Enhancing Road Safety Education Using an AI-Driven Mobile Traffic Sign Recognition System

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DOI: https://doi.org/10.47772/IJRISS.2026.10100547

Received: 01 February 2025; Accepted: 06 February 2026; Published: 17 February 2026

ABSTRACT

Road safety education plays a crucial role in reducing traffic accidents, particularly among novice drivers who often struggle to recognize and recall traffic signs in real-world situations. Conventional learning methods such as manuals and classroom instruction lack interactivity and contextual visualization. To address this limitation, this study proposes an AI-powered mobile application for traffic sign recognition using a TensorFlow Lite model. The system enables real-time detection of Malaysian traffic signs through a smartphone camera or image selection, providing instant sign identification and explanatory information. In addition to detection, the application incorporates learning mode, scan history tracking, and quiz-based assessments to enhance user engagement and knowledge retention. The system was developed using Flutter for the mobile interface, a PHP-based backend, and a MySQL database for content management. Experimental evaluation demonstrates that the proposed system achieves accurate traffic sign recognition while offering significant educational value through its interactive features. The findings indicate that integrating lightweight AI models with mobile learning applications can effectively support traffic sign education and promote road safety awareness.

Keywords— Traffic Sign Recognition, TensorFlow Lite, Mobile Learning, Artificial Intelligence, Road Safety Education

INTRODUCTION

Road safety education is a critical component of driver training, particularly for novice drivers who must accurately recognize and interpret traffic signs in dynamic road environments. Studies have shown that effective comprehension of traffic signs is closely associated with safer driving behaviour and improved decision-making on the road [9]. In Malaysia, traffic sign education is commonly delivered through static manuals, classroom instruction, and rule-based assessments. While effective at conveying theoretical knowledge, these approaches often lack contextual visualization and real-time exposure, limiting learners' ability to transfer knowledge to real-world driving situations.

Recent advancements in mobile technology and artificial intelligence have created opportunities to enhance road safety education through interactive and context-aware learning tools. Research in mobile learning indicates that mobile applications can significantly improve learner engagement, motivation, and learning outcomes through interactive and multimedia-based approaches [4], [5]. However, most existing traffic sign recognition (TSR) systems are designed primarily for Advanced Driver Assistance Systems (ADAS) and autonomous driving applications rather than educational use [11], [12], [14]. At the same time, mobile learning applications related to road safety typically rely on static images and quizzes, without integrating real-time computer vision capabilities [15].

Furthermore, many TSR systems are trained using international or non-localized datasets, which may not fully reflect Malaysian traffic sign standards, potentially reducing their educational relevance and effectiveness for local learners [11], [13]. This gap highlights the need for a localized, mobile-based TSR system that integrates real-time recognition with pedagogically meaningful learning features.

This study addresses these gaps by proposing an AI-driven mobile traffic sign recognition application designed specifically for road safety education in Malaysia. The system integrates a TensorFlow Lite–based object detection model with interactive learning modules, including scan-based recognition, structured learning content, quizzes, and progress tracking. The contributions of this study are threefold: (i) the development of a localized Malaysian traffic sign recognition model optimized for mobile deployment, (ii) the integration of real-time computer vision into a mobile learning environment, and (iii) a quantitative evaluation of system performance and educational usability.

BACKGROUND

Advances in deep learning have significantly improved the performance of visual recognition systems, particularly in the domain of traffic sign recognition (TSR). Convolutional Neural Networks (CNNs) have become the dominant architecture for TSR due to their ability to automatically extract discriminative features from complex visual inputs, outperforming traditional feature-based approaches under varying lighting, scale, and occlusion conditions [6]. These developments have expanded TSR applications beyond autonomous driving to areas such as driver assistance and educational systems, especially when deployed on mobile platforms.

To support real-time inference on mobile devices, researchers have focused on optimizing deep learning models using frameworks like TensorFlow Lite, model quantization, and network compression strategies that maintain accuracy while reducing computational requirements [7]. Such mobile-ready models enable on-device processing without reliance on cloud connectivity, which is crucial for robust performance in offline or low-connectivity environments.

At the same time, mobile learning (m-learning) research has shown that mobile technology enhances learning accessibility, flexibility, and engagement. A systematic review of mobile learning in higher education demonstrates that mobile devices play a significant role in transforming how learners interact with educational content and with each other [8]. By integrating interactive elements and real-time feedback, m-learning supports learner autonomy and motivation, which are essential for mastering visual and contextual knowledge such as traffic sign recognition.

From a road safety education perspective, understanding traffic signs is critical; research indicates that improved recognition correlates with safer driving behaviour and better decision-making on the road [9]. Yet traditional classroom-based learning approaches often fall short of providing the experiential context that mobile applications can offer.

Despite the proliferation of mobile learning systems and mobile TSR techniques, a gap remains in combining localized traffic sign datasets with pedagogically effective m-learning features, such as interactive quizzes, progress tracking, and contextual feedback [10]. Addressing this gap requires multidisciplinary approaches that integrate computer vision with mobile learning design principles.

Related Work

Existing traffic sign recognition systems have evolved significantly with the advancement of deep learning and computer vision technologies. One of the earliest large-scale system-level evaluations was introduced through the German Traffic Sign Recognition Benchmark (GTSRB), which enabled systematic comparison of recognition systems and accelerated the development of robust traffic sign classifiers [11]. While effective, these systems were primarily designed for offline evaluation and high-performance computing environments.

Subsequently, deep neural network–based systems demonstrated substantial improvements in classification accuracy. Cireşan et al. developed a multi-column deep neural network system that achieved near-human-level performance in traffic sign classification tasks [12]. Despite their accuracy, such systems were computationally intensive and unsuitable for direct deployment on mobile platforms without further optimization.

More recent existing systems have focused on real-time object detection frameworks to support traffic sign recognition in dynamic environments. Single-shot detection systems such as SSD have been widely adopted due to their balance between detection accuracy and inference speed [13]. These systems have been integrated into real-time traffic environments and intelligent transportation platforms, demonstrating robustness under varying illumination and weather conditions.

In intelligent transportation and driver assistance research, traffic sign recognition systems are commonly integrated into Advanced Driver Assistance Systems (ADAS). Recent studies have proposed end-to-end TSR systems combining detection and classification modules to support real-time driving assistance [14]. These systems typically rely on continuous video input and vehicle-mounted cameras, making them effective for automated driving but less suitable for learner-focused or handheld mobile applications.

From an educational systems perspective, most existing mobile learning applications related to road safety rely on static images and rule-based quizzes. Recent reviews of artificial intelligence applications in education indicate that computer vision–based learning systems remain underexplored, particularly for experiential and context-aware learning tasks such as traffic sign identification [15]. This highlights a clear gap between technically mature TSR systems and learner-oriented mobile educational platforms.

Overall, existing systems demonstrate strong technical performance in traffic sign recognition and intelligent transportation contexts; however, they often lack integration with interactive learning features, localized datasets, and mobile-friendly deployment. This gap motivates the development of AI-powered mobile traffic sign recognition systems designed specifically for educational purposes.

