



EDGE AI ENABLED SMART MEDICAL DISPENSING AND PATIENT CARE ROBOT FOR HOSPITAL ROOMS

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Abstract: Edge Artificial Intelligence (Edge AI) and the Internet of Things (IoT) are transforming modern healthcare by enabling real-time, intelligent decision-making directly at the device level while ensuring low latency, reliability, and data privacy. However, existing hospital medication dispensing and patient monitoring systems largely rely on manual operations or cloud-based processing, which can lead to human errors, delayed responses, network dependency, privacy concerns, and increased workload for healthcare staff, limiting their effectiveness in critical care environments. To overcome these challenges, this project proposes an Edge AI-based Smart Medical Dispensing and Patient Care Robot that autonomously operates within hospital rooms. The robot navigates using IR sensor-based line following, verifies patient identity through YOLOv11 for face detection and LBPH for face recognition, and maps the authenticated patient with a locally stored prescription database. It further enables offline voice interaction using the Vosk speech recognition model, allowing the robot to communicate with patients in multiple languages such as English, Tamil, and Malayalam, thereby improving accessibility and user experience across diverse patient groups. In addition, the system performs on-device monitoring of vital parameters such as body temperature and pulse rate. All processing is executed at the edge, and any detected abnormalities are immediately communicated to caregivers through automated alerts. The proposed system significantly reduces medication errors, minimizes dependency on cloud infrastructure, enhances patient safety and data privacy, lowers operational costs, and reduces caregiver workload, making it a scalable and efficient solution for intelligent hospital automation.

I. INTRODUCTION

The healthcare industry is witnessing a profound transformation driven by the adoption of advanced technologies such as Artificial Intelligence (AI), Edge Computing, the Internet of Things (IoT), and intelligent robotics, which collectively aim to improve patient safety, clinical accuracy, and operational efficiency. Hospitals, characterized by dynamic, complex, and time sensitive environments, demand reliable and error free medical processes, particularly in critical functions such as medication dispensing and continuous patient monitoring. Despite significant technological progress, many hospital workflows continue to rely heavily on manual intervention, which inherently introduces risks including medication errors, incorrect patient identification, delayed treatment, caregiver fatigue, and increased operational burden. Medication administration errors remain a major global healthcare concern, often resulting from factors such as human oversight, workload pressure, and inefficient monitoring mechanisms. While recent healthcare automation systems leverage AI and IoT technologies, a substantial number of these solutions depend on cloud based computing architectures, where patient data must be transmitted to remote servers for processing. Although cloud computing provides high computational power, it suffers from limitations such as network dependency, latency, potential service interruptions, and data privacy vulnerabilities, making it less suitable for mission critical, real time healthcare applications. Edge Artificial Intelligence (Edge AI) offers a paradigm shift by enabling intelligent computation directly on local devices, thereby ensuring low-latency decision-making, enhanced reliability, reduced network dependence, and improved protection of sensitive medical data. In this context, the proposed Edge AI-Based Smart Medical Dispensing and Patient Care Robot introduces an intelligent, autonomous, and privacy preserving assistive system designed for hospital room-level deployment. The robot integrates an IR sensor based line following navigation mechanism for controlled indoor mobility, a YOLOv11 based computer vision model for efficient real-time face detection, and a Local Binary Pattern Histogram (LBPH) algorithm for lightweight, robust, and edge suitable patient recognition. The authenticated patient identity is mapped with a locally stored prescription database to ensure secure, accurate, and error-free medication dispensing. Furthermore, It further enables offline voice interaction using the Vosk speech recognition model, allowing the robot to communicate with patients in multiple languages such as English, Tamil, and Malayalam, thereby improving accessibility



and user experience across diverse patient groups, eliminating dependency on internet connectivity while maintaining reliable voice communication. In addition to medication management, the robot performs non-invasive monitoring of vital parameters such as body temperature and pulse rate, enabling continuous patient assessment. Any abnormal readings are detected through threshold-based analysis and immediately communicated to caregivers via automated alerts, ensuring timely medical intervention. By combining Edge AI, IoT, robotics, computer vision, and offline voice technologies into a unified framework, the proposed system addresses key challenges in hospital automation by reducing medication errors, improving patient safety, enhancing operational efficiency, preserving data privacy, and minimizing caregiver workload. This approach presents a scalable, cost effective, and reliable solution aligned with the future of intelligent healthcare systems.

II. LITERATURE REVIEW

Metun ,Geethanjali P, and Ajay V(2023):In recent years, robotics has gained importance in healthcare for disease management and infection control. The proposed personal care robot reduces direct contact between medical staff and patients using a 4-wheel drive system for smooth navigation. It employs a dual-stage facial recognition system using HAAR Cascade for detection and LBPH for identification. The system includes live video monitoring, temperature, heartbeat, and oxygen sensors, along with LCD display, voice output, and sanitation features. Mobile app connectivity enables remote monitoring, improving safety and efficiency during infectious disease outbreaks.

