ADMI Jurnal Ilmiah Teknik
JUIT Vol 5 No. 1 | January 2026 | ISSN: 2828-6936 (Print), ISSN: 2828-6901 (online), Page. 178-193

Implementation Of Machine Learning for Freshwater Fish Detection

Ivan Maurits[1*], Priyo Sarjono Wibowo[2], Mochammad Akbar Marwan[3]
[1,2,3]Computer Science, Gunadarma University, Depok, Indonesia

Article History
Received : January 02, 2026
Accepted : January 27, 2026
Published : January 29, 2026
Available Online:
January 29, 2026

Corresponding author*:
Ivan_maurits@staff.gunadarma.ac.id

Cite This Article:
Ivan Maurits, Priyo Sarjono Wibowo, & Marwan, M. A. (2026). Implementation of Machine Learning for Freshwater Fish Detection. Jurnal Ilmiah Teknik, 5(1), 178–193.

DOI:
https://doi.org/10.56127/juit.v5i1.1427

Abstract: Recent advancements in mobile technology and machine learning have enabled the development of practical tools, such as Android applications, to assist in real-time fish species identification, particularly in the context of freshwater fisheries in Indonesia. **Objective:** This research aims to design and implement an Android application that helps anglers accurately identify and categorize freshwater fish species native to Indonesia. The app integrates machine learning-based image recognition to provide a practical tool for fishing enthusiasts while supporting conservation efforts for Indonesia’s freshwater biodiversity. **Methodology:** A quantitative approach was employed, focusing on mobile application development using Kotlin for Android. The application uses a TensorFlow Lite-based image recognition model for real-time image processing on mobile devices. Data for the model were gathered from publicly available fish species datasets. The system was tested across multiple Android devices to evaluate compatibility and efficiency. **Findings:** The application successfully identifies and classifies various freshwater fish species in Indonesia, providing users with accurate species profiles, biological characteristics, and appropriate bait recommendations. The system operates efficiently in real-time on mobile devices without relying on cloud computing, ensuring accessibility in remote areas. Testing results across different Android devices confirm the app's robustness and user-friendly interface. **Implications:** This research demonstrates the integration of mobile technology and machine learning in fisheries, offering a valuable tool for both recreational and professional anglers. The app promotes awareness of freshwater fish species preservation and supports sustainable fishing practices. Additionally, it can serve educational purposes by enhancing knowledge of local biodiversity and fostering fish conservation efforts. **Originality:** This research introduces an innovative mobile-based solution to freshwater fish identification. Unlike previous studies, which focused on desktop-based methods, this study offers a practical mobile application that operates efficiently in real-time on-site. The originality lies in combining machine learning and mobile technology to address fish identification challenges while contributing to biodiversity conservation.

Keywords: Android-based application; freshwater fish recognition; visual image classification; fishing assistance; artificial intelligence; TensorFlow Lite framework

INTRODUCTION.

Freshwater fishing has become an increasingly popular activity, particularly among novice anglers who are just beginning to engage with fishing as both a recreational pastime and a professional occupation. In recent years, there has been a notable increase in interest, with many newcomers seeking opportunities to learn and engage in freshwater fishing

(Nations, 2020). However, this growing interest comes with a significant challenge for beginner anglers: the difficulty of accurately identifying the species of freshwater fish present in specific aquatic environments. Without proper knowledge of the species available, anglers often struggle to apply appropriate fishing techniques, which can reduce their success rates and lead to a less satisfying experience (Cooke & Cowx, 2004). This issue is especially important because it may discourage new anglers from continuing the activity, which could affect the long-term participation in the sport and, in turn, impact local fishery economies and community engagement with sustainable practices.

The increasing participation in freshwater fishing highlights the urgent need for tools that assist novice anglers in overcoming these challenges. Freshwater fish inhabit a variety of environments, such as rivers, lakes, and ponds, with species like catfish, carp, gourami, and tilapia being common (Nelson et al., 2016). Despite the growing interest, many beginners lack the expertise to correctly identify these species and select the appropriate bait and techniques for different types of fish (Liu et al., 2021). As the activity becomes more popular, technological solutions, such as smartphone applications for fish identification, have become increasingly relevant. These technologies have the potential to support novice anglers in improving their fishing outcomes and enhance the educational experience, thus making the practice more accessible and enjoyable. The growing demand for such tools makes this an important issue to address both academically and practically, especially with the potential to improve resource management and promote sustainable fishing practices.