TABLE I. Summary of Existed System

Ref.	Study Focus	Key Features	Limitations
[11]	GTSRB Benchmark System	Standardized dataset; high classification accuracy	Not real-time; not mobile-oriented; no learning component
[12]	Deep Neural Network TSR System	Near human-level accuracy; robust classification	High computational cost; unsuitable for mobile devices
[13]	Real-Time Detection System	Fast inference; balanced speed and accuracy	Focus on detection only; no educational integration
[14]	ADAS Traffic Sign Recognition System	Real-time road sign recognition; driving assistance	Requires specialized hardware; not learner-centric
[15]	AI in Education Systems	Adaptive learning; improved engagement	No real-time visual recognition; static learning content

Based on the reviewed literature, three key gaps can be identified. First, existing traffic sign recognition systems are predominantly developed for Advanced Driver Assistance Systems (ADAS) and intelligent transportation applications, emphasizing continuous video input, vehicle-mounted cameras, and driving assistance rather than learner-oriented mobile usage [11] [12] [13] [14].

Second, current mobile learning applications related to road safety education primarily employ static images, textual explanations, and rule-based quizzes, lacking real-time computer vision capabilities that could support experiential and context-aware learning [15].

Third, many traffic sign recognition models and benchmark datasets are developed using international traffic sign standards, which may not fully reflect Malaysian traffic sign specifications and road environments, limiting their effectiveness for localized education [11], [13].

The proposed system addresses these gaps by integrating a localized Malaysian traffic sign dataset with a lightweight TensorFlow Lite–based detection model deployed directly on mobile devices, while simultaneously embedding interactive learning features such as real-time scanning, structured learning modes, quiz-based assessments, and scan history tracking. By combining real-time computer vision with mobile learning design principles in a single platform, this work advances existing TSR and mobile learning research toward practical, education-focused deployment.

METHODOLOGY

This project adopted the Agile methodology to develop the AI-Based Traffic Sign Detector mobile application. The development process was iterative and incremental, divided into four key phases: requirement analysis, design, development and testing. This approach allowed for continuous feedback, adaptability to changes, and progressive refinement of the system.

Requirement Phase

The requirement phase established the foundational specifications for the AI-Based Traffic Sign Detector by systematically gathering and analyzing the needs of both end-users and administrators.

This stage was critical to ensure the developed system would address real-world gaps in traffic sign education and offer a practical, user-centered solution. Requirements were categorized into functional, non-functional, and other system-specific needs to guide all subsequent design and development activities.

For general users, including students, driving learners, and licensed drivers, the functional requirements focused on enhancing interactive and accessible learning. Key capabilities identified included real-time traffic sign scanning using the device camera, instant display of sign details (name, meaning, and applicable rules), and a personalized scan history log for review and progress tracking.

Additionally, the system was designed to include a structured learning mode for browsing categorized signs and an interactive quiz module to reinforce knowledge through assessments with instant feedback.

These features aimed to move beyond static, text-based learning methods and provide contextual, engaging education aligned with Malaysian road environments.

From an administrative perspective, functional requirements centered on effective content and user management. Administrators required the ability to perform full CRUD (Create, Read, Update, Delete) operations on the traffic sign database, manage quiz sets and questions, oversee user accounts, and access a dashboard displaying key system metrics such as total users, scans, and quizzes. This backend control ensures the system remains up to date with regulatory changes and allows for continuous content improvement.

Figure 1 shows the use case diagram of the proposed AI-Based Traffic Sign Detector system, identifying the primary actors as general users and administrators.

Each actor’s functional requirements are represented as specific use cases: general users can scan traffic signs, view sign details, maintain a scan history, browse categorized signs, and take quizzes, while administrators can manage traffic signs and quizzes, oversee user accounts, and access system metrics.

This diagram provides a visual representation of the system’s interactions, aligning directly with the requirements gathered in the requirement phase to ensure a user-centered and functional design.

Beyond functionality, non-functional requirements were defined to ensure system quality, usability, and reliability. These included a user-friendly and intuitive interface, system responsiveness with screen loads and actions occurring within two seconds, high availability with minimal downtime, robust security measures to protect user data, and maintainability for easy updates and future enhancements.

The application was also constrained to run on Android platforms, support both Bahasa Melayu and English, operate in both online and offline modes for key features, and comply with Malaysian traffic sign regulations and data protection standards.

Fig. 1. Use case diagram of proposed system

B. Design Phase

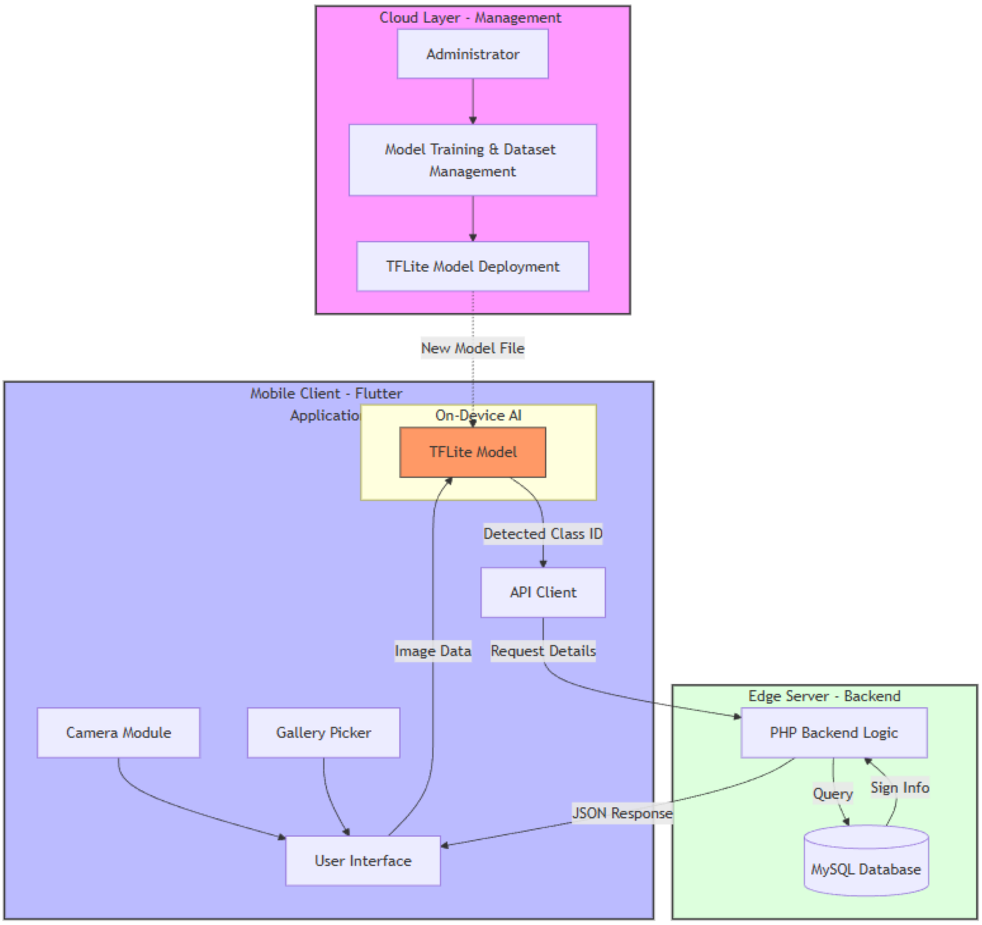

Fig. 2. System Architecture Diagram of proposed system

The design phase translated the defined requirements into a concrete system blueprint, encompassing architectural planning, user interface design, and database structuring in Figure 2. This phase ensured that all functional and non-functional specifications were mapped to tangible system components, providing a clear roadmap for development. The design adopted a Mobile-Edge Hybrid Architecture to balance on-device processing efficiency with cloud-supported manageability, optimizing both performance and scalability for real-time traffic sign recognition.