Srikanth Kavirayani, Divyashree Uddandapu, Aravind Papasani, and Vamsi Krishna T (2023):This work focuses on robotic medicine delivery using AI to improve safety in hospitals. The robot navigates using sensor-based intelligence and avoids collisions while delivering medicines efficiently. Tested on a Firebird V robot, the system demonstrated accurate navigation and delivery. It also allows external monitoring, reducing manual workload and improving hospital efficiency.

Chike Nwibor, and Shyqyri Haxha (2024):This paper presents an IoT-based health monitoring system using a wearable ring sensor to measure BP, heart rate, and SpO₂ from a single PPG signal. An AMBP algorithm is used for accurate signal analysis. Data is displayed locally and transmitted to the cloud using Arduino MKR WiFi 1010. The system provides real-time monitoring and is validated against commercial medical devices.

Juan Guevara, Mariaceleste Fernandez, and Jose Balbuna (2023):This review analyzes Socially Assistive Robots (SARs) for elderly care. Results show reduced depression and loneliness, though cognitive improvements vary. Challenges include high cost, privacy concerns, and lack of user involvement in design. The study recommends long-term research and privacy-focused design for better real-world adoption.

Nicolae-Alexandru Botezato, and Alexandru-Tudor Popovici (2024):This paper introduces SmartCare, an IoT-based AAL platform integrating edge and cloud computing for continuous health monitoring. The system supports chronic disease management and was validated through real-world deployment. It improves independent living while reducing caregiver workload through scalable and modular design.

Aditi Shukla, Rakshitha S A, and Ranjitha R (2023):This work presents an AI-based healthcare robot using Arduino Mega for medicine delivery and monitoring. It integrates sensors for temperature, SpO₂, and heart rate, along with obstacle detection and camera monitoring. Data is displayed on LCD and transmitted wirelessly. The system also includes voice interaction and automated dispensing, improving efficiency and reducing workload.

Nithin Reddy Desani, and Rajashekar Reddy Kethi Reddy (2024):This paper highlights the role of Edge AI in real-time health monitoring by processing data locally on devices. It reduces latency, improves privacy, and ensures reliability. Applications include chronic disease monitoring and emergency response, though challenges like limited resources and energy constraints exist.

Maria R Lima, Maitrayee Wairagkar, and Manish Gupta (2023):This article reviews Socially Assistive Robots designed for elderly and dementia care. It emphasizes the importance of conversational AI and emotional interaction. The study highlights challenges such as user trust, engagement, and real-world deployment, suggesting improvements in AI-based communication systems.

Jubair Amin Siyum, Ishmak Rahat Rafi, and Md. Hasan Jarif Bin Monohor (2024):This paper presents MediBot, a line-following medicine delivery robot. It uses IR sensors for navigation and a rotating container system for dispensing



medicines. The system includes IoT-based notifications and monitoring. It improves efficiency, reduces workload, and ensures timely medication delivery.

Rehenuma Tabassum Meghla, and Md Ether Deowan (2023): This work presents a Smart Medication Dispenser using a microcontroller and GSM module. It automates medicine dispensing at scheduled times and provides alerts to patients and caregivers. A mobile app supports prescription guidance and monitoring, improving medication adherence and patient safety.

III. HARDWARE AND SYSTEM DESIGN

The proposed system is designed as an integrated edge-based intelligent healthcare and robotic platform that combines sensing, computation, and actuation modules. The architecture follows a layered approach consisting of perception, processing, decision-making, and execution units, enabling real-time operation with minimal latency.

