified into both classes.

Discussions

The Telegram-based chatbot developed in this study is designed to automatically classify various types of community crime complaint reports. The classification model based on natural language processing (NLP) enables the chatbot to understand and automatically group reports into predetermined crime categories exhibiting exceptional accuracy in its predictions. The application of this technology is intended to improve the efficiency of handling complaints and to support law enforcement agencies in analyzing patterns of social crimes. Evaluation results show that the chatbot is able to respond quickly and accurately, achieve a strong level of precision when categorizing the reports. The interface of the developed chatbot is displayed in the figure above, showing how users can submit reports and receive classification results automatically.

For comparison, previous research conducted by Nanda et al. [21] on text classification using Support Vector Machine (SVM) achieved a model accuracy of 88%. Meanwhile, the fine-tuned IndoBERT model in this study achieved an accuracy of up to 0.9992. By utilizing a natural language processing (NLP)-based classification model, the chatbot is able to understand and group reports according to the predefined categories. Evaluation results show that the chatbot is able to respond quickly and accurately, with a high level of accuracy in classifying reports. These results align with the findings from Nanda et al. [21] which show that Transformer-based models provide more stable results in the context of non-English text classification compared to conventional machine learning-based models.

Moreover, while IndoBERT has proven to be highly effective in processing the given dataset, future enhancements should focus on refining the model to handle more complex or ambiguous sentence structures that may emerge in real-world applications. This could be achieved by training the model with a broader range of text data, ensuring that it is equipped to manage a variety of language styles and tones that are commonly used in informal crime reports. Additionally, the integration of real-time language models and dynamic updates to the system can further enhance the chatbot's capability to remain relevant as language and crime reporting evolve.

Conclusion

This study successfully developed a chatbot using the IndoBERT model to classify public complaint reports into five crime categories. The system achieved excellent performance metrics, with accuracy, precision, recall, and F1-score reaching 0.9992. By integrating NLP and data augmentation, the chatbot can automate the classification process and support law enforcement agencies in handling social crime reports efficiently. Future improvements include expanding the dataset, improving multi-label capabilities, and integrating with official police systems.

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Humanoid object detection moving in open space using YOLOv8

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Abstract: This study explores the application of the YOLOv8 algorithm in detecting humanoid objects in an open space environment, with a special focus on school areas such as parking lots. The main objective is to develop an intelligent system that can accurately identify students based on four uniform classifications: none, grey, batik, and department-specific uniforms. The system is designed to function effectively in real-time by analyzing image and video data. The research methodology begins with data acquisition using CCTV footage, followed by annotation and preprocessing using Roboflow. The dataset consists of 314 images with 1,649 labeled bounding boxes, which are then divided into training and validation sets. A yaml configuration file is created to interact with the YOLOv8 model. Training is performed using YOLOv8s variants, with experimental variations in image size, batch size, and epochs to optimize model performance. The evaluation results show that the model achieves a precision of 0.86, a recall of 0.92, and a mean Average Precision (mAP@0.50) of 0.93. Furthermore, visual testing confirms the system's ability to detect students with a total detection accuracy of 85%. Some minor errors were observed in distinguishing between visually similar classes, such as batik and department uniforms. These results demonstrate the robustness and reliability of YOLOv8 in dynamic real-world environments. This study concludes that YOLOv8 can be effectively applied to educational settings for surveillance or monitoring systems. Future research will focus on improving accuracy by expanding the dataset and incorporating more diverse categories of humanoid objects.

Keywords: deep learning, humanoid object, open space, YOLOv8

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Introduction

The advancement of information technology has grown rapidly along with the emergence of various innovations in the field of artificial intelligence (AI) [1]. One of the applications of AI that is currently being developed is the facial recognition and object detection system [2]. This system has an important role in various sectors, such as security, education, and attendance management [3]. Real-time facial recognition technology is considered an effective solution, because it is able to continuously capture and analyze facial data so that it can recognize a person's facial characteristics quickly and accurately [4].

The implementation of a face detection-based attendance system offers many advantages over conventional methods [5]. By utilizing a camera as input data, this system can automatically identify individuals without requiring physical contact, thus supporting the implementation of health protocols and operational efficiency [6]. In such a system, object detection technology plays an important role. Object detection is the process of identifying and determining the presence of an object in a digital image or video [7]. This method has been widely developed with various algorithms that have their own advantages in terms of speed and accuracy [8].

One of the object detection algorithms known to be effective and efficient is YOLO (You Only Look Once) [9]. YOLO is a deep learning-based algorithm that enables real-time object detection by dividing the image into grids and processing object predictions on each part of the grid simultaneously. This approach enables the processing of images or videos in one pass, making it very fast and suitable for real-time applications [10]. Aside from YOLO, several other object detection algorithms have also been widely used, such as Faster R-CNN, which offers high accuracy through a two-stage detection process SSD (Single Shot MultiBox Detector), known for its balance between speed and performance in real-time.

YOLOv8 is the latest iteration of the YOLO algorithm family that brings various improvements in terms of accuracy, efficiency, and detection speed. The YOLO (You Only Look Once) series has evolved significantly since its first release. YOLOv1 introduced real-time object detection by performing predictions in a single pass. YOLOv2 and YOLOv3 improved detection for smaller objects and added better backbone networks like Darknet-19 and Darknet-53. YOLOv4 integrated features like CSPDarknet and PANet, optimizing performance further for complex environments. YOLOv5, although unofficial, became widely adopted for its ease of use, flexibility, and support for deployment on various platforms. YOLOv6 and YOLOv7 continued to refine the trade-off between detection speed and accuracy with updated architectures and training techniques [11]. YOLOv8 uses a more optimal neural network architecture and is supported by more adaptive augmentation and training techniques, enabling object detection in various environmental conditions such as varying lighting, different object sizes, and complex backgrounds. Therefore, YOLOv8 is the main choice in development systems that require real-time response with high accuracy [12].

In various previous studies that have been conducted to create object detection using YOLO v8, such as studies Sholahuddin et al. [13] and Muntiari et al. [14], it is known that these studies only display one object. While in this study, the development is focused on detecting student objects with different classes. So this study can improve the system's ability to understand the details of the specified object.

This study aims to enable the performance of the YOLOv8 algorithm in detecting humanoid objects in school parking areas, both in image and video data. This study also tests the accuracy and algorithm of the algorithm in various dynamic environmental conditions. This study can contribute to the development of AI-based security and monitoring systems, especially in the context of education in the school environment. With the application of this technology, it is hoped that the monitoring system in schools will be more advanced, efficient, and adaptive to the needs of the times.

Methodology

In this section, the author will explain the research flow for detecting moving humanoid objects in open spaces using YOLO v8 starting with preparing the dataset, then the dataset is divided into two groups train and val, and a .yaml file is also created based on the data information, then the model training process is carried out followed by model evaluation and finally model testing. As shown in the Figure 1 below.

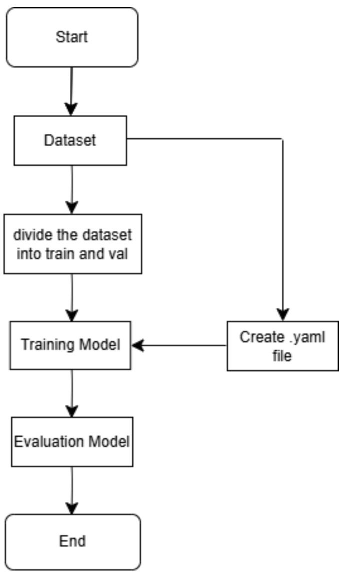

Figure 1. Flow diagram

Dataset

In Figure 1, the first stage begins with data collection taken from CCTV footage at SMK YPM 8 Sidoarjo, and roboflow as data processing. Roboflow is one of the best frameworks to help the labeling, pre-processing, and creating datasets, as well as inputting the dataset into the YOLOv8 algorithm [15].

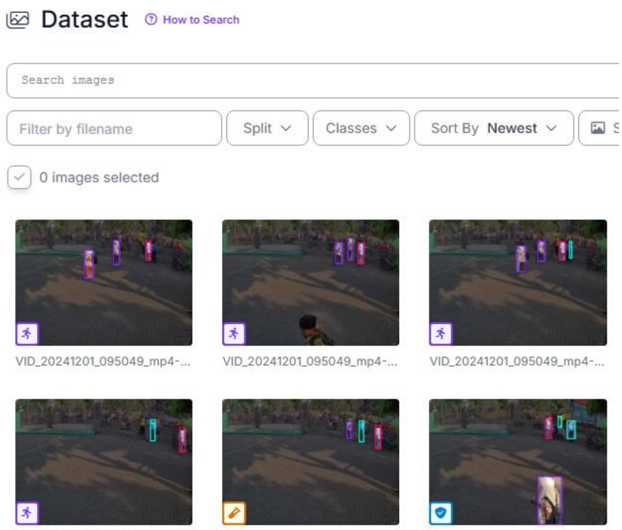

Figure 2. Dataset

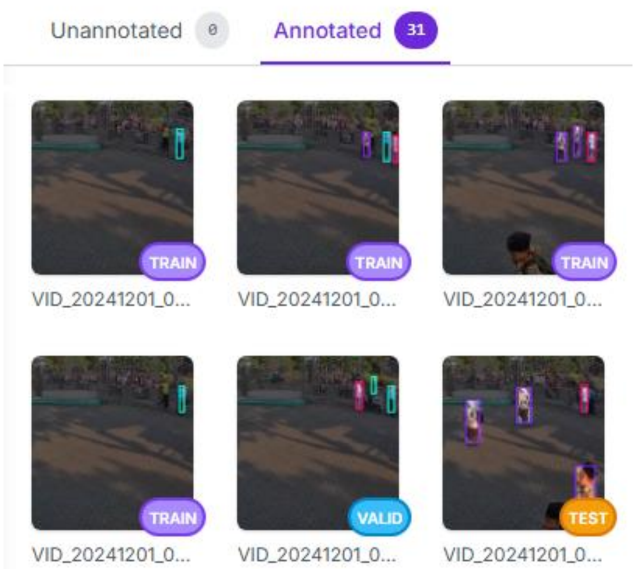

Figure 3. Annotation dataset/labeling

The dataset contains images as seen in Figures 2 and Figure 3 with a total of 314 data each. The dataset is used to contain four data classes, namely none, b_abu students, b_batik students, and b_jurusan students. Then from the annotation it is reprocessed in the form of a table containing data per-bounding box. So that the number of data for the none class is 791 data, b_abu students are 240 data, b_batik students are 460 data, and b_jurusan students are 158 data, then from the four classes it is added up to 1649 data from the initial number of 314, this number is obtained from all labeling or annotations per-body on each image.

The next stage is the division of train and val groups with a ratio of 783;37. the selection of this ratio is considered the best division in training data. Then create a yaml file as a bridge between the YOLO v8 model and the image input in the dataset. The yaml file contains brief information about the dataset, with a writing structure as in Figure 4 below.

```
File  Edit  Format  View  Help
train: ../train/images
val: ../valid/images
test: ../test/images

nc: 4
names: ['none', 'siswa b_abu', 'siswa b_batik', 'siswa b_jurusan']

roboflow:
  workspace: kahfi-xj5tf
  project: kahfi_objek1
  version: 1
  license: CC BY 4.0
  url: https://universe.roboflow.com/kahfi-xj5tf/kahfi_objek1/dataset/1
```

Figure 4. .Yaml file writing structure

Humanoid Object Detection Architecture

In this study, the configuration settings for the img, batch, and epoch variables were determined to obtain optimal results on one previously selected YOLO v8 variant, namely yolov8s[16]. YOLOv8s is a lightweight version of the YOLOv8 family that balances speed and accuracy, making it suitable for real-time applications. The architecture of YOLOv8 features improvements such as a fully convolutional backbone, decoupled head for classification and regression, and a simplified detection head that enhances both inference speed and detection precision. YOLOv8 also utilizes anchor-free detection, enabling it to better adapt to various object shapes and scales. After going through the training process, the model was tested with image input. The result in each image is a prediction bounding box with class divisions labeled as: "none", "siswa b_abu", "siswa b_batik", and "siswa b_jurusan", along with their predicted confidence values. Yolov8 architecture can be seen in Figure 5.

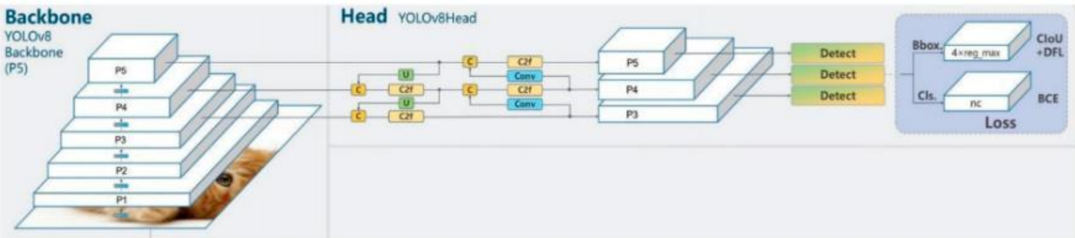

Figure 5. Yolov8 architecture

Humanoid Object Detection Using YOLOv8

In this study, the author uses the YOLO v8 variant, namely yolov8s. The writing structure of the training model command involves several things as follows.

Img

Img interpreted as a regulator of the input image or image size, the larger the size set, the more detailed the object to be detected, but requires more power. The smaller the image size, the faster the model training process which then lightens the computing performance. Several studies have determined the ideal image input size without having to lose much information, namely 416 X 416. in this study, it was determined using the img configuration at values 416 and 640. The selection of 640 was used as a comparison from 416.

Batch

Batch namely the number of images in one group. If the amount of data is 2738 images, with a batch size of 32, then the number of batches needed is 2738: 32 = 86 batches. The more batches used, the greater the memory consumption. In this study, four types of batches will be used starting from the numbers 8, 16, 32, and 64. This is done to determine the differences produced from the multiples of the previous batch.

Epoch

Epoch which is the number of rounds used during the training process. In this study, the epochs used are at 100, these numbers were chosen to minimize training time, and avoid epoch values that are too high because they do not always produce higher accuracy so that appropriate epoch settings are needed to obtain optimal results[17].

Data

Data which is a yaml file containing data collection information.

Weight

Weight refers to the model variant used, namely yolov8s which is available in a set of YOLO v8.

The YOLO v8 training model takes from Ultralytic Github data which then during the training process produces several values, namely the F1 value which is the average value between precision and recall. These results are obtained from the following mathematical statement.

F1-score is an evaluation metric that combines precision and recall to provide a more comprehensive perspective on the performance of a classification model. The goal is to balance precision and recall, especially when the distribution of positive and negative classes is imbalanced.

$$F1\ Score = \frac{2\ x\ Precision\ x\ Recall}{Precision +\ Recall} \tag{1}$$

Precision value is a measure that shows how many positive category data are correctly classified divided by the total data classified as positive. The equation for calculating precision value is as follows:

$$Precision = \frac{TP}{TP\ x\ FP} \tag{2}$$

The recall value shows the percentage of positive category data that is correctly classified by the system. The equation for calculating the recall value is as follows:

$$Recall = \frac{TP}{TP\ x\ FN} \tag{3}$$

Where TP is *True Positive*, shows the number of positive data that are correctly classified by the system, FP is *False Positive*, shows the number of positive data but is classified incorrectly by the system, FN is *False Negative*, shows the number of negative data but is classified incorrectly by the system.

mAP (mean Average Precision) is an evaluation metric used to measure the performance of object detection algorithms, including YOLO (You Only Look Once). mAP measures how well a model detects and classifies objects in an image. AP (Average Precision) is a measure of detection performance per object class. For example, if there are 4 types of objects (car, human, bicycle, motorcycle), then:

$$mAP = \frac{APmobile + APhuman + APbicycle + APmotorcycle}{4} \tag{4}$$

Where mAP *is average of AP*. AP is *Average Precison*, the average value of precision at various recall levels (usually from 0 to 1).

Accuracy is a measure of how well a system or model performs prediction or classification. In the context of object recognition, accuracy indicates the percentage of correct detections compared to the total number of detections made.

$$Accuracy = \frac{Correct\ Detections}{Number\ of\ Detections}\ x\ 100\% \quad (5)$$

Results and Discussions

Training Model

Based on the results of the model training process test that has been carried out for 100 epochs, the following 5 highest epochs of the results obtained can be presented in Table 1 below.

Table 1. YOLOv8 model test results

Epoch	Precision	Recall	mAP
17	0.86	0.92	0.93
43	0.83	0.88	0.91
49	0.85	0.85	0.89
41	0.85	0.89	0.91
24	0.86	0.89	0.92

Based on Table 1 above, the results at epoch 17 have the highest value with a precision of 0.86, a recall of 0.92, and mAP@0.50 reaching 0.93. These values indicate that the model is able to detect and localize objects with a high level of accuracy at various IoU thresholds.

Epoch 43 has a good balance of recall and mAP values, while epoch 49 shows high precision even though recall decreases slightly. Epochs 41 and 24 also show strong performance, with competitive recall and mAP values. Epoch 24 records the highest precision (0.86) of all the top five, making it the right choice for cases that require high sensitivity to false positives.

Precision, recall, and mAP values are considered good when they exceed 0.80. A precision of 0.86, as seen in epoch 24, indicates that 86% of the model's positive predictions are correct, which reflects a low rate of false positives and is considered strong. Whereas, a recall above 0.80 indicates that the model successfully captures most of the actual objects, minimizing false negatives. Meanwhile, mAP values closer to 1.0 indicate better overall accuracy across all object classes and thresholds. Therefore, the performance observed in epochs 24, 41, 43, and 49 can be categorized as high-quality based on these thresholds.

Figure 6 shows the results of the Confusion Matrix, providing a visual representation of how well the YOLOv8 model can detect Humanoid Objects. Analysis of the Confusion Matrix results shows that the number of correct detections is close to 1 for almost every object class. There are also exceptions in each class where there are 0.01 to 0.10 detection errors.