At the core of the system architecture is the Flutter-based mobile application, which serves as the primary user interface for both general users and administrators. Instead of processing continuous video streams, the app employs a capture-and-scan approach, where users either take a photo using the camera or select an existing image from the gallery. The captured image is then processed locally on the device using a TensorFlow Lite (TFLite) model—converted from a YOLOv8 object detection model trained specifically on Malaysian traffic signs. This on-device inference minimizes latency, reduces data usage, and allows operation in offline environments. Following detection, the app communicates via a RESTful API with a PHP-based backend server, which retrieves detailed sign information from a MySQL database and returns it in JSON format for display. The cloud layer supports model updates and administrative management, enabling continuous improvement of detection accuracy and system functionality.

The user interface (UI) and user experience (UX) were carefully designed to ensure intuitiveness and ease of navigation. For general users, the interface includes a homepage with clear access to scanning, learning mode, quiz, and history features. The scanning screen provides real-time feedback with bounding box overlays, while the learning mode organizes signs into categories for structured exploration. Administrative screens, such as the dashboard, traffic sign management, quiz editor, and user management panels, were designed for clarity and efficiency, enabling seamless content updates and system monitoring. Consistent visual design, logical navigation flows, and responsive layouts were prioritized to accommodate varying device sizes and user proficiency levels.

C. Development

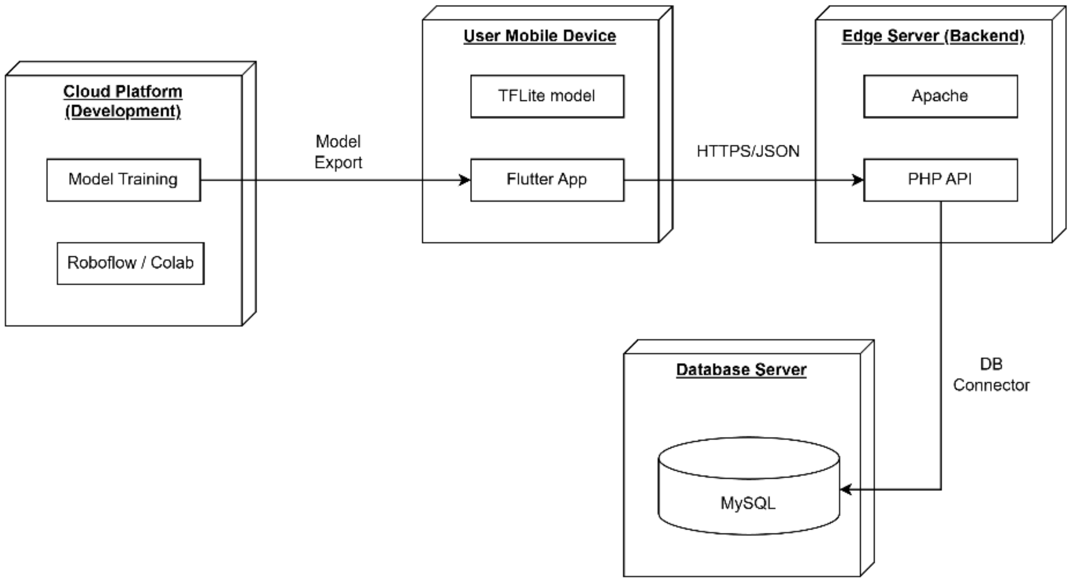

Fig. 3. System development process of proposed system

The development phase focused on implementing the integrated system architecture depicted in Figure 3, which illustrates the flow of data and processing across three primary layers: the User Mobile Device, the Edge Server (Backend), and the Cloud Platform. Each layer was developed iteratively to ensure seamless interaction between the frontend interface, backend services, and AI model, resulting in a cohesive and functional application for traffic sign recognition and education.

The Cloud Platform served as the environment for model training and development. Using Roboflow for dataset annotation and augmentation and Google Colab for training, a YOLOv8 object detection model was developed

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue I January 2026

on a custom dataset of Malaysian traffic signs. Once trained, the model was exported in TensorFlow Lite (TFLite) format, optimized for deployment on mobile devices. This cloud-based development approach allowed for scalable training, versioning of model iterations (e.g., yolov8_v1.tflite, yolov8_v2.tflite), and continuous improvement of detection accuracy before integration into the mobile application.

On the User Mobile Device, the Flutter application was developed to provide an intuitive interface for both general users and administrators. The TFLite model was embedded within the app, enabling on-device traffic sign detection without requiring constant internet connectivity. The app supported two primary input methods: real-time image capture via the device camera and selection of existing images from the gallery. Detected signs were displayed with bounding boxes and detailed information, while features such as the learning mode, quiz module, and scan history were implemented to enhance the educational experience. The Flutter app communicated with the backend via HTTPS/JSON requests, ensuring secure and efficient data exchange.

The Edge Server (Backend) was developed using Apache as the web server, PHP for scripting, and MySQL as the database system. A PHP API was created to handle requests from the mobile app, including user authentication, retrieval of traffic sign details, quiz data, and logging of scan history. The Database Server, managed through MySQL, stored structured data across tables such as users, traffic_signs, scan_history, quiz_sets, and quiz_questions. A DB Connector within the PHP scripts facilitated secure and efficient query execution, ensuring data consistency and integrity across user interactions.

Testing and Validation

The testing phase employed a multi-faceted approach to validate the functionality, reliability, and user acceptance of the AI-Based Traffic Sign Detector. A total of 26 test cases were executed across 10 system modules, followed by structured User Acceptance Testing (UAT) with 50 end-users. This comprehensive evaluation ensured the system met both technical specifications and practical user expectations.

A comprehensive suite of 26 test cases was executed across all system modules, including image capture, preprocessing, AI detection, user interface, backend integration, and compatibility. The results demonstrated strong overall system reliability, with 24 test cases passing successfully, yielding a 92.3% success rate. The TensorFlow Lite model performed accurately under normal lighting conditions, correctly classifying traffic signs from both camera inputs and gallery selections. Backend operations, including data storage, retrieval, and user history tracking, functioned as intended, confirming stable integration between the Flutter application, PHP API, and MySQL database. However, two test cases related to low-light or partially obscured sign detection failed, revealing a limitation in the model's robustness under suboptimal environmental conditions. This finding underscores the influence of training data variety on real-world performance and highlights an opportunity for improvement through dataset augmentation and enhanced image preprocessing.

