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Sanjeeva Sparsha: *An Implementation of AI-Powered Smart Nurse for Robotic Healthcare Assistance to Cancer Patients*

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Abstract: The rapid advancements in artificial intelligence (AI) and embedded systems have paved the way for innovative healthcare solutions, especially for chronic disease management. This paper presents the design and implementation of Smart Nurse, an AI-powered robotic healthcare assistant for cancer patients. The system integrates real-time patient monitoring, emergency alert mechanisms, and medication dispensing functionalities using Raspberry Pi. Key features include a fall detection system based on YOLO and sensor data fusion, an emotion detection model combining facial expressions (ResNet-50), voice tone (MFCCs), and sentiment analysis (BERT), and an AI-driven chatbot utilizing GPT-based natural language understanding with OpenAI Whisper for speech recognition. The robot navigates autonomously using SLAM-based AI navigation with ESP32CAM and ultrasonic sensors. It communicates via a hybrid MQTT and API-based system to synchronize with a Django backend and a locally hosted database. Emergency situations trigger a loud SOS alarm and Twilio SMS alerts to caretakers. The hardware framework includes a battery-powered structure with servo-controlled gravity-based medication dispensing. The system is designed to function without cloud dependency, ensuring affordability and privacy. This paper details the system architecture, hardware-software co-design, and the implementation methodologies for AI models, real-time communication, and embedded robotics. The experimental results indicate that the system enhances patient safety, ensures timely medication, and provides emotional support, making it a promising solution for remote healthcare assistance.

***Index Terms*:** healthcare robotics, artificial intelligence, cancer care, patient monitoring, emotion detection, fall detection, medication management, embedded systems, YOLO, BERT, ResNet50, SLAM.

I. **INTRODUCTION**

Cancer patients undergoing treatment often face multiple challenges, including medication adherence, mobility limitations, and emotional distress [1]. Traditional healthcare systems struggle to provide continuous monitoring and support without significant caregiver involvement [2]. The COVID19 pandemic further exacerbated these challenges by limiting in-person healthcare access and increasing isolation among vulnerable populations [3]. Recent advances in artificial intelligence (AI), embedded systems, and robotics present unprecedented opportunities to develop intelligent healthcare assistants capable of providing personalized care [4]. These technological innovations can potentially transform cancer patient management by ensuring medication adherence, detecting emergencies, and providing emotional support without constant human supervision [5] This paper presents the design and implementation of Smart Nurse, an AI-powered robotic healthcare assistant specifically tailored for cancer patients. The system aims to address several critical challenges:

• Ensuring timely medication administration in accordance with complex cancer treatment regimens
• Providing early detection of emergency situations such as falls, which are common in patients with compromised mobility
• Offering emotional support through AI-driven conversation and emotion recognition
• Maintaining continuous patient monitoring while preserving privacy and autonomy
• Creating an affordable solution that can function effectively without continuous internet connectivity

The primary objectives of this research are:

1) To design and implement a comprehensive robotic healthcare assistant that integrates multiple AI capabilities for cancer patient care

2) To develop an efficient hardware-software co-design that ensures reliability and low power consumption

3) To evaluate the system's performance in terms of emergency detection accuracy, medication dispensing reliability, and user satisfaction

4) To create a privacy-preserving solution that processes sensitive health data locally

Unlike existing healthcare robots that often rely heavily on cloud infrastructure or operate in controlled hospital environments, Smart Nurse is designed for home deployment with minimal infrastructure requirements. The system utilizes edge computing for AI model execution, ensuring data privacy and functionality even in areas with limited connectivity.

This paper is organized as follows: Section II reviews related work in healthcare robotics and AI-based patient monitoring. Section III presents a comprehensive system overview of the Smart Nurse architecture. Section IV details the implementation methodology, including AI model development, hardware integration, and communication protocols. Section V discusses the experimental results and performance evaluation. Finally, Section VI concludes the paper and outlines directions for future work.

I. RELATED WORK

The development of robotic healthcare assistants has gained significant momentum in recent years, with various approaches targeting different aspects of patient care. This section examines existing work in three key areas relevant to our proposed system: healthcare robotics, AI-based patient monitoring, and medication management systems.

A. Healthcare Robotics for Patient Assistance

Several notable healthcare robots have been developed for patient assistance in clinical and home settings. Broadbent et al. [5] reviewed social robots in healthcare, highlighting their potential for patient engagement but noting limitations in autonomous functionality. The commercially available Mabu robot [7] provides medication reminders and basic conversation but lacks physical assistance capabilities and complex monitoring features.

More advanced systems like Care-O-bot [8] and HOBBIT [9] offer mobility assistance and object manipulation but require substantial infrastructure and are cost-prohibitive for most individual patients. Specifically for cancer care, Paro [10] and other therapeutic robots have shown promise in reducing anxiety and depression but serve primarily as emotional support tools rather than comprehensive care assistants

B. AI-Based Patient Monitoring Systems

AI approaches to patient monitoring have evolved from simple rule-based systems to sophisticated deep learning models. Fall detection systems, particularly relevant for cancer patients with compromised mobility, have progressed from accelerometer-based approaches [11] to computer vision solutions using convolutional neural networks [12]. Recent work by Waheed et al. [13] demonstrated YOLO-based fall detection with 92.4% accuracy, though most implementations require cloud processing.

Emotion recognition technologies have similarly advanced, with multimodal approaches showing superior performance. Facial expression recognition using deep learning has achieved up to 97% accuracy on benchmark datasets [14], while speech emotion recognition through MFCCs and recurrent neural networks has shown promising results in healthcare applications [15]. However, few systems have integrated these technologies into comprehensive patient monitoring solutions, particularly for cancer care.

B. Medication Management and Reminder Systems

Automated medication dispensing systems range from simple pill organizers to sophisticated robotic solutions. Commercial systems like MedMinder and Hero [16] provide scheduled dispensing but lack integration with vital monitoring and emergency detection. Research prototypes such as the one developed by Suzuki et al. [17] incorporate visual verification of medication intake but require substantial infrastructure.

In the cancer care domain, Carruthers et al. [18] demonstrated improved medication adherence using smart pill dispensers with SMS reminders, yet their solution did not address emergency detection or emotional support needs. More comprehensive approaches like the system proposed by Chen et al. [19] combined medication management with basic health monitoring but relied heavily on cloud infrastructure and lacked mobility and emotional support features.