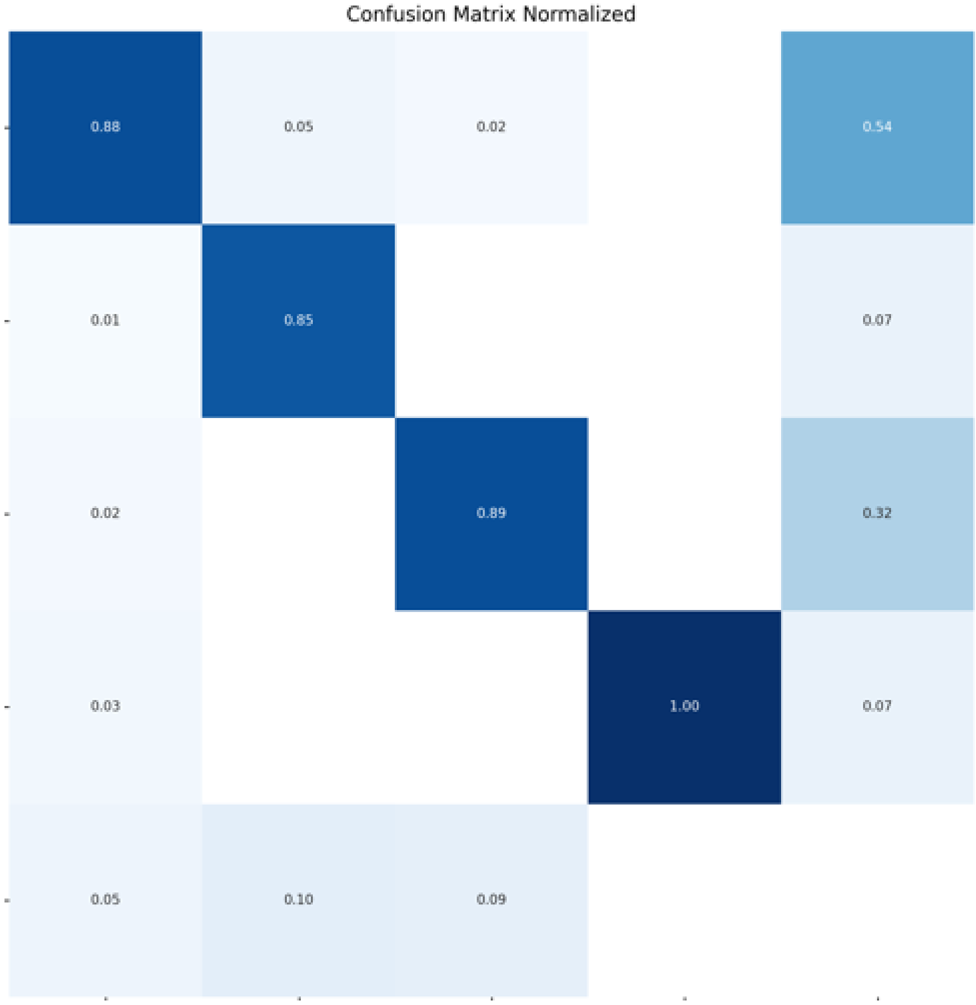

Figure 6. Confusion matrix

Figure 7 shows some graphs of the YOLOv8 training results as follows.

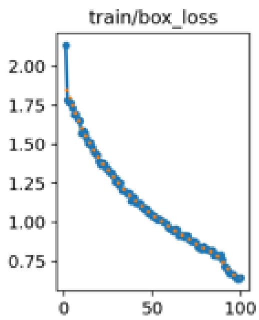

Figure 7. (a) Train/box_loss

Figure 7 (a) shows the decrease in bounding box loss during the training process. A lower loss value indicates an increase in the accuracy of the model in predicting the spatial position of objects.

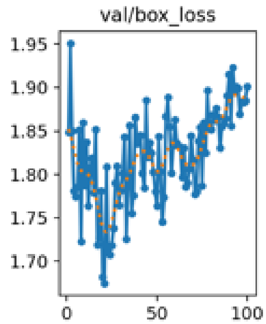

Figure 7. (b) val/box_loss

Figure 7 (b) shows the box loss value on the validation data. Fluctuations in this graph indicate model inconsistency when tested on untrained data, but are still within acceptable limits.

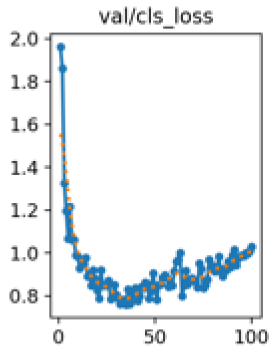

Figure 7. (c) val/cls_loss

Figure 7 (c) shows the classification loss on the validation data. The U-shaped curve indicates that there is an adjustment of the model to the existing object classes until it reaches the minimum loss value.

Figure 8 shows three graphs representing the performance of the YOLOv8 model in detecting humanoid objects. The first graph is the F1-Score curve of 0.88 at a Confidence Level of 0.368. The second graph is the Precision curve against the Confidence Level of the model, where all humanoid object classes achieve a Precision value of 1 at a Confidence Level of 0.812. While the third graph is the Recall curve against the Confidence Level of the model, with all humanoid object classes achieving a Recall value of 0.98 at a Convidence Level of 0.000.

These Confidence Level values reflect the model's prediction certainty thresholds. A Confidence Level of 0.368 indicates the optimal balance between precision and recall, as shown by the highest F1-Score. At a higher threshold (0.812), the model becomes more selective, producing highly accurate predictions (Precision = 1) but potentially missing some objects (lower recall). Conversely, at a Confidence Level of 0.000, the model accepts all predictions, resulting in very high object detection coverage (Recall = 0.98), but possibly including more false positives. Therefore, the choice of confidence level impacts the trade-off between accuracy and completeness of detection.

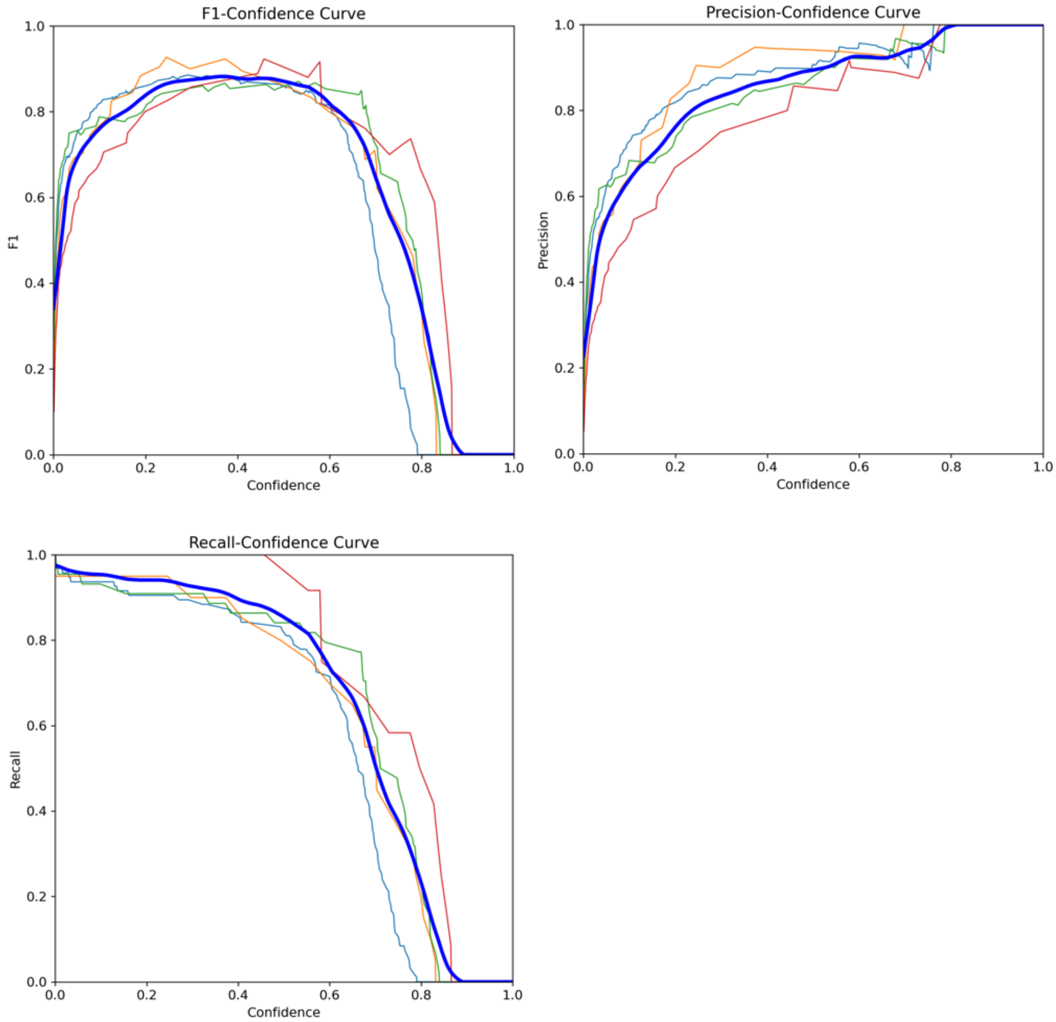

Figure 8. F1-Score Curve, Precision, Recall

Evaluation Model

To validate the accuracy off the research model, an evaluation of the model results in all model training scenarios is required. The evaluation is carried out by testing the image results that have certain conditions to determine the level of correctness of humanoid object detection in the model scenario. The following are the image results needed for the model evaluation process.

Figure 9. Model training results for model evaluation

In Figure 9, the model shows good and stable visual prediction performance according to the metric evaluation results. Important objects *(siswa)* can be recognized with high precision, but some cases of label overlap and low confidence predictions indicate that further fine-tuning can still improve more specific classification accuracy, especially for visually similar classes, the following are the results of a comparative evaluation of the level of correctness and error of each model in detecting objects presented in Table 2 below.

Table 2. Model accuracy evaluation results

Category	Number of detections	Correct detections	False detections	Accuracy
none	29	25	4	86.2%
siswa b_abu	7	6	1	85.7%
siswa b_batik	13	10	3	76.9%
siswa b_jurusan	11	10	1	90.9%

Based on the model accuracy evaluation results, the detection accuracy level reaches 85%, thus showing very good performance in detecting humanoid objects in real conditions.

Conclusion

The conclusion of this study shows that the implementation of the application with the YOLOv8 algorithm in detecting humanoid objects in open spaces, especially in identifying students in uniform, has succeeded in achieving the stated objectives. The best accuracy level reaches a precision value of 0.86, a recall value off 0.92 and a mAP @ 0.93 value during the training process by utilizing 791 images from the dataset. The evaluation results show a good level of accuracy reaching an accuracy value of 85%. These findings contribute to the development of information technology, especially in the field of intelligent surveillance systems, by validating the practical implementation of advanced AI algorithms in dynamic, real-world environments.
Future research will continue to develop the YOLO algorithm in its best version by incorporating a more representative training dataset, which will include a variety of humanoid objects. This will improve the algorithm's ability to accurately recognize and classify object features.

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Prototype design of crowdfunding-based student tuition payment E-Wallet management application (startup) at STMIK Bandung Bali

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Abstract: This research designed and developed a prototype e-wallet management application for crowdfunding-based tuition fee payment at STMIK Bandung Bali, addressing higher education cost challenges. Using Agile methodology, the development covered requirements analysis, UI/database design, payment gateway integration, and testing. Core functionalities include student data, academic history, billing, e-wallet balance, donor contributions, and campus operator disbursements. Functional testing showed 100% success across all 9 black-box test scenarios, confirming successful crowdfunding system implementation. However, load and stress tests on shared hosting (0.5 CPU, 256 MB RAM) revealed performance limitations. Response times increased sharply from 2.2 seconds (100 requests) to 14.6 seconds (200 requests), with over 95% system failure beyond 400 concurrent requests, indicating hosting resource constraints. Empirical user evaluations (10 students, 5 donors, 2 operators) confirmed high system effectiveness and usability, yielding average scores of 4.2 for effectiveness and 4.0 for usability (on a 5-point Likert scale). Security measures include private key API integration, AES password encryption, and restricted sensitive data access. This research's success lies in its specific technical solution for institutional tuition crowdfunding, integrating directly with STMIK Bandung Bali's financial management, differentiating it from general platforms.

Keywords: disbursement system, education donation, payment gateway, student E-Wallet management, tuition crowdfunding

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Introduction

The level of higher education in Bali reflects the commitment to human resource development in the region. In August 2023, of Bali's 2.62 million working population, 17.51% of them had a higher education (diploma or university) [1]. In this digital era, access to higher education requires efficient and adaptive financial management solutions. The reality on the ground shows that conventional tuition payment systems often face challenges, both in terms of administration and ease of access for users.

The 2018 and 2021 Education Support Statistics data released by the Badan Pusat Statistik (BPS) shows that the cost of higher education in private universities has increased by 4.2% in the last three years, from an average of IDR 16.3 million in 2018 to IDR 17 million in 2021 [2], [3]. This phenomenon, coupled with data on tuition payment arrears of 30.88% at STMIK Bandung Bali in the 2023/2024 academic year [4] and supported by the results of interviews with the Finance Department, shows that STMIK Bandung Bali students are in arrears with tuition payments due to poor billing systems and student financial problems. Underscoring the need for innovation in education payment and fund management systems, this challenge demands the development of a platform that not only facilitates financial transactions but also enables adaptive fund collection mechanisms.

Previous research has explored various technological solutions to the payment problem, including the use of e-wallets [5], [6], [7] and crowdfunding methods [8], [9], [10]. Crowdfunding has proven to be an effective method of raising funds. Common crowdfunding platforms such as GoFundMe or Kitabisa.com, although supporting educational campaigns [11], are designed as broad donation platforms with varied fund disbursement processes but are not directly integrated with the financial systems of educational institutions. The implementation of crowdfunding specifically for student tuition payments in an e-wallet format that is directly integrated with higher education financial management still requires further exploration from a technical prototype design point of view. The gap between the need for a modern payment system and the availability of specific integrated solutions is the basis for the urgency of this research.

This research focuses on designing and developing a prototype e-wallet application specifically designed to facilitate payment of tuition fees through crowdfunding methods for students at STMIK Bandung Bali. The main objective is to present a fully functional technical solution for the management of education finance. The novelty of this research is in the integration of the crowdfunding method into an e-wallet platform that is specifically intended for tuition fee payment in a university setting, with an automatic fund disbursement system to the institution's account and provision of education-specific transparency data. This differentiates it from general crowdfunding platforms that lack this kind of specialization and direct integration. The main contribution of this research is to the technical aspects of application development, including system architecture, feature implementation, functional and non-functional testing, to provide a reference model for future similar systems.

Methodology

This research uses a prototype development approach with Agile methodology. This iterative and flexible approach was chosen to enable rapid adaptation to needs and feedback during the development process [12], [13], [14]. The object of the research is a prototype of an e-wallet management application for crowdfunding-based tuition payments at STMIK Bandung Bali.

System analysis and design using the Unified Modeling Language (UML) to visualize the architecture, workflow, and interactions between system components [15]. Development of a web-based application prototype was carried out using the Codeigniter framework version 4.6. Payment integration is done through the Duitku payment gateway that supports Application Programming Interface (API) disbursement of funds directly to bank accounts. Data on study history, grades, and tuition payment bills of STMIK Bandung Bali students are used for data simulation in prototype development and testing.

The research implementation follows the Agile cycle which consists of several stages: [16]:

1. Needs Analysis: Identification of functional needs includes donor registration, donation submission, student data management, payment, fund withdrawal. Non-functional needs includes security, ease of use, application performance based on tuition fee issues, crowdfunding potential, and specific needs of STMIK Bandung Bali. Data was collected through literature study and user needs analysis.
2. Design: Designing the application architecture, database model, user interface (UI) design, and system workflow using UML diagrams. The focus of design is on the main features that support interactions between students, donors, and the campus in the process of crowdfunding tuition payments and e-wallet management.
3. Implementation: Development of a web-based application prototype in accordance with the design specifications that have been made. This stage includes the implementation of application features and integration with the payment gateway API to facilitate donation and fund disbursement transactions.
4. Testing: Functionality testing of the application prototype utilized the black-box testing method. The predefined test scenarios covered various aspects of functionality, including registration, donations, payments, withdrawals, and notifications. The purpose of the testing was to verify that the application functioned as required.
5. Evaluation: Analyze the test results to identify the successes and failures of each test scenario. This evaluation aims to ensure that all features are working as expected and to identify potential improvements or further development on the prototype.

The main parameter observed during functional testing is the level of successful execution of each predefined test scenario. This includes verification of the suitability between input and expected output, successful integration with the payment gateway in conducting donation and fund disbursement transactions, as well as the validity and accuracy of the data displayed in the application. Non-functional testing is done by testing system load and evaluation by users. The flow of the agile method can be seen in Figure 1.

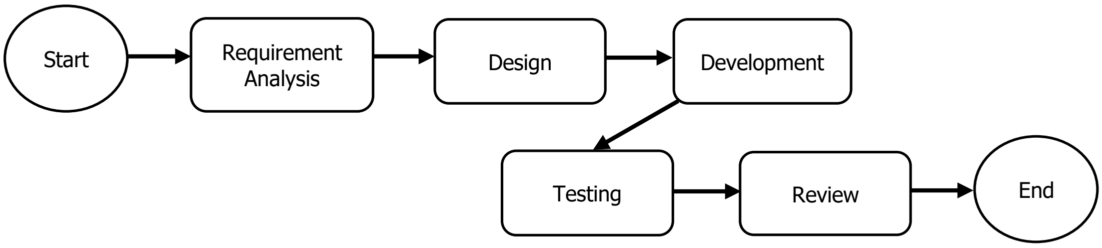

Figure 1. Agile method

Results and Discussions

Analysis of the running system

Currently, the tuition fee payment system at STMIK Bandung Bali still relies on manual processes or separate and unintegrated systems between bills and payments. Students must face challenges in accessing payment information, while the administration has difficulty managing efficiently and transparently. The use of E-Wallet technology is currently not fully integrated with the tuition payment system, so the efficiency and connection between students and the administration can still be improved. A more inclusive and sustainable payment model through the crowdfunding method has also not been implemented. Crowdfunding can be a solution to expand community participation in supporting the sustainability of higher education.