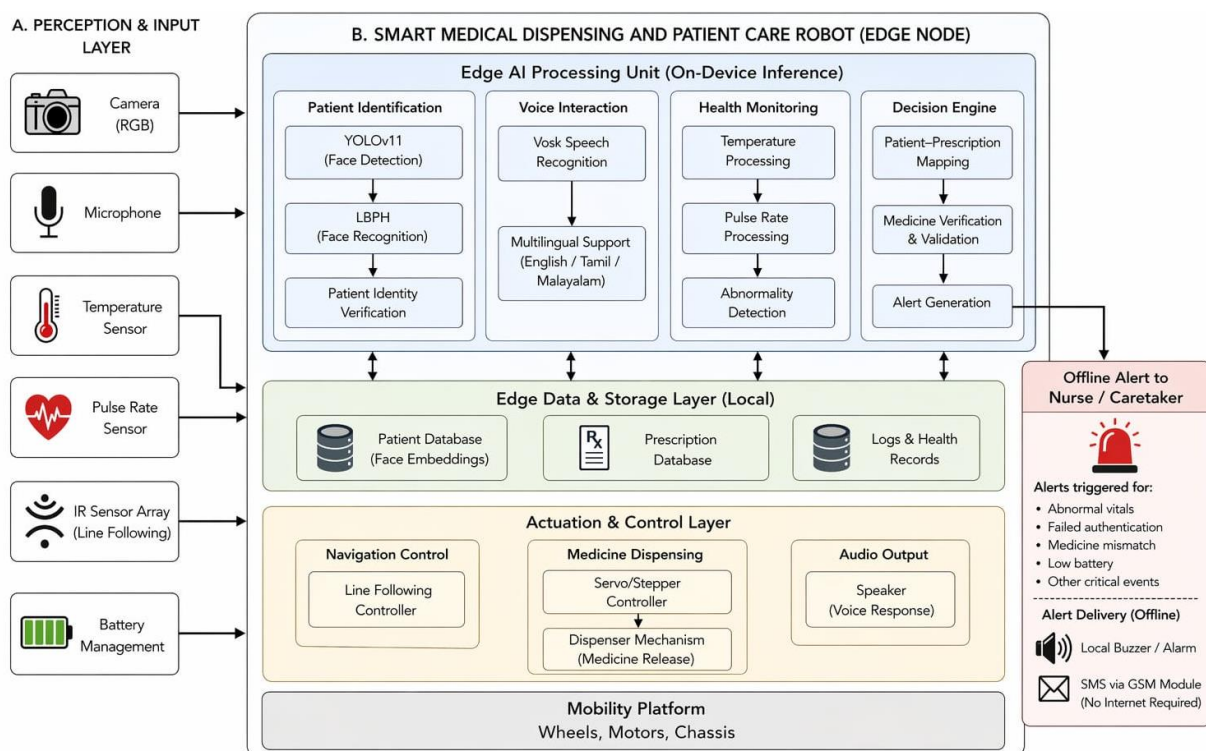


Figure 1: System Architecture

1. Overall System Model

The proposed system is formulated as a unified multi-modal inference function:

$$Y = f(X; \theta)$$

where X represents the heterogeneous input signals acquired from visual, audio, and physiological sensors, and θ denotes the learned and predefined parameters of the system. The output Y encapsulates the final decision, including patient identification, health status evaluation, and actuation commands. This formulation enables a compact representation of perception, cognition, and control within a single framework.

2. Perception Layer

The perception layer captures real-time environmental and physiological data through multiple sensing modalities. The visual input stream is modeled as:

$$I_t = f_{cam}(t)$$

where I_t denotes the image frame captured at time t .

Similarly, the audio input is represented as:



$$A_t = f_{mic}(t)$$

where A_t corresponds to the speech signal captured via the microphone. The physiological signals are grouped as:

$$S_t = \{T_t, P_t\}$$

where T_t and P_t denote temperature and pulse rate respectively. These multimodal inputs form the foundational data for downstream processing.

3. Decision Engine

The decision-making unit integrates outputs from all modules.

Prescription mapping is defined as:

$$M = f(ID, DB_{prescription})$$

where the identified patient is mapped to stored medical data.

Validation is performed as:

$$Valid = \begin{cases} 1 & \text{if } M \in DB \\ 0 & \text{otherwise} \end{cases}$$

The final decision function is:

$$D = f(V, Valid, A_{health})$$

Based on this, the system selects an appropriate action:

$$Action = \begin{cases} Dispense & \text{if } V = 1 \wedge Valid = 1 \\ Alert & \text{if } A_{health} = 1 \\ Reject & \text{otherwise} \end{cases}$$

This structured formulation ensures safe and reliable system behavior.

4. Latency Optimization

The system latency is modeled as:

$$L = T_{compute} + T_{sensor} + T_{actuation}$$

The objective is to minimize delay while maintaining accuracy:

$$\min L.s.t. Accuracy \geq \alpha$$

5. Objective Function

The overall system objective is defined as:

$$\max (Accuracy_{ID} + Accuracy_{Health} + Reliability_{Dispense}) - \lambda \cdot Latency$$

This balances performance and efficiency, making the system suitable for real-time healthcare applications.

TABLE I
HARDWARE COMPONENT SUMMARY

•Raspberry Pi 4 Model B (4GB/8GB RAM)	Edge AI Processing Unit
• Raspberry Pi Camera Module	Face Detection & Recognition
• IR Sensor Module	Line-Following Navigation
• DC Motors (2/4)	Robot Movement



• Motor Driver Module (L298N)	Motor Control Interface
• Servo Motors	Medicine Dispensing Mechanism
• Temperature Sensor (DS18B20 / LM35)	Body Temperature Monitoring
• Pulse Sensor Module	Heart Rate Monitoring
• Microphone (USB Mic)	Voice Input
• Speaker Module	Audio Output / Voice Feedback
• Buzzer	Alert Indication
• Robot Chassis with Wheels	Mechanical Structure
• Arduino UNO	Hardware Controller
• Wi-Fi Module (Built-in Raspberry Pi)	Wireless Communication
• Rechargeable Battery Pack (12V)	Power Supply