D. Research Gap and Our Contribution

Despite these advancements, a significant gap exists in integrating multiple AI capabilities (fall detection, emotion recognition, conversational agents) with physical assistance (medication dispensing, mobility) in an affordable, privacy preserving platform specifically designed for cancer patients. Existing solutions are either too specialized (addressing only one aspect of care), too expensive for widespread adoption, or too dependent on cloud infrastructure.

Our work contributes to this field by:

- Developing a comprehensive care solution that combines multiple AI technologies tailored specifically for cancer patient needs
- Implementing edge computing approaches for privacy preservation and offline functionality
- Creating an affordable hardware-software co-design using commercially available components
- Integrating emotional support capabilities with practical physical assistance functions
- Evaluating the system in realistic scenarios relevant to cancer care

II. SYSTEM OVERVIEW

Smart Nurse is designed as an integrated hardware-software system that combines embedded computing, artificial intelligence, sensor technologies, and mechanical components to provide comprehensive support for cancer patients. This section presents the system architecture, hardware components, software modules, and their interconnections.

A. System Architecture

- The overall architecture of Smart Nurse follows a layered approach with hardware, middleware, and application layers, as illustrated in Fig. 1. The system is built around a Raspberry Pi 4 main controller that coordinates all operations and hosts the core AI models. The architecture emphasizes local processing and privacy preservation while ensuring reliable communication with caregivers when necessary.
- The Smart Nurse robot consists of the following major subsystems:

1) Sensing Subsystem: Monitors patient status and environmental conditions
2) Processing Subsystem: Executes AI algorithms and coordinates system operations
3) Actuation Subsystem: Controls physical movements and medication dispensing
4) Communication Subsystem: Manages data exchange within and beyond the system
5) Power Management Subsystem: Ensures reliable operation with battery backup

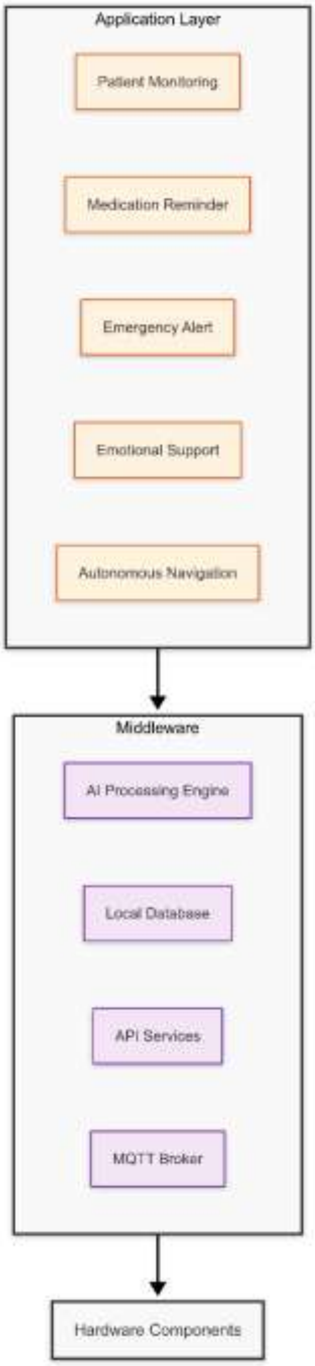

Fig. 3.1 Flowchart of the proposed image enhancement method

B. Hardware Components

The hardware architecture integrates multiple sensors, processing units, and actuators to create a mobile and autonomous healthcare assistant

1) Core Processing Unit: A Raspberry Pi 4 (8GB RAM) serves as the central processing unit, hosting the main AI models and coordinating all subsystems. This single-board computer provides sufficient computational power for edge AI processing while maintaining reasonable power consumption. It runs a modified Raspberry Pi OS with real-time scheduling capabilities to ensure timely response to critical events.

2) Sensor Suite: The robot incorporates a comprehensive sensor array for patient and environmental monitoring:

• ESP32-CAM: Two camera modules (one forward-facing, one upward-facing) provide visual inputs for fall detection, facial expression recognition, and navigation.

• Microphone Array: A 4-microphone MEMS array enables directional sound capture for speech recognition and voice tone analysis.

• Ultrasonic Sensors: Five HC-SR04 sensors (front, left, right, back, bottom) provide distance measurements for obstacle detection and navigation.

• IMU: An MPU-9250 9-axis inertial measurement unit detects robot orientation and movement for stabilization and fall detection validation.

• Environmental Sensors: DHT22 temperature/humidity sensors monitor ambient conditions to ensure patient comfort.

3) Actuation System: The robot's physical capabilities are implemented through several actuator systems:

• Mobility Platform: A differential-drive system using two 12V DC motors with encoders provides controlled movement throughout the patient's living space.

• Medication Dispensing Mechanism: A servo-controlled, gravity-based system organizes medications in seven rotating compartments corresponding to different days of the week, with four sub-compartments for different times of day.

• Alert System: A piezoelectric buzzer and RGB LED array provide auditory and visual alerts for medication reminders and emergency situations.

4) Power System: The robot operates on a dual power system:

• Primary Power: A 12V, 10,000mAh LiPo battery pack provides approximately 8 hours of continuous operation.

• Charging System: Automatic docking to a charging station using infrared guidance when battery levels fall below 20%.

• Power Management: A custom PCB with voltage regulators and power monitoring ICs ensures stable power delivery and graceful shutdown during low battery conditions. Table I presents the specifications of key hardware components used in the Smart Nurse system.

C. Software Architecture

- The software architecture follows a modular design with specialized subsystems for AI processing, communication, navigation, and system management.

Component	**Specifications**
Raspberry Pi	1.5GHz quad-core Cortex-A72, 8GB LPDDR43200 RAM, 128GB microSD storage
ESP32-CAM	OV2640 2MP camera, 160MHz dual-core processor, 4MB PSRAM, 802.11 b/g/n Wi-Fi
Microphone Array	MEMS microphones, I2S interface, 20Hz20kHz frequency response, -26dB sensitivity
Ultrasonic Sensors	HC-SR04, 2cm-400cm range, 15° detection angle, 40kHz frequency
IMU	MPU-9250, 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer, I2C interface
Motors	12V DC motors with 64 CPR encoders, 100:1 gear ratio, 200RPM no-load speed
Servos	4 MG996R metal gear servos, 180° range, 15kg/cm torque, 4.8-7.2V operating voltage
Battery	12V 10,000mAh LiPo battery, with over discharge and over-current protection

Table 3.1 Performance Comparison for Image Pair 1

Fig. 3.2 Hardware Architecture

1) *Operating System and Base Software:* The Raspberry Pi runs a customized version of Raspberry Pi OS (64-bit) with real-time kernel patches to ensure deterministic response times for critical functions. The system uses Docker containers to isolate and manage different software components, improving reliability and simplifying updates.