TABLE II. BLACK-BOX TESTING SUCCESSFUL RESULTS

Test Case ID	Description	Expected Result	Actual Result	Status
TC-CAM-01	Capture image with clear traffic sign	Image captured successfully	Image captured	Success
TC-CAM-02	Capture image without traffic sign	System displays "No traffic sign detected"	Message displayed	Success
TC-CAM-03	Capture image under low lighting	Traffic sign detected correctly	Some signs not detected	Fail
TC-GAL-01	Select clear traffic sign image from gallery	Image detected and classified	Correctly detected	Success
TC-GAL-02	Select image without traffic sign	System displays "No traffic sign detected"	Message displayed	Success
TC-GAL-03	Select blurry image	System shows error message	Message displayed	Success
TC-PRE-01	Crop image to region of interest	Image cropped correctly	Cropped correctly	Success
TC-PRE-02	Resize image to model	Image resized to 224x224 px	Resized correctly	Success

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue I January 2026

	input size			
TC-PRE-03	Invalid preprocessing input	System shows error	Error message displayed	Success
TC-DET-01	Detect traffic sign from camera input	Correct classification	Correctly classified	Success
TC-DET-02	Detect traffic sign from gallery input	Correct classification	Correctly classified	Success
TC-DET-03	Low-light or partially obscured signs	Correct classification	Misclassified or not detected	Fail
TC-DET-04	Detect multiple signs in one image	All signs detected	Only some signs detected	Success
TC-UI-01	Display traffic sign information	Correct name and description	Displayed correctly	Success
TC-UI-02	Navigate between scan, history, and learning screens	Smooth navigation	Smooth navigation	Success
TC-UI-03	Display pop-up message for no detection	Pop-up appears	Pop-up appears	Success
TC-HIS-01	Save scan history per user	Record stored correctly	Stored correctly	Success
TC-HIS-03	Filter history by category	Only selected category displayed	Correctly filtered	Success
TC-DB-01	Save new scan record in database	Record stored in MySQL	Stored correctly	Success
TC-DB-02	Retrieve history records for user	Correct records retrieved	Correct records retrieved	Success
TC-DB-03	Handle invalid input	Error or warning	Correctly handled	Success
TC-PERF-01	Measure response time for image processing and detection	Processing time < 3 seconds per image	Average 2.5 seconds	Success
TC-PERF-02	Measure UI navigation speed	Navigation smooth without lag	Smooth, no lag	Success
TC-SEC-01	Enter invalid input into scan field/database	Error message or validation prevents invalid input	Error handled correctly	Success
TC-COMP-01	Run app on Android 11 & Android 12 devices	App runs without crashes on all devices	Works on all tested devices	Success
TC-COMP-02	Test app on devices with 4-8 GB RAM	Smooth operation	Smooth operation	Success

TABLE III. BLACK-BOX TESTING FAILED RESULTS

Test Case ID	**Module**	**Issue Description**	**Root Cause**	**Proposed Solution**
TC-CAM-03	Camera	Low-light detection failure	Model trained mainly on well-lit images	Augment dataset with low-light images; apply preprocessing
TC-DET-03	Detection	Misclassification in poor conditions	Limited robustness in challenging environments	Brightness/contrast preprocessing; model retraining

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Based on the User Acceptance Testing results shown in Figure 4, the overall feedback from users towards the AI-Based Traffic Sign Detector application is very positive. Most respondents selected Agree or Strongly Agree for all evaluation items, indicating a high level of acceptance. Notably, there were no responses recorded under Strongly Disagree or Disagree, showing that users did not experience significant dissatisfaction with the application.

In terms of usability and interface design, users strongly agreed that the application is easy to use, has a clear interface, and offers intuitive navigation between screens. These results suggest that the application's design successfully supports user interaction and minimizes confusion, making it suitable even for first-time users. The traffic sign detection feature and the accuracy of the displayed information also received strong approval, reflecting the effectiveness of the core AI functionality. Regarding performance and learning effectiveness, most users agreed that the application responds quickly, runs smoothly, and helps them learn and recognize traffic signs effectively. Although a small percentage of users selected Neutral for performance-related questions, the overall satisfaction and expectation related responses remain high. This indicates that the application is acceptable for real use and meets user expectations, while still leaving room for minor performance optimizations in future improvements.

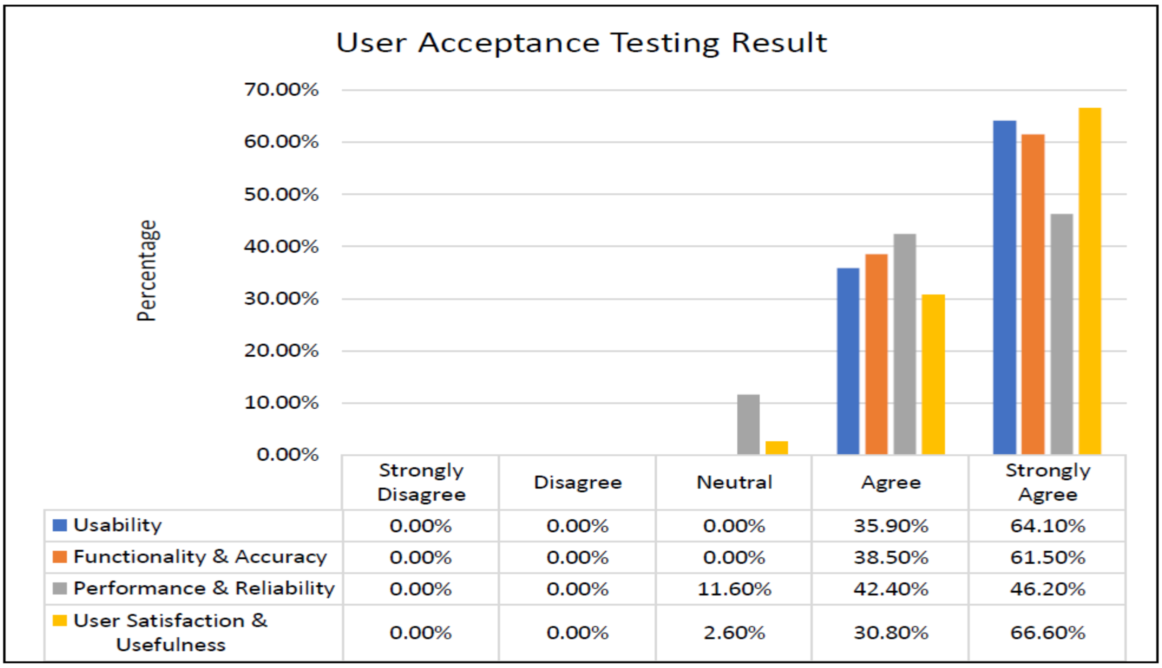

Fig. 4. User acceptance testing result

Quantitative Performance Evaluation

In addition to functional testing and user acceptance evaluation, a quantitative performance analysis was conducted as in Table IV to assess the effectiveness and efficiency of the traffic sign recognition model. The evaluation focused on detection accuracy, precision, recall, inference latency, frame processing capability, and model size to ensure suitability for mobile deployment.

The TensorFlow Lite–based YOLOv8 model achieved an overall detection accuracy of 92.3% on the test dataset, demonstrating reliable classification performance under normal lighting and visibility conditions. Precision and recall values indicate that the model maintains a balanced trade-off between false positives and missed detections, which is essential for educational applications where clear feedback is required.