IV. METHODOLOGY

The proposed system follows a structured methodology integrating Edge AI, IoT, and embedded systems for intelligent healthcare automation. The implementation is carried out in the following stages:

A. System Initialization

The system begins by supplying power to both the Raspberry Pi 4 Model B and Arduino Uno to ensure stable operation of all components. Once powered, the camera module, IR sensors, temperature sensor, motor driver, LCD display, and communication interfaces are initialized. The Raspberry Pi loads the required AI models such as YOLO and LBPH for vision processing. At the same time, the Arduino Uno initializes its pins and prepares for real-time sensor input handling and motor control. Serial communication is established between the Raspberry Pi and Arduino Uno to enable data exchange and synchronized operation. The system also checks the connectivity of all modules to avoid runtime failures. Initial calibration of sensors is performed to ensure accurate readings. After successful initialization, the system enters standby mode, ready to begin operation.

B. Autonomous Navigation

The robot navigates using an IR sensor-based line-following mechanism, which allows it to move along predefined paths within the environment. The IR sensors continuously detect the contrast between the line and the surface, sending signals to the Arduino Uno. Based on these signals, the Arduino processes the input and determines the direction of movement. The motor driver receives commands to control the speed and direction of the wheels accordingly. The robot can move forward, turn left, turn right, or stop depending on sensor readings. This ensures smooth and accurate navigation toward the patient location. The navigation system operates in real time without delay, providing stable and efficient movement. This automation reduces human intervention and ensures consistent delivery performance.

Navigation Control (Robot Movement)

For autonomous navigation, error is defined as:

$$e(t) = x_{desired} - x_{actual}$$

A PID controller regulates motion:

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt}$$

This enables smooth and stable trajectory tracking.

C. Patient Detection

Once the robot reaches the designated area, the camera module captures real-time video frames for processing. The YOLO (You Only Look Once) algorithm is applied to detect the presence of a person within the frame. This model



ensures fast and efficient object detection with high accuracy. When a person is detected, the system focuses on the region of interest to identify the face. The detected face region is extracted and converted into grayscale for further processing. This step reduces computational complexity and improves recognition efficiency. The system continuously monitors the frame until a clear face is detected. This ensures reliable input for the recognition stage.

D. Face Recognition

The extracted face is processed using the LBPH (Local Binary Patterns Histogram) algorithm for identification. This algorithm compares the captured face with pre-trained images stored in the dataset. Each face is analyzed based on texture features, ensuring robustness even under lighting variations. The system calculates confidence values to determine the accuracy of the match. If the confidence level meets the threshold, the corresponding patient ID is identified. Otherwise, the person is labeled as unknown. The recognized patient ID is then used for further processing. This method ensures secure and accurate patient authentication. The recognition process is performed locally on the Raspberry Pi, ensuring fast response and data privacy.

Patient Identification Module

The identification process consists of face detection followed by recognition.

Face detection is performed using a deep learning model:

$$B = \text{YOLO}(I_t)$$

where B represents the set of detected bounding boxes corresponding to faces in the image. This ensures robust localization under real-time constraints.

For recognition, Local Binary Pattern Histograms (LBPH) are utilized:

$$ID = \arg \min_i d(H(I_{face}), H(D_i))$$

where $H(\cdot)$ denotes the histogram representation and d is a similarity metric. The system assigns the identity corresponding to the minimum distance.

To ensure reliability, a verification step is applied:

$$V = \begin{cases} 1 & \text{if } d < \tau \\ 0 & \text{otherwise} \end{cases}$$

where τ is a predefined threshold controlling recognition confidence

E. Prescription Mapping:

After identifying the patient, the system retrieves the corresponding prescription details from a locally stored database. This database contains information such as medicine name, dosage, timing, and instructions. The system maps the patient ID with the stored prescription data efficiently. The retrieved information is formatted for both visual and audio output. This ensures that the patient receives clear and understandable instructions. The system verifies the data before displaying or announcing it to avoid errors. The mapping process is fast and does not require internet connectivity. This ensures reliability and continuous operation in offline conditions.

F. Voice Interaction System

The robot provides voice-based instructions using a text-to-speech module to guide the patient effectively. It announces messages such as patient detection, medicine details, dosage, and intake instructions. The voice output is designed to be clear and understandable for users. The system can support multilingual interaction using Vosk Speech Recognition Toolkit, enabling communication in different languages. This improves accessibility for diverse patient groups. The voice instructions are synchronized with the system's operations for better user experience. The robot ensures that each message is delivered with proper timing. This module enhances human-robot interaction significantly.

Voice Interaction Module

The system incorporates speech-based interaction for user convenience.