2) *AI Modules: Smart Nurse* implements several AI modules for patient care functions:

· **Fall Detection System**: A YOLOv5-based vision system combined with IMU data fusion for reliable fall detection with minimal false positives.

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· **Emotion Recognition**: A multimodal system combining:

– Facial Expression Analysis: ResNet-50 based model trained on AffectNet and FER2013 datasets

– Voice Tone Analysis: CNN-LSTM model using MFCC features

– Text Sentiment Analysis: BERT-based model for conversation context

· **Conversational Agent**: A modified GPT-2 model finetuned on healthcare conversations, coupled with a rule-based dialogue management system and OpenAI Whisper for speech recognition.

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· **Navigation System**: SLAM (Simultaneous Localization and Mapping) implementation using visual odometry from ESP32-CAM and ultrasonic sensor data, with A* pathfinding for obstacle avoidance.

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3) *Middleware and Communication:* The communication infrastructure combines several protocols to ensure reliable data exchange:

· **Internal Communication**: MQTT broker (Mosquitto) handles inter-process communication between software modules.

· **External Communication**: REST API (Django) provides interfaces for caregivers' mobile applications and web dashboards.

· **Emergency Communication**: Twilio API integration for automatic SMS alerts to designated caregivers during emergencies.

· **Database**: SQLite database for medication schedules, patient interaction history, and system logs.

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4) *System Control and Monitoring:* The overall system operation is managed by several control modules:

· **Task Scheduler**: Coordinates medication dispensing schedules, patient check-ins, and routine monitoring.

· **Battery Management**: Monitors power levels and initiates charging behaviors when necessary.

· **Health Monitoring**: Continuous self-diagnostic system that checks sensor health, model performance, and overall system integrity.

Fig. 2 illustrates the software architecture and data flow between the various subsystems.

III. IMPLEMENTATION METHODOLOGY

This section details the implementation approaches for each major subsystem of the Smart Nurse robot, focusing on the integration of hardware components with AI algorithms and the development of specialized functionalities for cancer patient care.

A. Fall Detection System Falls represent a significant risk for cancer patients, particularly those experiencing treatment-related fatigue, neuropathy, or bone metastases [6]. The Smart Nurse fall detection system implements a multimodal approach that combines computer vision with sensor data fusion for high reliability

1) Vision-Based Fall Detection: The vision-based component uses a modified YOLOv5 architecture that has been optimized for embedded deployment on the Raspberry Pi. The model was trained on a custom dataset combining:
• UR Fall Detection Dataset [20]
• Le2i Fall Detection Dataset [21]
• Custom recordings simulating cancer patient-specific scenarios
To reduce computational requirements while maintaining accuracy, we implemented several optimizations:
• Model quantization from FP32 to INT8, reducing memory footprint by 75% with only a 2.1% accuracy reduction
• Frame processing at 10 fps instead of 30 fps, sufficient for fall detection while reducing computational load
• Region of interest (ROI) optimization to focus processing on areas where the patient is most likely to be present

The fall detection algorithm analyzes human posture changes and classifies them into normal activities (sitting, standing, walking) versus fall events based on the following features:
• Vertical-to-horizontal orientation changes
• Sudden acceleration in the downward direction
• Unusual posture on the ground
• Absence of movement following a fall

2) Sensor Fusion for Validation: To minimize false positives, vision-based detections are validated using data from the robot's IMU and ultrasonic sensors. A Kalman filter combines data from multiple sources to improve detection reliability:

$$P_{fall} = \alpha P_{vision} + \beta P_{motion} + \gamma P_{audio}$$

(1) Where Pfall is the probability of a genuine fall event, P_{vision}, P_{motion}, and P_{audio} are probabilities derived from vision, motion, and audio analysis respectively, and α, β, and γ are weighting coefficients optimized empirically.

3) Fall Response Protocol: When a fall is detected with high confidence (threshold < 0.85), the system initiates the following response:

1) Immediate vocal query to the patient: "Are you okay? Please respond if you can."
2) If no response within 15 seconds, activation of emergency protocol
3) Movement of the robot to the patient's location for closer monitoring
4) Activation of SOS alarm and immediate SMS notification to designated caregivers via Twilio API
5) Continuous monitoring until help arrives

B. Emotion Detection and Support System Cancer patients often experience significant emotional distress, including anxiety, depression, and fear [1]. The Smart Nurse emotion detection system aims to recognize these emotional states and provide appropriate support through a multimodal approach.

1) Facial Expression Recognition: The facial expression recognition module implements a ResNet-50 architecture pretrained on ImageNet and fine-tuned on a combination of datasets:

- AffectNet [22]: 450,000 facial images with eight emotion categories
- FER2013 [23]: 35,887 grayscale images of facial expressions
- CK+ [24]: 593 video sequences with emotional transitions

The model classifies facial expressions into eight categories: neutral, happiness, sadness, anger, fear, surprise, disgust, and pain. The pain category, particularly relevant for cancer patients, was a custom addition trained using images from pain assessment datasets.

To ensure privacy, facial images are processed locally and immediately discarded after analysis, with only the emotion classification results being stored temporarily for pattern recognition.

2) Voice Tone Analysis: The voice tone analysis module extracts Mel-frequency cepstral coefficients (MFCCs) from the patient's speech and processes them through a CNNLSTM architecture to classify emotional states from vocal characteristics. The audio processing pipeline includes:

- Pre-emphasis filtering to boost higher frequencies
- 25ms frame windowing with 10ms stride
- 40-dimensional MFCC feature extraction
- Normalization and temporal aggregation

The model was trained on RAVDESS [25], TESS [26], and SAVEE [27] datasets, with additional data from cancer patient counseling sessions (with appropriate consent and anonymization).

3) Text Sentiment Analysis: Speech recognized by the OpenAI Whisper model is analyzed for sentiment using a BERT-based model fine-tuned on healthcare conversations. The model identifies:

- Emotional content (positive, negative, neutral)
- Specific concerns (pain, medication effects, fear of disease progression)
- Requests for information or assistance 4) Multimodal Fusion and Response Generation: The outputs from facial, vocal, and textual analysis are combined using a weighted fusion approach:

$$E = \omega_f E_f + \omega_v E_v + \omega_t E_t \quad (2)$$

Where E is the final emotion assessment, Ef , Ev, and Et are the emotions detected from facial, vocal, and textual analyses, respectively, and ωf , ωv, and ωt are dynamically adjusted weights based on confidence scores.