In answering these challenges, this research will propose an experimental research methodology approach. The experimental method allows for direct testing and evaluation of the effectiveness of the application of methods and technologies in the development of an integrated tuition payment system. The application of E-Wallet technology and crowdfunding methods will be carried out by designing and developing system prototypes.

System Design and Development

In the analysis and design using UML tools. From the results of surveys and interviews [15], the resulting analysis of functions and users is described in the form of use cases in Figure 2. A total of 4 actors are involved:

1. Administrators can register campus operators and reconcile donation and withdrawal transactions.
2. Campus operators can upload student data, verify students, and withdraw funds according to bills. Upload Study Plan data and Study Result or Academic Transcript data needed for information to donors, that it is true that the student who will be given a donation is studying at STMIK Bandung Bali. The data can also be used by donors to analyze students ranging from college activeness, grades to GPA obtained.
3. Donors can view student data, study history, bills or the amount of funds needed by students, the amount of donations that have been obtained by students, make donations, and view donation history.
4. Students can view tuition bills, nominal donations given by donors, view the transaction history of incoming and outgoing money, and view E-Wallet balances.

The entire flow of activities is depicted in the form of an activity diagram in Figure 3. Students make donation requests to the campus, then the campus will upload student data including bills that will be seen by donors. Donors who will make donations can see student data.

Then the donor can make a donation. If the donation has been entered, there will be a notification to the student and the campus. The campus can disburse funds according to the bill and incoming donations.

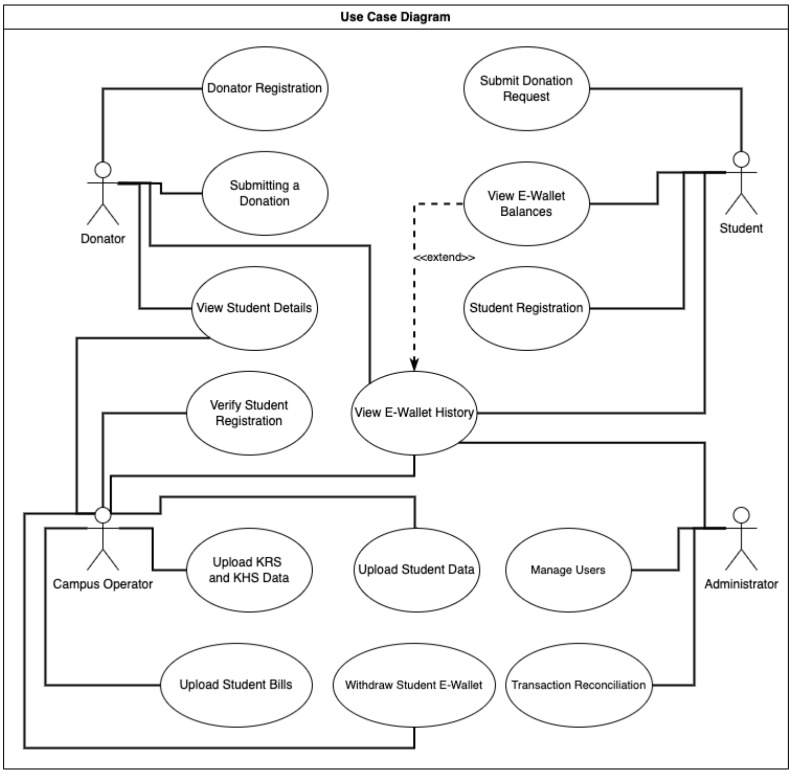

Figure 2. Use case diagram E-Wallet management application

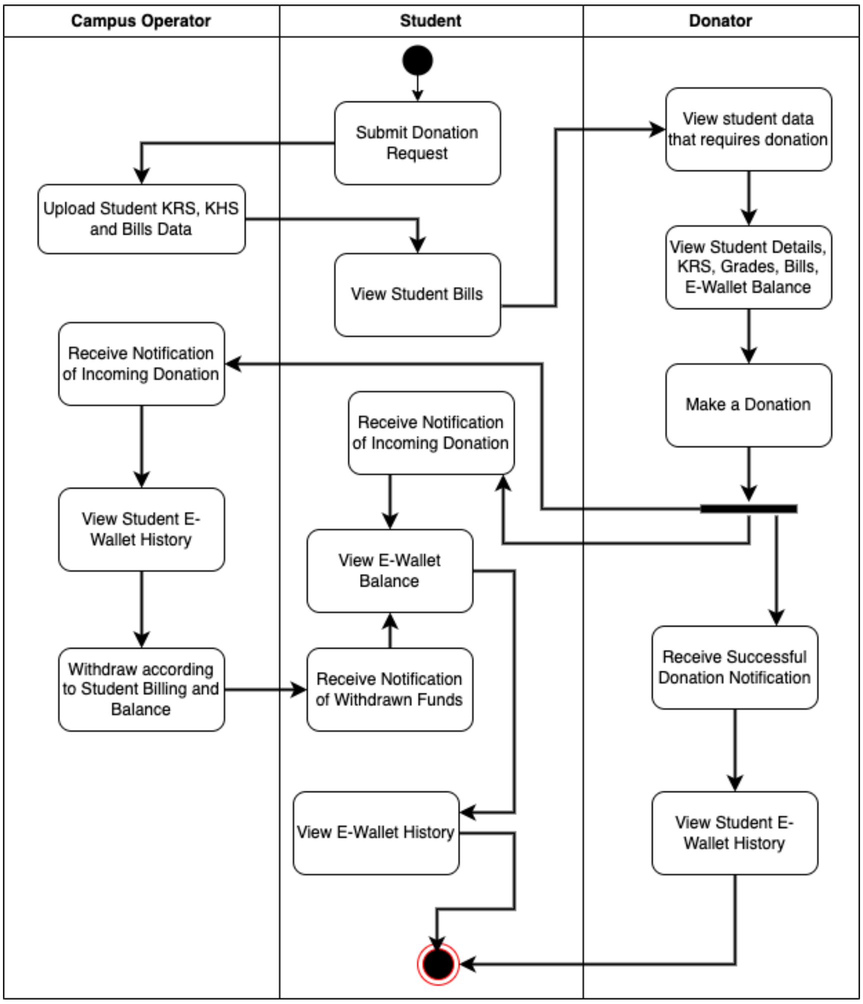

Figure 3. Activity diagram overall

How to donate can be seen in Figure 4. Donors view student details and then press the donate button. The donor enters the donation amount and selects the payment method. This payment method is provided by the payment gateway. Each payment method has a different payment fee depending on the payment method chosen by the donor. The payment fee is determined by the payment gateway provider. The donor then presses the send button, then the system will interact with the payment gateway via API. Payment Gateway will create a payment link and display the payment page. After the donor successfully makes a payment, the payment gateway will make a call-back to the E-Wallet management application and process the donation transaction that has been stored in the database.

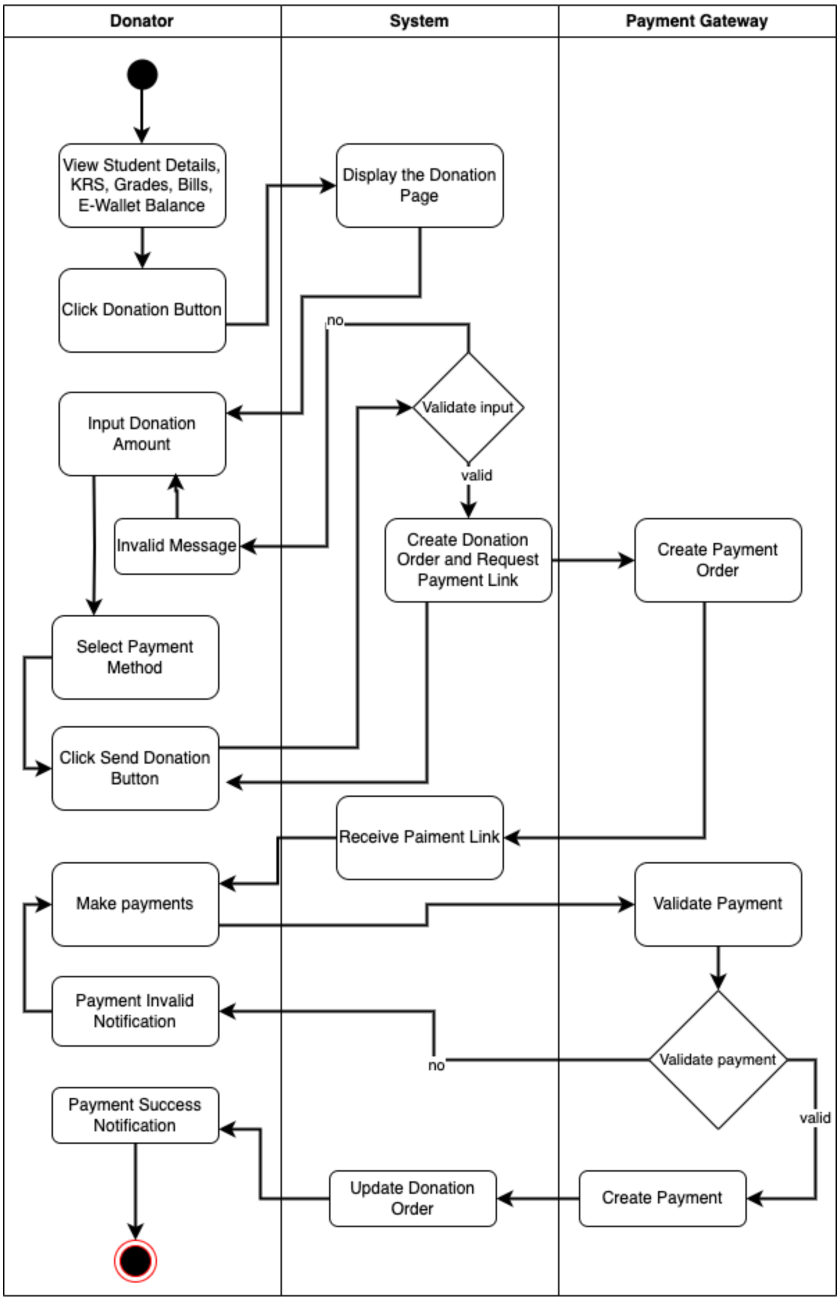

Figure 4. Activity diagram of sending donation

Withdrawal of donation funds is carried out directly by the campus through the campus operator. Withdrawal funds will be automatically sent to the registered campus account, so it cannot be transferred to another account. Fund disbursement requests will be validated by the system before the disbursement request is processed. The validation carried out is checking the E-Wallet balance, and checking the balance on the payment gateway. If all are valid, the payment gateway will process automatically and transfer the amount of funds available in the student's e-wallet and not greater than the total student bill to the registered campus account.

Implementation

This E-Wallet application is web-based. The front page uses one page that contains the Home, About Us, Donate, Services and Contact Us sections. There is a login button in the header that can be used by user login donors, campus operators and students. In the Donation section, a list of students who received donations is displayed. To be able to make a donation, donors must go through the login process. The front page can be seen in Figure 5 dan Figure 6.

Figure 5. Top Front Page

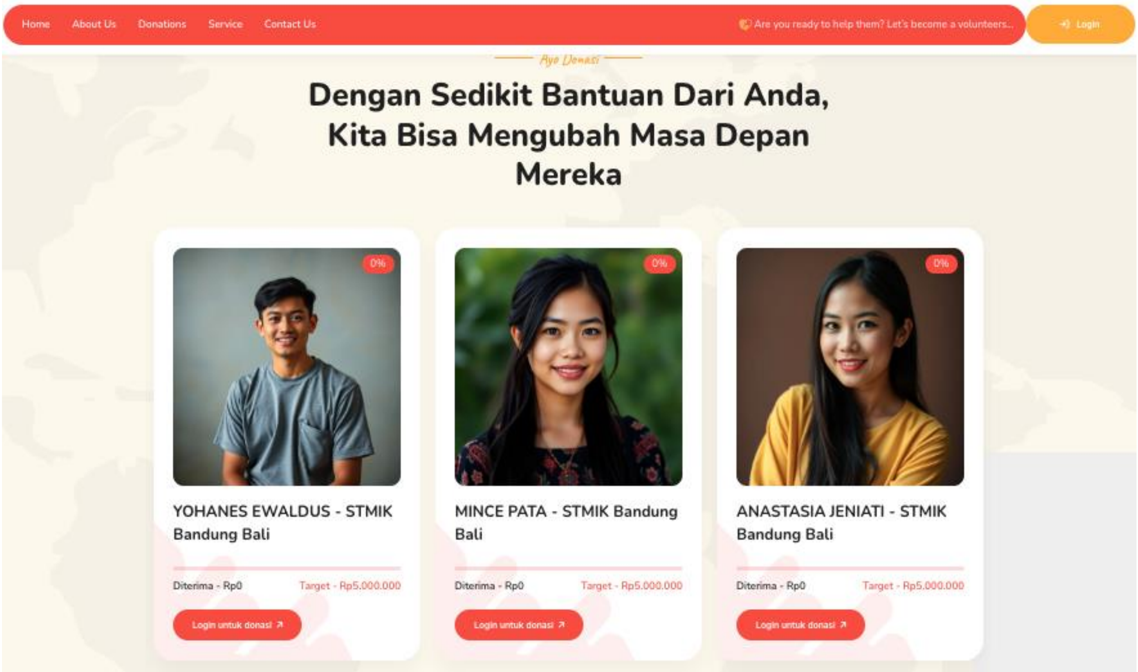

Figure 6. List page of students who receive donations

Donors can register on the registration page as shown in Figure 7. Donors who have registered can log in on the login form depicted in Figure 8. Donors who have logged in will be directed to the dashboard page. The menus that can be accessed by donors are the Student Menu to see the details of students who receive donations; the Transaction Menu to see a list of transactions that have been made by donors, be it successful transactions, pending transactions or canceled donation transactions. The donor dashboard page displays the total donations that have been successfully made and the donation history. The donor dashboard page can be seen in Figure 9.

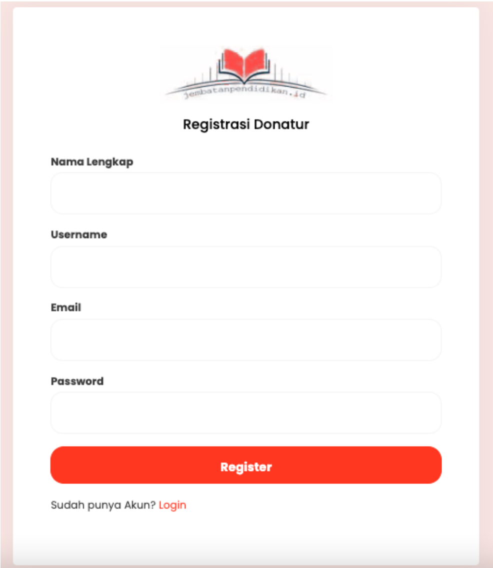

Figure 7. Donator registration form

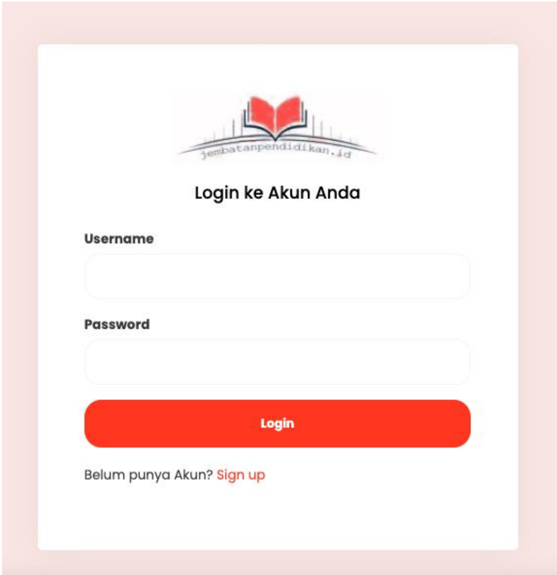

Figure 8. Login form

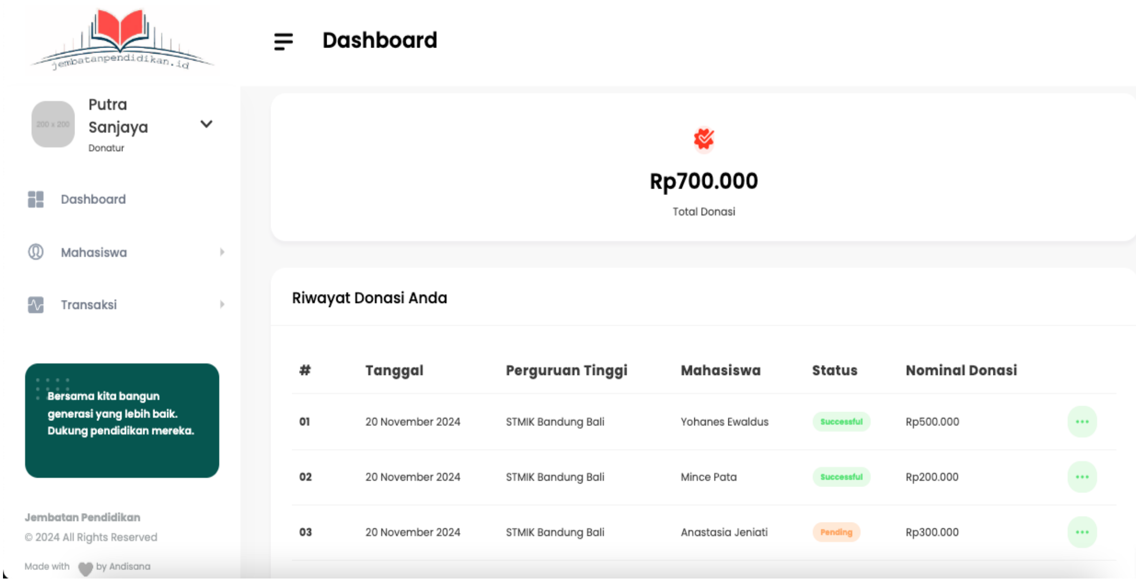

Figure 9. Dashboard donatur

Donors can select students to donate to. The application will redirect to the student details page which contains information about the student. The information displayed on the student details page is a photo, name, study program, campus name, and study information, as well as the value and amount of the bill, which can be seen in Figure 10. The donor presses the donation button, then is directed to the donation nominal input page as shown in Figure 11. On the page there is a button that contains a nominal that can be selected directly, or the donor can input another nominal as desired. On the next page (Figure 12), Donors are directed to choose a payment method. Each payment method has a different fee that has been set by the payment gateway provider. The fee is charged to the Donor. If the Donor has chosen a payment method, the total amount to be paid will be calculated. After the Donor presses the Pay button, the application will communicate with the payment gateway using the API, then the application page will redirect to the payment page provided by the payment gateway provider, (Figure 13). Payment has a waiting time, if it exceeds that time, then the donation is considered canceled and the donation status in the application becomes canceled. When the Donor successfully makes a payment, the payment gateway will make a call-back to the E-Wallet management application and process the Donation to enter the E-Wallet balance of the donated Student. The E-Wallet display can be seen in Figure 14.