Machine learning (ML) has shown significant promise in addressing some of the challenges faced by novice anglers. Various models, including YOLOv5 and Faster R-CNN, have been demonstrated to improve fish detection accuracy by refining bounding boxes and optimizing confidence scores (Hamzaoui et al., 2025; Ranjan et al., 2023). The K-Nearest Neighbor (KNN) algorithm has also been effective in classifying fish species, with accuracy reaching up to 90% for Nile Tilapia, offering a fast and reliable approach for fish identification (Fouad et al., 2016; Mustafidah et al., 2025). Deep learning models, such as DenseNet and VGGNet16, have further enhanced classification accuracy, with DenseNet achieving a remarkable 97% accuracy in identifying six freshwater fish species (Shiam Prodhan et al., 2024; Wang et al., 2020). However, a major challenge in applying these models is the lack of large, diverse, and representative datasets, which limits the applicability of these models to real-world fishing environments and restricts their scalability across different geographical regions.

Another area of research has focused on integrating IoT sensors with ML algorithms to monitor water quality in aquaculture environments, which has implications for both fish health and species identification. Real-time monitoring systems that measure key parameters such as pH, temperature, and dissolved oxygen are crucial for maintaining fish health (Borah et al., 2024; Istiqomah et al., 2024). Additionally, buoy-type devices using algorithms like K-means clustering have been found to effectively monitor water quality while minimizing power consumption by transmitting data only when significant changes occur (Balmaceda et al., 2022). The use of UAV-based multispectral imaging in conjunction with ML models such as XGBoost and RF has further improved the precision of water quality assessments (Liu et al., 2021). Despite these advancements, challenges related to the scalability and cost of implementing such systems in diverse environmental conditions persist, indicating a need for more cost-effective and adaptable solutions for widespread use in various aquaculture locations.

In addition to these technological advancements, smartphone-based applications for fish species detection have gained significant traction. Rahman demonstrated that machine learning algorithms applied to smartphone-captured images can reliably classify freshwater fish species, showing that these applications can be highly effective even in challenging conditions (Rahman et al., 2021). Setiawan and Lestari reported that deep learning models integrated into mobile systems can maintain high classification performance despite issues such as low or uneven lighting (Setiawan & Lestari, 2022), further enhancing their utility in real-world fishing environments. Additionally, these mobile applications offer practical guidance to novice anglers, providing information about suitable bait and fishing techniques for specific species, thus improving the overall fishing experience (Hadi et al., 2023). However, while these applications show promise, they require further development to address challenges such as environmental variability and dataset limitations, which may affect their effectiveness in diverse conditions.

The goal of this research is to develop an advanced freshwater fish detection system that integrates machine learning models with smartphone-based applications to assist novice anglers in identifying species accurately and efficiently. This study aims to bridge the gaps identified in existing research by improving the diversity of datasets used in machine learning models, enhancing model adaptability to different environmental conditions, and developing a user-friendly interface for anglers. The research will focus on creating a practical and efficient tool that not only helps anglers identify fish species but also provides them with actionable advice related to fishing techniques, bait selection, and suitable fishing gear for specific species.

RESEARCH METHOD

Requirement Analysis

This phase focuses on identifying and defining all requirements necessary for the application development process (Pressman & Maxim, 2020). The requirements analysis is divided into two main categories: hardware requirements and software requirements, both of which serve as fundamental components to support the successful implementation of the system (Sommerville, 2016).

The development process utilizes a laptop as the main hardware platform with updated specifications, including an Intel Core i7-1165G7 processor to enhance computational performance, 32 GB of RAM to support intensive development activities and machine learning workflows, 1 TB of solid-state storage to accommodate application resources, datasets, and development tools, and integrated Intel® Iris® Xe Graphics to manage graphical and visualization tasks efficiently (Corporation, 2021).

In the development of this application, a set of alternative software tools is utilized to support the implementation, deployment, and evaluation stages. The application is developed using Visual Studio Code equipped with the Android SDK and Kotlin plugins as the main development environment, while Genymotion is employed as the device virtualization platform to simulate Android devices for functional testing and performance validation (Developers, 2023; Genymotion, 2023).

System Design

At this stage, the system architecture and interaction flow of the proposed application are systematically designed. This process includes the development of navigation structures, use case diagrams, and activity diagrams to represent system functionality and user interactions. In addition, this phase involves designing the user interface to ensure that the application delivers an appropriate, functional, and user-friendly visual layout.

The use case diagram (Figure 1) illustrates the interaction between users and the core functionalities of the application. These functionalities are designed to provide users with seamless access to explore detailed information, perform image-based scanning, and review previously recorded usage data through the application history feature.

