CHAPTER-1

INTRODUCTION

Nowadays the population of elderly people is increasing day by day which is also leading to increase of elder people suffering from challenges like memory loss,feeling loneliness and their ethical & safety concerns. These challenges majorly plays an major impact their quality of life and also their mental and health condition. Traditional old methods for caretaking and present available technologies often are lacked in providing complete and personalized support. This project would try to address the challenges which involves of artificial intelligence and robotics technologies. The methods and techniques applied here, such as Natural language processing(NLP), computer vision, and some IoT-enabled sensors, help the system to be for personal care assistance. In our project we have real-time health monitoring,system and conversational companion for emotional support, medication reminders, and intrusion detection for safety. The main motive of our project is to establish an affordable, scalable robot system that is easy to use for old people and supports their well-being of elderly people which improve their quality of life.

By focusing on the development of a hybrid approach that blends AI-driven tools with human-friendly design, this project will aim at delivering a solution that meets the most functional needs while answering some ethical concerns and ensures adoption by most users. Report on problem statement, technological framework, and proposed solutions: how AI and robotics can change the direction in geriatric care towards higher quality of life for seniors.

CHAPTER-2

Problem Definition

All the problems faced by elderly people, like memory loss, loneliness, and safety concerns, need solutions that are efficient and user-friendly. Old-school methods to geriatric care often lack a proper coverage of the aforementioned issues, which leads to major gaps in real time monitoring, emotional support, and intrusion detection.

Our project focuses on the challenge of designing an AI-enhanced robot that addresses these problems whilst being cost-effective and user-friendly.

The main question is: How do we develop a robot that incorporates advanced Al algorithms, NLP, and real time monitoring in a way that's efficient and useful for elderly people?

Prioritising ethical values and making sure it's adaptable, this project explores developing an AI-human hybrid robot that gives support whilst following the constraints of geriatric care systems.

CHAPTER-3

DATA

4.1 DATA OVERVIEW :

For this project, different types of data are needed to enable the system's three main functionalities:

1. Emotion detection

2. Health monitoring

3. Intrusion detection.

All these modules need certain types of input to train, test, and implement machine learning models properly.

For emotion recognition, facial images and/or video frames with emotional states like happiness, sadness, anger, fear, and surprise are required. These points of data are needed to train convolutional neural networks (CNNs) that can classify realtime emotional states from facial expressions.

Data such as heart rate, body temperature, and activity level will be acquired from IoT-enabled sensors with the aim of detecting such anomalies indicating possible deterioration of health so that the robot could raise an alarm or notify the caregiver.

Data collected can be for intrusion detection applications that include simulated data or real data collected from motion sensors, contact triggers, and camera feeds.

All datasets used in this project go through careful preprocessing to ensure data quality, class balance, and applicability in real-time. The whole data pipeline is privatised, low latency, and accurate truthful predictions, thus telling the story of intelligent behaviour within the robotic system.

4.2 DATASET :

Facial Emotion recognition dataset :

This phase of the project was augmented considerably by the process of implementation and experimentation of the emotion recognition module, which used the FER-2013 (Facial Expression Recognition 2013) dataset. The FER-2013 dataset is publicly accessible on Kaggle and provides facial emotion classification tasks, which are mostly found in computer vision.

In particular, FER-2013 is a collection of 35,887 gray-scale face pictures, with pixels resolution 48×48 pixels, that is labeled to belong to one out of the seven emotions (Disgust, Fear, Angry, Happy, Surprise, Neutral, Sad). The set consists of three groups, namely: Training (28,709 pics), Public Test (3,589 pics), and Private Test (3,589 pics).

To prevent the model from overfitting and improve the quality of the model, the data set was pre-processed in the following ways:

Scaling images into values ranging between 0 and 1 pixels.

Class weight balancing to counter the fact that there existed an imbalanced emotional class distribution.

The treated dataset was utilised to train a Convolutional Neural Network (CNN) model. With 67.19% test dataset performance, the model was a solid benchmark for emotion recognition research programs that are geared towards implementation in real-world robotic systems. The dataset and the model actually serve the platform through which a robot understands and empathically listens.

Health monitoring Dataset :

The health monitoring datasets used for this project are most important in the provision of real-time assessment of an elderly user's bodily condition.
The data is gathered from medical website physionet.org to gather cardiac related datasets and from kaggle we gathered most of the datasets in the form of CSV file. We pre-processed the datasets and removed some of the unwanted parameters and we merged all the individual CSV to one grand dataset file which we have used for training our models.
Such datasets generally contain sensor-recorded data from wearable or embedded health monitoring sensors like heart rate monitors, temperature sensors, blood pressure cuffs, and

oxygen saturation monitors. Each dataset contains time-stamped physiological data together with related metadata such as user ID, activity status (e.g., resting, walking), and environmental status.
The dataset includes key classes such as Heart Rate (bpm),SpO2 Level (%),Systolic Blood Pressure (mmHg),Diastolic Blood Pressure (mmHg),Body Temperature (°C),Fall Detection,Data Accuracy (%),Heart Rate Alert,SpO2 Level Alert,Blood Pressure Alert,Temperature Alert. If some parameters is above critical level it will indicate as abnormal. The datasets contain over 50,000 values in CSV file.
The information is captured periodically to monitor trends, detect anomalies, and prompt alerts in the case of abnormal readings. Also captured are emotional health metrics like stress or anxiety levels, which can be deduced from voice recognition or face detection, to enable emotional well-being tracking. All these sets of data are required in order to train the machine learning models to make predictions about possible health dangers and offer tailor-made care advice.