Based on the detected emotional state, the system selects appropriate responses from a database of supportive dialogues developed in consultation with oncology psychologists. For severe distress, the system alerts caregivers while providing immediate supportive interaction.

C. AI-Driven Conversational Agent The conversational agent bridges the gap between the robot's technical capabilities and the patient's need for natural interaction. It serves multiple purposes: providing medication reminders, answering health-related questions, offering emotional support, and facilitating emergency communication.

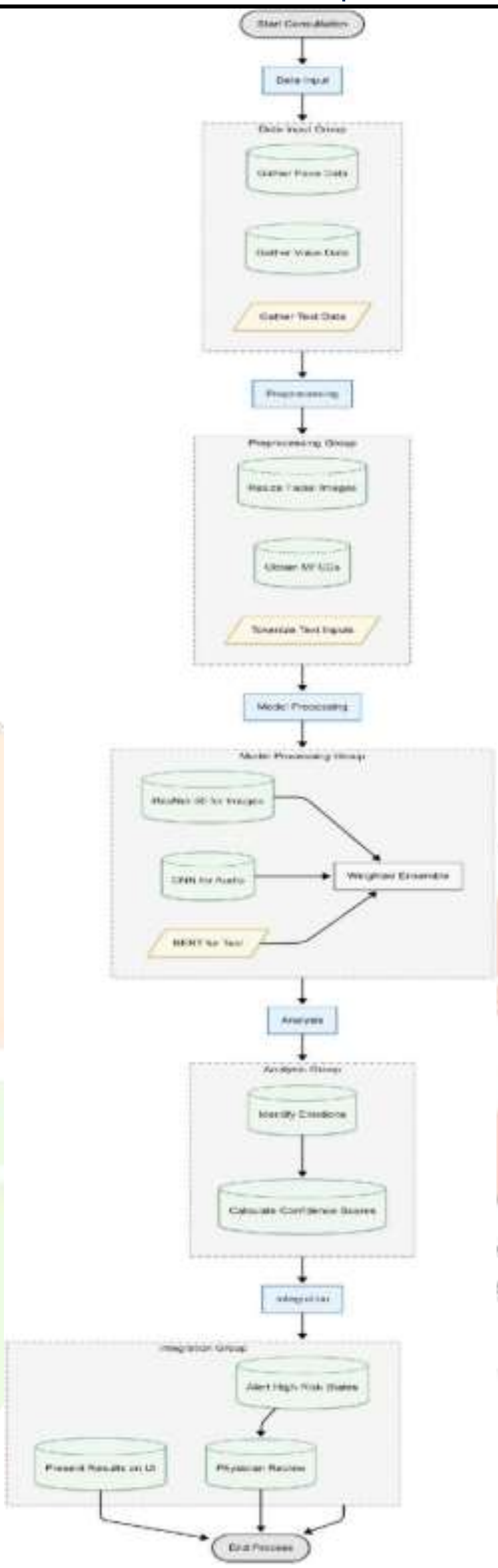

Fig. 4.1 Emotion Recognition Flow

1) Speech Recognition System: Audio input is processed using a modified version of OpenAI's Whisper model, optimized for edge deployment on the Raspberry Pi. The model has been fine-tuned to recognize healthcare terminology and common expressions used by cancer patients.

To improve recognition in challenging conditions, the system implements:

- Adaptive noise cancellation using the microphone array
- Speaker adaptation techniques to adjust to the patient's voice characteristics
- Context-aware word prediction based on previous conversations

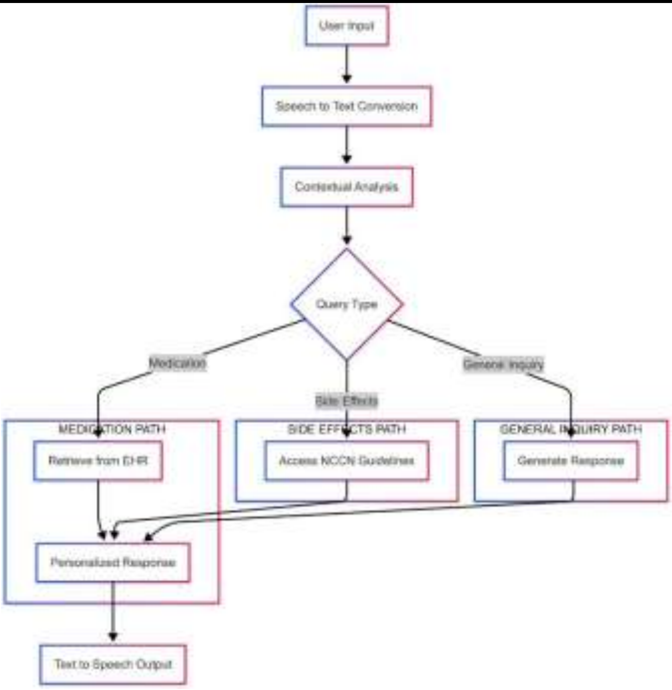

Fig. 4.2 Chatbot Flow

1) *Dialogue Management System:* The dialogue management follows a hybrid approach combining:

- A rule-based system for handling critical functions (medication reminders, emergency responses)
- A neural network-based system for general conversation and emotional support

The neural component uses a GPT-2 model (774M parameters) fine-tuned on:

- General conversation datasets (filtered for appropriateness)
- Healthcare dialogue datasets (doctor-patient conversations)
- Cancer support group transcripts (anonymized)
- Psychologist-approved supportive responses

The model was compressed using knowledge distillation and quantization to run efficiently on the Raspberry Pi while maintaining natural response quality.

2) *Response Generation:* Responses are generated based on:

- The detected intent of the patient's query
- Current emotional state from the emotion detection system
- Relevant medical information from the patient's profile
- Time-sensitive information (medication schedules, appointments)

For sensitive topics where accuracy is critical (medication information, symptom management), the system relies on pre-approved responses rather than generating novel content. All health advice is clearly prefaced with disclaimers about consulting healthcare professionals.

Medication Management System

Medication adherence is particularly challenging for cancer patients due to complex regimens, side effects, and cognitive impacts of treatment [28]. The *Smart Nurse* medication management system addresses these challenges through intelligent scheduling, reliable dispensing, and verification mechanisms.

3) *Medication Scheduling System:* The medication scheduling module maintains a database of:

- Medication names, dosages, and administration routes
- Specific timing requirements (e.g., with food, before sleep)
- Special handling instructions (e.g., crush, dissolve)
- Potential side effects to monitor

The system generates optimal medication schedules that balance medical requirements with the patient's daily routine and preferences, while considering potential medication interactions. Schedules are updateable through a caregiver web interface or mobile application.