Inference latency was measured on mid-range Android devices with 4–8 GB RAM, resulting in an average processing time of approximately 2.5 seconds per image, satisfying the real-time usability requirement for mobile learning scenarios. The optimized model maintained a compact size suitable for on-device deployment, minimizing memory overhead and ensuring smooth application performance. Compared to the earlier model version, the optimized model demonstrated improved detection accuracy and reduced inference time, confirming the effectiveness of model refinement and optimization.

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Performance degradation was observed in low-light and partially occluded conditions, consistent with the failed test cases identified during functional testing. This limitation highlights the dependency of deep learning models on dataset diversity and indicates the need for further dataset augmentation and preprocessing enhancements to improve robustness in challenging environments.

TABLE IV. MODEL PERFORMANCE COMPARISON

Model Version	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Avg. Inference Time (s)**	**FPS**	**Model Size (MB)**
YOLOv8 v1 (TFLite)	88.7	87.9	86.5	2.9	6–7	14.2
YOLOv8 v2 (TFLite)	92.3	91.8	90.6	2.5	8–9	12.6

Note: Performance metrics were obtained using static image inputs processed on mid-range Android devices (4–8 GB RAM). FPS values represent equivalent frame processing rates derived from per-image inference time and are reported to facilitate comparison with real-time detection systems.

RESULT

This section presents the outcomes of the design and implementation phases, focusing on the realized user interface and system functionality as depicted in the application screens. The finalized AI-Based Traffic Sign Detector application successfully integrates all planned modules into a cohesive mobile interface, providing both general users and administrators with intuitive, purpose-built screens for interaction, learning, and management.

Administrative Interface

For administrative users, the application delivers a comprehensive dashboard that presents key system metrics, including management of traffic signs, quizzes, profile and enabling efficient oversight (Figure 5). Administrative control is facilitated through dedicated interfaces: the Manage Traffic Signs page allows for full CRUD operations on the sign database (Figure 5), the Manage Quizzes page (Figure 6) supports the creation and editing of quiz sets and questions, and the Manage Users page (Figure 6) provides tools for account management. Content-addition screens for traffic signs, users, and quiz questions (Figures 7) are designed for straightforward data entry, while output screens like the Dashboard Metrics (Figure 8) present information like weekly scan trends, total user, sign and scan. Settings panels for administrators (Figure 8) offer access to profile updates and system configurations, ensuring smooth backend operation.