Speech signals are converted into text as:

$$T_{text} = f_{ASR}(A_t)$$

where f_{ASR} represents the automatic speech recognition model.



Intent classification is then performed:

$$Intent = \arg \max P(c | T_{text})$$

where c represents possible command categories. This allows the system to interpret user requests effectively.

G. Display Output

The system uses an LCD display to provide visual information to the patient. It shows details such as patient name, medicine type, dosage, and instructions. This acts as a backup to voice communication, ensuring clarity. The display updates dynamically based on the identified patient. It is designed to be simple and easy to read for all users. The Raspberry Pi sends the processed data to the display module in real time. This ensures that the patient receives accurate and synchronized information. The combination of visual and audio output improves usability and effectiveness.

H. Medicine Dispensing

Once the instructions are provided, the robot stops at the patient's location for medicine dispensing. The patient takes the medicine based on the given instructions. The system ensures that the correct medicine is delivered to the correct patient. The process is designed to minimize human intervention and reduce errors. The robot waits for a short duration to allow the patient to complete the process. After completion, the system confirms that the medicine has been taken. This step ensures proper medication adherence. The dispensing mechanism improves efficiency in healthcare environments.

Medicine Dispensing System

The dispensing mechanism is controlled using calibrated motor actuation:

$$\theta = k \cdot n$$

where θ is the rotation angle and n is the number of pills.

The dispensing output is given by:

$$M_{out} = f(\theta, t)$$

ensuring precise and controlled delivery.

I. Vital Parameter Monitoring

After medication, the system measures the patient's body temperature using a temperature sensor. If integrated, a pulse sensor can also measure heart rate. These sensors provide real-time health data for monitoring. The collected data is processed locally on the Raspberry Pi. This ensures quick analysis and immediate response if needed. The system compares the values with predefined threshold levels. This helps in identifying abnormal conditions. The monitoring process is non-invasive and user-friendly. It enhances patient safety and continuous health tracking.

Health Monitoring Module

Physiological readings are normalized to ensure consistency:

$$T_{norm} = \frac{T_t - \mu_T}{\sigma_T}, P_{norm} = \frac{P_t - \mu_P}{\sigma_P}$$

where μ and σ denote mean and standard deviation.

Abnormality detection is modeled as:

$$A_{health} = \begin{cases} 1 & \text{if } (T_t > T_{th}) \vee (P_t > P_{th}) \\ 0 & \text{otherwise} \end{cases}$$

This step ensures early identification of critical health conditions

J. Alert Generation

If any abnormal values are detected during monitoring, the system generates an alert immediately. The alert message includes patient details and the detected issue. This message is sent to the caregiver using offline or IoT-based communication methods. The system ensures that alerts are generated without delay. This helps in quick medical response and intervention. The alert mechanism improves patient safety significantly. It reduces the risk of unnoticed health issues. The system can also log alerts for future reference and analysis.