Speech Emotion Recognition Dataset:
For our speech-based emotion recognition system implementation, we used Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS). It is high-quality, emotion-specific database, and was chosen due to the relevance of the project to geriatric care.It has 7,356 audio recordings produced by 24 professional actors (12 female, 12 male) displaying eight emotions: calm, happy, sad, angry, fearful, surprise, disgust, neutral.
We chose RAVDESS for a number of reasons. First, the recordings were professional-quality created in a commercial studio space (48kHz, 16-bit), which means that there was very little interference (i.e. distractions) in the recording and we will have good and clean features to extract from. Second, to have some level of male / female balance, we believed that using RAVDESS gave our model a variety of voice characteristics (vocal traits) in order to potentially help generalization. Third the emotions in the dataset were all emotional expressions of more relevance to our geriatric monitoring project (e.g. happiness, sadness, fear, neutral) and very good indicators for change in well-being in the elderly.
The recordings were developed using a consistent format in which actors produce two lexically-matched statements in a North American accent: ""Kids are talking by the door" and "Dogs are sitting at the door." These two statements are produced using differing emotional states (normal and strong) providing training examples with some subtlety that were beneficial for our model to differentiate the subtle emotional variables, an important characteristic to track when monitoring the emotional states of older users that may display emotions in a more subtle way.

CHAPTER 4

DESIGN DETAILS

4.1 Novelty

The approach innovates through introducing an AI-based robotic care support system with combined real-time monitoring of health, emotion-driven companionship, and intrusion detection into one interface. Its innovation factor is the use of personalized interaction through AI that learns and accommodates emotional and physical demands of older people and provides a human-like, interactive experience compared to rule-based static systems.

4.2 Innovativeness

This system combines several AI models (involving emotion detection, fall detection, intrusion detection) with IoT devices and a robotic interface. It leverages natural voice commands, pop-up notifications, and real-time caregiver alerts (call or SMS), developing an interactive ecosystem beyond a normal monitoring solution. The ability of the system to learn user behavior and refresh responses is a significant innovation.

4.3 Interoperability

The architecture accommodates interoperability between different platforms and devices. The robot exchanges information with IoT sensors, cloud-based AI components, and caregiver apps (web and mobile). It is capable of operating with standard APIs and protocols, and compatibility with third-party healthcare platforms and devices is possible.

4.4 Performance

The system is designed with fast and responsive data processing and alert set up. Lightweight AI models are placed on edge devices (ensure response times are fast) and more intensive processing (emotion responses) are offloaded to the cloud. The most important functions of the system, fall detection, communication and alerts to caregivers are performed quickly (typically on the order of seconds) both for cognitive load of the human caregiver and for optimal reliability.

4.5 Security

Data privacy and confidentiality are addressed by encrypting all personal information when being sent and when at rest. User access is determined by the user's obligation (e.g. caregiver vs. system admin) so that access to data is controlled. The system also takes standard precautions with respect to data protection, and health data related to users (emotions, health) is only accessible by authorized individuals.

4.6 Reliability

Systems are set up with multiple failsafe options (different alert options depending on the platform) to facilitate continuous monitoring, even with short interruptions in connectivity. The primary user channel is app notification and a backup option of SMS/call if it fails. Ongoing monitoring of health and connectivity, and frequent updates to the robot and its components ensure reasonable expectations of reliability over time.

4.7 Maintainability

The maintenance of our geriatric care robot needs to be user-friendly for users who don't have any idea about technology . Any component must be easily replaceable, with no specialized tools required, just like worrying about replacing the batteries in a remote control. We have referenced a self-diagnostic feature whereby the robot will communicate that there is a problem using simple voice messages, rather than technical codes, when necessary.

4.8 Portability

The robot needs to operate in real-life home settings of elderly people. We have kept the weight low so that it is easy to move whenever needed without heavy lifting. We must prioritize working battery capacity for overnight because emergency assistance is most important at that time, coupled with a simple charging system, which the robot can operate on its own. We have considered narrow spaces common in a house such as narrow hallways, bathroom doorways, and messy rooms. The robot will change its interaction height with the user, such as when the user is standing, seated in a chair, or lying in bed.

4.9 Legacy to Modernization

To many older adults, established healthcare routines and familiar technology is important. Rather than replace these routines and technologies, our robot will integrate with them. It connects with legacy emergency alerts, conventional medication organizers, and familiar household devices. We have planned for gradual adoption where the robot ideally first complements existing methods, and subsequently may take on more responsibilities. This respects the comfort of the elderly person in using familiar systems and the sequencing of support capabilities from new sources of support.

4.10 Reusability

As needs change, our robot must change too - like a Swiss Army knife that reveals different tools as needs arise. For example, Dad may only need medication reminders when he first gets the robot, and later may need fall detection. The robot should grow with him without having to purchase an entirely new system that could be expensive. Different personalities require different engagement styles too. My mother-in-law loves jokes and chit chat while my own mom prefers direct and to-the-point conversation. One robot should be able to offer both styles. Ultimately when situations change in significant ways, families should be able to reset and reuse the robot for another loved one, preserving both the emotional and financial investment.

4.11 Application Compatibility

To be effective, our geriatric care robot needs to interoperate with existing health care technology. The system communicates with conventional medical devices using open protocols rather than through proprietary systems.. Both the robot and the robot's, family members can communicate with normal consumer devices - no specialized hardware is required. The design allows for multiple modes of interaction to happen at the same time; users can choose the one they prefer or are most comfortable with.

4.12 Resource Utilization

Affordability requires that we are good stewards of our resources. The power management system keeps consumption low during low-usage periods but retains capabilities to monitor daytime activity. Sensitive information is processed locally to preserve privacy, but the robot may access cloud-hosted resources to do more complex analyses only when required. Storage management is based on what health data is critical versus what is to be archived. The system must be flexible in utilizing its resources based on the current needs of the user.