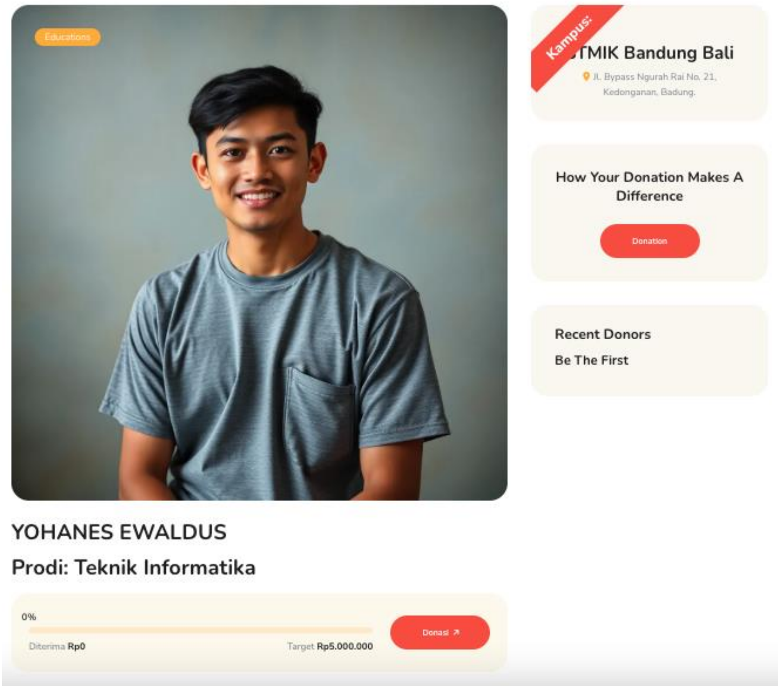

Figure 10. Form student detail

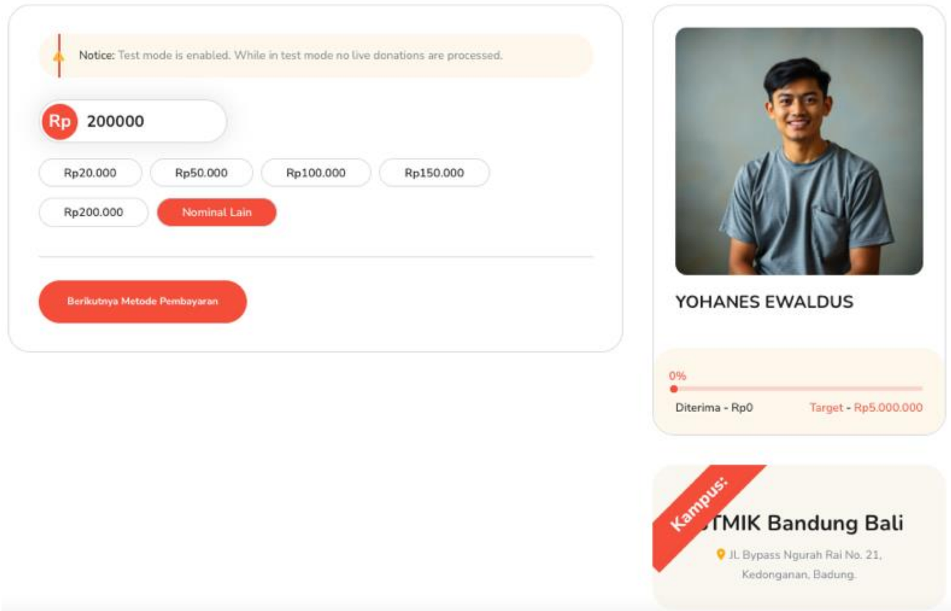

Figure 11. Form input donation amount

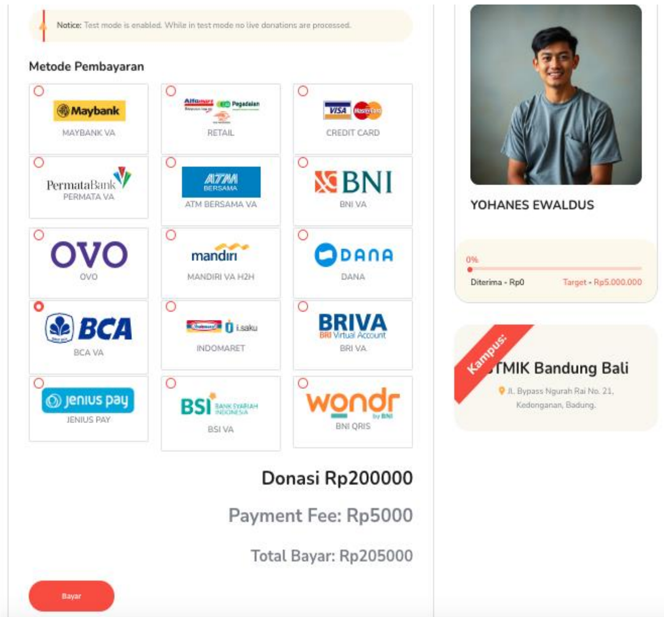

Figure 12. Payment method selection

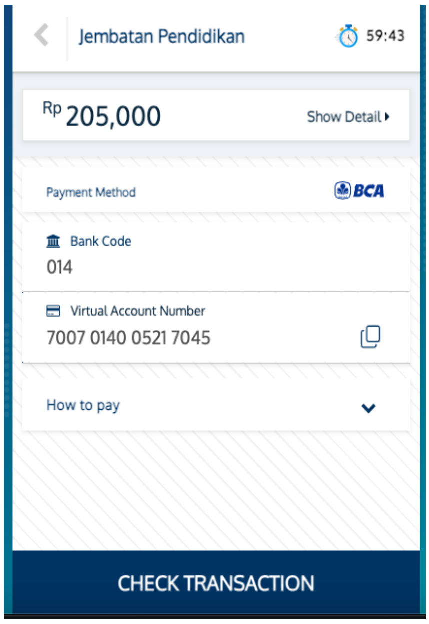

Figure 13. Payment form

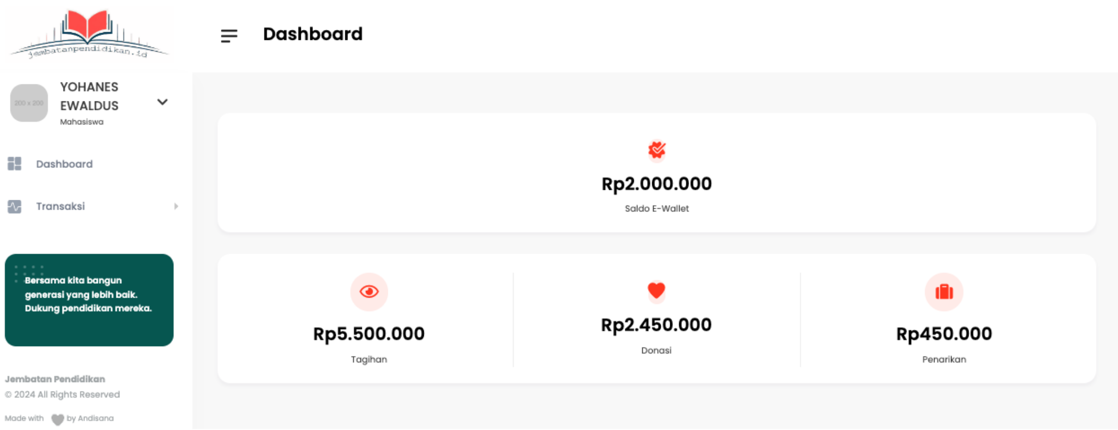

Figure 14. Student E-Wallet

Testing

Functional Testing

Testing in this study uses the black-box method, which plans test case scenarios and expected results [17]. The test scenarios carried out are Donor Registration, Donors View Student Details, Campus Operators Upload KRS and KHS Data, Campus Operators Upload Bills, Donors Send Donations, Donors Make Payments, Students View E-Wallet Balances, Campus Operators Withdraw Student E-Wallets, Students View E-Wallet History. The test results can be seen in Table 1.

Table 1. Blackbox testing

No	Scenario	Test Case	Expected Result	Result
1	Donator Registration	Prospective donors do not have an account and register	Donor account data is entered into the database and donors can login.	Succeed
2	Donator View Student Details	Donor chooses one of the students who needs donation	The student details page appears with the appropriate information	Succeed
3	Campus Operator Upload KRS and KHS Data	Operator uploads student KRS and KHS data	Student KHS and KRS data appear on the student details page	Succeed
4	Campus Operator Upload Bill	Operator uploads student bill data	Student bills appear on the donation details page	Succeed
5	Donator Submitting a Donation	Donors choose one of the students and enter a donation of 500,000. Choose BCA Virtual Account payment method	Donation transaction data is created and the payment page appears	Succeed
6	Donator do Payment	Donor makes payment by transferring to BCA Virtual Account	The payment is successfully received, the donation transaction is recorded and the student's E-Wallet balance is increased.	Succeed
7	Student View E-Wallet Balance	Students open the E-Wallet page and view the balance	The E-Wallet page opens and the balance appears according to the transactions that have occurred	Succeed
8	Campus Operator Withdraw Student E-Wallet	Campus Operator withdraws funds from students amounting to 500,000	The student's E-Wallet balance was reduced and the registered account received a transfer of 500,000	Succeed
9	Student View E-Wallet History	Students open transaction history on their E-Wallet	Display E-Wallet history according to transactions that have been made	Succeed

System Load and Stress Testing

Load and stress tests were conducted for 60 seconds per scenario using Apache JMeter to measure the performance and resilience of the system [18], particularly the donation functionality, under increased concurrent user load. The system was deployed on shared hosting with limited specifications: 0.5 Core Max CPU, Max 256 MB RAM, 10 Entry Processes, and 15 NPROC (Number of Processes). This test aims to identify bottlenecks and system failure points. The test results are summarized in Table 2.

Table 2. System Load and Stress Test Results

Requests	Error %	Average Response Time (ms)	Throughput (Transactions/s)	Network Received (KB/sec)
50	0.00%	2129.88	0.8	17.86
100	1.00%	2231.64	1.63	36.31
200	5.50%	14674.63	2.56	54.87
300	3.33%	30856.29	2.68	58.5
400	95.25%	71789.92	2.97	10.69
500	96.40%	72462.54	3.71	12.52

Evaluation of Effectiveness, Usability, and User Trust

This evaluation was conducted through a questionnaire survey with three main user groups: students, donors, and campus operators. A total of 16 respondents participated in this evaluation, consisting of 10 students, 5 donors, and 2 campus operators. The questionnaire was designed to collect data on:

1. Effectiveness: The extent to which the system fulfills its primary purpose and helps users accomplish their tasks.
2. Usability: Ease of learning and using the system, navigation, and overall user satisfaction.
3. User Trust: Users' perceptions of data security, system reliability, and validity of the information presented.

A Likert scale (1=Strongly Disagree, 5=Strongly Agree) was used to measure the respondents' level of agreement with certain statements. The evaluation results are presented in Table 3.

Table 3. Average Effectiveness, Usability, and User Trust Evaluation Score

Evaluation Category	Score Average (Students, N=10)	Score Average (Donors, N=5)	Score Average (Operators, N=2)
Effectiveness	4.2	4.6	4.0
Usability	4.0	4.2	3.5
User Trust	3.8	4.0	3.0

Discussions

The results of black-box testing in Table 1 show that this prototype of an e-wallet management application for crowdfunding-based tuition payments functions in accordance with the designed requirements and specifications. The successful execution of all test scenarios indicates that the main features of the application, from user registration to the donation and withdrawal process, have been implemented properly.

The system load and stress test results in Table 2 show the limited capacity of the system in a limited shared hosting environment:

1. At 50-100 requests, the system demonstrates optimal performance with minimal error rates (0.00% at 50 requests, 1.00% at 100 requests) and average response times below 2.2 seconds. Increased throughput indicates the system's initial ability to handle the load.
2. Significant degradation begins at 200-300 requests. Response times drastically jump (>14 seconds at 200 requests, >30 seconds at 300 requests), accompanied by an increase in error rates (5.50% at 200 requests). This is attributed to resource limitations (Max CPU 0.5 Core, Max RAM 256 MB, Entry Processes, and NPROC), hindering simultaneous request processing.
3. Total system failure at 400-500 requests. Error rates skyrocket above 95%, with average response times exceeding 71 seconds. A sharp decline in network traffic (around 10-12 KB/sec) confirms server incapacitation, indicating an inability to effectively process or send/receive data due to severe resource starvation.

The evaluation results of 10 students, 5 donors, and 2 campus operators in Table 3 show a generally positive perception of the system. The effectiveness aspect was rated highly by all three groups (students 4.2, donors 4.5, operators 4.0), indicating the system's success in meeting core functional needs and supporting the designed workflows, such as the donation process, donation tracking, and fund withdrawal. Usability was also rated favorably by the majority of respondents (students 4.0, donors 4.2), with an intuitive interface and efficient process flow. There were suggestions for improvement of the administration features (operator 3.5). The level of user trust showed variation; donors (4.0) showed good trust in the transparency and security of donations, students (3.8) had doubts regarding data privacy, and operators (3.0) emphasized the importance of sensitive data security. Comprehensively, the evaluation showed good system acceptance, but highlighted crucial issues such as data privacy and administrative feature enhancements as the focus of further development to build trust and long-term user experience.

One important finding is the transparency of student data (study data, grades, and bills) presented to donors before they make a donation. This feature answers the need for clear and accountable information, which can increase donor trust and participation in supporting student education.

The payment gateway integration (Duitku) successfully facilitates the automated and real-time donation payment process, and enables the disbursement of funds directly to the campus account. This automation reduces the potential for manual errors and increases transaction efficiency, which is a significant advantage over traditional tuition fee payment systems that are often manual and time-consuming. Research on payment gateway adoption in the context of digital finance shows that the ease and security of transactions offered can increase user participation [19].

The student e-wallet management feature allows students to see the funds collected transparently [20] and campus operators to withdraw funds according to the bill. The centralized withdrawal system to the campus account also provides better control and accountability in the management of donation funds.

This prototype integrates multiple layers of security to safeguard sensitive data and transaction integrity:

1. Use of Private Key for Payment Gateway API: All communication with the Payment Gateway Provider is facilitated through a secure API, where authentication is performed using a private key exclusively provided by the Payment Gateway Provider.
2. Password Encryption with AES (Advanced Encryption Standard): User passwords are stored in the database after being encrypted using the AES algorithm. With this encryption, if the database is successfully accessed unauthorizedly, the user password cannot be read in its original form.
3. Restriction of Access to Sensitive Data: Access to grade details and student data is restricted to registered donors only. This ensures that students' financial information and personal data are not exposed to the public or unauthorized parties.

Conclusion

This research successfully designed and developed a prototype of an e-wallet management application for crowdfunding-based tuition payments at STMIK Bandung Bali, utilizing the Agile software development method. Its core functionalities, including student data integration and transparent transaction processes, were successfully implemented.

Functional testing yielded a 100% success rate across all 9 black-box test scenarios. However, load and stress tests revealed significant performance limitations on shared hosting (0.5 CPU, 256 MB RAM). While optimal below 100 requests per minute, response times drastically degraded at 200 requests, and the system experienced complete failure above 400 requests, indicating a critical need for enhanced resources.

Empirical user evaluations involving 10 students, 5 donors, and 2 campus operators confirmed the system's effectiveness and usability, with average scores of 4.2 and 4.0 respectively (on a 5-point Likert scale). Security was addressed through private key API integration, AES password encryption, and restricted sensitive data access.

Technically, this prototype validates the crowdfunding-based e-wallet as a tuition payment solution and offers a reference model for educational institutions. Future work should focus on production-ready implementation, comprehensive testing, and further integration for broader application.

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2. Lembaga Layanan Pendidikan Tinggi (LLDikti) Wilayah VIII with contract number: 2927/LL8/AL.04/2024 Dated June 28, 2024.
3. P3M STMIK Bandung Bali.