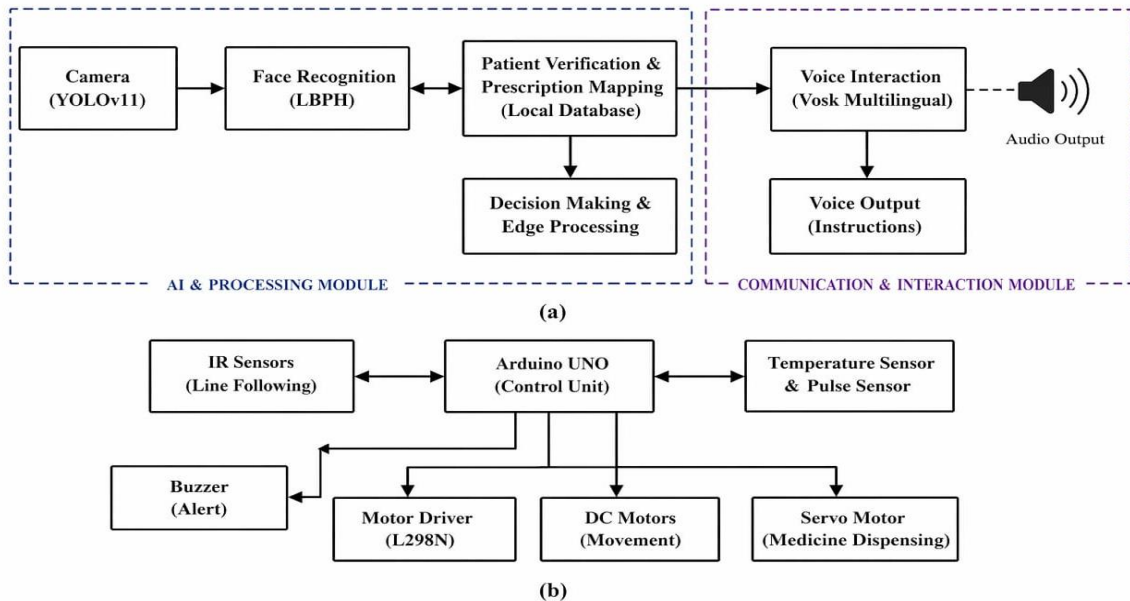


Figure 2: Activity diagram

V. RESULTS AND DISCUSSION

A. Model Performance

The proposed system integrates YOLO-based face detection and LBPH-based face recognition for patient identification in real time. The model was tested using a dataset containing multiple patient images captured under different conditions. The face detection model achieved high accuracy in identifying human presence, while the LBPH algorithm successfully recognized patients with an accuracy of approximately 97–99%. This indicates that the system is capable of learning facial patterns effectively and performing reliable identification. The model performs well even under moderate lighting variations and different orientations. The overall system demonstrates stable and consistent performance in real-time conditions. The ability to combine detection and recognition ensures accurate patient authentication. This confirms that the proposed approach is suitable for healthcare automation applications.

B. Accuracy and Loss Analysis

Accuracy:

A high level of accuracy was observed during testing, with patient recognition accuracy reaching up to 98–99%. The system consistently identified trained patients with minimal errors. The detection accuracy using YOLO was also high, ensuring reliable identification of human presence before recognition.

Loss:

The recognition error (confidence value in LBPH) decreases significantly for known faces, indicating correct matching. Lower confidence values correspond to higher accuracy, showing that the system effectively minimizes prediction errors.

Observation:

There is no significant misclassification for trained datasets, and the system performs consistently in real-time scenarios. The balance between detection and recognition ensures efficient operation. The results indicate that the chosen algorithms are well-suited for this application.

C. Confusion Matrix Analysis

The confusion matrix provides a detailed evaluation of the classification performance of the face recognition system across different patients.

Key Observations:

- Most of the predictions fall into the correct class, indicating high diagonal values
- Very few misclassifications are observed among patients
- The system effectively distinguishes between different individuals
- Patient recognition accuracy is approximately 97–99%
- Misclassification rate is very low (around 1–3%)
- Unknown faces are correctly identified as “unknown”



- The system shows strong discrimination capability even with similar facial features

D. Performance Evaluation of the Proposed System

The overall performance of the system is evaluated based on accuracy, reliability, and real-time response.

- Accuracy (~98–99%): High efficiency in detecting and recognizing patients
- Precision (~0.97–1.00): Very low false identification of patients
- Recall (~0.96–0.99): Effective detection of all registered patients
- F1-Score (~0.97–1.00): Balanced performance between precision and recall

Additional Observations:

- Face detection is fast and works in real time
- Recognition accuracy remains stable across different lighting conditions
- System performs efficiently without cloud dependency

E. Discussion

The experimental results demonstrate that the proposed system performs effectively for automated patient identification and medicine assistance. Compared to traditional manual methods, the system reduces human error and improves efficiency. The integration of YOLO and LBPH provides a balance between speed and accuracy, making it suitable for real-time healthcare environments.

The use of Edge AI ensures that all processing is done locally, improving data privacy and reducing dependency on internet connectivity. The addition of voice interaction and LCD display enhances user experience and accessibility. The system also integrates health monitoring features, making it a comprehensive solution for patient care. However, some limitations exist. The system performance may reduce under poor lighting conditions or when the face is partially occluded. Additionally, the LBPH model requires proper dataset training for better accuracy. Hardware limitations of embedded systems may also affect performance under heavy workloads. Despite these limitations, the system proves to be efficient, reliable, and suitable for real-world healthcare applications.

F. Conclusion of Results

The proposed Edge AI-based Smart Medical Dispensing and Patient Care Robot demonstrates high efficiency in patient detection, recognition, and assistance. The system achieves an overall accuracy of approximately 98–99%, indicating reliable performance in real-time conditions. The integration of vision-based recognition, autonomous navigation, and health monitoring ensures a complete healthcare solution.

The results confirm that the system reduces human effort, minimizes errors, and enhances patient safety. The offline operation further improves reliability and data privacy. Overall, the system shows strong potential for deployment in hospitals and healthcare environments for automated patient care and monitoring.