CHAPTER-5

HIGH LEVEL SYSTEM DESIGN

AI-Enhanced Robotic Geriatric Care system architecture is structured specifically to bring artificial intelligence, sensor information, and human-robot interaction together into a unified and modular structure. The system aims to respond to the essential requirements of the elderly, i.e., emotional care, health monitoring, and home protection, through real-time response, low-latency inference, and caregiver alarm.

The architecture consists of the following main components:

1. Sensor & Input Layer:
This layer receives real-time feedback from:
A camera module for facial expression analysis.
IoT sensors such as heart rate monitors, temperature sensors, and activity trackers for health tracking.
Environmental sensors such as motion sensors and door -or- window contact sensors for intruder detection.

2. Al-Model Layer
Robot brain. It consists of:
A Convolutional Neural Network (trained on FER-2013) for facial emotion detection.
Place holder modules for detection of health anomalies using time-series techniques (LSTM, Isolation Forest).
Intrusion detection via decision tree or RNN models.

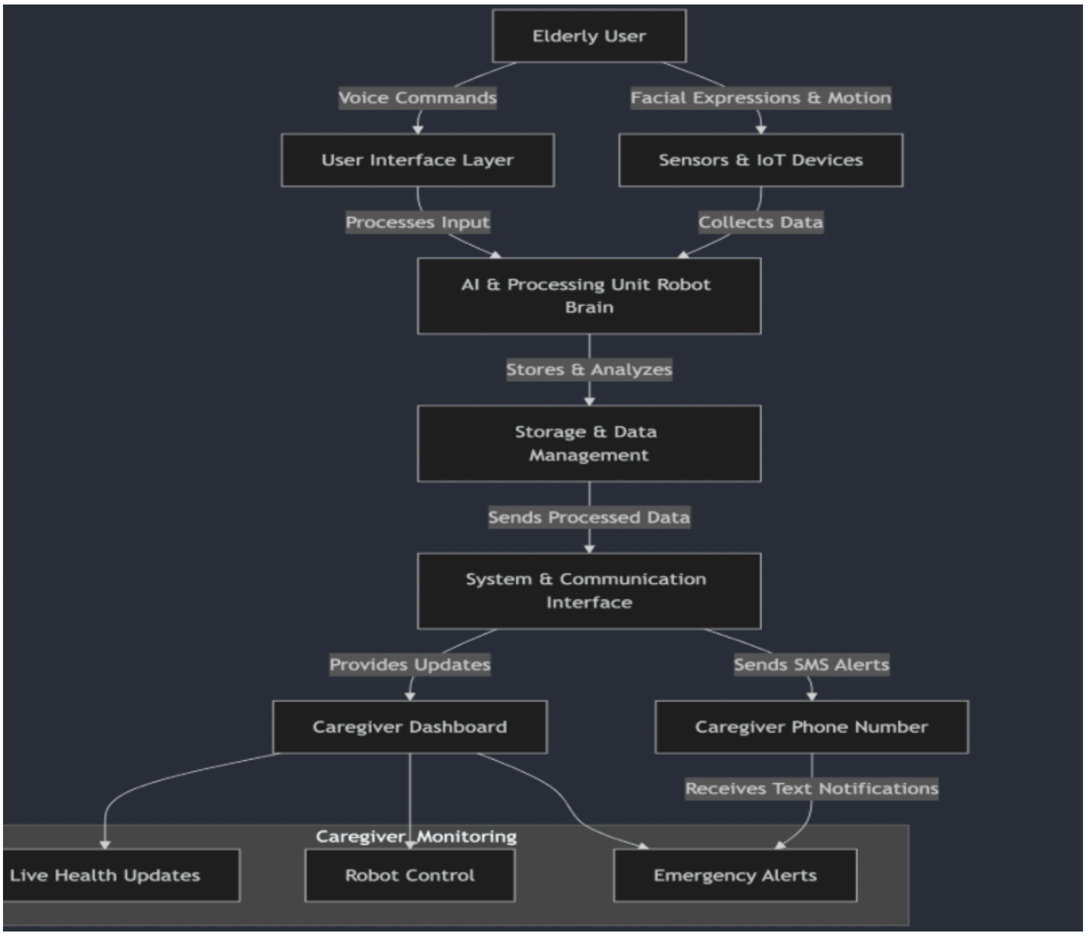
3. Alert & Decision Logic
Actions by the system on AI prediction, i.e., displaying empathy, alerting caregivers, or issuing security alarm sounds.
Alarms during future stages will be provided through cell app notification or email.

4. Voice command interface for ease of use by seniors.
Dialogue responses are stimulus-cued based on observed emotion or user input.
Scalability designs for multimodal interaction (facial + speech emotion) in future phases.

5. Hardware & Deployment Layer
Models are optimized to deploy on low-power, edge hardware.
The architecture supports modular upgrade, i.e., individual components (e.g., sensors or models) can be added without needing to redesign the entire system.