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Android-based multi-IoT fish feeding system: An end-to-end information system approach

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Abstract: The ornamental fish industry in Indonesia has experienced significant growth, positioning the country as the second-largest global exporter of ornamental fish in 2020. However, fish shop owners still face operational challenges, especially in managing consistent and timely feeding across multiple aquariums. Manual feeding practices often lead to inefficiencies and can compromise fish health and water quality. This study presents an end-to-end fish feeding information system integrated with an Android mobile application, designed to address these challenges. System development in this study employs waterfall method. The system supports automated fish feeding routines, device management, and multi-user access with token-based authentication, enabling fish shop owners to operate multiple feeders under a single account. Communication between IoT devices and the backend server utilizes MQTT, ensuring independent control of each feeder through unique topics. The system introduces a novel architecture that supports multi-user, multi-device operations in an end-to-end feeding workflow, improving scalability and efficiency compared to existing single-device systems. System testing, including black box and load testing, demonstrated robust performance, with all test scenarios passing successfully and an error rate of 0.00% during high-load simulations involving up to 100 virtual users. These results indicate that the system effectively addresses existing limitations in fish feeding management and is capable of supporting multiple users and fish feeder devices simultaneously. Further development is recommended to enhance infrastructure, security, and scalability for real-world deployment.

Keywords: automated fish feeding, android, information system, IoT, mobile application

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Introduction

Ornamental fish are among the most popular types of pets across various demographic in Indonesia [1]. The hobby of keeping ornamental fish continues to grow, supported by both community development and the increasing scale of aquaculture industry. According to the International Trade Center, Indonesia ranked third globally in ornamental fish exports in 2019, following Japan and Singapore. That year, the export value reached USD 7.8 million for marine ornamental fish and USD 25.2 million for freshwater ornamental fish [2]. By 2020, Indonesia had captured 11.35% of the global market share, becoming the world's second-largest ornamental fish exporter [3]. These figures underscore the economic potential of ornamental fish as a leading commodity in the country.

This growth has not only increased public interest in ornamental fish as pets but has also driven the expansion of fish shops across Indonesia. These fish shops typically manage multiple aquariums with various freshwater species. However, many of these businesses still rely on manual operations, which introduces significant challenges in aquarium and fish management. One of the most pressing issues for fish shops owner is feeding management, which is also one of fish welfare issues of ornamental fish trade [4].

Manual feeding practices often lead to inefficiencies, such as delayed feeding and inconsistent portions [5]. These problems are compounded when managing a large number of aquariums, making it difficult for fish keeper to remember and follow proper feeding and maintenance schedules. Inaccurate or inconsistent feeding does not only result in material losses, but also degrades water quality and jeopardizes fish health [6]. Overfeeding contributes to excess waste and poor water conditions, while underfeeding inhibits growth and lowers immunity [7]. This problem shows how important it is to maintain the quality and quantity of feeding to maintain the quality of fish products for ornamental fish shops.

To address these operational challenges, an automated fish feeding system is needed to support consistent and timely feeding routines. Automated fish feeding technology has been shown to improve both operational efficiency and feed consumption [8]. Several studies on IoT-integrated fish feeding systems have been conducted previously, including by Izak Habel et al. in 2023 [9], Komang Martadana Wijaya et al. in 2023 [10], Rafly Fernanda et al. in 2022 [11], and Husnul Khatimi et al. in 2022 [12]. These studies offered systems that enable remote monitoring and control of fish feeding. However, these previous systems have not provided a mechanism for managing multi-user authentication and are typically limited to single-IoT-device communication. Moreover, most existing systems do not provide features for fish feeder device registration and management independently, making them unsuitable for scaling to users who operate multiple fish feeders on their aquariums.

These limitations have significant implications in real-world applications, particularly in fish stores on hatcheries that operate multiple aquariums. Without multi-user support, the systems cannot be collaboratively accessed or supervised by more than one employee, reducing flexibility and increasing the risk of mismanagement. Similarly, the inability to register and manage multiple feeder devices under a single account makes the system impractical for environments where different tanks require separate feeding schedules. These constraints highlight the need for a scalable, multi-user, multi-device management system, a gap this study intends to address.

Unlike previous systems that primarily support single-user or single-device interaction, this study proposes an end-to-end multi-IoT-device fish feeding information system integrated with an android mobile application. The system is uniquely designed to handle the entire process from device installation and scheduling to real-time feeding execution and monitoring via mobile. It also introduces support for multi-user authentication and multiple device management under a single account, enabling fish shop owners to control several fish feeders independently. This approach reduces operational complexity and addresses scalability issues commonly faced by shops managing multiple aquariums. By integrating feeding automation, device management, and mobile control, the proposed solution offers a novel architecture that enhances efficiency and sustains optimal aquarium conditions.

Methodology

The research in this study employs the waterfall method, a structured and step-by-step (sequential) approach commonly used in system development [13]. The model of waterfall method is illustrated in Figure 1. The waterfall model begins with requirement analysis. This initial phase aimed at analysing and clearly defining the user's software requirements and specifications [14]. System design is the phase where system requirements are allocated to both hardware and software components, forming the overall system architecture. Implementation is the stage where the system is developed and implemented by writing software code. Integration and system testing is the phase where individual program units are integrated and tested as a completed system to verify whether it meets the defined software requirements. At this stage, the integration between the API, the mobile app, and the existing prototype IoT-based fish feeder device is carried out. In addition, comprehensive system testing is performed using black box testing and load testing. Operation and maintenance are the final phase, where the system and application are fully deployed and used by end users, while ongoing maintenance is carried out.

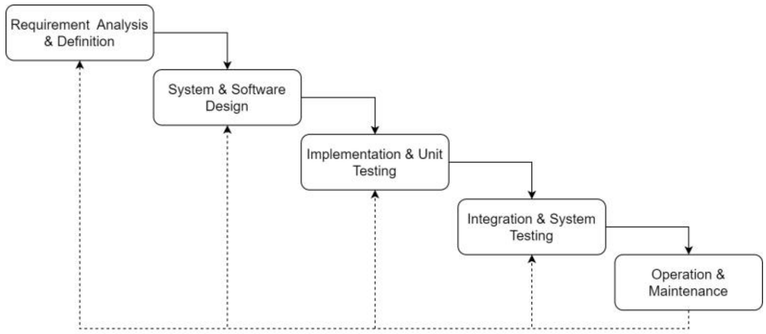


Figure 1. Waterfall model

System Design

System design describes the design of the overall fish feeding information system based on the results of the system requirement analysis that have been carried out. In this study, the system design includes system overview, use case diagram, database design, user and IoT fish feeder communication scheme.

System Overview

System overview illustrates the general workflow and architecture of the system in a visual format. The overview of end-to-end multi-IoT-device fish feeding information system based on Android mobile application is depicted in Figure 2.

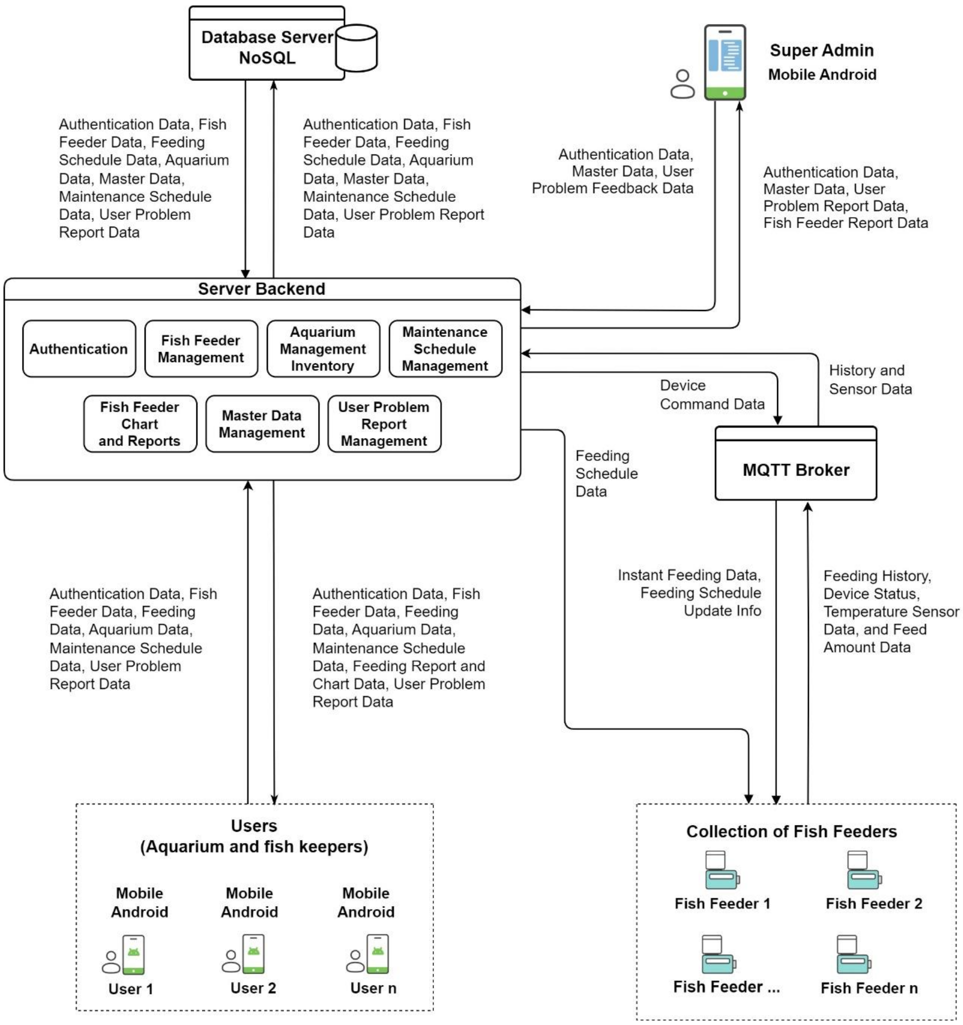


Figure 2. System overview

Several key entities are involved in the system, including a database server, backend server, MQTT broker, IoT fish feeder, and Android mobile frontend (user and super admin). The database server stores and provides access to data used by the system. The backend server processes data received from the frontend before storing it in the database and vice versa. It also communicates with the IoT fish feeder both directly and through the MQTT broker. The backend handles various service modules such as authentication management, fish feeder device management, aquarium inventory management, scheduled maintenance management, feeder reports and charts, master data management, and user problem report management. The frontend provides the user interface, displaying data retrieved from backend and enabling users to input data that will be processed and stored. There are two frontend applications, one for general user role and one for super admin role, both developed for Android mobile platforms. The super admin manages master data, monitors and responds to user issue reports, and oversees fish feeder usage reports. The general user responsible for caring for fishes and aquariums. They input authentication data, fish feeder information, feeding schedules, aquarium data, maintenance schedules, and problem report. The fish feeder device executes fish feeding commands and sends sensor data and feeding history to the database through the backend. The MQTT broker facilitates real-time communication between the backend and the fish feeder, especially for immediate actions such as feeding or updates to the feeding schedule. The system is designed to support multiple Android mobile users and multiple fish feeder devices, allowing each user to control more than one feeder unit simultaneously.

Use Case Diagram

A Use Case Diagram illustrates the interactions between users and the system. This diagram also be defined as a functional description of a system from perspective of its users [15]. The use case diagram of end-to-end multi-IoT-device fish feeding information system is presented in Figure 3. The use case diagram identifies two primary actors, the super admin and the user. The super admin is responsible for managing the entire fish feeding information system. This role has full access to master data management, fish feeder management, fish feeder report, problem report handling, and also information and library. The user can manage fish feeder and feeding data, aquarium inventory, maintenance schedules, view feeder reports, submit user problem report, and access information and library.

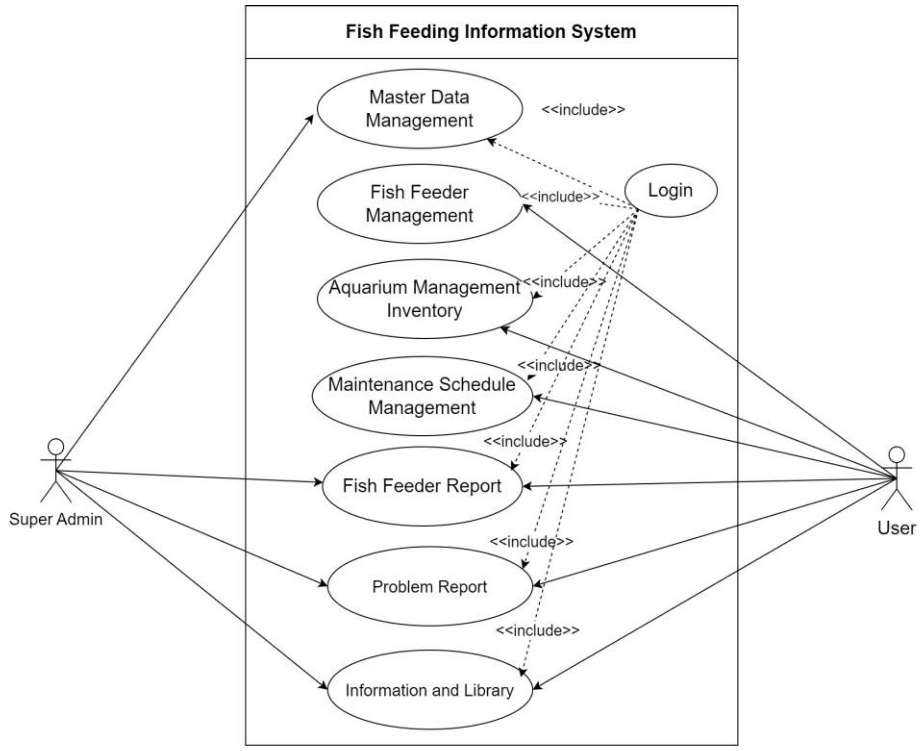


Figure 3. Use case diagram

Database Design

The database for the fish feeding system is designed using a NoSQL database approach. This NoSQL database allow us to store data in a JSON-like format, making it easy to represent and query nested hierarchical structures. This structure and format allow NoSQL database to excel in terms of speed performance compared to RDBMS [16]. The database is built using MongoDB, which organizes data into collections and documents [17]. The design of database is illustrated through a Physical Data Model, as shown in Figure 4. This database design adopts a NoSQL model, which enables embedded relationships by storying multiple data entries within a single field. The database consists of several collections, including user collection, OTP collection, device collection, deviceOrigin collection, feedingHistory collection, information collection, aquarium collection, fish collection, component collection, problemReport collection, sensorData collection and maintenanceSchedule collection.

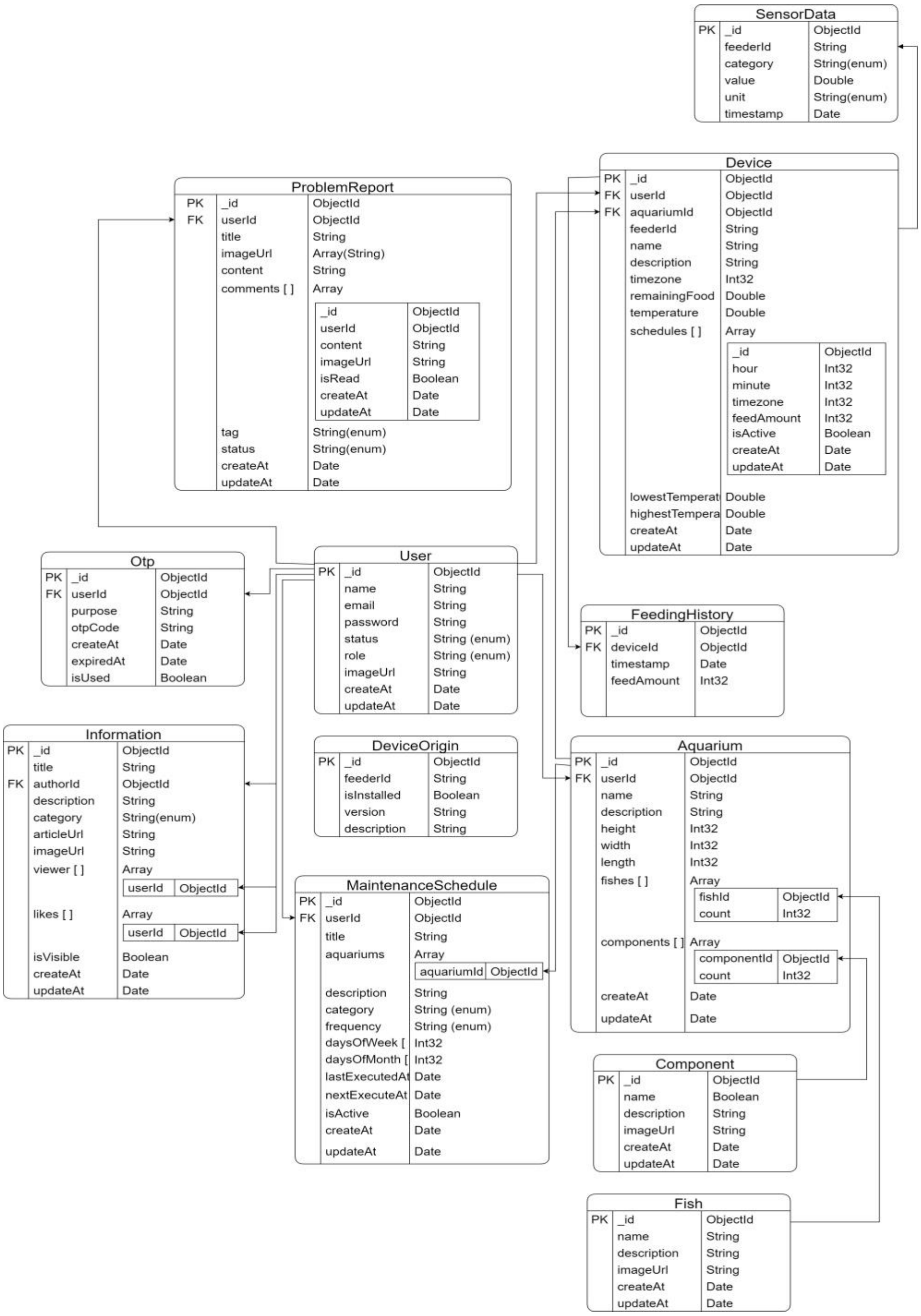


Figure 4. Physical data model

System Communication

The communication in the fish feeding system utilizes two types of protocols, HTTPS and MQTT. HTTPS (Hypertext Transfer Protocol Secure) is a communication protocol between the client and the server via the internet that is protected by encryption. It is used for interactions between the Android user and the server. MQTT, on the other hand, is used for communication between the IoT device (the fish feeder) and the server. This protocol is lightweight and follows a publish (PUB) and subscribe (SUB) communication [18]. MQTT allows the communication with low latency, enabling high responsiveness for features such as real-time feeding, schedule synchronization commands, and sensor data transmission.