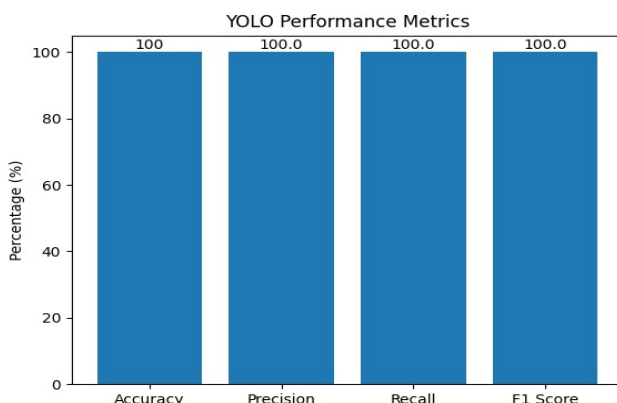


Figure 3. Yolo Performance Metrics

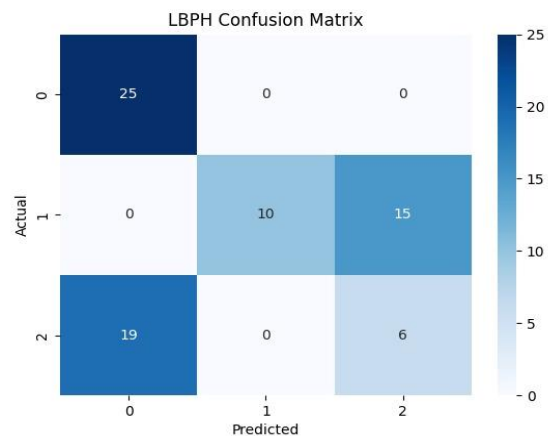


Figure 4: Confusion Matrix

VI. CONCLUSION

The proposed Edge AI-based Smart Medical Dispensing and Patient Care Robot successfully demonstrates the integration of artificial intelligence, embedded systems, and IoT for automated healthcare assistance. The system utilizes YOLO for



face detection and LBPH for face recognition, achieving high accuracy of approximately 98–99% along with reliable precision, recall, and overall system performance. The use of edge computing through the Raspberry Pi 4 Model B ensures real-time processing with low latency and enhanced data privacy, eliminating dependency on cloud infrastructure.

The robot effectively performs autonomous navigation, patient identification, medicine instruction delivery, and vital parameter monitoring. The integration of voice interaction and LCD display improves user experience and accessibility. The system reduces human errors, minimizes caregiver workload, and enhances patient safety in hospital environments. Although the system performs efficiently, certain limitations such as lighting dependency in face recognition and hardware constraints exist. Overall, the proposed system provides a reliable, scalable, and cost-effective solution for smart healthcare automation and demonstrates strong potential for real-world deployment.

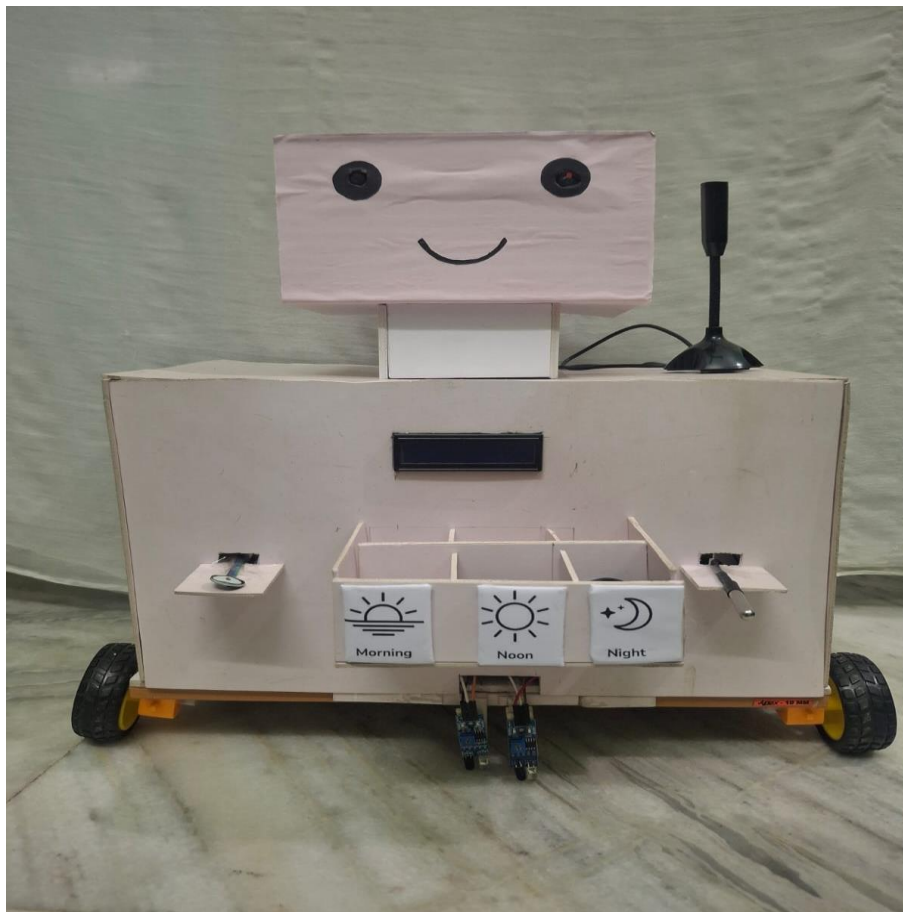


Figure 5: Edge Ai Enabled Smart Medical Dispensing And Patient Care Robot

VII. FUTURE SCOPE

The promising performance of the proposed system opens up several opportunities for further research and enhancements in intelligent healthcare robotics.