6. Data Flow

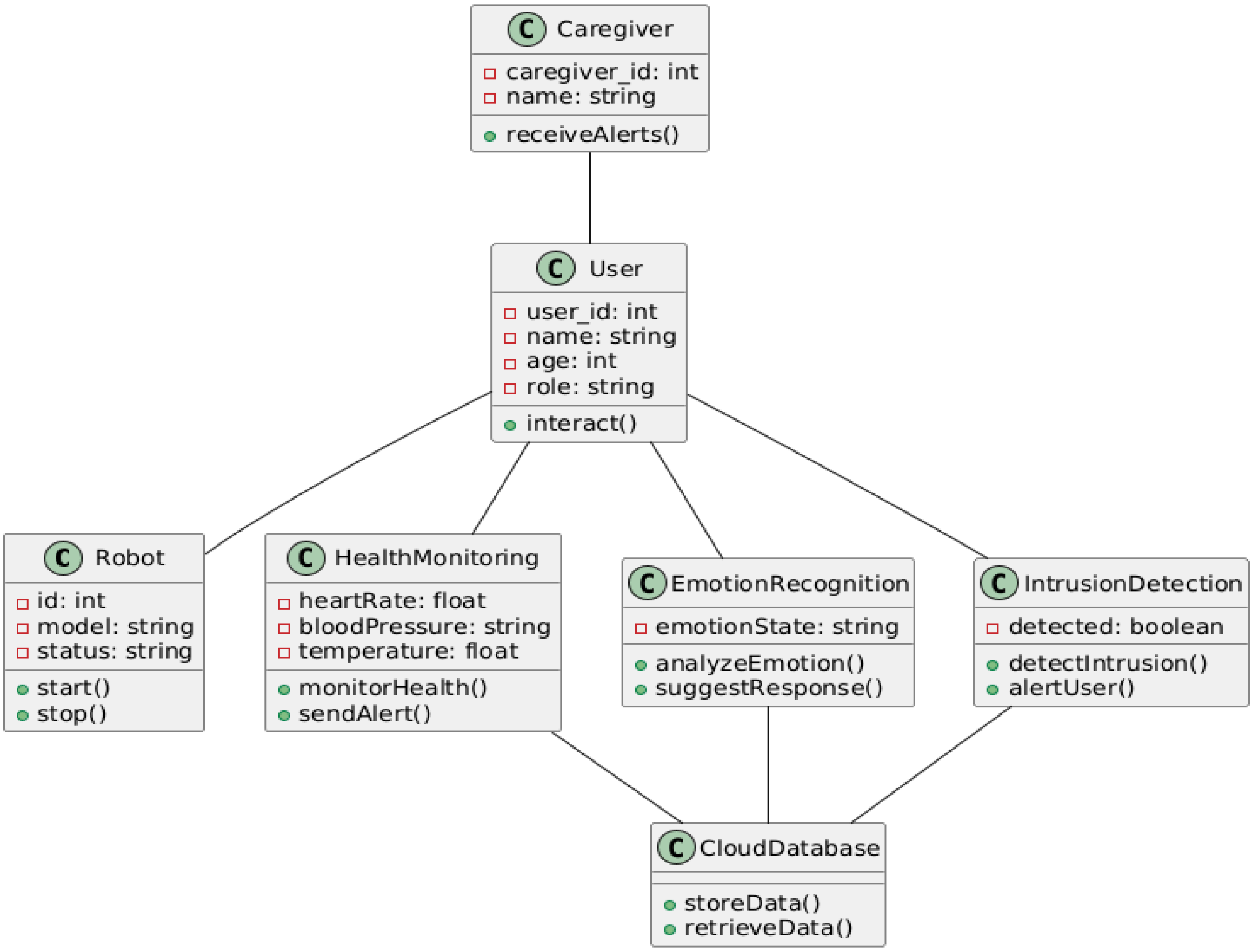
Input → Preprocessing → Model Inference → Decision → Action/Response
Data is locally processed to enable privacy. Sensitive logs are synced with cloud servers to enable users with extra analytics only after approval.



CHAPTER 6

DESIGN DESCRIPTION

6.1 Master Class Diagram :



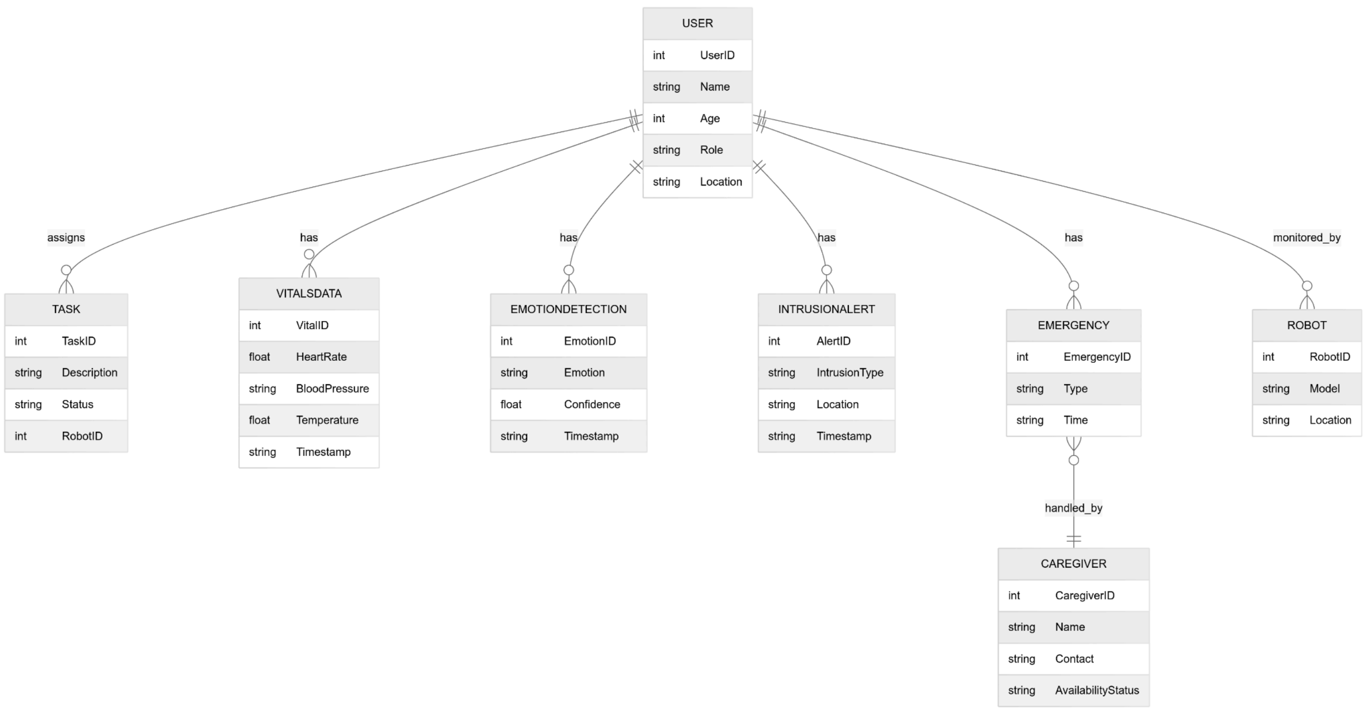
The Master Class Diagram outlines the core structure of the AI-Enhanced Robotic Geriatric Care system. At the center is the User class, representing the elderly individual, with attributes like ID, name, age, and role. Users interact with the system through the `interact()` method.