The backend services implement comprehensive input data validation, including mandatory value check, data type validation, unique email verification, and ID validation. For secure information access, all REST API requests are protected using JSON Web Token (JWT) authorization, which authenticates and enforces role-based access control. A new token is generated upon user login and is set to expire after seven days. MQTT communication between device and backend is secured using CA (Certificate Authority) certificate, TLS encryption, and unique feeder IDs, ensuring confidentiality and integrity of the fish feeder communication.

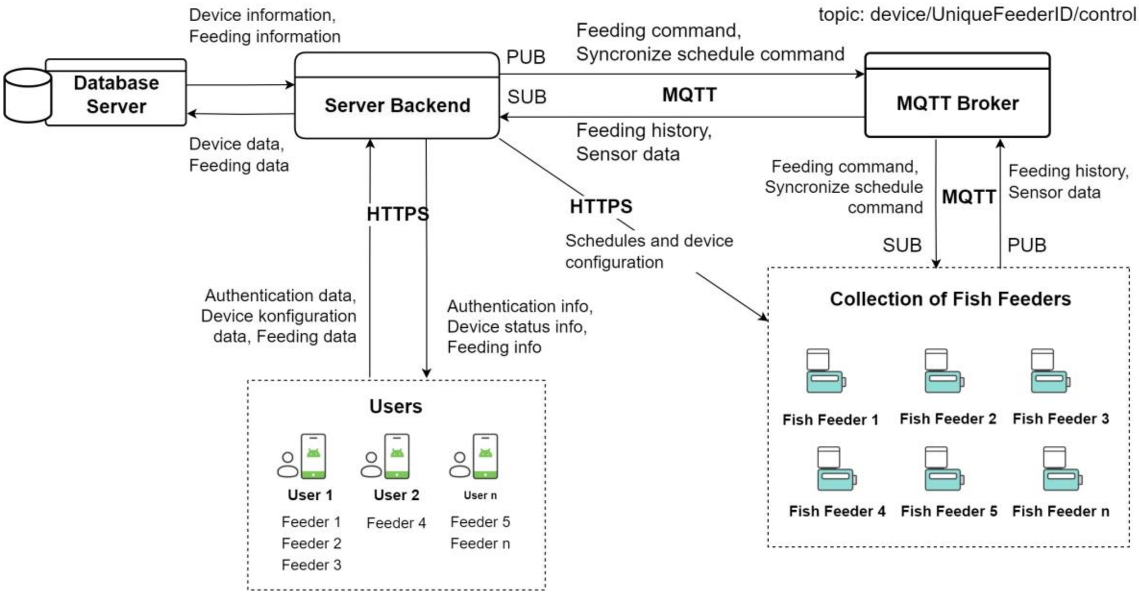


Figure 5. System communication diagram

Figure 5 illustrates the communication flow within the system. Users interact with the system via APIs on the backend server, sending authentication data, device configuration data, and feeding data, and receiving authentication information, device status, and feeding information. These API communications use the HTTPS protocol. Each user must register their fish feeder so the device data can be linked to their account. Fish feeders communicate with the backend through an MQTT broker, enabling real-time messaging, but can also communicate directly via HTTPS API. Both the fish feeder and the backend use publish and subscribe communication on the topic device/UniqueFeederID/control. Each fish feeder has a unique feeder ID, ensuring independent communication per device. The backend publishes feeding commands and schedule synchronization data, while the fish feeder publishes feeding history and sensors data. Due to limited payload resources, schedule data synchronization is requested over HTTPS rather than MQTT. All data is stored in the server database for future use.

IoT Fish Feeder

The IoT fish feeder is a device designed to ensure automatic, consistent, and accurate fish feeding according to a predefined schedule. The IoT fish feeder device used in this study is a prototype previously developed, as depicted in Figure 6. This device was built using an ESP8266 microcontroller and is equipped with several sensors, including a DS18B20 sensor for measuring the water temperature in the aquarium and a load cell sensor for detecting the remaining fish food in the container. The feeding system is powered by an SG90 servo to push the grain feed with a size of 1mm. This device communicates via MQTT and HTTPS, as explained in the system communication section. This study does not cover the wiring details or component circuitry within the IoT device, as its focus is on developing the information system to support integration between the IoT device and the mobile application.

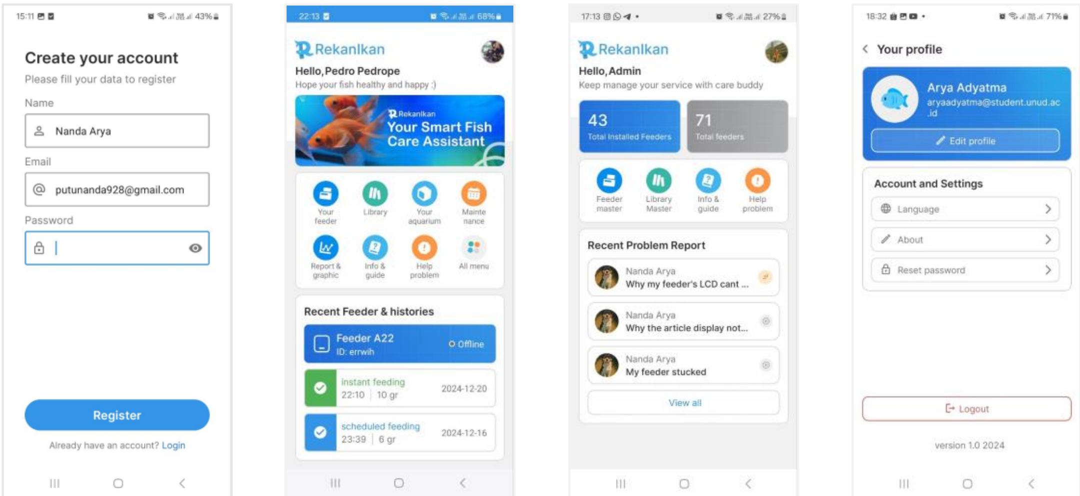
Figure 6. Fish feeder prototype

Results and Discussions

Results

App User Interface

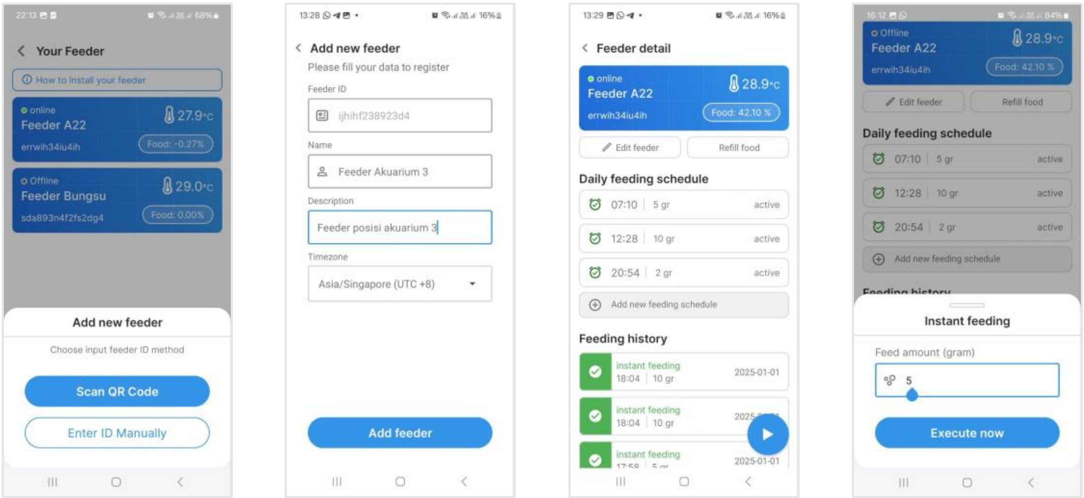
The user interface (UI) is a crucial component in the information system development. It serves as the bridge between users and the system to ensure seamless interaction [19]. The entire user interfaces were built on the Android mobile platform using the Android Studio IDE in Kotlin programming language. The user interface of fish feeding information system is divided into two based on its role, namely the user interface for user role and the user interface for the super admin role.



(a) (b) (c) (d)

Figure 7. User interface of register page, home page, and profile page

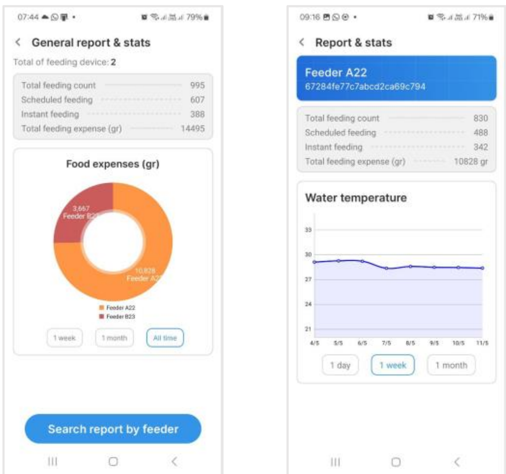
Figure 7 shows the user interface of the fish feeding system. Every user has to create an account first to enjoy the features provided in register page as shown in Figure 7 (a). User who already have an account and successfully login will be directed to the home page. The home page is divided into two, first for general user role as shown in Figure 7 (b) and second for super admin as show in Figure 7(c). The user home page provides several features such as feeder management, library, aquarium management, maintenance schedule management, report and graphic, info and guide, and user problem report. Meanwhile, the super admin home page provides feeder master data management, library master management, guide info management, and user report handling. Users can view their profile details on the profile page shown in Figure 7 (d).



(a) (b) (c) (d)

Figure 8. User Interface of Fish Feeder Management

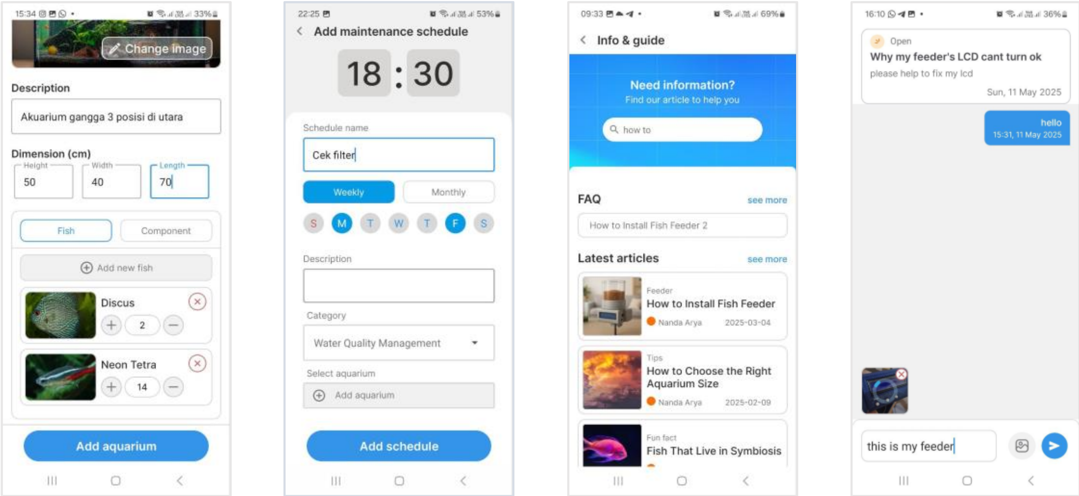
Figure 8 illustrates the user interface for the fish feeder management menu. Users can independently install and register their fish feeder using two methods, by scanning the device's QR code or manually entering the device ID, as shown in Figure 8 (a). The registration process requires input such as the device ID, name, description, and the time zone where the feeder is located (Figure 8 (b)). Once the data is verified, the device will be successfully added to the system. Figure 8 (c) displays the interface for a registered and active device. It shows information such as the device's status, feeding schedules, and feeding histories. Users can also trigger a real-time feeding action by pressing the blue floating play button and specifying the desired amount in grams, as illustrated in Figure 8 (d). Every executed feeding will be followed by push notification from the server that indicated successful feeding.



(a) (b)

Figure 9. User Interface of Fish Feeder Report and Stats

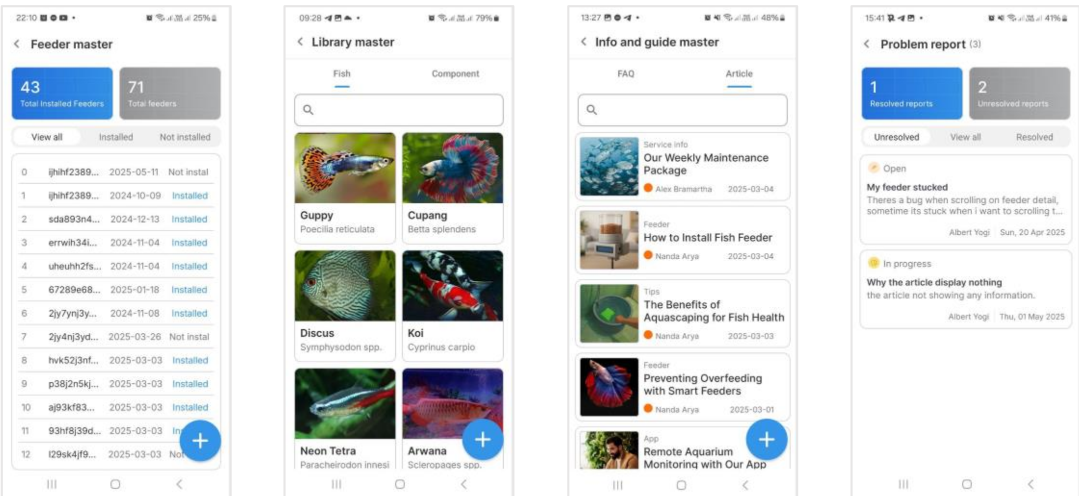
Figure 9 shows the user interface of the fish feeder report and statistics feature. Users with multiple devices can view an overall report of all their feeders. Figure 9 (a) presents the general report and statistics view, which includes feeding statistics across all fish feeder devices. Users can also access more detailed device-specific reports, as shown in Figure 9 (b). This page displays feeding statistics and a temperature trend graph based on data captured by feeder's sensor.



(a) (b) (c) (d)

Figure 10. User Interfaces of Additional User Role App Features

The application offers additional features to support users in maintaining their aquariums, such as aquarium management, maintenance scheduling, guide information, and problem report chat as shown in Figure 10. Figure 10 (a) displays the aquarium management feature, which helps users keep track of their aquariums. To add a new aquarium, users need to provide an image, name, description, dimension, and details of the fish and components inside the aquarium. Figure 10 (b) shows the page for adding aquarium maintenance schedules. Users can set schedules on a weekly or monthly basis and link them to a specific aquarium. Active schedules will trigger automatic reminder notifications. User can visit the info and guide page, which contains a collection of FAQs and articles related to fish care and the app's services, as shown in Figure 10 (c). Additionally, users can report issues or problems related to the app or the fish feeder device through the problem report feature. All reports will be sent to the super admin for the resolution (Figure 10 (d)).



(a) (b) (c) (d)

Figure 11. User Interfaces of Super Admin Role App Features

The super admin side of the application provides several features to assist in managing service-related data. There are four main features namely feeder master management, library master management, info and guide master management, and problem report management, as shown in Figure 11. Super admin can manage master data used for registering fish feeders by general users. Figure 11 (a) displays the dashboard of the feeder master page, which shows the total number of installed devices. Super admins can add multiple feeder master entries at once using the blue floating button. They can also manage master data for fish and aquarium components via the library master page, as seen in Figure 11 (b). This data is utilized by users when managing aquariums and accessing the library feature. All FAQ entries and articles can be managed on the info and guide master page, shown in Figure 11 (c). Figure 11 (d) illustrates the problem report management page, where super admins can monitor and respond to incoming reports. For each report, they are required to engage in a chat discussion with the user and update the report's processing status accordingly.

Backend and Cloud Service

The backend is a critical component of the fish feeding information system. Backend is responsible for behind-the-scenes processes such as database interactions and executing server-side logic [20]. Additionally, the backend functions as the central integration hub for the other services required by the system, such as FCM (Firebase Cloud Messaging) for push notifications, HiveMQ as the MQTT broker, and MinIO as the cloud object storage. The entire backend and API on this information system was built using the Express JS framework using the JavaScript language.

The backend system requires a server that can operate continuously to host and execute the backend codebase. In this research, the entire backend is deployed on the Railway serverless platform. Railway is a cloud-based Platform as a Service (PaaS) that provides an environment for managing container-based backend applications. The backend is deployed in the Singapore region, aiming to minimize communication latency with users, the majority of whom are located in Indonesia. The allocated resources include up to 8 vCPUs and 8GB of RAM.