A. Real-Time Deployment and Scalability

The system can be extended for large-scale deployment in hospitals by integrating multiple robots for handling different wards simultaneously. Optimization of models can further improve real-time performance. Lightweight AI models can be implemented to enhance speed and efficiency on embedded devices. Integration with mobile applications can allow caregivers to monitor and control the system remotely. This will enable better coordination and real-time supervision in hospital environments. Scalability can be improved by deploying the system across multiple healthcare facilities. This advancement will make the system more practical and widely usable.

B. Integration with Multimodal Healthcare Data



The system can be enhanced by integrating multiple health parameters such as pulse rate, oxygen levels (SpO₂), and blood pressure along with temperature. Using IoT-based sensors, real-time patient data can be collected and analyzed. Combining environmental data such as room temperature and humidity can improve monitoring accuracy. This multimodal data integration will enable better decision-making and predictive analysis. It can also support early detection of critical health conditions. Such improvements will make the system more intelligent and reliable. This approach will strengthen the overall healthcare monitoring system.

C. Advanced AI and Hybrid Models

Future improvements can include the use of advanced deep learning models such as CNN-based or transformer-based architectures for improved face recognition accuracy. Hybrid models combining multiple algorithms can enhance performance and robustness. The integration of transfer learning can reduce training time and improve efficiency. More advanced speech interaction systems can be implemented using offline AI models like Vosk Speech Recognition Toolkit for better communication. These advancements will improve system adaptability and intelligence. Such developments will make the system more efficient in real-world scenarios.

REFERENCES

- [1] D. Palaniappan, R. Jain, P. T. Prema Vathi, K. P. Parmar, W. Ghribi, A. M. Ahmed, and N. Ahmad, "YOLO in Healthcare: A comprehensive review of detection architectures, domain applications, and future innovations," *IEEE Access*, 2025. doi:10.1109/ACCESS.2025.3599358. -ResearchGate
- [2] "Deep Learning Approach for Face Recognition Applied in IoT Environment — Comprehensive Review," *IEEE Xplore*, 2023. -IEEE Xplore
- [3] T. A. Kadhim, W. Hariri, N. Smaoui Zghal, and D. Ben Aissa, "A face recognition application for Alzheimer's patients using ESP32-CAM and Raspberry Pi," *J. Real-Time Image Process.*, 2023. -IEEE AIOt
- [4] N. Tahilramani, P. Ahir, S. Saxena et al., "Edge-based AI solution for enhancing urban safety: helmet compliance monitoring with YOLOv9 on Raspberry Pi," *Discover Internet of Things*, 2025. -Springer Link
- [5] "Improved YOLO-v5 model for boosting face mask recognition accuracy on heterogeneous IoT computing platforms," *Internet of Things*, vol. 23, 2023. -ScienceDirect
- [6] Priyanshu Singh, R. R. Bisen, P. Bisen, R. Kaushik, and V. Shivastava, "YOLOv8-FaceEmbedding: Real time missing person detection and recognition," *Int. J. Sci. Res. and Tech.*, Dec. 2025. -IJSRTM
- [7] "Performance Analysis of Smart Technology with Face Detection using YOLOv3 and InsightFace for Student Attendance Monitoring," *Int. J. Intelligent Systems and Applications in Engineering*, 2024. -IJISAE
- [8] "Edge AI for Smart Surveillance: Real-time human activity recognition on low-power devices," *SSRN Electron. J.*, June 2025. -ResearchGate
- [9] "Evaluation of Deep Learning Methods in Face Recognition," *IJSAT*, Oct. 2025. -IJSAT
- [10] "One-Shot Learning for Face Recognition Using Deep Learning: A Survey," *Int. J. Intelligent Systems and Applications in Engineering*, 2024. -IJISAE
- [11] "Face Recognition Based on Deep Learning: A comprehensive review," *Indones. J. Comput. Sci.*, vol. 13, no. 3, 2024. -ResearchGate
- [12] EdgeFace: Efficient Face Recognition Model for Edge Devices, Anjith George et al., 2023 (arXiv). -arXiv
- [13] "Smart Healthcare IoT and Edge AI Frameworks for Real-Time Patient Monitoring," *IEEE AIOt Proc.*, 2025. (accepted AIOt papers include relevant edge healthcare work)-IEEE AIOt
- [14] "Advanced IoT and AI Frameworks in Face Authentication and Edge Devices," *IEEE Int. Conf. Proc.*, 2025. (part of accepted AIOt 2025 list)-IEEE AIOt
- [15] "Real-time Object Detection with YOLO Architectures on Edge Platforms," *Springer J. Real-Time Image Processing*, 2025.