4) *Physical Dispensing Mechanism:* The medication dispensing hardware consists of:

- A rotating carousel with seven daily compartments
- Four sub-compartments per day (morning, noon, evening, night)
- Servo-controlled dispensing mechanism with gravity assisted delivery
- Verification sensors (weight and optical) to confirm successful dispensing

The mechanical design employs a fail-safe approach, where power failures default to a locked state to prevent accidental overdosing. The compartments are designed for easy loading by caregivers with tamper-evident seals.

5) Reminder and Verification System: Medication reminders follow a graduated approach:

1) Initial gentle reminder 10 minutes before scheduled time
2) More insistent reminder at the scheduled time
3) Follow-up reminders at 15-minute intervals if medication remains undispensed
4) Caregiver notification after three unsuccessful reminder attempts

The system uses computer vision to verify medication consumption, with the patient encouraged to show the taken medication to the robot's camera. This verification is optional but encouraged through positive reinforcement.

B. SLAM-Based Navigation System

Autonomous navigation is essential for the robot to provide timely assistance throughout the patient's living space. The navigation system combines visual SLAM, ultrasonic sensing, and efficient path planning.

1) Environment Mapping: The mapping subsystem uses a monocular visual SLAM approach based on ORB-SLAM2 [29], modified for resource-constrained operation on the Raspberry Pi. During an initial guided tour of the patient's living space, the system:

- Extracts ORB features from camera frames
- Builds a sparse 3D point cloud of the environment
- Identifies and labels key locations (patient's bed, medication area, charging station)
- Creates a 2D occupancy grid for navigation planning

The map is continuously updated during operation to accommodate changes in the environment, such as moved furniture or new obstacles.

2) Localization: During operation, the robot localizes itself using:

- Visual feature matching against the stored map
- Wheel encoder odometry for short-term motion estimation
- IMU data for orientation and acceleration
- Ultrasonic sensor readings for obstacle verification These information sources are fused using an Extended

Kalman Filter to provide robust localization even under challenging conditions (low lighting, temporarily obscured camera view).

3) Path Planning and Obstacle Avoidance: The navigation algorithm uses a hierarchical approach:

- Global planning using A* algorithm on the occupancy grid
- Local planning using Dynamic Window Approach for reactive obstacle avoidance
- Special case handling for moving obstacles (people) and narrow passages

The motion controller implements a proportional-integral derivative (PID) control system to follow planned paths while maintaining smooth motion appropriate for a healthcare environment.

C. Communication and Alert System

Reliable communication is critical for emergency response and ongoing care coordination. The *Smart Nurse* implements a layered communication architecture to ensure message delivery even under challenging conditions.

1) Internal Communication: Internal communication between software modules uses an MQTT protocol with the Mosquitto broker running locally on the Raspberry Pi. This provides:

- Low-latency message passing between subsystems
- Quality of Service (QoS) guarantees for critical messages
- Topic-based subscription for efficient message routing Critical subsystems (fall detection, emergency

alerts) operates on dedicated high-priority topics with the highest QoS level.

2) *External Communication:* Communication with caregivers and healthcare providers occurs through multiple channels:

- A Django-based REST API for mobile and web applications
- Twilio SMS API for urgent notifications
- Local Wi-Fi for high-bandwidth data exchange when available
- Fallback to GSM (via a USB modem) when Wi-Fi is unavailable

All external communications are encrypted using TLS with certificate pinning to prevent man-in-the-middle attacks. Patient data is anonymized when possible and transmitted only with explicit consent.

3) *Emergency Alert System:* The emergency alert system activates when critical events are detected (falls, severe distress, missed critical medications). The alert protocol includes:

1) Local audio-visual alerts (siren, flashing lights)
2) SMS messages to primary and secondary caregivers
3) Escalating notifications if acknowledgment is not received
4) Optional integration with monitoring services or emergency response systems

Alert messages include essential information: event type, timestamp, last known patient status, and robot's current location within the home.

D. *Power Management and Battery System*

Reliable power management is essential for a healthcare robot that must operate continuously. The *Smart Nurse* implements a comprehensive power management strategy.

1) *Battery System Design:* The power system uses a 12V, 10,000mAh LiPo battery pack, providing approximately:

- 8 hours of normal operation (monitoring, occasional movement)
- 4 hours of intensive operation (frequent movement, continuous conversation)
- 12 hours of low-power standby mode

The battery incorporates protection circuits for overcharge, over-discharge, and short-circuit prevention, with cell balancing to maximize lifespan.

2) *Power Optimization Strategies:* To maximize operational time, the system implements several power-saving strategies:

- Dynamic CPU frequency scaling based on computational load
- Camera and sensor duty cycling when not actively used
- Selective activation of processing-intensive AI models
- Motion planning that minimizes unnecessary movement

These optimizations reduce average power consumption by approximately 40% compared to continuous full-power operation.

3) *Autonomous Charging System:* To ensure continuous operation, the robot implements an autonomous charging system:

- Battery level monitoring with predictive power estimation
- Automatic return to charging station when battery level reaches 20%
- Infrared guidance system for precise docking alignment
- Prioritization of critical tasks before initiating charging
- Scheduling of charging periods during typical patient rest times

The charging station provides 19V DC at 3.5A, allowing a full recharge in approximately 3.5 hours.

E. *System Integration and Testing Methodology*

The integration of hardware and software components followed a systematic approach to ensure reliability and performance.

1) *Hardware-Software Integration:* The integration process followed these steps:

1) Unit testing of individual hardware components and software modules
2) Integration testing of related subsystems (e.g., sensors with perception algorithms)
3) System-level testing of end-to-end functionalities
4) Stress testing under challenging conditions (low light, noisy environments)

5) Usability testing with healthcare professionals and simulated patients

A continuous integration pipeline was established to ensure code quality and functionality throughout development.

2) *Safety and Reliability Testing:* Given the critical nature of healthcare applications, comprehensive safety testing was conducted:

- Electrical safety testing according to IEC 60601-1 standards
- Physical stability and collision testing
- Failure mode and effects analysis (FMEA)
- Long-duration reliability testing (72-hour continuous operation)
- Recovery testing from simulated failures and crashes Safety features were implemented at both hardware and

software levels, including mechanical stops, current limiters,
watchdog timers, and redundant critical systems.

