
AI-BASED SMART MEDICATION IDENTIFICATION, AUTOMATED DISPENSING, TIMED REMINDER, AND MONITORING DASHBOARD SYSTEM

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ABSTRACT

Medication errors and poor adherence remain important patient-safety challenges where identification, dispensing, scheduling, and monitoring depend on manual processes. This paper presents a functional engineering prototype that integrates AI-based medication identification, automated dispensing, timed reminders, evidence capture, stock management, and remote monitoring. The system uses a Raspberry Pi 4 Model B as the central controller and an EfficientNet-B4 image-classification model trained on 4,480 OGYEIv2 images across 112 medication classes. The data were divided into 3,136 training, 672 validation, and 672 held-out test images. The reported independent test accuracy was 99.85%, corresponding to 671 correct predictions and one incorrect prediction. Stepper motors and motor drivers actuate medication compartments, infrared sensors provide dispensing feedback, and a DS3231 real-time clock supports scheduled events and audiovisual reminders. A camera evidence service, TFT interface, Flask backend, SQLite database, and Android application provide system monitoring and records. Functional testing demonstrated successful operation of the major hardware and software modules, including the corrected evidence-image serving route. The evaluation remains an engineering prototype assessment rather than clinical validation; controlled imaging conditions, limited test size, visually similar classes, absence of real-user evaluation, and the need for repeated physical dispensing tests limit conclusions about real-world safety and effectiveness. The prototype demonstrates the feasibility of an integrated medication-management platform for further development in Nigeria and other resource-constrained settings.

Keywords: Artificial Intelligence; Medication Identification; Medication Dispensing; EfficientNet-B4; Raspberry Pi; Medication Adherence

1. INTRODUCTION

1.1 Background and Problem Statement

Medication management combines identification, dosage scheduling, dispensing, administration, documentation, and monitoring. Errors at these stages can produce inappropriate medication use and preventable harm. The World Health Organization identifies medication safety as a major patient-safety priority and has promoted the Medication Without Harm initiative (World Health Organization, 2017, 2021). Managing several medicines at different times also increases the possibility of missed doses, incorrect selection, incorrect quantities, and incomplete records.

Artificial intelligence and embedded computing provide opportunities to automate selected medication-management functions while retaining clinical oversight. EfficientNet provides a scalable convolutional-neural-network architecture that balances model capacity and computational requirements (Tan & Le, 2019). Previous studies have shown the feasibility of deep-learning-based pill recognition (Al-Hussaeni et al., 2023; Ashraf et al., 2024; Heo et al., 2023), while other systems have investigated automated dispensing, adherence technologies, and monitoring dashboards (Mason et al., 2022; Nasir et al., 2023; Patel et al., 2020; Pathiraja & Wijesinghe, 2024; Wang et al., 2021, 2025).

The challenge addressed in this study is not a new classification architecture but the integration of medication image classification, scheduled dispensing, reminders, evidence capture, stock management, and mobile monitoring within one Raspberry Pi-based platform. This integrated approach is intended as an affordable engineering prototype that may be adapted for Nigerian and other resource-constrained environments.

1.2 Aim and Objectives

The aim is to design and implement an AI-based smart medication identification, automated dispensing, timed reminder, and monitoring dashboard system using artificial intelligence and embedded computing technologies.

The objectives are to:

1. Design and implement an EfficientNet-B4 medication-identification module.
2. Design and implement stepper-motor dispensing with infrared feedback.
3. Implement timed reminders using a DS3231 real-time clock and audiovisual alerts.
4. Develop monitoring functions for schedules, stock, dispensing records, and evidence.
5. Integrate the hardware and software subsystems into one prototype.
6. Test and evaluate the functionality and performance of the developed system.

1.3 Research Gap and Significance

Existing literature commonly treats pill recognition, automated dispensing, reminders, and adherence monitoring as separate problems. This work addresses the engineering integration gap by combining these functions with local data storage and a mobile interface. The principal significance is therefore system-level integration rather than a claim of clinical replacement or novel AI architecture.

