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Utilizing the intelligence edge framework for robotic upper limb rehabilitation in home

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ABSTRACT

Robotic devices are gaining popularity for the physical rehabilitation of stroke survivors. Transition of these robotic systems from research labs to the clinical setting has been successful, however, providing robot-assisted rehabilitation in home settings remains to be achieved. In addition to ensure safety to the users, other important issues that need to be addressed are the real time monitoring of the installed instruments, remote supervision by a therapist, optimal data transmission and processing. The goal of this paper is to advance the current state of robot-assisted in-home rehabilitation. A state-of-the-art approach to implement a novel paradigm for home-based training of stroke survivors in the context of an upper limb rehabilitation robot system is presented in this paper. First, a cost effective and easy-to-wear upper limb robotic orthosis for home settings is introduced. Then, a framework of the internet of robotics things (IoRT) is discussed together with its implementation. Experimental results are included from a proof-of-concept study demonstrating that the means of absolute errors in predicting wrist, elbow and shoulder angles are 0.8918^0, 2.6753^0 and 8.0258^0, respectively. These experimental results demonstrate the feasibility of a safe home-based training paradigm for stroke survivors. The proposed framework will help overcome the technological barriers, being relevant for IT experts in health-related domains and pave the way to setting up a telerehabilitation system increasing implementation of home-based robotic rehabilitation. The proposed novel framework includes:

- A low-cost and easy to wear upper limb robotic orthosis which is suitable for use at home.
- A paradigm of IoRT which is used in conjunction with the robotic orthosis for home-based rehabilitation.
- A machine learning-based protocol which combines and analyse the data from robot sensors for efficient and quick decision making.

Specifications table

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More specific subject area:	*Rehabilitation robotics, IoT*
Name of your method:	*Using the internet of robotics things (IoRT) framework for home-based upper limb rehabilitation*
Name and reference of original method:	*N/A*
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Introduction

Neurological injuries such as stroke result in disability in the form of complete loss or reduction in upper limb functional ability [1]. It is estimated that close to one billion individuals (15% of the world's population) across the globe experience some form of disabilities such as muscle weakness, partial or full loss of motions and strengths [2]. It has been reported in [3] that 70% of people with stroke experience arm weakness and 62% of these will not recovery dexterity [4]. During conventional treatments, patients' limb movements are carried out manually by the therapists. During the last two decades the use of robotic devices for upper limb physical therapy of stroke survivors [5–10] has gained popularity in rehabilitation clinics around the globe [11–15]. Several robotic systems have been developed and clinically evaluated with stroke survivors for upper limb rehabilitation [16,17]. These robotic devices can provide more systematic, repetitive, objective, and customized physical therapy sessions as compared to manual physical therapy [18,19].

These upper limb rehabilitation robots have primarily been designed for use in the rehabilitation clinics where the stroke survivors undergo rehabilitation under the supervision of physical therapists. This practice has demonstrated encouraging results in the form of functional improvements in the upper limbs of stroke survivors [20]. A recent study has presented the effectiveness of home-based upper limb rehabilitation in stroke survivors [21]. During the post-clinic stage of rehabilitation, stroke survivors could undergo robot assisted physical therapy in their homes or other community level residential settings, where physical therapists can remotely supervise them. To make this possible, safe solutions need to be developed, with a certain level of autonomous decision-making algorithms to enable therapists to remotely handle many patients simultaneously. To utilize robots for upper limb rehabilitation at home, there is a need to develop a new framework and associated technologies which make it possible for the physical therapists to not only remotely supervise and assess the progress of patients but also have remote control of these robots to adapt the therapy and the exercises, prevent compensatory movements and incorrect movement patterns.

Several preliminary efforts have been reported in the literature relating to robotic upper limb home-based rehabilitation. A home-based approach based on Internet-of-Things (IoT) has been proposed [22], but this IoT based approach involves manual physical therapy instead of a robotic rehabilitation system. Home-based robotic bilateral upper limb rehabilitation systems have been reported in the literature that can adjust the robot applied assistance based on the feedback on electromyography (EMG) signals collected from the arms of the patients [23–25]. However, such work requires placement of EMG sensors on the arms of stroke survivors and this placement is difficult to achieve accurately in home-based settings [26]. A robotic exoskeleton for upper limb rehabilitation has also been developed for home use [27] and preliminary evaluation in the form of wearability of the exoskeleton has been performed. However, capacity for remote supervision and details of the control of this exoskeleton have not been reported. Another IoT based upper limb rehabilitation robot was reported that uses interaction pressure feedback between human and robot from a piezoresistive sensor and writes on a STM32 controller to realize impedance control [28]. However, this system lacked remote supervision from a therapist.

From the above discussion on representative citations from the existing work on robot-assisted upper limb rehabilitation at home, it is apparent that so far, the remote supervision of rehabilitation robots facilitating intervention by therapists has not been reported. There is an urgent need of a remotely supervised home-based stroke rehabilitation of upper limb impairments. It is proposed therefore, to develop a new paradigm which can provide a safe and objective robotic home-based physical therapy to stroke survivors [24]. This paper presents a novel framework for home-based training of upper limb movements using as an example a functional prototype of upper limb rehabilitation robot system. A proposed paradigm of the internet of robotics things (IoRT) includes the components such as patient data acquisition together with its security and encryption, hardware physical and logical interfaces, remote monitoring and intervention by therapist. Data aggregation and initial inferencing based on Machine Learning (ML) is carried out over the cloudlets. According to authors' best knowledge this is the first instance of development and preliminary evaluation of the paradigm of IoRT, reported in literature.