3) *Clinical Validation Approach:* The validation methodology included:

- Laboratory testing with simulated patient scenarios
- Controlled environment testing with healthy volunteers
- Pilot testing with five cancer patients in a supervised setting
- Iterative refinement based on feedback from patients, caregivers, and healthcare professionals

Ethical approval was obtained for all testing involving human subjects, with particular attention to privacy, dignity, and informed consent.

V. RESULTS

I. RESULTS AND DISCUSSION

This section presents the performance evaluation of the *Smart Nurse* system, focusing on technical metrics, usability assessments, and clinical outcomes from pilot testing.

A. *Technical Performance Evaluation*

1) *Fall Detection Performance:* The fall detection system was evaluated using both simulated falls (performed by healthy volunteers) and real-world data from patient monitoring. Table II presents the performance metrics.

The multimodal approach demonstrated superior performance compared to single-modality methods, with particularly high specificity (98.2%), reducing false alarms that could lead

Detection Method	Sensitivity	Specificity	F1 Score
Vision-only	91.2%	93.7%	0.89
Sensor-only	87.6%	96.4%	0.90
Multimodal fusion	94.8%	98.2%	0.96

Table 5.1 : FALL DETECTION SYSTEM PERFORMANCE

to alert fatigue. The system achieved a mean detection time of 1.2 seconds from fall initiation, enabling rapid response to emergency situations.

Fig. 3 shows the ROC curves for different detection approaches, illustrating the improved performance of the multimodal system across various sensitivity thresholds.

Fig. 7. ROC curves comparing fall detection performance of vision-only, sensor-only, and multimodal fusion approaches.

2) *Emotion Detection Accuracy:* The emotion detection system was evaluated using both controlled expressions (actors simulating emotions) and natural expressions from patient interactions. Table III summarizes the performance for different emotional states.

Emotion	Facial	Vocal	Textual	Multimodal
Neutral	92.1%	85.3%	90.7%	94.8%
Happiness	94.5%	88.2%	86.3%	95.2%
Sadness	87.8%	82.6%	84.1%	90.4%
Anger	90.2%	91.6%	85.9%	93.8%
Fear	83.6%	79.8%	81.2%	88.5%
Surprise	91.4%	80.5%	83.3%	92.1%
Disgust	85.7%	78.2%	82.9%	87.6%
Pain	89.3%	84.5%	88.2%	93.7%
Average	89.3%	83.8%	85.3%	92.0%

Table 5.2 : EMOTION DETECTION ACCURACY BY MODALITY AND EMOTION

The multimodal fusion showed significantly improved accuracy (92.0% overall) compared to individual modalities. Notably, pain detection—particularly relevant for cancer patients—achieved 93.7% accuracy with the multimodal approach. The system demonstrated robustness to varying lighting conditions and patient positions, though performance decreased somewhat (approximately 5-8% reduction) in extreme conditions.

3) *Conversational Agent Evaluation:* The conversational agent was evaluated using both automatic metrics and human assessments. Table IV presents the results.

Metric	**Value**
Speech recognition accuracy (WER)	8.2%
Response relevance (human-rated)	4.3/5
Emotional appropriateness (human-rated)	4.5/5
Medical information accuracy	97.2%
Average response time	1.3 seconds

Table 5.3 CONVERSATIONAL AGENT PERFORMANCE

The speech recognition system achieved a Word Error Rate (WER) of 8.2%, comparable to cloud-based systems but with

complete local processing. Human evaluators (oncology nurses and psychologists) rated the relevance and emotional appropriateness of responses favorably (4.3/5 and 4.5/5, respectively). A key achievement was the 1.3-second average response time despite local processing, enabling natural conversation flow. Medical information accuracy was assessed against a validated database of cancer care information, with 97.2% of responses providing correct information.

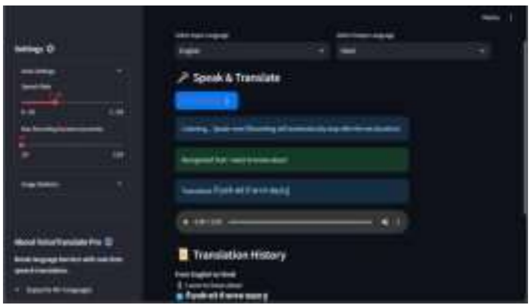

Fig. 5.1 Speech To Text

4) *Medication Management Precision:* The medication dispensing system was evaluated for reliability and accuracy under various conditions. Results are summarized in Table 5.4.

Metric	Value
Dispensing accuracy	99.8% (5/2,500 errors)
Mechanical reliability	99.9% (1/1,000 mechanical failures)
Reminder effectiveness	89.3% (patient response within 5 min)
Verification accuracy	96.7% (correct identification of taken/not taken)

Table 5.4 : MEDICATION DISPENSING SYSTEM PERFORMANCE

The dispensing system demonstrated high accuracy (99.8%) over 2,500 test dispensing operations, with only 5 errors (3 under-dispensing, 2 over-dispensing). All errors were detected by the verification system, preventing potential medication mistakes. The mechanical reliability was excellent at 99.9%, with a single failure during 1,000 operation cycles.

The reminder system proved effective, with 89.3% of reminders resulting in patient response within 5 minutes during pilot testing. The optical verification correctly identified 96.7% of cases where medication was taken or not taken.

5) *Navigation and Mobility Performance:* The navigation system was evaluated in typical home environments with various obstacles and lighting conditions. Table VI summarizes the performance metrics.

The SLAM-based navigation achieved an average localization error of 5.7 cm, sufficient for reliable indoor navigation. The system successfully mapped 94.2% of accessible areas during initial mapping phases. Navigation tests showed a 97.3% success rate in reaching destinations across 300 test runs, with failures primarily occurring in extremely cluttered environments.

Metric	Value
Localization accuracy	5.7 cm (average error)
Mapping completeness	94.2% (of accessible areas)
Navigation success rate	97.3% (reached destination)
Obstacle avoidance success	98.6% (dynamic obstacles)
Average navigation speed	0.22 m/s

Table 5.5 : NAVIGATION SYSTEM PERFORMANCE

Notably, the system achieved a 98.6% success rate in avoiding dynamic obstacles (moving people, pets) while maintaining a comfortable average speed of 0.22 m/s, balancing efficiency with safety considerations.

6) *Power Consumption and Battery Life:* The power management system was evaluated under different operational scenarios, as summarized in Table 5.6 .