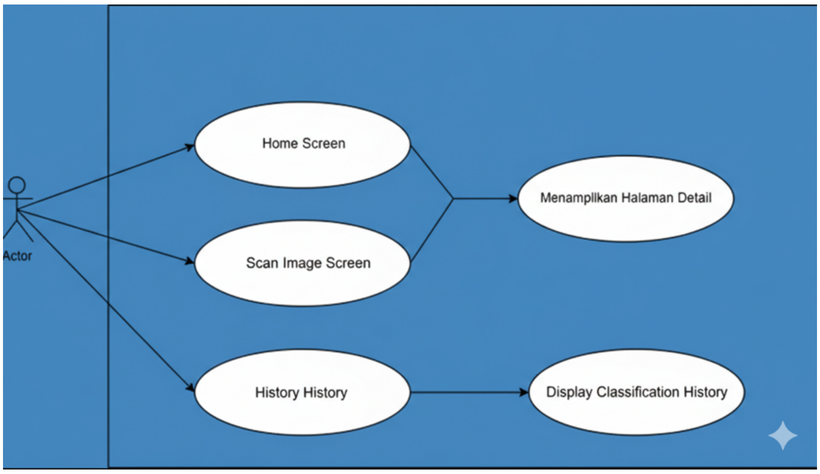


Figure 1. Use Case Diagram

The following activity diagram (Figure 2) represents the operational flow of the features implemented within the application. This diagram is intended to provide a clear overview of the primary steps involved in each feature and to illustrate how processes are executed in a structured manner.

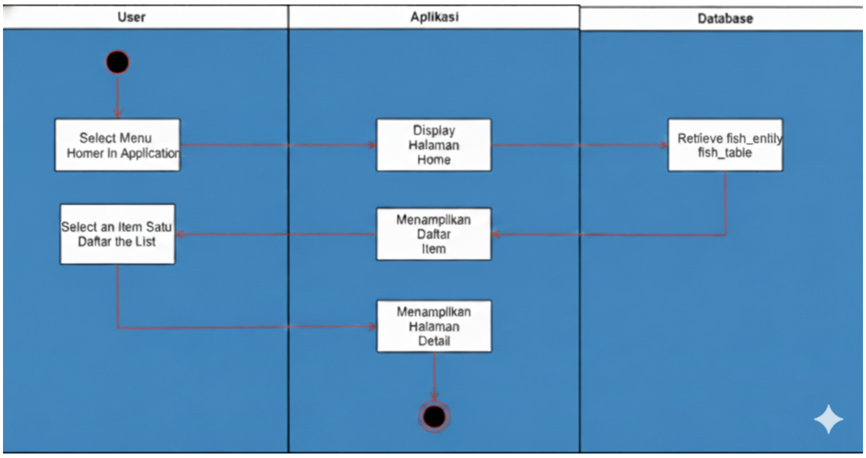


Figure 2. Home Page Activity Diagram

The diagram depicts the interaction workflow among the user, the application, and the database layer. The sequence begins when the user selects the "Home" menu within the application, which triggers the system to display the home screen. Subsequently, the application queries the database to retrieve data from the fish_table entity and presents a list of available items to the user. The user then selects one of the displayed items, prompting the application to load and display the detailed view associated with the selected item. Overall, this diagram illustrates a simple and structured process for data retrieval, item listing, and detail visualization within the application. The next activity diagram, presented in Figure 3, illustrates the workflow of the Scan page within the application.