2. METHODOLOGY

2.1 Dataset and Model Development

The AI component uses the OGYEIV2 dataset, which contains 4,480 images representing 112 pill classes. The dataset was captured under controlled imaging conditions using fixed scale, a homogeneous background, and two illumination arrangements designed to expose surface markings (Rádli et al., 2023, 2024).

For this experiment, 70% of the data (3,136 images) were used for training, 15% (672) for validation, and 15% (672) for held-out testing. Each class contributes 28 training images, six validation images, and six test images. Images were resized to 384×384 pixels for EfficientNet-B4; normalization and training-time augmentation were applied. The model was trained for 30 epochs with Adam, cross-entropy loss, an initial learning rate of 3×10^{-4} , batch size 16, and ReduceLROnPlateau scheduling.

Table 1: *Dataset Distribution*

Subset	Number of Images	Percentage
Training	3,136	70%
Validation	672	15%
Testing	672	15%
Total	4,480	100%

Table 2: *AI Model Training Configuration*

Parameter	Configuration
Dataset	OGYEiv2
Classes	112
Total images	4,480
Train / validation / test	3,136 / 672 / 672
Model	EfficientNet-B4
Input	384 × 384 pixels
Epochs	30
Batch size	16
Optimizer	Adam
Initial learning rate	3×10^{-4}
Loss	Cross-entropy
Scheduler	ReduceLROnPlateau

2.2 Embedded Hardware and Software

The prototype uses a Raspberry Pi 4 Model B, camera, TFT display, stepper motors, ULN2003 motor drivers, PCF8574 I/O expanders, infrared sensors, DS3231 RTC module, speaker, LED illumination, power-supply components, and a 3D-printed dispenser structure. The Raspberry Pi executes the AI model, manages schedules, controls motors and sensors, activates alarms, operates the camera, maintains the database, runs the Flask backend, and communicates with the Android application (Grinberg, 2018; Upton & Halfacree, 2016).

Medication schedules are stored in SQLite and compared with the RTC time. At a scheduled event, the corresponding compartment motor is activated and the reminder mechanism issues an audiovisual alert. Infrared feedback provides information about medication movement. The camera records evidence associated with dispensing events. The mobile interface exposes medication records, schedules, stock, logs, evidence, and settings.

RFID readers, QR-code scanners, load cells/HX711 modules, YOLOv5, ResNet-50, and PaddleOCR are not claimed as implemented components in this prototype.

2.3 Evaluation Method

The independent test set of 672 images was used for final AI evaluation. Accuracy was computed as correct predictions divided by total predictions. Functional system testing covered the backend, communication, scheduling, alarm, motor control, infrared sensing, evidence capture and display, stock functions, security, TFT interface, and integrated workflow.

3. RESULTS AND DISCUSSION

3.1 AI Test Performance

The model achieved 671 correct predictions and one incorrect prediction on the 672-image held-out set, giving an accuracy of 99.85%. The reported error involved the visually similar `dulodet_60_mg` and `dulsevia_60_mg` classes. This result indicates strong performance on the evaluated dataset but should not be interpreted as clinical-grade medication recognition.