The Robot class handles operations with attributes such as ID, model, and status. It can be started or stopped via the `start()` and `stop()` methods. The robot connects to various modules such as HealthMonitoring, EmotionRecognition, and IntrusionDetection to provide comprehensive care.

HealthMonitoring tracks vital signs like heart rate, blood pressure, and temperature. It continuously checks the user's health using `monitorHealth()` and alerts caregivers when needed. The EmotionRecognition module analyzes the user's emotional state and provides supportive responses. Meanwhile, IntrusionDetection ensures user safety by detecting unauthorized presence and sending alerts.

The Caregiver class receives notifications and can act accordingly, while the CloudDatabase stores and retrieves important data for future reference. This design ensures that all components work together to deliver intelligent, safe, and personalized care for elderly users.

6.2 ER diagram :



The Entity-Relationship (ER) Diagram for AI-Enriched Robotic Geriatric Care system shows the main entities present and their interactions. The core of the system is the User entity, where crucial details like user ID, name, age, role, and location are stored. This entity is linked to various other entities, each of which represents the modules handling distinct care services.

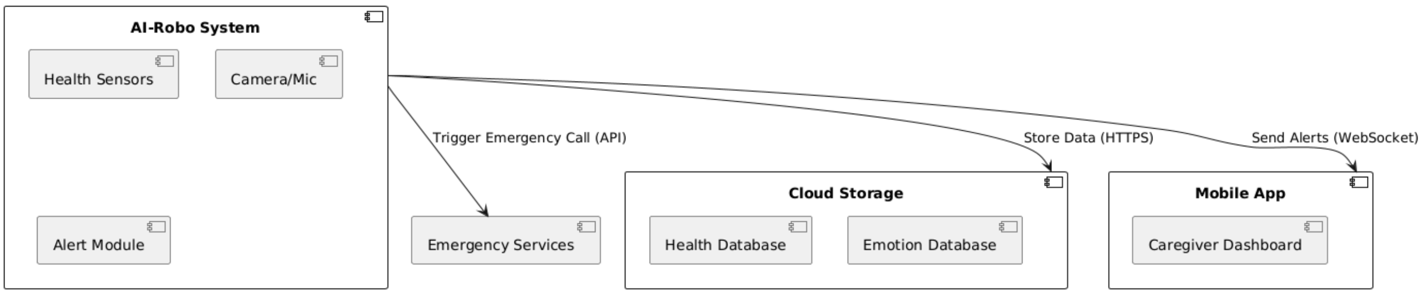
The Robot entity, which is defined by its ID, model, and location, is tasked with helping and communicating with the user. The Task entity is associated with both the robot and the user, recording scheduled tasks with attributes such as task ID, description, and status.

VitalsData saves the health parameters like heart rate, blood pressure, temperature, and reading timestamp. Likewise, EmotionDetection saves the emotional state of the user, with fields like emotion type and confidence level.

For security, the IntrusionAlert entity records data on any intrusion detection activity with a timestamp. For emergencies, the Emergency entity keeps incident type and time, and is linked with the Caregiver entity, such as caregiver ID, name, contact information, and availability status.

This ER model enables seamless interaction between users, robot systems, monitoring modules, and caregivers to enable real-time, AI-based geriatric care provision.