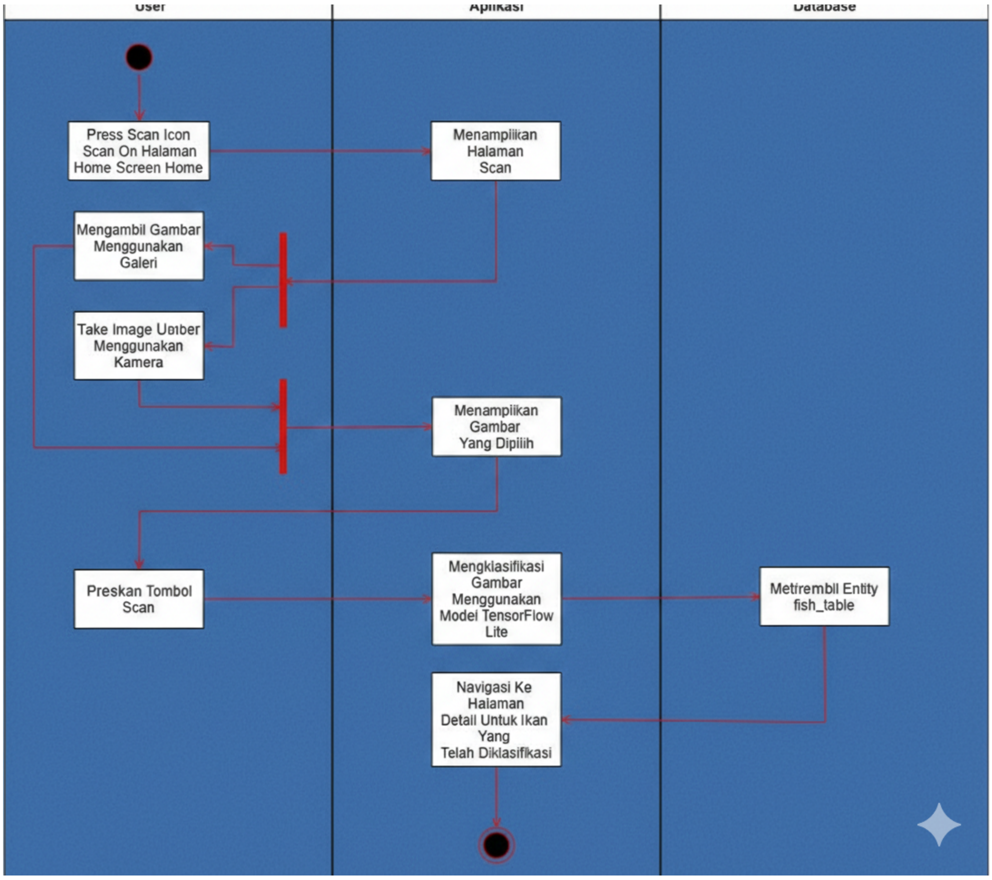


Figure 3. Scan Page Activity Diagram

The diagram in Figure 3 illustrates the activity flow of the image scanning and classification process within the application. The sequence begins when the user selects the scan icon on the home page, which directs the system to display the scan interface. At this stage, the user is provided with the option to acquire an image either from the device gallery or by capturing a new image using the camera. Once an image is selected, the application displays the chosen image on the screen.

Subsequently, the user initiates the scanning process by pressing the scan button, prompting the application to perform image classification using a TensorFlow Lite–based machine learning model. Upon completion of the classification process, the application retrieves the corresponding data from the fish table in the database and redirects the user to the detail page associated with the identified fish species. Overall, this diagram represents the end-to-end interaction flow from image selection to the presentation of classification results. Furthermore, Figure 4 presents the activity diagram for the history page of the application.

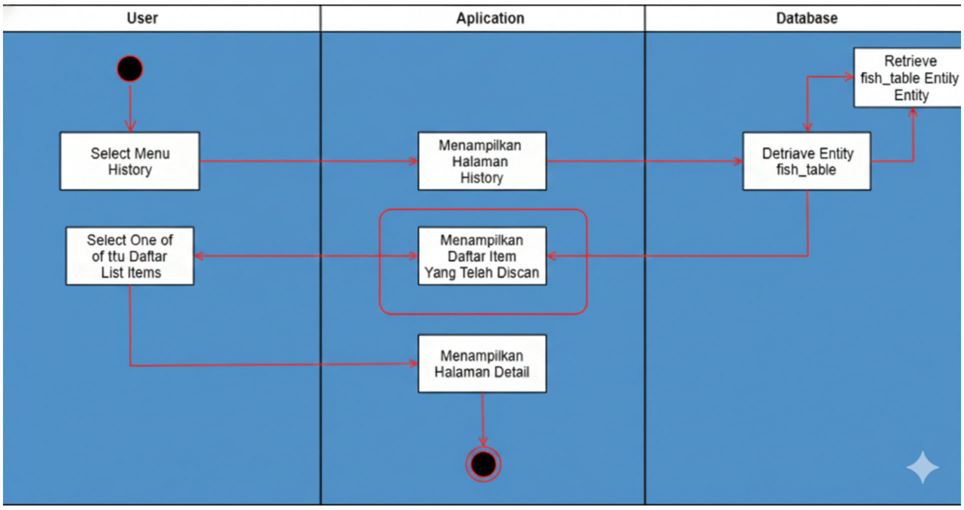
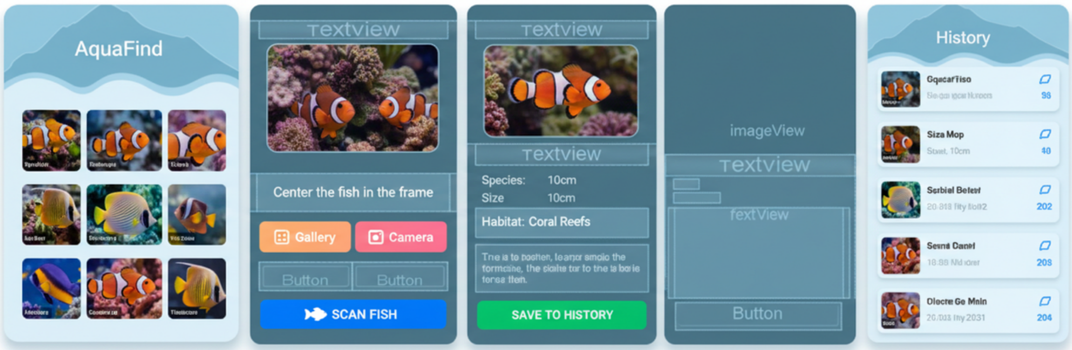