Testing

The testing of the fish feeding information system was carried out using blackbox testing and load testing techniques. Black box testing evaluates the software without examining its internal code. This technique is focusing solely on the provided inputs and the expected outputs [21]. This black box testing was carried out both independently by author at home and by an employee of the Gangga Fish ornamental fish shop.

Table 1. Summary of black box testing results by test group on mobile app

Test Group	Number of Test Cases
Register	6
Login	4
Home	3
Profile	5
Feeder	5
Library	5
Aquarium	6
Maintenance	5
Report and graphic	3
Info and guide	8
Problem report	8
Feeder master	7
Library master	11
Info and guide master	11
Problem report admin	7
Notification	6
Total	**100**
All test cases passed successfully (100%)	

Black box testing was applied to all features on both the super admin and user sides. This technique was also used to ensure that the integration between the feeding device and the system functioned properly. Table 1 presents the list and results of black box testing conducted on the mobile application. The test cases are grouped based on main pages and features, with the number of scenarios varying according to the complexity of each function. Based on the results, all 100 test cases were successfully executed without any failures and met the predefined functional expectations. This mobile application was tested on multiple devices including Vivo Y16 Android version 12 with 8GB RAM and Samsung A54 Android version 14 with 8GB RAM to ensure compatibility and performance consistency. All features on these devices work properly without any significant issues.

A preliminary usability test was conducted with one employee from a local ornamental fish shop, Gangga Fish. The employee was asked to perform 27 general scenarios in user role features. This basic task such as user authentication, device installation, feeding schedule creation, feeding execution, aquarium management, maintenance schedule creation, and user report creation through the mobile app. The user was able to complete all test scenarios successfully and provided positive feedback regarding the service clarity and ease to use.

Load testing is a method used to evaluate system performance under varying levels of load request [22]. This testing ensures that the APIs in the developed fish feeding information system can handle the expected load as planned, providing insights into the system's performance and behavior. The tests were performed on several API endpoints using the Postman application. The endpoints tested included login, get all fish feeders, get fish feeder by ID, and get all feeding history. Figure 12 shows the load testing of the login endpoint, executed using Postman. The load testing was conducted using a ramp-up load profile over a 20-minute duration with 100 virtual users (VUs).

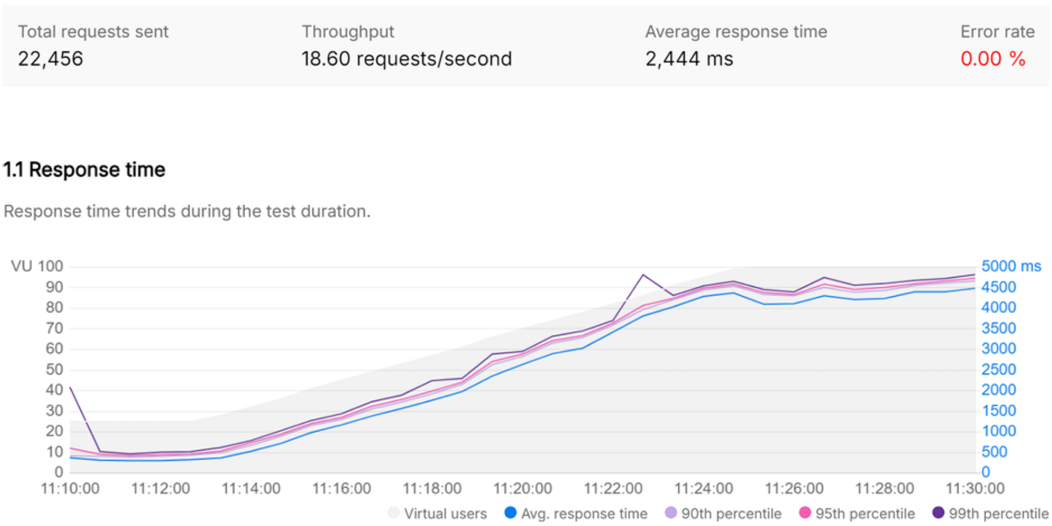


Figure 12. Load testing on login endpoint using Postman

Similar testing procedures were applied to the remaining three endpoints which are get all fish feeders, get fish feeder by ID, and get all feeding history. All the load testing data are summarized in Table 2. This table presents the total number of requests sent, throughput, average response time, and error rate for the four tested endpoints. The results demonstrate that all tests were successful, with an error rate of 0.00%. The highest total number of requests sent was recorded in the load test for the "get feeder by ID" endpoint, while the lowest number was recorded in the test for the "login" endpoint.

Table 2. Summary of load testing results

Endpoints	Total Request Sent	Troughput (request/s)	Average response time (ms)	Error rate (%)
Login	22,456	18.60	2,444	0.00
Get all feeders	62,382	51.66	61	0.00
Get feeder by ID	66,078	54.68	53	0.00
Get all history	27,924	23.12	1,787	0.00

Black box testing also applied to the fish feeding and fish feeder device functionality, the results are described in Table 3. This testing ensures that functionality of the feeding device works consistently and as expected. This testing consists of several scenarios and each scenario run 20 times repetition. All scenarios were successfully carried out with their respective results in the table. These results show that the system integration of the fish feeder has met the functional needs as well as reliability in emergency situations such as internet disconnection.

Table 3. Summary of fish feeder and feeding testing results

Testing Scenario	Results
Duration of fish feeder connection	2 minutes 12 secs 47 ms (average)
Duration of instant feeding delay	1 sec 34 ms (average)
Accuracy of scheduled feeding time	100% (on schedule)
Execution of instant feeding	100% (executed)
Notification of executed feeding	100% (executed)
Notification of delayed executed feeding	100% (executed)
Notification of disconnected feeder device	100% (executed)

Discussions

The end-to-end fish feeding information system developed in this study is designed to support automated fish feeding, complete with features that assist in fish and aquarium care. The application is built comprehensively, from device registration to autonomous feeding. It incorporates token-based authentication using JWT to support multi-user access with different roles, and enables operation of multiple feeders under a single user account. This is made possible through MQTT communication with unique topics, allowing each feeder to operate independently. The android application includes two main roles, super admin (responsible for monitoring and managing operational data) and user (who uses the app to care for their fish).

System testing was conducted to ensure performance met the standards, using both black box testing and load testing techniques. The black box testing was carried out both independently by the author and an employee from the Gangga Fish. The black box testing covered 100 scenarios across all super admin and user features, all of which passed successfully without errors. Additionally, a preliminary usability testing involving 27 general user scenarios was conducted by the fish shop employee, who completed all task without difficulty and provided positive feedback. For performance evaluation, load testing was conducted using a 20-minute ramp-up simulation with 100 virtual users. Result showed that all four tested endpoints passed with an error rate of 0.00%. The "get feeder by ID" endpoint recorded the highest total requests (66,078) with an average response time of 53 ms, as it only retrieves a single record based on an ObjectID in MongoDB. The login endpoint had the lowest total request (22,456) with an average response time of 2,444 ms, due to authentication processes involving email matching, password decryption, and simultaneous token creation for 100 clients.

This research demonstrates that the end-to-end fish feeding information system can handle multiple users and fish feeder devices simultaneously, filling a gap in previous research. However, further improvement is needed to optimize system security and cloud infrastructure as well as increase user and device testing to simulate large-scale market usage. This system is also open to potential to be further integrated with another cloud platforms to enable real-time synchronization, remote device monitoring, and scalable data analytics. Such integration would support larger deployment in smart aquaculture farming ecosystem.

Limitations

While this proposed system demonstrates effective integration of multi-user and multi-IoT-device functionality in a controlled environment, several limitations remain. First, the system has not yet been tested with large-scale condition involving up to 100 fish feeder devices simultaneously and up to 100 real users. This may affect the reliability of the backend performance in field conditions. Second, the test only uses two android devices, namely Android version 14 with 8 GB RAM and Android version 12 with RAM 12 GB. These testing devices are not representative of the overall the overall specifications available in the community. Third, data encryption on this system communication is limited to HTTPS and basic MQTT SSL/TLS. Additional security layers such as end-to-end encryption are not yet implemented. Lastly, the end-user test involved only a single participant due to limited device availability. These finding are not sufficient to generalize usability across broader user groups in real-world scenario.

Conclusion

The end-to-end multi-IoT-device fish feeding information system based on Android mobile application developed in this study successfully demonstrates its ability to automate fish feeding, handle multiple devices and users, and perform reliably under load. System testing covering both black box and load testing showed strong and reliable performance. All test scenarios passed without issue, and high-load simulations with up to 100 virtual users resulted in a 0.00% error rate. Further development is recommended to optimize system performance, security, and infrastructure, as well as to expand testing to simulate large-scale usage scenarios, ensuring the system is robust for real-world deployment.

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Intelligence attendance monitoring system using Real-Time Face Recognition and Raspberry Pi

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Abstract: Recognition technology with Raspberry Pi to transform attendance management practices in educational institutions and workplaces. By harnessing advanced technologies like the Haar Cascade Classifier and Local Binary Patterns (LBP) algorithm, the system exhibits strong performance in accurately detecting and identifying faces across diverse environmental settings. Through rigorous experimental evaluation, the system achieves its highest accuracy in the distance comparison test at 30 cm, with an average accuracy of 92.4%. Similarly, it demonstrates optimal performance in the light comparison test at 100 lux, achieving an average accuracy of 91.3%. These results underscore the system's effectiveness in identifying faces in close proximity and under suitable lighting conditions. Overall, the proposed system offers a promising solution for optimizing attendance management processes while mitigating the shortcomings of traditional recording methods. By providing a reliable and efficient means of tracking attendance, it lays a solid groundwork for enhancing productivity and outcomes in both educational and professional settings.

Keywords: attendance management, face recognition, Haar Cascade Classifier, Local Binary Patterns, Raspberry Pi

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Introduction

Attendance is accumulating data to ascertain the number of students enrolled at a school. Attendance and absence recording is an activity that can never be abandoned. The reason for this is that for students or office workers, during work or lecture activities, the absence record will be a prerequisite for taking the exam as well as a benchmark for the activity of an employee who works and a reflection of the performance of employees or students from companies or educational institutions [1], [2]. Even if students cannot take the exam, they may still receive a failing grade if their attendance or absences are not adequately recorded. When it comes to an employee or employees, things are handled differently; they might be subject to sanctions in various ways, such as having their income reduced or even being fired. Therefore, attendance, or the attendance record, significantly reduces the likelihood of these occurrences.

However, it is essential to note that most student attendance recording during lecture hours is still often carried out traditionally. It involves the lecturer calling out the names of each student individually so that they may be entered on the attendance form [3]. It is a significant problem. In addition to allocating a sizeable budget for things like paper, ink, and other such supplies, hiring specialized specialists to take turns taking attendance requires significant time and money because of the progression of time and advancements in information technology, particularly in software and the internet. The convenience of using mobile or online applications to access and retrieve information is cited as one reason their utilization is deemed more effective and efficient. Because of this, we need to know how important it is to digitize our job to save on expenses, time, and effort.

Information systems are a development in the application of information technology. An information system is an information system that collects, processes, stores, analyses, and disseminates information for a particular purpose [4]. Another definition is a collection of hardware and software designed to convert raw data into usable information [5]. Almost all medium- to large-scale endeavors employ an information system to facilitate operation. Information systems are so helpful for activities that they are frequently used for making decisions.

Traditional attendance recording methods, reliant on manual attendance forms, are plagued by inherent inefficiencies, including time wastage, inaccurate attendance records, and susceptibility to errors such as false attendance or incorrect data entry. Innovative solutions such as Smart Attendance have emerged in response to these challenges, offering intelligent applications designed to mitigate these issues and optimize the attendance management process. By harnessing the power of intelligent attendance systems, organizations can realize enhanced efficiency, flexibility, and accuracy in tracking and summarizing attendance data.

An employee attendance application with additional features, including temperature monitoring for early detection of COVID-19 [6], was developed in prior research. This study proposes a COVID-19 early detection system by integrating temperature monitoring and expert systems into employee attendance systems. Every employee who wishes to participate must input their attendance information into the system. Before recording the employee's presence, the system will analyze employee temperature information from the temperature monitoring and expert systems to determine whether the employee will likely be confirmed with COVID-19. Companies can use the results of this early detection to determine whether an employee can continue working in the office or must work from home [7].

In this innovative employee attendance application, a temperature monitoring system is integrated to enhance workplace safety by detecting potential COVID-19 cases. The system utilizes the MLX90614 temperature sensor, which emits an infrared beam converted into an electric current, generating a voltage subsequently transformed into a digital signal. Complementing this sensor, an Arduino Nano V3 microcontroller processes the sensor data, while a Wi-Fi module facilitates data transmission to a central server. Once on the server, the temperature sensor data is stored and processed, forming a crucial component in the early detection of COVID-19 cases. By combining temperature readings with other indicators within an expert system, the application can identify individuals with elevated temperatures, signaling potential infection risks. This temperature monitoring system is strategically positioned at the office entrance, enabling employees to conveniently measure their temperature and record attendance before entering the premises. This proactive approach promotes workplace safety and contributes to the overall public health efforts in combating the spread of infectious diseases such as COVID-19.

In contrast to research [8], which utilized RFID (Radio Frequency Identification) technology, RFID technology enables remote identification. The proposed system utilizes the OpenCV Python library. This library is utilized because it facilitates the development of face recognition systems. Using OpenCV, face detection will occur in real time.

This study addresses the inherent inefficiencies of manual attendance recording systems prevalent in educational institutions and workplaces by proposing an innovative solution: an Intelligent Attendance Monitoring System utilizing real-time face recognition technology integrated with Raspberry Pi. By recognizing the limitations of traditional methods and emphasizing the need for automation and accuracy, this research aims to revolutionize attendance management processes. The proposed system offers a more efficient and secure means of recording attendance by integrating advanced technologies, such as real-time face recognition. It contributes to enhancing workplace safety in the context of the COVID-19 pandemic by facilitating early detection of potential cases. Moreover, by prioritizing data accuracy and security, this study establishes a robust foundation for attendance monitoring systems, ensuring reliable records and safeguarding against unauthorized access.

Methodology

Data Collection

In this research, the Attendance Monitoring System was subjected to comprehensive testing using facial data from ten individuals, seven registered in the database. The testing protocol involved capturing facial images at varying distances of 30 cm, 40 cm, and 50 cm under different light intensities of 20 lux, 100 lux, and 200 lux. Each individual's facial data was sampled 200 times to ensure thorough testing and reliable face recognition performance. Through this rigorous testing process, face detection accuracy was evaluated across different distance and lighting conditions, providing valuable insights into the system's performance and reliability in real-world scenarios.

Face Recognition

Face Recognition is a technological method that can recognize and match human faces with digital images or databases containing input image data from faces; face recognition is also an efficient technique and one of the most preferred biometric modalities for identifying and verifying individuals compared to voice, fingerprints, iris, retina scan of the eye, gait, ear geometry, and hand geometry [9]. Visage Recognition is a system that measures the physiological features of the human visage, such as the eyes, nostrils, and mouth. Face detection, feature extraction, and face recognition are the three fundamental stages of developing a robust facial recognition system. The initial phase, face detection, aims to locate and identify the image of a human face obtained by the system. The feature extraction step involves extracting the feature vector for each human visage identified in the first phase. In the final phase of facial recognition, features extracted from human faces are compared with all facial template databases to recognize human faces [10].

Haar Cascade Classifier

Face detection using the Haar Cascade Classifier is widely used in various applications, including developing an Intelligent Attendance Monitoring System using Real-Time Face Recognition and Raspberry Pi. The Haar Cascade Classifier method, known for its efficiency and speed in detecting faces [11], has been applied in different contexts such as home security [12], [13], government official recognition [14], multimedia applications [15], and even in web-based real-time face detection systems [16].

In attendance monitoring, the Haar Cascade Classifier is crucial in accurately detecting faces. It is noted that the accuracy of face detection using this method can reach up to 75% [12] and 85% [13]. Additionally, the Haar Cascade Classifier effectively detects multiple faces in real-time scenarios [14], making it suitable for applications requiring swift and efficient face recognition processes. Moreover, the Haar Cascade Classifier includes the path to the frontal face Haar Cascade classifier for successful face detection [15]. This method and other trained face detection algorithms have been utilized in various systems, showcasing its versatility and reliability [17]. The consistent improvement of detection accuracy and real-time performance further reinforces its role as a foundational technique in computer vision-based applications. The sequence of image transformations in Figure 1 illustrates how increasing complexity and segmentation in visual patterns may mirror layered approaches in face detection systems.

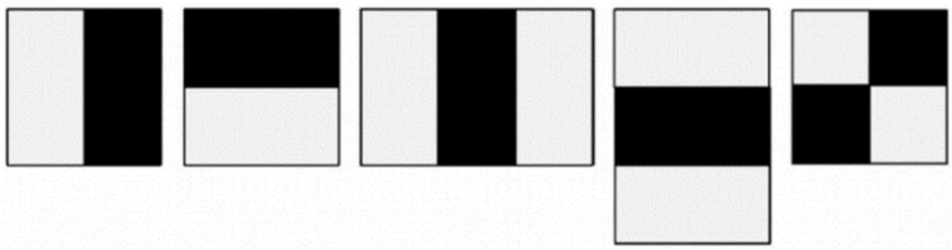


Figure 1. Haar feature

Local Binary Patterns (LBP)

Face detection using Local Binary Patterns (LBP) is widely used in computer vision and image processing. In an Intelligence Attendance Monitoring System Using Real-Time Face Recognition and Raspberry Pi, utilizing LBP for face detection is crucial in accurately identifying and recognizing faces in real time.

LBP is effective for feature extraction in facial recognition systems by analyzing pixel intensity patterns in a local neighborhood to capture texture information efficiently [18]. LBP has been integrated into various systems, such as surveillance systems for security applications, where it is combined with the Haar cascade for real-time monitoring of secured areas [19]. Additionally, LBP has been applied in developing robust facial expression recognition systems to address scale variations and texture loss challenges in traditional LBP methods [20].