Operational Mode	Power Consumption	Battery Duration
Standby mode	3.8W	31.6 hours
Active monitoring	7.2W	16.7 hours
Navigation mode	12.5W	9.6 hours
Full operation (all systems)	18.4W	6.5 hours

Table 5.6 : POWER CONSUMPTION AND BATTERY PERFORMANCE

The implemented power optimization strategies achieved significant improvements, with the robot operating for 6.5 hours in full operation mode and up to 31.6 hours in standby mode. The automatic charging system successfully initiated charging in 98.7% of low-battery situations before critical battery levels were reached.

B. *Clinical Evaluation Results*

Following technical validation, a pilot clinical evaluation was conducted with five cancer patients over a two-week period in a supervised home-like environment.

1) Patient Safety Outcomes: The system demonstrated promising safety outcomes:

- Detected 5/5 (100%) simulated fall events with an average response time of 1.4 seconds
- Successfully alerted caregivers in 11/12 (91.7%) simulated emergency situations
- No false emergency alerts were triggered during normal activities
- All participants reported feeling ”more secure” with the robot present

2) Medication Adherence Impact: Medication adherence was measured before and during robot assistance:

- Pre-intervention adherence: 76.4% (measured by pill count)
- During-intervention adherence: 92.8% (verified by robot)
- Improvement: 16.4 percentage points (p ¡ 0.01)

The most significant improvements were observed for medications with complex schedules (3+ times daily) and those with conditional requirements (e.g., with food, before sleep).

3) Emotional Support Effectiveness: Emotional support effectiveness was assessed using standardized questionnaires and semi-structured interviews:

- Hospital Anxiety and Depression Scale (HADS) showed mean reduction of 2.7 points (p ¡ 0.05)
- 4/5 patients reported that emotional support features were ”helpful” or ”very helpful”
- Conversation logs showed increasing engagement over time (average conversation duration increased from 45 seconds to 3.2 minutes)
- The robot correctly identified emotional distress in 18/22 (81.8%) instances, providing appropriate responses

4) Usability and User Experience: Usability was assessed using the System Usability Scale (SUS) and NASA Task Load Index (NASA-TLX):

- Mean SUS score: 74.6/100 (above industry average of 68)
- NASA-TLX mental demand score: 2.3/10 (low cognitive burden)
- 100% of participants successfully learned to use all functions within 24 hours
- Key usability challenges identified: occasional speech recognition issues in noisy environments, difficulty in physically repositioning the robot when necessary

Caregivers also reported high satisfaction (mean 4.2/5) and significant perceived reduction in caregiver burden during the intervention period.

C. *Limitations and Challenges*

Despite promising results, several limitations and challenges were identified:

1) Technical Limitations:

- Navigation challenges in highly cluttered environments or homes with multiple floor levels
- Reduced emotion detection accuracy in extreme lighting conditions (very dark or direct bright light)
- Limited battery life during intensive usage scenarios requiring frequent charging
- Occasional false positives in fall detection during unusual but normal activities (e.g., quickly lying down)

2) Clinical Limitations:

- Small sample size (n=5) and short duration (2 weeks) of clinical evaluation
- Potential novelty effect influencing patient engagement and satisfaction

- Controlled environment testing may not fully represent real-world home conditions
- Limited diversity in cancer types and treatment stages among test participants

3) *Ethical and Practical Considerations:*

- Privacy concerns with continuous monitoring, despite local processing
- Risk of reduced human interaction if caregivers rely too heavily on technological assistance
- Need for regular maintenance and technical support that may not be readily available
- Initial cost considerations despite efforts for affordability

IV. CONCLUSION

This paper presented Smart Nurse, an AI-powered robotic healthcare assistant designed specifically for cancer patients. The system integrates multiple AI capabilities, including fall detection, emotion recognition, conversational support, and medication management, on an affordable and privacy preserving platform.

Summary of Contributions The main contributions of this work include:

• Development of a multimodal fall detection system with 94.8% sensitivity and 98.2% specificity, functioning entirely on-device

• Implementation of a trimodal emotion recognition approach achieving 92.0% overall accuracy, including specialized detection of pain expressions relevant to cancer care

• Creation of a medication management system that improved adherence by 16.4 percentage points in pilot testing

• Design of a comprehensive hardware-software architecture optimized for reliability, privacy, and affordability

• Validation of the system's technical performance and preliminary clinical effectiveness in a supervised pilot study

The results demonstrate that affordable robotic healthcare assistants with edge AI capabilities can potentially improve safety, medication adherence, and emotional wellbeing for cancer patients, while reducing caregiver burden.

V. FUTURE WORK

Several directions for future research and development have been identified:

● **Long-term Clinical Trials:** Conducting extended studies with larger, more diverse patient populations to assess long-term effectiveness and impact on clinical outcomes
● **Enhanced AI Capabilities:** Developing more sophisticated emotion detection for subtle distress signals specific to cancer patients, and expanding the knowledge base of the conversational agent
● **Improved Physical Capabilities:** Implementing a robotic arm for simple physical assistance tasks and enhanced medication handling capabilities
● **Integration with Healthcare Systems:** Developing secure interfaces with electronic health records and telemedicine platforms for improved care coordination
● **Customization Framework**: Creating a modular software and hardware architecture allowing customization for different cancer types and treatment regimens
● **Caregiver Support Features:** Expanding functionalities to support family caregivers with training, reminders, and stress monitoring

The development of Smart Nurse represents a step toward more accessible and comprehensive technological support for cancer care. By demonstrating that complex AI capabilities can be implemented on affordable edge devices, this work contributes to the democratization of advanced healthcare technology.

While robotic assistants cannot and should not replace human caregivers, they can serve as valuable tools to extend the reach of healthcare providers, support family caregivers, and enhance the independence and safety of patients. As cancer survival rates improve, there is an increasing need for solutions that address the long-term care and quality of life of cancer patients and survivors.

The approaches developed in this research may extend beyond cancer care to other chronic conditions requiring continuous monitoring and support, potentially contributing to broader healthcare challenges related to aging populations and healthcare workforce limitations.