Figure 4. History Page Activity Diagram

The diagram in Figure 4 illustrates the activity flow for accessing and reviewing previously scanned items within the application. The process begins when the user selects the "History" menu, prompting the system to display the history page. The application then retrieves relevant data from the fish_table in the database and presents a list of items that have been scanned earlier. After the user selects a specific entry from the list, the application navigates to the corresponding detail page to display comprehensive information about the selected item. Overall, the diagram represents a structured interaction process from viewing historical records to accessing detailed item information.

Interface Design

At this stage, the user interface of the application is designed in Figure 5 to provide a visual representation of how the application will appear during execution. The interface layout is created using XML-based layout features in Android Studio, serving as a blueprint for the application's visual structure and user interaction elements.



(1) Home (2) Image Scanner (3) Detail Menu (4) History Menu

Figure 5. Interface Design

The home menu interface is designed to display a RecyclerView-based list containing freshwater fish species that can be classified by the application. This list is presented in an ordered format to facilitate easy browsing. In addition, a scan button is positioned at the bottom-right corner of the screen, allowing users to navigate directly to the image scanning page.

The scan page interface includes an ImageView component that serves as a preview area for images obtained either from the device camera or the image gallery. This page is equipped with three functional buttons: a gallery button for selecting images from local storage, a camera button for capturing images in real time, and an analyze button used to initiate image classification using the TensorFlow Lite model.

The detail page interface enables users to view a relevant image of the identified fish along with its species name and detailed information regarding physical characteristics and behavioral traits. Additionally, this page provides bait recommendations suitable for catching the identified species, as well as a comprehensive species description. A navigation button is placed at the bottom of the page to allow users to return to the main menu.

The history menu interface is designed to store and display information generated from previous freshwater fish image scans. This page presents a list of previously scanned items, enabling users to review past results. Furthermore, a dedicated button is provided to allow users to clear the entire scan history efficiently.

Model Training

The model training process utilizes a platform known as Teachable Machine, which enables users to develop machine learning models through an intuitive, web-based interface

(Lab, 2023). In this stage, the model is trained to recognize seven categories of freshwater fish that are commonly found in Indonesia, namely gourami, catfish, betik, snakehead, tilapia, carp, and mujair. Each class is represented by a collection of image samples that serve as training data, allowing the model to learn visual features and perform accurate identification and classification tasks (Goodfellow et al., 2016).

By employing Teachable Machine, the training process becomes more accessible and efficient, particularly for developers without extensive expertise in machine learning, while still supporting integration into mobile applications (Wexler et al., 2019). The procedure for using Teachable Machine begins with defining the freshwater fish classes, followed by uploading image datasets to the Teachable Machine web platform. The images are sourced from folders stored in Google Drive and assigned labels corresponding to their respective classes, as illustrated in Figure 6. This labeling process is a critical step, as proper annotation directly influences the model's ability to distinguish and classify fish species accurately during the inference phase (Zhang et al., 2018).

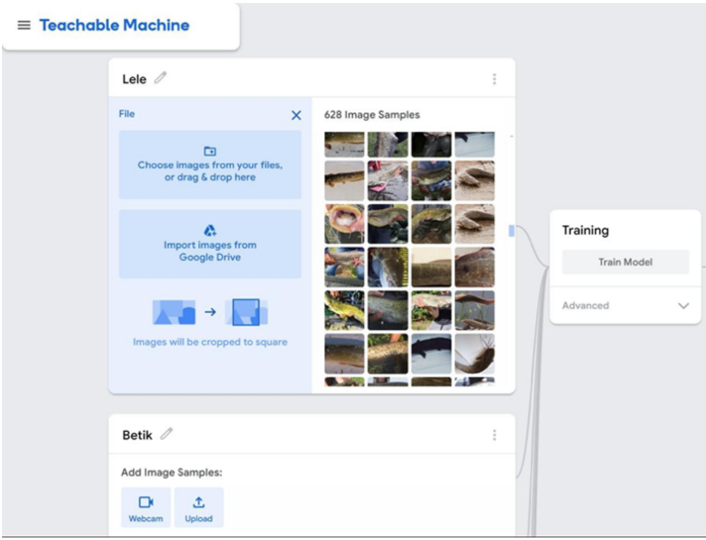


Figure 6. Dataset in Cloud

Once all images have been successfully uploaded, the next step is to initiate the training process by selecting the "Train" button provided on the Teachable Machine platform. The training procedure is executed automatically by the system. During this process, the input images are internally transformed into structured representations, including XML (Extensible Markup Language) formats, and subsequently processed into binary data. These binary representations are then reconstructed into image-based model parameters, as illustrated in Figure 7, forming the basis for the trained classification model.