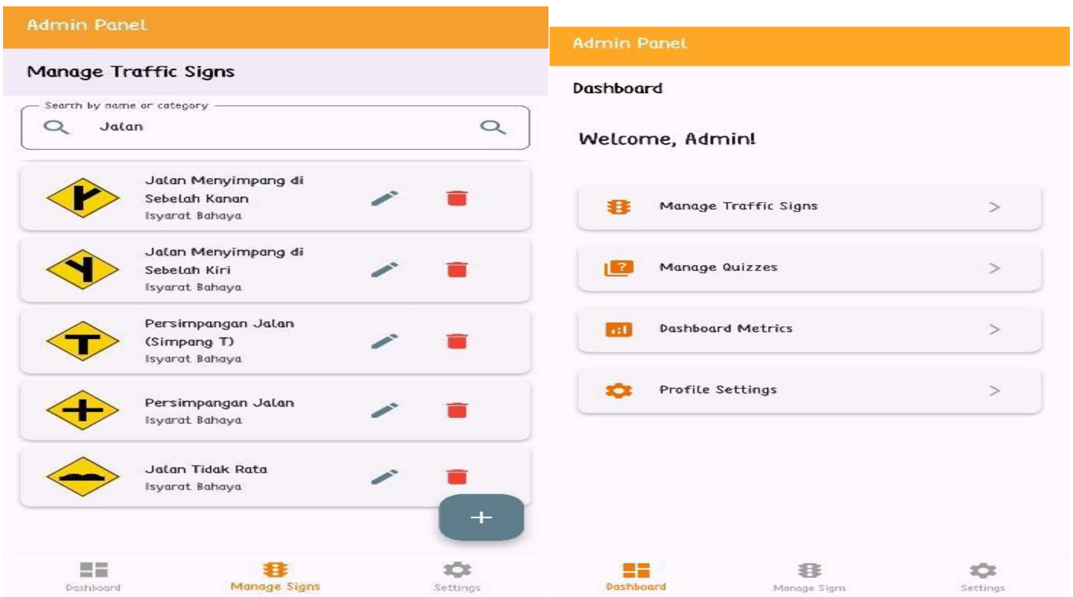

Fig. 5. Dashboard and Traffic signs management page

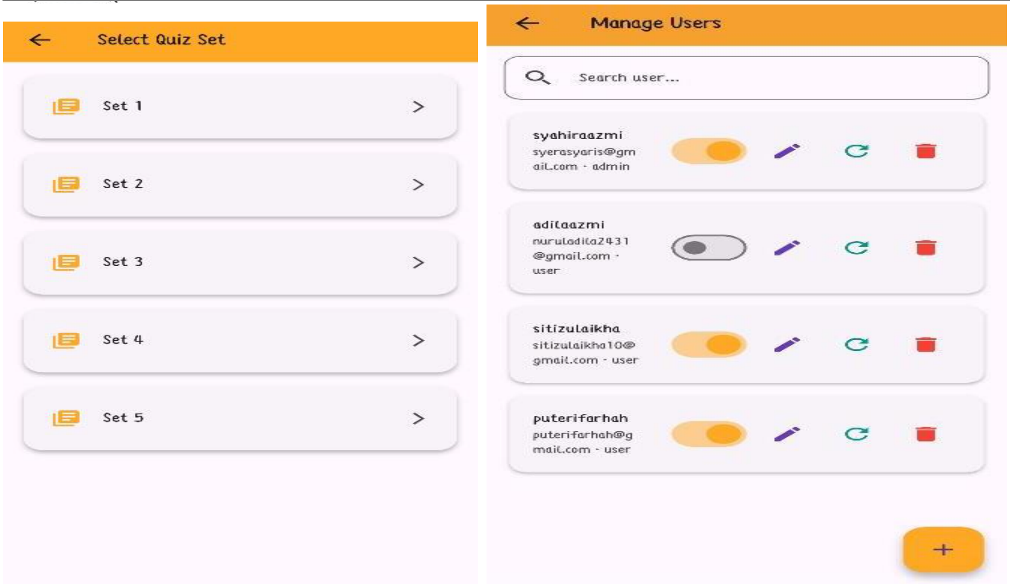

Fig. 6. Quiz and profile management page

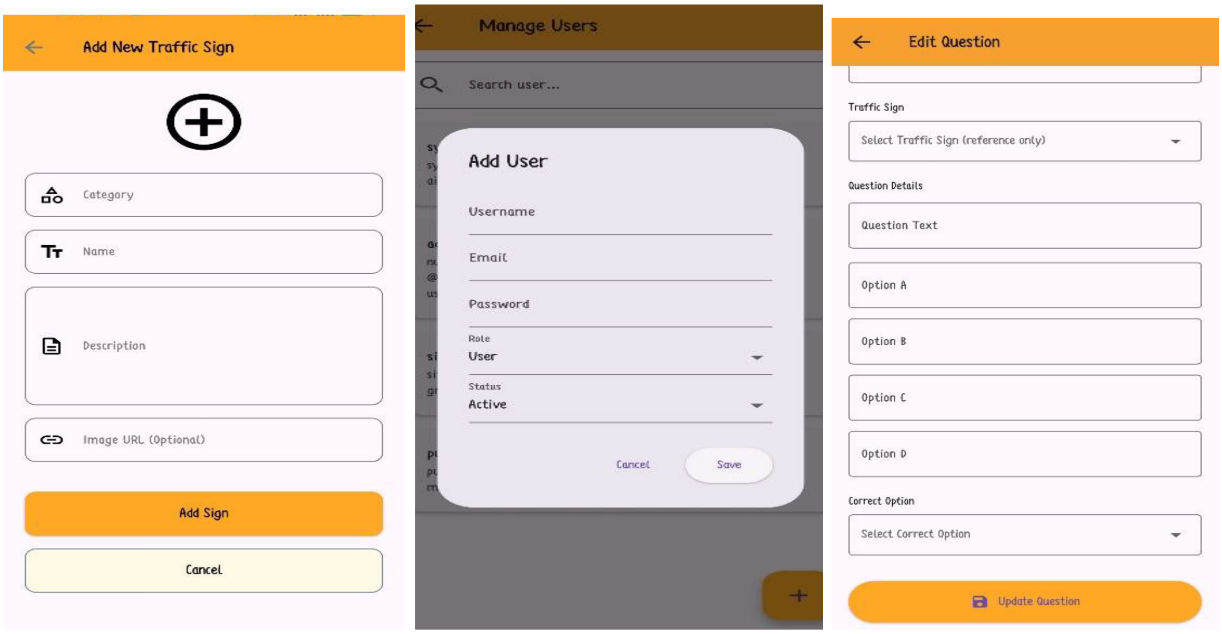

Fig. 7. Content-addition page

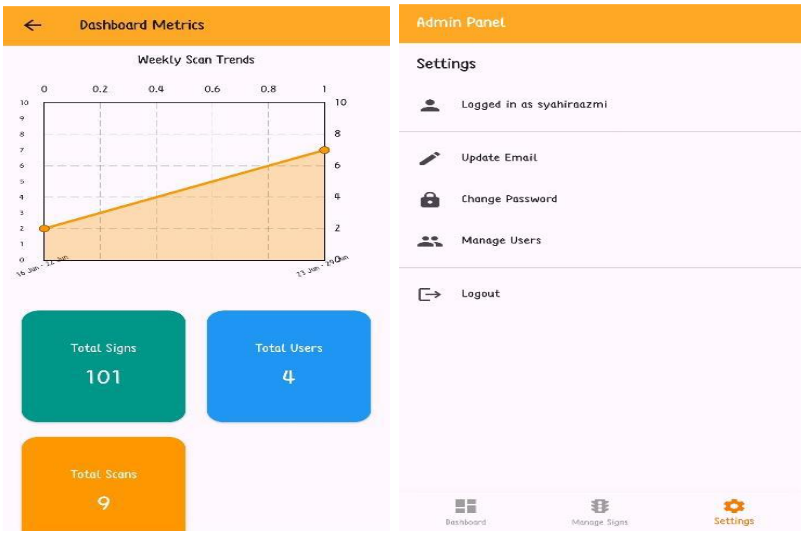

Fig. 8. Dashboard metrics and Admin settings page

B. General user Interface

For general users (students, learners, and drivers), the application offers a streamlined and educational experience. The User Menu Homepage (Figure 9) serves as the central navigation hub, providing direct access to scanning, learning, history, and quiz features. The Scan Sign page (Figure 9) supports real-time detection via the device camera, displaying results with bounding boxes and detailed pop-up information (Figure 10). The Learning Mode page (Figure 10) organizes traffic signs into browsable categories, with each sign linking to a dedicated Sign Info page (Figure 11) that displays its name, meaning, and relevant rules. User progress is tracked through the Scam History page (Figure 11), which logs past scans and supports filtering by category, while the Quiz Questions page (Figure 12) delivers interactive assessments to reinforce knowledge. The user-specific Settings page (Figure 12) allows for personal profile updates and password management.