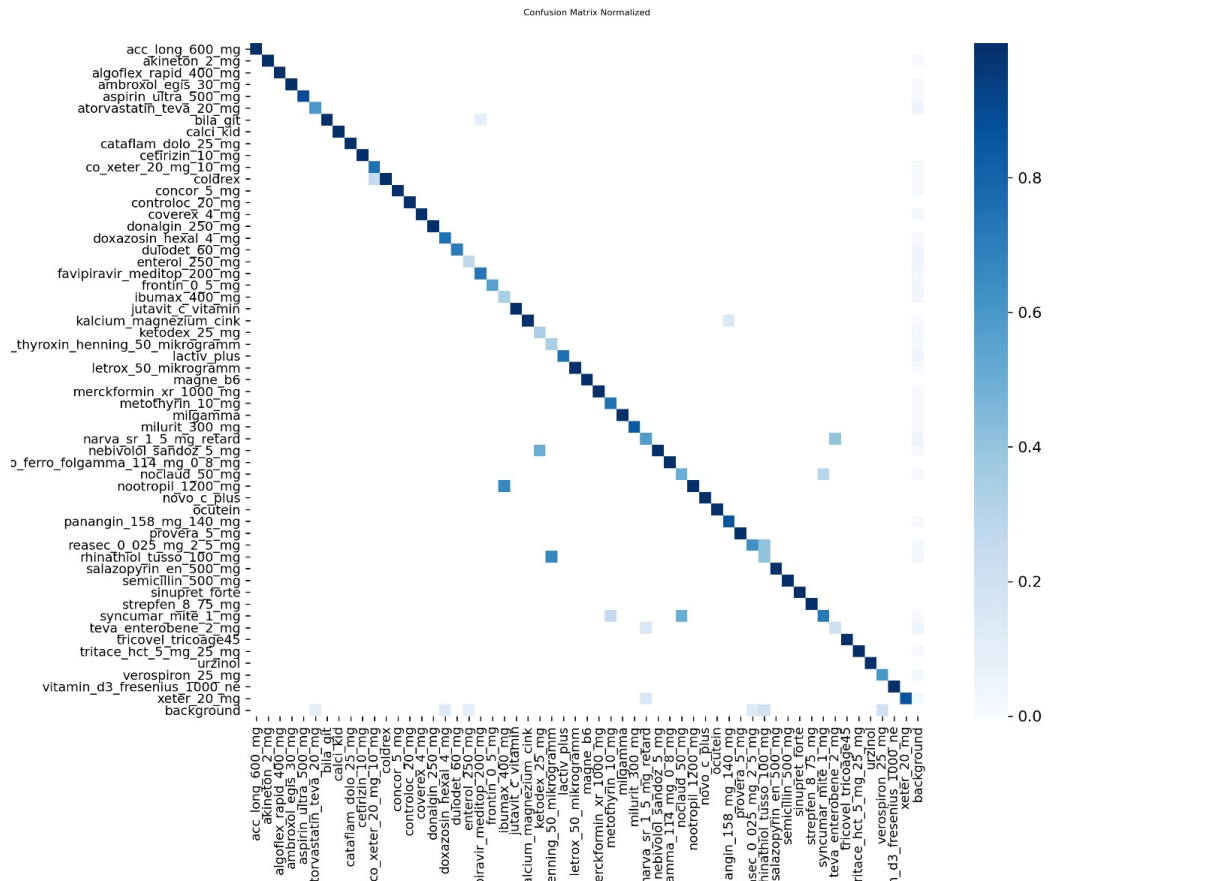


Figure 1: Normalized confusion matrix of the EfficientNet-B4 model on the held-out test set

The supplied normalized confusion matrix shows a strong concentration along the principal diagonal, consistent with high class-wise recognition on the controlled test set. The visually similar dulodet_60_mg and dulsevia_60_mg classes are the reported source of the single classification error. Because normalized matrices show relative class-wise prediction distributions, the figure is interpreted together with the aggregate result of 671/672 correct predictions.

Table 3: Held-Out Test Performance

Metric	Result
Classes	112
Training images	3,136
Validation images	672
Test images	672
Correct predictions	671
Incorrect predictions	1
Test accuracy	99.85%

3.2 System-Level Functional Results

Subsystem and integrated tests demonstrated successful operation of the Raspberry Pi backend, medication-management services, scheduling logic, stepper-motor control, infrared sensing, buzzer activation, camera evidence capture, TFT interface, stock functions, and Android communication. An evidence-image serving defect was identified during development: metadata was stored correctly, but associated images were not displayed in the mobile application. Correcting the backend image-serving route restored retrieval and display of raw and annotated evidence images.