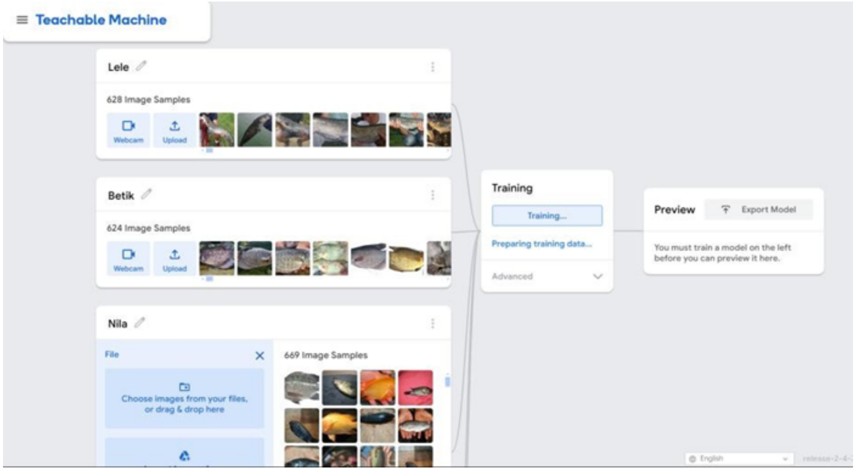
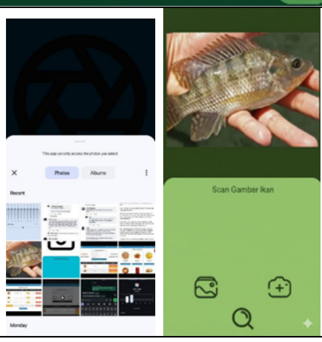


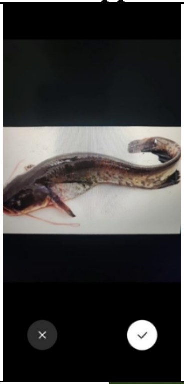
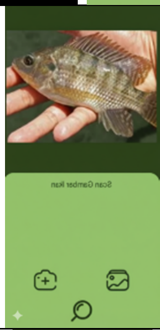
Figure 7. Model Training

RESULT AND DISCUSSION

This stage describes the application testing process conducted to evaluate system performance and functionality. The testing is carried out using the black-box testing method, which focuses on validating application features from the user's perspective. This approach does not examine the internal system logic or implementation details; instead, it assesses observable outputs and user interactions to ensure that the application operates as intended.

Tabel 1. Test Result

No.	Test Case	Result	Application View	Explanation
1	Launching the Application	Displaying the Home Page Containing a List of Detectable Fish Species		Displaying the Home Page Featuring a List of Detectable Fish Species
2	Selecting an Image via the Gallery Feature on the Scan Page	Opening the Gallery and Successfully Selecting an Image		The application successfully opens the gallery and allows the user to select an image

No.	Test Case	Result	Application View	Explanation
3	Capturing an Image Using the Camera Feature on the Scan Page	Opening the camera and successfully capturing an image in real time.	 	The application successfully opens the camera and captures an image in real time.
4	Performing Fish Image Detection on the Scan Page	Opening the Detail Page and Successfully Detecting the Image		The application successfully opens the detail page and accurately detects the image.
5	Opening the History Page	Displaying a List of Previously Detected Images		The application successfully displays a list of previously detected images.

Following the completion of the testing phase, it can be concluded that all application features operate correctly and meet the expected requirements. To further ensure compatibility and reliable performance across different Android devices, feature testing was conducted on the following five Android devices.

Tabel 2. Android Devices Used for Testing

No	Device Name	Result
1	Samsung Galaxy A13	The application operated smoothly, and all functionalities performed as expected
2	Xiaomi Redmi 9	The application functioned properly, with all features running without issues.
3	OPPO A16	The application executed successfully, and every feature worked correctly
4	Vivo Y21	The application ran reliably, and all available features were fully functional.
5	Realme Narzo 30A	The application performed well, with all features operating as intended.

Based on testing conducted on five different devices in Table 2, it can be concluded that the application operates smoothly and all features perform properly across various types of devices. This indicates that the application demonstrates strong compatibility for users with diverse Android devices. The testing process involved a range of device specifications, ensuring that the application delivers a consistent user experience on each platform.