6.3 External Interface Diagram :

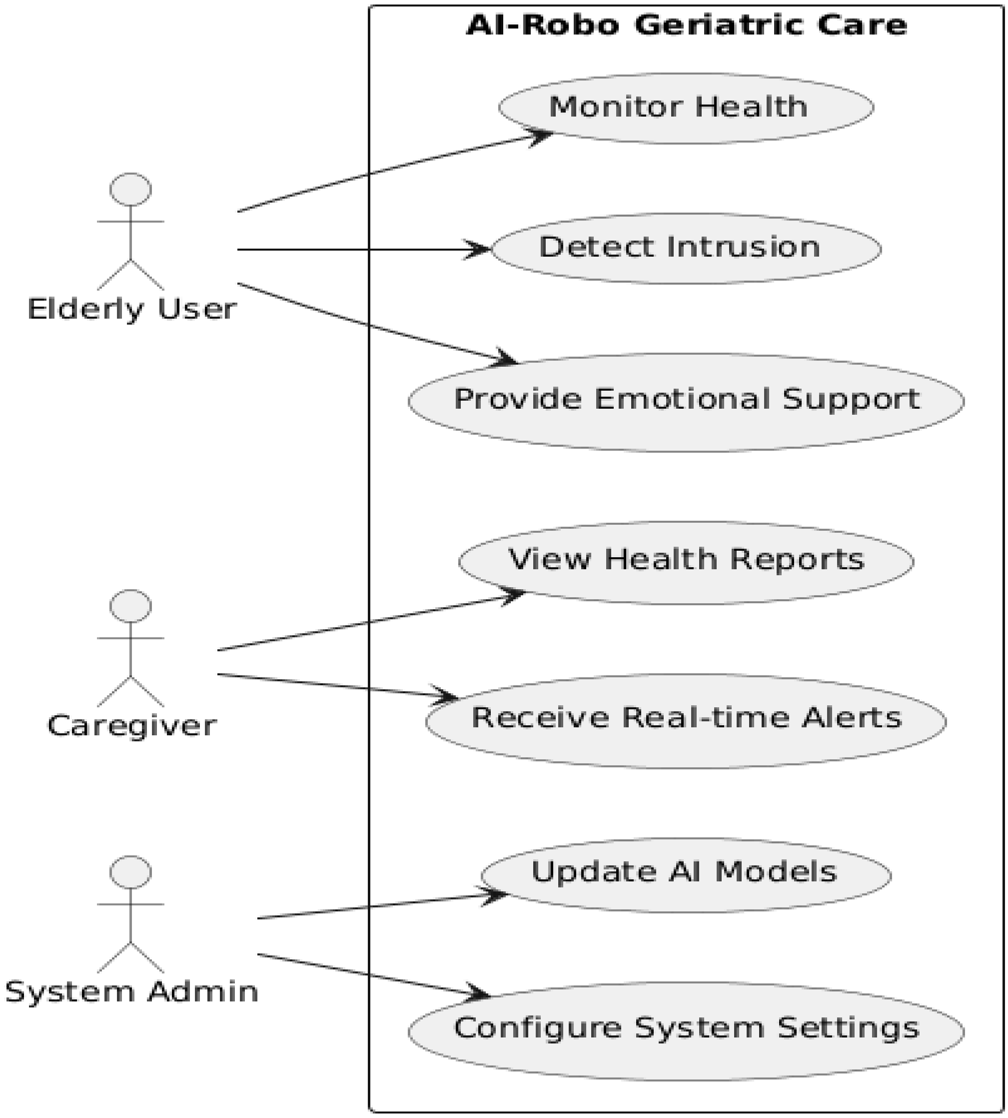


The AI-Robo System also comprises a number of internal modules such as Health Sensors, a Camera/Microphone, and an Alert Module, which all together monitor the health of the elderly. For functioning effectively and initiating timely interventions, the system also interacts with a number of external units One of the most important external interfaces is with Emergency Services. Once the Alert Module identifies a critical health anomaly or an emergency scenario such as a fall, it initiates an emergency call through API. This automatic call ensures that assistance is sent without human intervention, increasing the user's safety.

Apart from real-time emergency management, the system also ensures ongoing health and emotion tracking through interaction with Cloud Storage. Data from health sensors and emotional profiling is uploaded on a regular basis through a secure HTTPS connection to two databases: the Health Database and the Emotion Database. This ensures long-term storage, allowing caregivers and doctors to monitor developments over time and make informed decisions based on data.

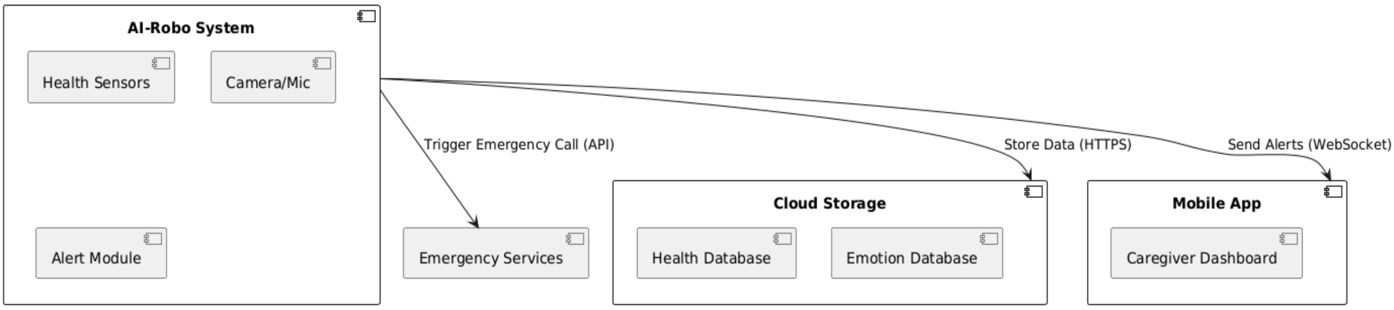
The third significant external interface is the Mobile App, a gateway that links the AI-Robo System with caregivers or relatives.The system provides instant messages and notifications in the shape of WebSocket connections to the Caregiver Dashboard within the application. This indicates that caregivers are constantly updated on the user's current status and can respond immediately if needed. Overall, these external interfaces form a robust, responsive, and interconnected environment that makes the AI-Robo System an intelligent and efficient solution for elderly care

6.4 Use case Diagram :



The use case diagram describes the interaction between various user roles and the features of the AI-Robo Geriatric Care System. Three main actors are defined: Elderly User, Caregiver, and System Admin. The Elderly User is able to interact with the system to track their health, identify any unauthorized access for security, and gain emotional support through AI modules. The Caregiver is also a crucial person to observe and react to health-related information; they are permitted to access detailed health reports and receive real-time notifications in the event of any abnormality or emergency situation. The System Admin has to maintain and update the system; they are authorized to update AI models for improved performance and configure overall system settings to ensure hassle-free and secure operations. This diagram describes the user-centered design of the system and how different stakeholders interact with the system to achieve comprehensive geriatric assessment.