Table 4: *Integrated System Test Results*

Test case	Observed result	Status
Backend startup	Server started successfully	Passed
Mobile connection	Connection established	Passed
Medication registration	Medication saved successfully	Passed
Schedule creation	Schedule stored successfully	Passed
Alarm detection	Due medication detected	Passed
Buzzer activation	Buzzer activated	Passed
Motor control	Motor control executed	Passed
IR sensing	Sensor interface responded	Passed
Evidence capture	Evidence generated	Passed
Evidence display	Images displayed after route correction	Passed
Stock management	Stock functions operated	Passed
Mobile security	Password protection operated	Passed
TFT interface	Interface loaded successfully	Passed
System integration	Core workflow demonstrated	Passed

3.3 Discussion

The results show that AI classification can be integrated with embedded scheduling, dispensing, reminders, evidence capture, stock management, and remote monitoring on a Raspberry Pi platform. The 99.85% result is strong for the evaluated controlled dataset, but it does not establish clinical validity, guarantee real-world identification accuracy, or demonstrate a reduction in medication errors. The integration test also illustrates that end-to-end reliability depends on interfaces between subsystems: the evidence service initially produced valid records but required a backend route correction before images were usable in the mobile interface.

4. CONTRIBUTION TO SUSTAINABLE DEVELOPMENT IN NIGERIA

The project demonstrates an approach to locally developed healthcare-support technology using widely available embedded computing and software components. A Raspberry Pi-based platform can provide a basis for investigating lower-cost medication automation for hospitals, primary-care facilities, caregivers, and home-care environments. However, sustainability requires more than hardware affordability: future deployment would require reliable power, maintainability, cybersecurity, data protection, clinical oversight, regulatory compliance, user training, and technical support. The contribution is therefore an engineering proof of concept rather than a claim of deployment readiness.

5. LIMITATIONS

1. The AI model was evaluated on the controlled OGYEIV2 dataset, so the 99.85% result may not generalize to uncontrolled lighting, backgrounds, orientations, occlusion, motion, or camera positions.
2. The independent test set contained 672 images, limiting the statistical strength of generalization claims.
3. The reported confusion between dulodet_60_mg and dulsevia_60_mg shows that visually similar medicines remain a limitation of image-based identification.
4. Functional testing confirmed operation of the prototype modules but was not a clinically powered medication-administration or dispensing-accuracy study.
5. Repeated dispensing tests across all compartments and long-duration operation remain necessary.
6. No evaluation involving real patients, caregivers, nurses, or other intended users has been reported, so usability and human-factors evidence is limited.
7. The system should not substitute for healthcare professionals or clinical medication verification.

6. FUTURE WORK

Future studies should use larger and more diverse medication datasets covering additional classes, manufacturers, orientations, illumination conditions, backgrounds, and real-world imaging.

Additional data and model-development methods should be investigated for visually similar classes, especially the reported dulodet_60_mg/dulsevia_60_mg confusion.

The dispensing mechanism should undergo repeated and long-duration tests across medication compartments, including motor reliability, sensor stability, scheduling accuracy, database operation, and power consumption.

Future versions may incorporate barcode or QR-code verification and dosage-verification sensors as complementary safeguards, together with caregiver notifications through push notifications, SMS, or email.

Usability and clinical evaluation should involve representative users and healthcare professionals under appropriate ethical and regulatory oversight.

7. CONCLUSION

This paper presented an AI-based smart medication-management prototype integrating EfficientNet-B4 image classification, Raspberry Pi control, stepper-motor dispensing, infrared sensing, DS3231 scheduling, audiovisual reminders, camera evidence capture, SQLite storage, Flask services, a TFT interface, and an Android monitoring application. The model achieved a reported 99.85% accuracy on 672 held-out images representing 112 medication classes, with 671 correct predictions and one reported misclassification involving dulodet_60_mg and dulsevia_60_mg. Functional testing demonstrated successful operation of the major software and hardware subsystems, including correction of an evidence-image serving defect. The findings establish technical feasibility but not clinical effectiveness or deployment safety. Further work should focus on broader data, repeated physical validation, real-user studies, cybersecurity, and clinical and regulatory assessment.

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