DISCUSSION

The testing results demonstrate that the application successfully performs the intended functions, confirming its ability to assist users in identifying freshwater fish species accurately. The black-box testing process validated all key features from a user perspective, including image selection from the gallery, real-time image capture via the camera, accurate fish species detection, and proper functionality of the history page. The application worked smoothly on all the Android devices tested, including Samsung Galaxy A13, Xiaomi Redmi 9, OPPO A16, Vivo Y21, and Realme Narzo 30A, with no issues encountered during the testing phase.

The application's functionality can be attributed to its effective integration of machine learning algorithms for fish species detection, which ensures that fish images are analyzed accurately. The use of the gallery and camera features, along with the real-time processing of images, directly contributes to a seamless user experience. Additionally, the successful operation across various devices indicates that the application's underlying architecture is optimized for compatibility with different hardware specifications, suggesting that device-specific performance issues were effectively managed.

Comparing the results of this study with previous research, such as Rahman (Rahman et al., 2021) and Setiawan & Lestari, it is evident that this application builds on the advancements in fish species detection using machine learning (Setiawan & Lestari, 2022). Similar studies have shown the effectiveness of deep learning models for identifying fish species under varying environmental conditions. However, this research differs by focusing on the user experience of novice anglers, ensuring that the application is not only accurate but also user-friendly and accessible across multiple Android devices. The findings from this study underscore the novelty of offering a multi-functional app that combines fish detection with practical guidance for fishing, which is less commonly seen in existing applications.

The successful implementation of fish species detection via a mobile application has significant implications for both recreational fishing and sustainable fishery management. For novice anglers, the app can serve as an educational tool, helping them to better understand fish species and select the appropriate techniques for successful fishing. This, in turn, could enhance the overall fishing experience, fostering greater participation in the activity. Moreover, the ability to maintain a history of detected species allows users to track and improve their fishing skills over time. On a broader scale, this development contributes to the growing use of mobile applications in environmental monitoring and conservation efforts, where accurate identification of aquatic species is crucial.

The positive consequences of the application's functionality include increased efficiency in fish species identification, which is crucial for beginners to make informed decisions on bait and fishing techniques. The app's success across multiple devices indicates its accessibility, making it a valuable tool for a wide audience. However, there are potential limitations. For example, although the app performs well on the tested devices, unforeseen issues may arise with future updates or different hardware. Additionally, the app's reliance on machine learning algorithms means that it may face challenges in more complex or rare fish species detection if the dataset is not regularly updated or expanded.

Based on the findings, it is recommended that further development focus on expanding the app's database of fish species, incorporating new species detected in different geographic regions, and continuously updating the dataset to ensure accuracy and relevance. Regular updates to the app should also address potential compatibility issues with new Android devices. Additionally, to improve the overall user experience, further user feedback could be collected to identify any usability improvements or additional features that could be integrated, such as real-time fishing tips or more personalized recommendations based on historical detection data.

CONCLUSION

The application testing has demonstrated that the app functions effectively across a wide range of Android devices, from Android 10 to Android 14. All features of the application, including fish species recognition, accurate classification, and detailed information provision (such as species descriptions, distinguishing characteristics, and suitable bait recommendations), operated smoothly without any issues. The application proved to be a reliable tool for novice anglers, aiding them in identifying and classifying freshwater fish species commonly found in fishing locations throughout Indonesia.

This research contributes significantly to the field of mobile application development in environmental and recreational activities, particularly in fisheries. By integrating machine learning algorithms with user-friendly interfaces, this application provides a novel solution for assisting anglers in fish species identification. It bridges the gap between novice knowledge and the technical expertise required for successful fishing, making it an important contribution to both recreational fishing practices and the growing use of mobile technology for environmental monitoring. The application's ability to recommend suitable fishing techniques based on fish species adds further value by promoting sustainable and efficient fishing practices.

While the research successfully demonstrates the effectiveness of the application across a range of Android devices, there are limitations to the study. One limitation is that the app's performance was not tested on devices running Android versions older than Android 10, which may result in compatibility issues on legacy devices. Furthermore, the dataset used for fish species recognition is currently limited, and the application's accuracy may decrease when identifying rare or newly discovered fish species. Future research should focus on expanding the fish species database, testing compatibility across a wider range of devices and Android versions, and conducting longitudinal studies to evaluate the app's performance over time and across different geographical regions. Additionally, incorporating user feedback could further refine the application, enhancing its usability and functionality for a broader audience.

REFERENCES

Balmaceda, E. T. et al. (2022). Machine Learning-Based Algorithm for Fish Kill Evaluation using Differential Changes of Input Parameters via Wireless Communication. *2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management, HNICEM 2022*. https://doi.org/10.1109/HNICEM57413.2022.10109461

Borah, A. R. et al. (2024). Real-Time Monitoring of Aquarium Conditions to Ensure Optimal Fish Health. *2nd International Conference on Intelligent Data Communication Technologies and Internet of Things, IDCIoT 2024*, 1555–1559. https://doi.org/10.1109/IDCIoT59759.2024.10467906

Cooke, S. J., & Cowx, I. G. (2004). The role of recreational fishing in global fish crises.