6.5 External Interfaces Diagram :



The external interface diagram of the AI-Robo System for Geriatric Care illustrates how the system interacts with other external stakeholders to enable effective monitoring, alerting, and caregiving. The system has internal modules like Health Sensors, Camera/Mic, and an Alert Module that work together to collect real-time health and emotional data from the elderly users. This information is securely transmitted over HTTPS to Cloud Storage, which is divided into two databases: the Health Database for storing physiological metrics, and the Emotion Database for storing emotional state records. In cases of emergency, the Alert Module initiates an Emergency Call through an API call to Emergency Services so that help can be obtained in real time.At the same time, the system triggers notifications via WebSocket communication to a Mobile App on which caregivers can track patients remotely via the Caregiver Dashboard in real-time. This streamlined flow of data and alerts between the AI-Robo system and add-on modules guarantees an effortless and reactive geriatric care experience, augmenting safety, emotional care, and timely medical intervention.

6.6 Deployment and Packaging Diagram :

6.6.1 Packaging Diagram :

Fig : Packaging Diagram

The packaging diagram shows the modular structure of the AI-Enhanced Robotic Geriatric Care System. The robot consists of five main components:

Emotion Recognition: Utilizes OpenCV and NLP models to identify emotions via facial expressions and speech.

Health Monitoring: Merges IoT sensors (e.g., blood pressure, heart rate) with a real-time data stream for anomaly detection.

IIntrusion Detection: Scans camera and motion streams to generate security alerts.

Conversational Assistant: Manages speech interactions and medication reminders.

Caregiver Dashboard: Provides a web-based interface for real-time alerts and visualization of health data.

The dependencies are TensorFlow Lite for slim AI models and MQTT for IoT transport.

6.6.2 Deployment Diagram :

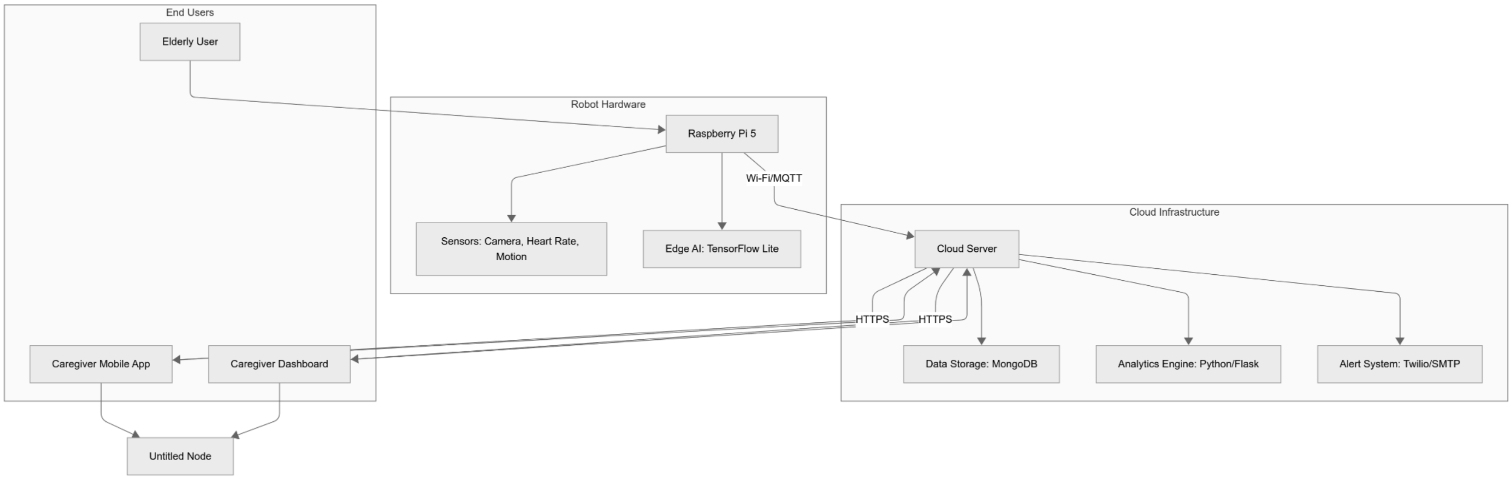


Fig: Deployment diagram

The system's cloud and physical infrastructure are laid out in the deployment diagram: Robot Hardware: The sensor data (heart rate, camera) is processed locally with a Raspberry Pi 5 for edge AI, TensorFlow Lite running on low-latency.Cloud Infrastructure: Sorensen of anonymized health information is stored within MongoDB, analytics is carried out using Python/Flask, and notifications using Twilio/SMTP.End Users: Directly interacts with users using caregivers to access care while the users being elderly rely on them.Correct communication for interactions between cloud and robot occurs with MQTT on real-time updates on sensors as well as secure access via HTTPS from caregivers.

CHAPTER 7

TECHNOLOGIES USED

The AI Enriched Robotic Geriatric Care system combines a number of newer technologies to deliver intelligent, real-time, responsive care. The technologies were chosen based on compatibility, performance and flexibility in the hardware and software components.

1. Artificial Intelligence & Machine Learning

- Computer Vision (OpenCV, Tensorflow, Keras) Applied to facial emotional recognition using Convolutional Neural Networks (CNN) which have been trained on the FER-2013 dataset.This enables the robot to label an emotional state in real-time.
- Speech Emotion Recognition (Librosa, CNN-LSTM) Used for emotion classification from voice by extracting the features such as MFCC and chroma. This becomes feasible for emotional companionship through voice.
- Health anomaly detection (LightGBM, Random Forest, CNN, deep learning) Used in health monitoring with time-series physiological signals. Utilized to mark anomalies in vitals like heart rate, SpO_2, and temperature.