In conclusion, using Local Binary Patterns (LBP) in face detection for intelligent attendance monitoring systems using real-time face recognition with Raspberry Pi provides a robust and efficient solution. By leveraging LBP's texture analysis capabilities and integrating it with deep learning techniques, researchers have developed accurate and reliable systems for facial recognition and attendance monitoring. As illustrated in Figure 2, the LBP procedure involves comparing each pixel with its surrounding neighbors to generate a binary pattern, which is then converted into a decimal value for texture classification.

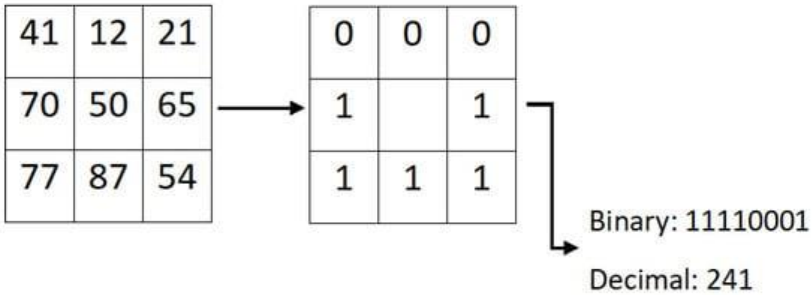


Figure 2. Local Binary Patterns (LBP) procedure

Raspberry Pi

Raspberry Pi is a versatile and portable device that has been extensively utilized in face recognition systems. The Raspberry Pi has been employed in various face recognition applications due to its portability and effectiveness [21]. Researchers have successfully implemented face recognition systems for tasks such as classroom attendance and door security using Raspberry Pi [22]. The use of the Raspberry Pi in real-time monitoring through face detection provided by the OpenCV library has been highlighted in the literature [23]. Additionally, the Raspberry Pi has been utilized in systems for student attendance through face recognition, showcasing its utility in educational settings [24].

Moreover, the Raspberry Pi has been integrated into smart technologies for attendance monitoring, reducing costs and enabling connectivity with diverse devices [25]. The device has also been utilized in the development of autonomous systems, such as self-driving car prototypes, demonstrating its capabilities as a processing unit [26]. Furthermore, the Raspberry Pi has been instrumental in the implementation of various algorithms, including those for text detection and recognition, showcasing its role in advancing computer vision applications [27]. As illustrated in Figure 3, the compact, single-board design of the Raspberry Pi allows for seamless integration into edge-computing solutions for such applications.

Figure 3. Raspberry pi

Design System

Figure 4 is a detailed diagram of a computer data processing process for an attendance system utilizing face recognition technology. The process starts with a camera, likely connected to a Raspberry Pi, capturing images in real time. These images are then processed for face recognition, where the system identifies recognized faces against a database. The diagram also mentions managing face data, including storing and retrieving facial data points for comparison. The attendance system is indicated to serve users such as lecturers and students, suggesting its application in educational settings like offices or lecture halls. Feedback mechanisms and data management processes are highlighted as integral parts of the system, ensuring that the face data is accurately recorded and utilized for attendance.

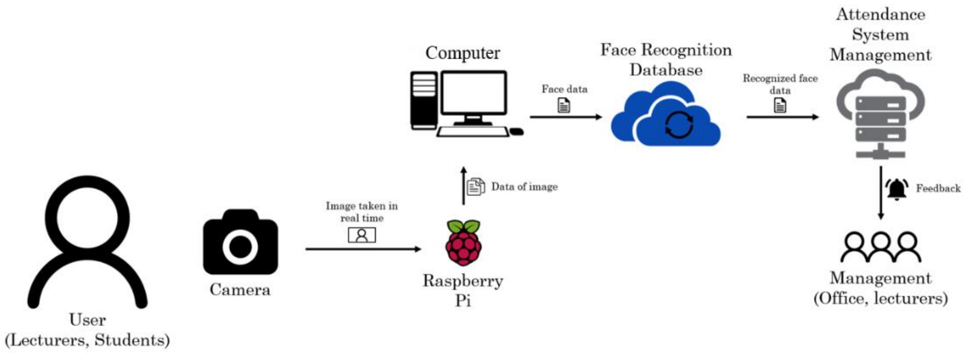


Figure 4. Design system

The Intelligence Attendance Monitoring System, akin to Figure 5, first receives video input from a CCTV camera, capturing real-time footage of individuals. Each video frame is then analyzed to detect faces using facial detection algorithms. Upon detection, the system crops and saves these facial images for further processing. Subsequently, the protected images are compared against a database of known faces to determine if they match any registered students or individuals. Upon identification, the system marks the corresponding student as present in the attendance record. The attendance data is then compiled and securely stored within the system, updating the overall attendance records for the session or class. Feedback mechanisms may provide real-time notifications to administrators and students regarding attendance status. Additionally, a user interface allows administrators to access and manage attendance records, while students may also have access to view their attendance information. This system streamlines the attendance marking process in education by integrating Raspberry Pi and face recognition technology.

Figure 5. Attendance marking process

The block diagram presented in Figure 6 illustrates the sequential steps involved in registering individuals within the system. Initially, the process commences with the CCTV camera capturing video input, which is subsequently processed to generate a dedicated storage folder. Within this folder, the system extracts facial images by cropping them from the frames of the video feed. These cut facial photos serve as the foundational data for creating a comprehensive database, which undergoes training to enable accurate recognition of individuals. During the training phase, basic information about the individuals, such as names or identification numbers, is incorporated into the database. Once the training process is complete, all pertinent data, including the cropped facial images and associated individual information, are meticulously stored within the database for future reference and recognition purposes. This systematic approach ensures the system has the necessary resources to identify and authenticate individuals effectively during subsequent attendance monitoring activities. Establishing a robust database through this registration process lays a solid foundation for facilitating efficient and accurate attendance tracking within educational institutions and workplaces.

Figure 6. Registration block diagram

System Block Diagram

The workflow begins like Figure 7, with the capture of facial images via the USB webcam, which is then processed by the Raspberry Pi 3 using a face recognition algorithm. Successful identifications are logged into the system as attendance entries. Data can be managed remotely over WiFi, and attendance records may be displayed on the monitor for live monitoring or administrative purposes. This intelligent system streamlines attendance management, reducing errors and saving time.

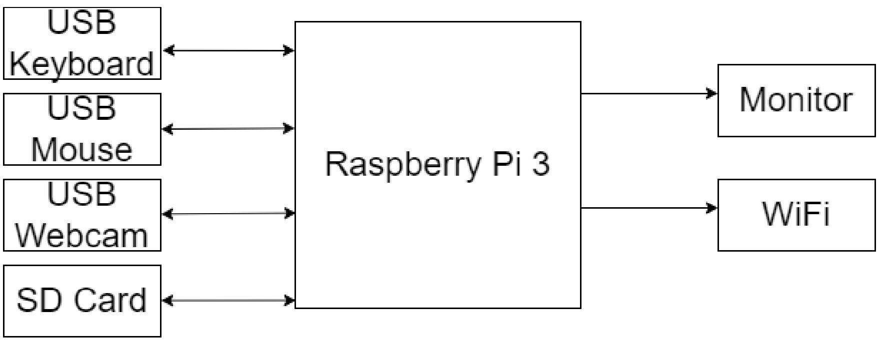


Figure 7. System block diagram

Results and Discussions

System Overview

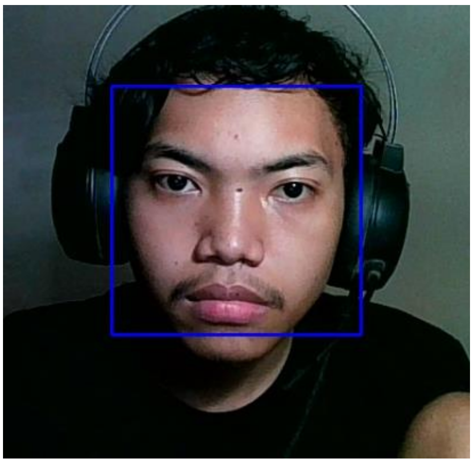
The system begins with the setup of Raspberry Pi, configuring it with necessary peripherals such as a camera module for capturing real-time video feed and a Wi-Fi module for data transmission (Figure 8). Leveraging the OpenCV Python library, the system implements face detection and recognition algorithms, including the Haar Cascade Classifier and Local Binary Patterns (LBP) algorithm, to accurately detect and recognize faces from the captured video feed. Upon successfully recognizing registered individuals, the system marks their attendance in real-time, with feedback mechanisms providing notifications to administrators and users regarding attendance status. Attendance records and facial data are securely stored on the Raspberry Pi or transmitted to a central server for further processing and analysis. Administrators can access and manage attendance records through a user interface, ensuring seamless monitoring and administration.

Figure 8. Rassbery Pi implementation

Implementation Face Recognition

In the initial stages of the registration process, the real-time camera feed undergoes preprocessing to enhance the efficiency of facial recognition algorithms. This preprocessing step involves converting the RGB camera picture to grayscale, a fundamental operation that simplifies subsequent image analysis while retaining essential facial features. Once converted to grayscale, the image is analyzed using the highly effective Haar Cascade technique, renowned for its adeptness in detecting objects within images, particularly faces. Employing this technique, the system scans the grayscale image, identifying and delineating facial features from non-facial items. To facilitate visual comprehension and streamline the identification process, the recognized faces are prominently highlighted with a distinct blue box, as depicted in Figure 9 (a). This visual representation serves a dual purpose, it aids in differentiating detected faces from other objects within the image. It provides a clear indication of successful facial recognition. In instances where successful detection occurs, as illustrated in Figure 9 (b), each identified user's face is meticulously delineated and labeled, showcasing the system's ability to recognize individuals despite varying environmental conditions and facial expressions. This process of repeated identification, spanning 200 iterations per user, not only ensures robustness in recognition but also enhances the system's adaptability to diverse scenarios and user profiles.

Once an item is identified within the captured video feed, the registration process seamlessly transitions to the crucial phase of facial recognition. Leveraging advanced technology, the face recognition system employs the Local Binary Patterns (LBP) algorithm, a robust and efficient method for analyzing facial features. This algorithm meticulously compares each captured face with the comprehensive histogram stored in the database, which encapsulates unique characteristics and patterns associated with each individual's facial structure. Through this meticulous comparison process, the system endeavors to ascertain the individual's identity by matching their facial features with the stored data. This technology is instrumental in accurately identifying the face's owner, enabling precise recognition and authentication within the Intelligent Attendance Monitoring System.



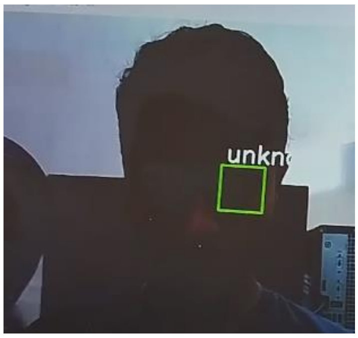
(a)

(b)

Figure 9. Object identification (a), real-time image data from webcam (b)

In Figure 10 (a), the successful facial recognition results are displayed, demonstrating the system's ability to identify individuals based on their facial features accurately. Each recognized face is correctly matched with its corresponding identity from the database, showcasing the effectiveness of the LBP algorithm in facilitating precise recognition and authentication. In Figure 10 (b), a scenario is depicted where the system encounters difficulty in detecting and recognizing a face. Despite the system's best efforts, it fails to match the captured facial features with any entry in the database, failing to identify the individual. This situation may arise due to factors such as poor lighting conditions, occlusion of facial features, or discrepancies between the captured image and the stored data.

(a)



(b)

Figure 10. Success for recognise the face (a), failed for recognise the face (b)

Face Recognition Testing

Distance Comparison

To evaluate the performance of the face detection system, experiments were conducted using three distance settings: 30 cm, 50 cm, and 80 cm, all under a controlled light intensity of 100 lux. These settings were chosen to simulate realistic scenarios where users may be positioned at various distances from the camera during face recognition. The results, summarized in Table 1, provide accuracy percentages for each distance, and the outcomes were categorized as either "Detected" (for registered faces) or "Unknown" (for unregistered faces).

The accuracy for each test case was calculated using the standard formula:

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

Where,
TP (True Positive) = Positive data that is correctly classified.
TN (True Negative) = Negative data that is correctly classified.
FP (False Positive) = Negative data that is correctly classified.
FN (False Negative) = Positive data that is classified as unfavorable.

Table 1. Face recognition result for distance comparison

Data	Face Status	Accuracy (%)			Status Detection
		30 cm	50 cm	80 cm	
1	Registered	98	80	0	Detected
2	Unregistered	100	98	70	Unknown
3	Registered	91	77	20	Detected
4	Registered	82	76	0	Detected
5	Registered	80	88	40	Detected
6	Registered	99	98	30	Detected
7	Registered	89	85	50	Detected
8	Registered	88	60	0	Detected
9	Unregistered	100	80	60	Unknown
10	Unregistered	97	99	99	Unknown
Average		92.4	84.1	52.7	

Each face (both registered and unregistered) was tested 10 times across different distance settings. This repetition allowed for a robust validation of the system's ability to consistently detect or reject faces based on their registration status. By performing the test 10 times, the evaluation ensures statistical reliability and minimizes anomalies caused by brief lighting fluctuations or motion. The average accuracy achieved was 92.4% at 30 cm, 84.1% at 50 cm, and 52.7% at 80 cm, indicating that the system performs best at close range, with detection performance decreasing as distance increases.

Light Comparison

The comprehensive evaluation of the face detection system encompassed varied light intensities of 20 lux, 100 lux, and 200 lux, each meticulously tested at a consistent distance of 30 cm. This methodical approach ensured a thorough exploration of the system's performance under different lighting conditions while maintaining a standardized proximity level. To obtain reliable accuracy values, each face both registered and unregistered was tested 10 times under each lighting condition. The outcomes of these repeated trials were analyzed using a standard accuracy formula, considering true positives, true negatives, false positives, and false negatives. This repetitive testing ensured statistical reliability, minimized anomalies, and provided clear insight into the impact of light intensity on detection performance. As illustrated in Figure 11, the face detection system was evaluated under three distinct lighting conditions 20 lux (a), 100 lux (b), and 200 lux (c) highlighting the system's ability to respond to variations in illumination.

(a) (b) (c)

Figure 11. Light intensities of 20 lux (a), 100 lux (b), and 200 lux (c)

Table 2. Face recognition result for light comparison

Data	Face Status	Accuracy (%)			Status Detection
		20 lux	100 lux	200 lux	
1	Registered	40	95	84	Detected
2	Unregistered	64	97	88	Unknown
3	Registered	20	85	82	Detected
4	Registered	16	88	65	Detected
5	Registered	28	94	77	Detected
6	Registered	0	84	66	Detected
7	Registered	30	91	65	Detected
8	Registered	0	85	77	Detected
9	Unregistered	50	96	86	Unknown
10	Unregistered	60	98	77	Unknown
Average		38.5	91.3	76.7	

The data analysis concerning face detection accuracy at different light intensities reveals crucial insights into the system's performance. It is evident that light intensity plays a pivotal role in determining the accuracy of face detection, with higher light intensities correlating with improved detection rates. For instance, at 20 lux, the average accuracy is 38.5%, which significantly increases to 91.3% at 100 lux and slightly decreases to 76.7% at 200 lux. This underscores the significance of optimal lighting conditions in ensuring reliable facial recognition outcomes. Moreover, the distinction between registered and unregistered faces is noteworthy, with registered individuals consistently exhibiting higher detection accuracy. This emphasizes the system's proficiency in recognizing individuals whose facial data is stored within the database. Overall, while the system demonstrates commendable performance across various light intensities, there are still opportunities for enhancement, particularly in refining algorithms to better handle varying lighting conditions and improving detection accuracy for unregistered faces. By addressing these areas, the system can further bolster its reliability and effectiveness in real-world applications such as attendance monitoring and identity verification, thereby maximizing its utility in diverse operational settings.

Conclusion

In conclusion, developing an Intelligent Attendance Monitoring System utilizing real-time face recognition technology integrated with Raspberry Pi represents a significant advancement in attendance management processes. This research introduces a groundbreaking solution to enhance attendance tracking in educational institutions and workplaces by addressing the inefficiencies inherent in manual recording systems through automation and accuracy. Leveraging advanced technologies such as the Haar Cascade Classifier and Local Binary Patterns (LBP) algorithm, the proposed system demonstrates robust performance in detecting and recognizing faces under varying environmental conditions.

The experimental evaluation of the face detection system provides valuable insights into its performance across different scenarios. In the distance comparison test, the system exhibits an average accuracy of 92.4%, showcasing its effectiveness in identifying faces at varying distances from the camera. Despite fluctuations, the system maintains impressive performance overall, with noticeable differences in accuracy between registered and unregistered faces.

Similarly, the light comparison test highlights the pivotal role of light intensity in determining detection accuracy. The system demonstrates optimal performance under adequate lighting conditions with an average accuracy of 91.3% at 100 lux. However, there is a slight decrease in accuracy to 76.7% at 200 lux, indicating the need for further refinement to ensure consistent performance across different light intensities.

Overall, the Intelligent Attendance Monitoring System presents a promising solution for streamlining attendance management processes while addressing the challenges posed by traditional recording methods. This system lays a robust foundation for enhancing workplace productivity and educational outcomes by prioritizing automation, accuracy, and efficiency.

Through continued refinement and optimization, it has the potential to revolutionize attendance-tracking practices and facilitate seamless integration into diverse operational settings, ultimately maximizing its utility and effectiveness.

As a suggestion for future research, exploring the integration of additional biometric modalities, such as iris recognition or voice recognition, could further enhance the system's capabilities and security features. Additionally, investigating the feasibility of continuously implementing machine learning techniques to adapt and improve the system's performance over time could contribute to its long-term success and reliability.

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