BioScience, *54*(9), 857–859. https://doi.org/10.1641/0006-3568(2004)054[0857:TRORFI]2.0.CO;2

Corporation, I. (2021). *Intel® Core™ i7-1165G7 processor specifications*. https://www.intel.com

Developers, A. (2023). *Android Studio and SDK tools documentation*. Google. https://developer.android.com

Fouad, M. M. et al. (2016). A fish detection approach based on BAT algorithm. *Advances in Intelligent Systems and Computing*, *407*, 273–283. https://doi.org/10.1007/978-3-319-26690-9_25

Genymotion. (2023). *Genymotion user guide: Android emulator for app testing*. https://www.genymotion.com

Goodfellow, I. et al. (2016). *Deep learning*. MIT Press.

Hadi, S. et al. (2023). Local dataset-driven image classification for freshwater fish species using convolutional neural networks. *International Journal of Intelligent Systems and Data Science*, *7*(3), 66–75. https://doi.org/10.1504/IJISDS.2023.132145

Hamzaoui, M. et al. (2025). An Optimized Bounding Box Technique for Enhanced Underwater Fish Detection. In *Lecture Notes on Data Engineering and Communications Technologies* (Vol. 250, pp. 108–118). https://doi.org/10.1007/978-3-031-87778-0_10

Istiqomah, R. F. et al. (2024). My I-Pond : Water Quality Monitoring with IoT and Machine Learning to Reduce Pond Cultivation Failure for Farmers. *Proceeding of the IEEE International Conference on Smart Instrumentation, Measurement and Applications, ICSIMA*, *2024*, 150–155. https://doi.org/10.1109/ICSIMA62563.2024.10675577

Lab, G. C. (2023). *Teachable Machine: Train a computer to recognize images, sounds, and poses*. https://teachablemachine.withgoogle.com

Liu, S. et al. (2021). Application of mobile and image recognition technologies in fish species identification. *Aquaculture and Fisheries*, *6*(5), 423–430. https://doi.org/10.1016/j.aaf.2020.08.003

Mustafidah, H. et al. (2025). The most optimum distance calculation method on k-nearest neighbor algorithm in image classification of freshwater fish. *AIP Conference Proceedings*, *3234*(1). https://doi.org/10.1063/5.0259421

Nations, F. and A. O. of the U. (2020). *The state of world fisheries and aquaculture 2020*. FAO.

Nelson, J. S. et al. (2016). *Fishes of the world* (5th (ed.)). Wiley.

Pressman, R. S., & Maxim, B. R. (2020). *Software engineering: A practitioner's approach* (9th (ed.)). McGraw-Hill Education.

Rahman, M. A. et al. (2021). Freshwater fish species identification using machine learning and mobile image acquisition. *Journal of Computing and Informatics*, *9*(2), 101–110. https://doi.org/10.31289/jci.v9i2.4567

Ranjan, R. et al. (2023). Effects of image data quality on a convolutional neural network trained in-tank fish detection model for recirculating aquaculture systems. *Computers and Electronics in Agriculture*, *205*. https://doi.org/10.1016/j.compag.2023.107644

Setiawan, R., & Lestari, D. (2022). Deep learning-based freshwater fish recognition on mobile platforms under varying illumination conditions. *Journal of Artificial Intelligence Research and Applications*, *4*(1), 45–54. https://doi.org/10.30762/jaira.v4i1.2891

Shiam Prodhan, M. et al. (2024). Advancing Fish Species Identification in Bangladesh: Deep Learning Approaches for Accurate Freshwater Fish Recognition. *Lecture Notes in Networks and Systems*, *834*, 113–122. https://doi.org/10.1007/978-981-99-8349-0_10

Sommerville, I. (2016). *Software engineering* (10th (ed.)). Pearson Education.

Wang, H. et al. (2020). Study on Freshwater Fish Image Recognition Integrating SPP and DenseNet Network. *2020 IEEE International Conference on Mechatronics and Automation, ICMA 2020*, 564–569. https://doi.org/10.1109/ICMA49215.2020.9233696

Wexler, J. et al. (2019). The What-If Tool: Interactive probing of machine learning models. *IEEE Transactions on Visualization and Computer Graphics*, *26*(1), 56–65. https://doi.org/10.1109/TVCG.2019.2934619

Zhang, L. et al. (2018). Deep learning for remote sensing data: A technical tutorial on the state of the art. *IEEE Geoscience and Remote Sensing Magazine*, *6*(2), 22–40. https://doi.org/10.1109/MGRS.2018.2795608