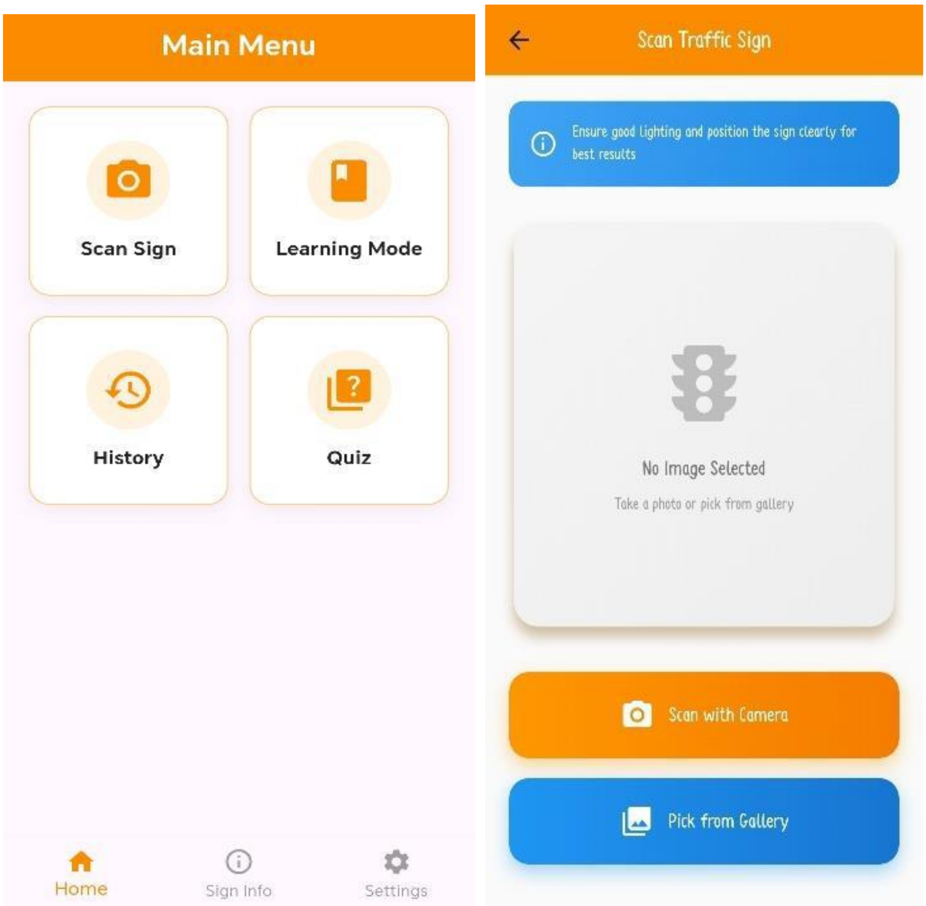

Fig. 9. User menu and Scan sign page

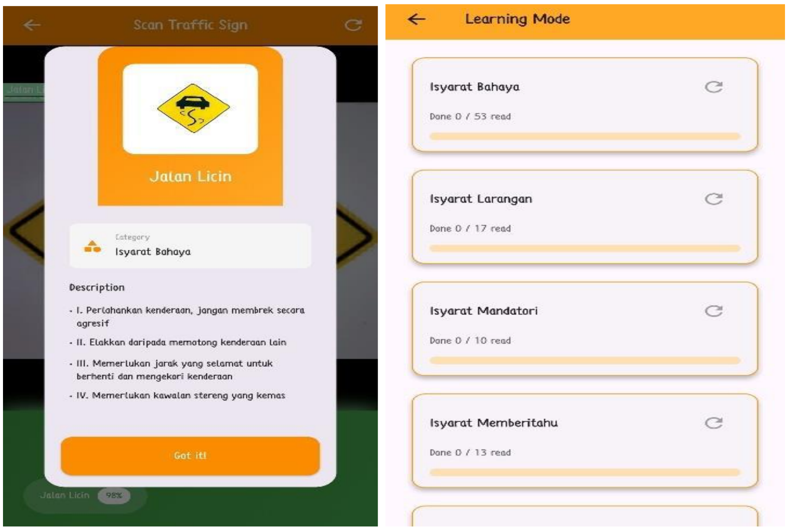

Fig. 10. Scan sign info and Learning mode page

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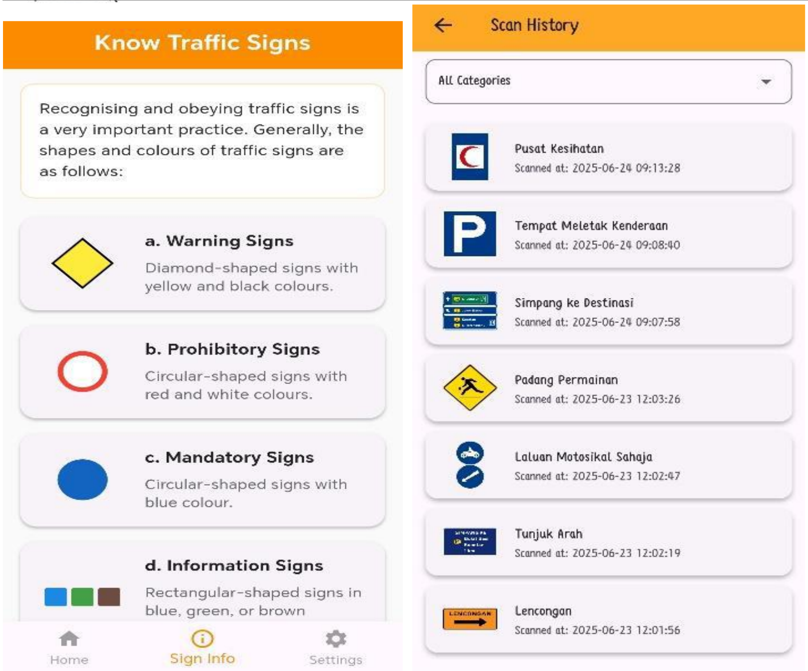

Fig. 11. Sign info and Scan history page

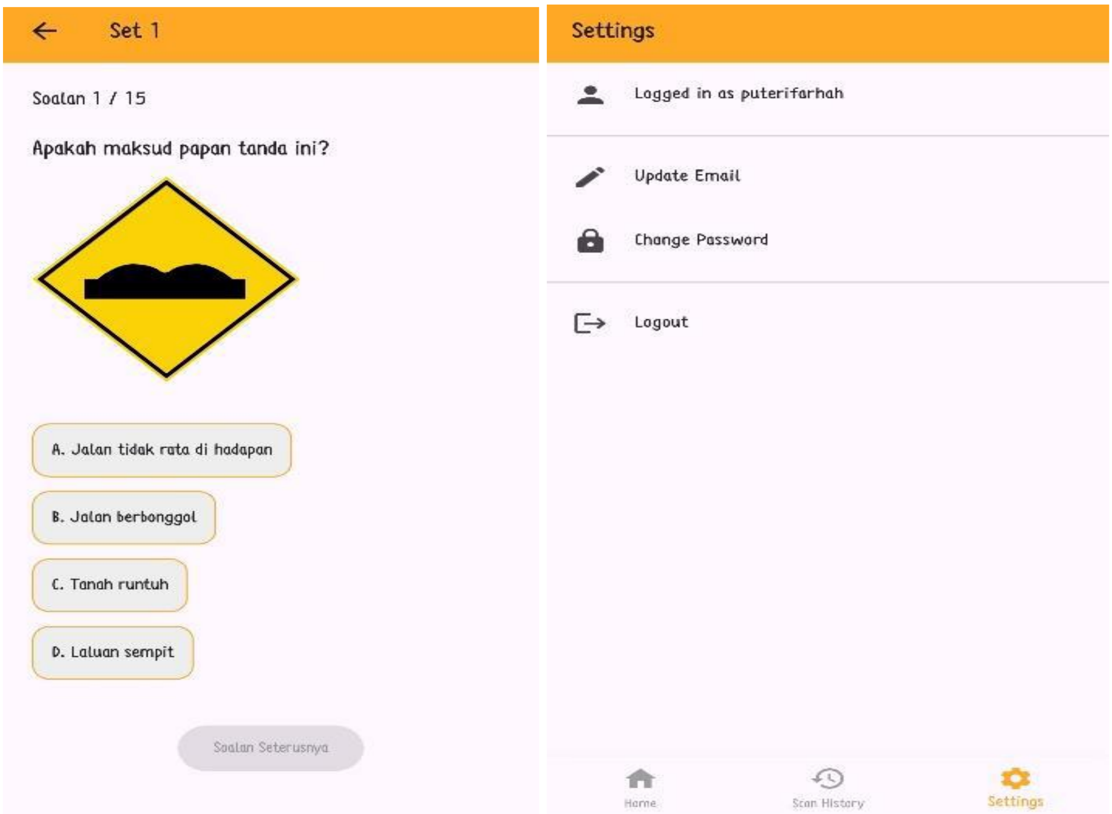

Fig. 12. Quiz questions and user setting page

C. Authentication Interfaces

The interface design consistently emphasizes clarity, accessibility, and ease of navigation. Input forms such as Login (Figure 13) and Registration (Figure 13) are designed for simplicity. The overall layout adheres to Flutter's Material Design principles, ensuring visual consistency, responsive behaviour across Android devices, and alignment with the usability requirements defined during the design phase. These results confirm that the application's front-end successfully translates the proposed system architecture into a functional, user-centred tool for traffic sign education and management.