2. Development Tools & Frameworks

- Python: Primary language employed for developing the AI models and backend logic.
- Keras/Tensorflow: Mandatory frameworks to train deep learning models to be deployed.
- OpenCV: For image processing/computer vision capability functions.
- Scikit-learn: For training traditional machine learning models.
- Flask: Web back-end framework.
- Librosa: For pre-processing speech emotion recognition audio.

CHAPTER 8

DATA PREPROCESSING AND IMPLEMENTATION

Phase 2 involves the integration and development of the major modules of the robotic system based on AI. Phase 2 consists of 2 major sections:

8.1. Data collection and preparation

8.1.1 Data Sources:

Facial Emotion Data: Use public datasets like FER-2013 from kaggle which has around 36k grayscale images of people showing 7 emotions: neutral, sad, happy, angry, fear, disgust, and surprised.

Health Data: Record wearable IoT sensor readings (heart rate, activity, sleep) and self-reported health data.

Security Data: Simulated or real intrusion situations based on motion sensors, door/window contacts, and optional camera feeds.

8.1.2 Data Preprocessing:

Cleaning: Remove noise, manage missing values, and correct inconsistencies

Annotation: Tag emotional, health, and security data for training.

Feature Extraction: Derive significant patterns such as pitch, tone, sensor trends.

Data Augmentation: Increase dataset diversity through methods such as noise addition and synthetic data.

8.1.3 Data Splitting:

Split into training, validation, and test sets.

8.2. AI Model Implementation

8.2.1 Emotion Recognition:

Deep Learning: CNNs for vision-based and RNNs/Transformers for audio-based emotion recognition.

Classical ML: SVMs or Random Forests as light options.

8.2.2 Health Monitoring:

Anomaly Detection: Unusual health trend detection using CNN and deep learning.

Time Series Analysis: Using ARIMA or LSTMs for health trend prediction.

8.2.3 Intrusion Detection:

Machine Learning: Decision Trees, Random Forests, or Gradient Boosting for sensor-based intrusion detection.

Deep Learning: Autoencoders/RNNs to identify deviation from regular activity.

8.2.4 Model Training & Evaluation:

Train on the data, hyperparameter tune, and test based on accuracy, precision, recall, and F1-score.

Advantages of this Methodology:

Refined AI: Ongoing testing and retraining enhance model precision.

User-Centric: Feedback incorporation makes it user-friendly.

Lower Risk: Incremental deployment identifies faults early.

Adaptable: Accommodates shifting needs and tech developments.

Better Quality: Early fault identification results in an improved end product.

Limitations of This Approach:

Time-Consuming: Each iteration needs planning and doing.

Resource Hogs: Time, funds, and staff need it.

Scope Creep: Uncontrolled feature growth is enabled by flexibility.

Integration Challenges: Integrate modules can be difficult.

Documentation Burden: Maintaining records current is challenging.

User Fatigue: Excessively large quantities of feedback decrease user engagement.

CHAPTER 9

CONCLUSION OF PROJECT PHASE-2

The Capstone project phase-2 is completed. We collected Datasets to train the models We collected datasets based on Facial emotion recognition which is to detect the health condition of old person by analysing their face emotion in real time. We got good accuracy for certain models like CNN etc and for the model which we got best accuracy we selected it for implementation. Overall predicting Health condition of an old person through capturing face emotions in real time is successfully completed.

We collected Health monitoring Datasets we scrapped most of the medical websites online websites and after pre-processing concatenating all the dataset to form complete dataset with 50,000+ values we trained the models by this dataset.We trained CNN,light GBM, random forest model etc. In all of these we got best accuracy for lightGBM which we will implement in robot also. The model will predict the health condition of an person by taking health parameters such as Heart rate, blood pressure, stress level, body temperature, Spo2 level etc.

we created a speech-based emotional recognition system to assist the mental and emotional health of older people. We utilized a collection of.mp3 sound files containing several emotions including happiness, sadness, anger, fear, and neutrality—chosen because they relate to health markers. Following audio preprocessing to feature such as MFCCs, chroma, and spectral contrast, we trained our CNN-LSTM model, which did an excellent job in emotion state classification. This model allows our AI-Robo system to sense emotional shifts in real time and react accordingly, thus improving general care for the elderly.

CHAPTER 10

PLAN OF WORK FOR CAPSTONE PROJECT PHASE - 3

Phase-3 plan is to integrate and deploy the trained AI models into our robotic prototype, Geri. Geri is a mobile robot with LIDAR sensors for real-time obstacle detection and path planning, which provides safe indoor navigation.

In this phase, we plan to implement the following core functionalities:

Facial Emotion Recognition: With the pre-trained CNN model applied to the FER-2013 dataset, we will attach a high-resolution camera to Geri to capture and examine facial expressions in real time to provide empathetic responses based on emotional indicators.

For Health monitoring we will implement all the sensors required for our project IOT sensors majorily used and when some anomaly occurs in persons health it will alert the care taker.

Speech-Based Emotion Recognition: Microphone modules and audio sensors will be mounted to capture the speech of the user, which will be analyzed by using a CNN-LSTM model. It will allow Geri to decode the emotional tone of voice and accordingly provide companionship or assistance.

We also intend to , Have a modular mounting system for sensors for ease of upgrades and maintenance.   Real-time synchronization of alerts and vitals to the caregiver mobile dashboard using MQTT and HTTPS protocols. Optimize all the models that are deployed to execute effectively on Raspberry Pi 5 with TensorFlow Lite to guarantee low latency and offline capabilities when required.Initiate initial user testing in managed environments to test performance, user acceptance, and simplicity of use.

In this Phase we have scheduled to conclude our project totally by executing all the above-said features

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