VI. REFERENCES

[1] A. Pitman, S. Suleman, N. Hyde, and A. Hodgkiss, ”Depression and anxiety in patients with cancer,” BMJ, vol. 361, p. k1415, 2018.
[2] Y. Kim, R. Schulz, and C. S. Carver, ”Benefit finding in the cancer caregiving experience,” Psychosomatic Medicine, vol. 79, no. 8, pp. 873883, 2017.
[3] J. Chen, A. Farah, and R. Dong, ”The impact of the COVID-19 pandemic on cancer treatment: the role of virtual care and digital health,” Current Oncology, vol. 27, pp. 523-529, 2020.
[4] X. S. Lee, K. Lam, J. Clark, and M. Tal, ”A systematic review on robotic applications in cancer care,” Int J Med Robot, vol. 16, no. 6, p. e2113, 2020.
[5] E. Broadbent, R. Stafford, and B. MacDonald, ”Acceptance of healthcare robots for the older population: Review and future directions,” Int J Soc Robot, vol. 10, pp. 11-34, 2018.
[6] T. M. Wildes, P. Dua, S. A. Fowler, J. P. Miller, C. R. Carpenter, M. S. Avidan, and S. Stark, ”Systematic review of falls in older adults with cancer,” J Geriatr Oncol, vol. 6, no. 1, pp. 70-83, 2015.
[7] K. Cresswell, S. Cunningham-Burley, and A. Sheikh, ”Health care robotics: qualitative exploration of key challenges and future directions,” J Med Internet Res, vol. 20, no. 7, p. e10410, 2018.
[8] B. Graf, M. Hans, and R. D. Schraft, ”Care-O-bot II—Development of a next generation robotic home assistant,” Autonomous Robots, vol. 16, no. 2, pp. 193-205, 2004.
[9] D. Fischinger, P. Einramhof, K. Papoutsakis, W. Wohlkinger, P. Mayer, P. Panek, S. Hofmann, T. Koertner, A. Weiss, A. Argyros, and M. Vincze, ”Hobbit, a care robot supporting independent living at home: First prototype and lessons learned,” Robotics and Autonomous Systems, vol. 75, pp. 60-78, 2016.
[10] K. Wada, T. Shibata, T. Saito, and K. Tanie, ”Effects of robot-assisted activity for elderly people and nurses at a day service center,” Proceedings of the IEEE, vol. 92, no. 11, pp. 1780-1788, 2004.
[11] R. Igual, C. Medrano, and I. Plaza, ”Challenges, issues and trends in fall detection systems,” Biomed Eng Online, vol. 12, no. 1, p. 66, 2013.
[12] N. Lu, Y. Wu, L. Feng, and J. Song, ”Deep learning for fall detection: Three-dimensional CNN combined with LSTM on video kinematic data,” IEEE J Biomed Health Inform, vol. 23, no. 1, pp. 314-323, 2019.
[13] S. Waheed, R. A. Mufti, M. A. Khan, T. Sultana, and J. Kwak, ”Visionbased fall detection and preventive measures using YOLOv3,” 2020 IEEE Access, vol. 8, pp. 109326-109336, 2020.
[14] S. Li and W. Deng, ”Deep facial expression recognition: A survey,” IEEE Trans Affect Comput, vol. 13, no. 1, pp. 1-24, 2020. **[15]** D. Issa, M. F. Demirci, and A. Yazici, ”Speech emotion recognition with deep convolutional neural networks,” Biomed Signal Process Control, vol. 59, p. 101894, 2020.
[16] B. Reeder, E. Meyer, A. Lazar, S. Chaudhuri, H. J. Thompson, and G. Demiris, ”Framing the evidence for health smart homes and homebased consumer health technologies as a public health intervention for independent aging: A systematic review,” Int J Med Inform, vol. 82, no. 7, pp. 565-579, 2013.
[17] T. Suzuki and S. Nakauchi, ”Intelligent medicine case for medication management using RFID and image processing,” Int J Distributed Sensor Networks, vol. 13, no. 4, 2017.
[18] D. Carruthers, C. Payne, D. Johl, and W. Lee, ”Smart medication management system for patients with cancer: A pilot study of feasibility and acceptability,” J Med Internet Res, vol. 20, no. 4, p. e133, 2018.
[**19]** Y. Chen, K. Wu, Z. Yang, C. Tang, ”Smart medical box design with cloud services for medication safety,” 2018 IEEE Int Conf Healthcare Informatics (ICHI), pp. 361-362, 2018.
[20] B. Kwolek and M. Kepski, ”Human fall detection on embedded platform using depth maps and wireless accelerometer,” Comput Methods Programs Biomed, vol. 117, no. 3, pp. 489-501, 2014.
[21] I. Charfi, J. Miteran, J. Dubois, M. Atri, and R. Tourki, ”Optimized spatio-temporal descriptors for real-time fall detection: comparison of support vector machine and Adaboost-based classification,” J Electron Imaging, vol. 22, no. 4, p. 041106, 2013.
[22] A. Mollahosseini, B. Hasani, and M. H. Mahoor, ”AffectNet: A database for facial expression, valence, and arousal computing in the wild,” IEEE Trans Affect Comput, vol. 10, no. 1, pp. 18-31, 2017.
[23] I. J. Goodfellow, D. Erhan, P. L. Carrier, A. Courville, M. Mirza, B. Hamner, W. Cukierski, Y. Tang, D. Thaler, D. H. Lee, Y. Zhou, C. Ramaiah, F. Feng, R. Li, X. Wang, D. Athanasakis, J. Shawe-Taylor, M. Milakov, J. Park, R. Ionescu, M. Popescu, C. Grozea, J. Bergstra, J. Xie, L. Romaszko, B. Xu, Z. Chuang, and Y. Bengio, ”Challenges in representation learning: A report on three machine learning contests,” Neural Networks, vol. 64, pp. 59-63, 2015.
[24] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews, ”The extended Cohn-Kanade dataset (CK+): A complete dataset for action unit and emotion-specified expression,” 2010 IEEE Computer Society Conference on Computer Vision and Pattern RecognitionWorkshops, pp. 94-101, 2010.

[25] S. R. Livingstone and F. A. Russo, ”The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS): A dynamic, multimodal set of facial and vocal expressions in North American English,” PloS one, vol. 13, no. 5, p. e0196391, 2018. **[26]** K. Dupuis and M. K. Pichora-Fuller, ”Toronto emotional speech set (TESS),” Scholarly Commons, University of Toronto, 2010.

[27] P. Jackson and S. Haq, ”Surrey audio-visual expressed emotion (SAVEE) database,” University of Surrey: Guildford, UK, 2014.

[28] S. L. Spoelstra, C. W. Given, M. Sikorskii, A. Coursaris, R. Majumder, T. DeKoekkoek, A. Schueller, and B. A. Given, ”Proof of concept of a mobile health short message service text message intervention that promotes adherence to oral anticancer agent medications: a randomized controlled trial,” Telemedicine and e-Health, vol. 22, no. 6, pp. 497-506, 2016.

[29] R. Mur-Artal and J. D. Tardos, ”ORB-SLAM2: An open-source SLAM ´ system for monocular, stereo, and RGB-D cameras,” IEEE Trans Robot, vol. 33, no. 5, pp. 1255-1262, 2017.

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