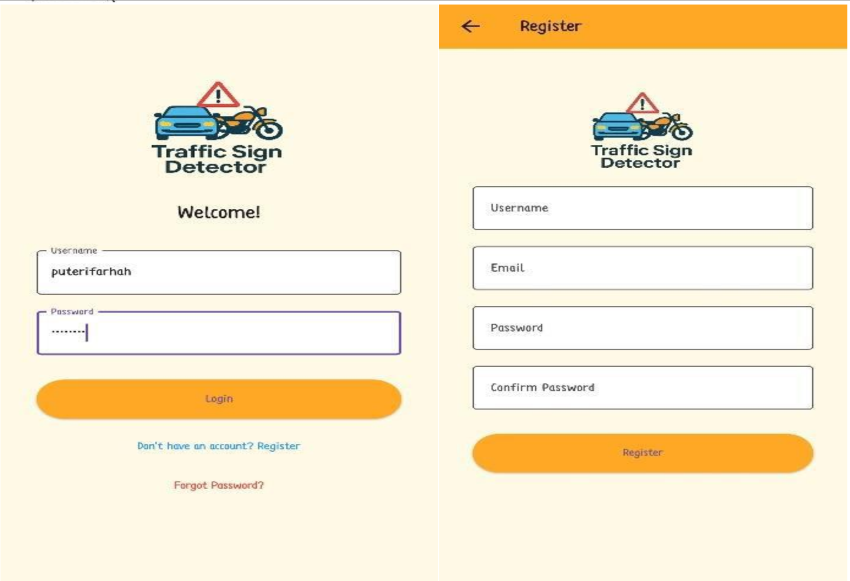

Fig. 13. Login and register page

CONCLUSION

This study presented an AI-driven mobile traffic sign recognition system designed to enhance road safety education through the integration of real-time computer vision and interactive mobile learning features. Unlike most existing traffic sign recognition systems that primarily target Advanced Driver Assistance Systems (ADAS), the proposed solution focuses on learner-oriented educational use and is tailored specifically to Malaysian traffic sign standards.

The system successfully integrates a lightweight TensorFlow Lite–based object detection model into a Flutter-based mobile application, enabling on-device recognition of traffic signs using static image inputs. Quantitative evaluation demonstrated that the optimized model achieved a detection accuracy of 92.3% with acceptable inference latency and memory footprint for deployment on mid-range Android devices. These results confirm the feasibility of deploying AI-based traffic sign recognition models on mobile platforms for educational purposes without reliance on specialized hardware or continuous internet connectivity.

In addition to technical performance, user acceptance testing indicated high levels of usability, satisfaction, and perceived learning effectiveness. The inclusion of interactive features such as learning mode, scan history, and quiz-based assessments supports contextual understanding and reinforces knowledge retention, addressing the limitations of traditional static learning approaches.

Overall, this work contributes to the advancement of road safety education by bridging the gap between traffic sign recognition research and mobile learning applications. By combining localized datasets, real-time AI-based recognition, and pedagogically informed design, the proposed system demonstrates a practical and scalable approach to enhancing traffic sign education and road safety awareness in Malaysia.

FUTURE WORK

To enhance the robustness and real-world applicability of the AI-Based Traffic Sign Detector system, several directions for future development are proposed. First, the dataset used for training the TensorFlow Lite model should be expanded and augmented to include a wider variety of environmental conditions, such as low-light, rain, partial occlusion, and varying angles. This would improve the model's accuracy and reliability in challenging real-world scenarios. Additionally, transitioning from static image detection to real-time video-based recognition would allow the system to support continuous sign detection during driving, making it more practical for in-vehicle road safety assistance.

Further optimization of the AI model through techniques such as quantization, pruning, or the adoption of more efficient neural architectures could reduce inference latency and improve performance on devices with limited computational resources. Expanding the system's accessibility features—such as adding multilingual support, voice feedback, and compatibility with screen readers—would also make the application more inclusive and user-friendly for diverse learner groups, including those with visual impairments.

Integration with emerging technologies such as augmented reality (AR) could provide an immersive learning experience, allowing users to visualize traffic signs in context within their real environment. Moreover, enabling over-the-air model updates would ensure that the detection system remains current with new traffic signs and regulatory changes without requiring manual application updates. Finally, extending platform compatibility to iOS and web-based interfaces would broaden the system's reach and usability across different devices and user preferences. These enhancements collectively hold the potential to transform the application from an educational tool into a comprehensive, adaptive, and widely deployable solution for road safety education and driver training.

ACKNOWLEDGEMENT

The authors would like to express gratitude to Fakulti Teknologi Maklumat dan Komunikasi (FTMK), Universiti Teknikal Malaysia Melaka (UTeM) for their invaluable support and resources provided throughout this research.

REFERENCES

1. Gangoso, E. P. J., Aca-ac, R. J. R., & Sarabia, P. Z. G. (2025). Real-time mobile app traffic sign recognition with YOLOv10 and CNN for driving education. The International Journal of Computational Science, Information Technology and Control Engineering, 12(2). https://doi.org/10.5121/ijcsitce.2025.12201
2. Benhamida, A., Varkonyi-Koczy, A. R., & Kozlovszky, M. (2020). Traffic Signs Recognition in a mobile-based application using TensorFlow and Transfer Learning technics. IEEE, 000537–000542. https://doi.org/10.1109/sose50414.2020.9130519
3. Loghashankar, H., & Nguyen, H. (2023). Real-Time traffic sign detection: a case study in a Santa Clara suburban neighborhood. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2310.09630
4. Vázquez-Cano, E., & Castañeda, L. F. (2022). Mobile learning and its effect on learning outcomes and critical thinking. Applied Sciences, 14(19), 9105. https://doi.org/10.3390/app14199105
5. Arinova, B., Pyatkina, D., Latysheva, V., & Stroiteleva, N. (2022). Mobile applications in education: Implementation aspects and impact on student competencies development. International Journal of Web-Based Learning and Teaching Technologies, 17(1), 1–17. https://doi.org/10.4018/IJWLTT.305805
6. Zhu, Z., Liang, D., Zhang, S., Huang, X., Li, B., & Hu, S. (2016). Traffic-sign detection and classification in the wild. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2110–2118. https://doi.org/10.1109/CVPR.2016.232
7. A. Howard et al., "Searching for MobileNetV3," 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Korea (South), 2019, pp. 1314-1324. https://doi.org/10.1109/ICCV.2019.00140
8. Naveed, Q. N., Choudhary, H., Ahmad, N., Alqahtani, J., & Qahmash, A. I. (2023). Mobile Learning in Higher Education: A Systematic Literature review. Sustainability, 15(18), 13566. https://doi.org/10.3390/su151813566
9. Shinar, D., & Vogelzang, M. (2013). Comprehension of traffic signs with symbolic versus text displays. Transportation Research Part F Traffic Psychology and Behaviour, 18, 72–82. https://doi.org/10.1016/j.trf.2012.12.012
10. Kumar, R., & Sharma, P. (2025). Leveraging interactive mobile Technologies for Enhanced learning Outcomes A Systematic review. Journal Mobile Technologies (JMS), 3(1), 1–8. https://doi.org/10.59431/jms.v3i1.540
11. Stallkamp, J., Schlipsing, M., Salmen, J., & Igel, C. (2012). Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition. Neural Networks, 32, 323–332. https://doi.org/10.1016/j.neunet.2012.02.016
12. Cireşan, D. C., Meier, U., Masci, J., & Schmidhuber, J. (2012). Multi-column deep neural network for traffic sign classification. Neural Networks, 32, 333–338. https://doi.org/10.1016/j.neunet.2012.02.023

13. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. European Conference on Computer Vision (ECCV), 21–37. https://doi.org/10.1007/978-3-319-46448-0_2
14. Maldonado-Bascón, S., Lafuente-Arroyo, S., Gil-Jiménez, P., Gómez-Moreno, H., & López-Ferreras, F. (2007). Road-sign detection and recognition based on support vector machines. IEEE Transactions on Intelligent Transportation Systems, 8(2), 264–278. https://doi.org/10.1109/TITS.2007.895311
15. Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. IEEE Access, 8, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510