In the following Section "Upper Limb Rehabilitation Robot", the upper limb robot is introduced with a brief explanation of its working capabilities. The proposed IoRT paradigm for robotic home-based rehabilitation is followed in Section "Paradigm of the Internet of Robotics Things (IoRT)" with appropriate illustrations and detailed descriptions of its integrated modules. The experimental implementation used to validate the proposed IoRT framework is provided in Section "Proposed Experimental IoRT Framework".

Method details

Upper limb rehabilitation robot

An upper limb rehabilitation robot has been developed by the authors improving on their previous prototype [23]. The distal arm impairment, being the most disabling consequence of a neurological damage, has been prioritized in this research. The rehabilitation robot developed during this study, therefore, provides active wrist and elbow motions and supports other required upper limb motions passively. The proposed robot can provide elbow flexion-extension and forearm pronation-supination motions (Fig. 1.1). The actuators, which are two brushless DC motors (BLDC), employ two stage cycloidal gearbox and have an onboard magnetic encoder for the measurement of angular positions. The BLDC motors used are AK80–6 motors which are marketed by T-MOTOR ®. These BLDCs are controlled using the CAN (Controller Area Network) protocol which is a standard designed that allows the microcontroller and other devices to communicate with each other without any host computer. This robot also uses incremental encoders to

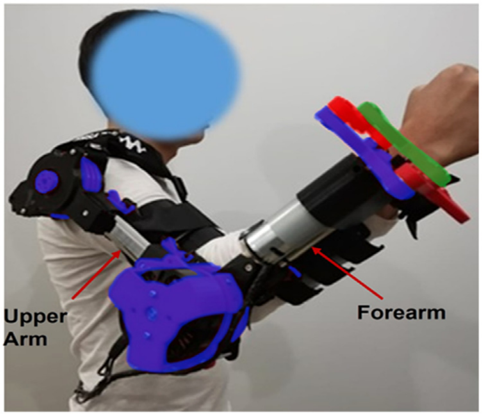

Fig. 1.1. Wearable Upper Limb Rehabilitation Robot.

measure flexion-extension motion at shoulder (θ_s) and elbow (θ_e) in the sagittal plane, and forearm pronation-supination motions (θ_w).

For an ergonomic robot design, it is vital that the attachment system allows donning and doffing single handed and rather quickly. Therefore, the attachment system of the proposed robot has been designed to be completely donned with a single hand in less than 2 mins. If additional help is needed, the process can be easily managed by a caregiver, with a little training beforehand. The robot is attached to a human limb with simple fasteners (Velcro) and straps constructed with nylon and polyester. The robust attachment system can quickly transfer robot motions, and yet flexible enough to remain compliant to changes in arm postures. The robot is also entirely located on the arm and therefore, does not hinder movements of other joints. The actuators have onboard encoders for speed and position sensing while electrical power input to the motors measured via an electrical power metre gives an estimate of the torque on motor's output shaft. Towards ensuring safety, mechanical locks are provided in the robot joints to limit its range and direction of motions, whereas circuit breakers used in the controller limit the motor currents to contain motor speeds within safe limits.

The robot's forearm and upper arm parts are made from aluminium and their lengths can be adjusted to suit different users' arm lengths. The robot's elbow joint is connected with the motor shaft through a cycloidal gear that provides small translational motion together with the intended rotation. Such motion at the robot elbow allows the robot joint to remain aligned with the human joint during various arm motions. The interaction force between the human upper limb and the robot is controlled using zero vector as the commanded force. The force controller, thus implemented, can help in achieving back drivability in the actuation system [29]. This further means that the actuator can be driven backward with ease to provide safe human interaction. This wearable upper limb robot is integrated within the IoRT paradigm for providing the rehabilitation at home sitting with the help of sensors, machine learning and a cloud-based platform. Paradigm of the IoRT is further explained using a flow chart in the next Section.

Paradigm of the internet of robotics things (IoRT)

In this work, the IoRT based physical therapy incorporates home-based rehabilitation with a wearable upper limb robot. This novel approach offers a home rehabilitation system for assisting patients remotely by the physiotherapist on different sites via intelligent IoT and visual servoing ML tools.

The Fig. 2.1 illustrates the paradigm of IoRT for a patient sitting at home and the physiotherapist available at remote location.

I. Patient Data Acquisition

Patient specific data *i.e.,* the upper limb movements in terms of the joint angles θ_s, θ_e, and θ_w (in a sagittal plane) are obtained through encoders for position monitoring, joint torques are estimated from the electrical power measurements of the motors, and patients' body temperature is measured using LM 35 temperature sensor. The data from these sensors is communicated to the cloudlet for further signal processing using ML tool.

Security of patient specific data is ensured by using authentication certificates over IoT devices and also while connecting with a Message Queue Telemetry Transport (MQTT) client. A singular cryptographic key is used, for the sake of simplicity, to encrypt and decrypt patients' data while in-transit and at-rest.

II. Hardware Physical Interface:

The hardware physical interface *i.e.,* sensors, actuators, Internet Protocol (IP) cameras, Raspberry Pi (a small microcontroller), local server, edge devices, servers and networking device etc. are embedded within the wearable robot system.

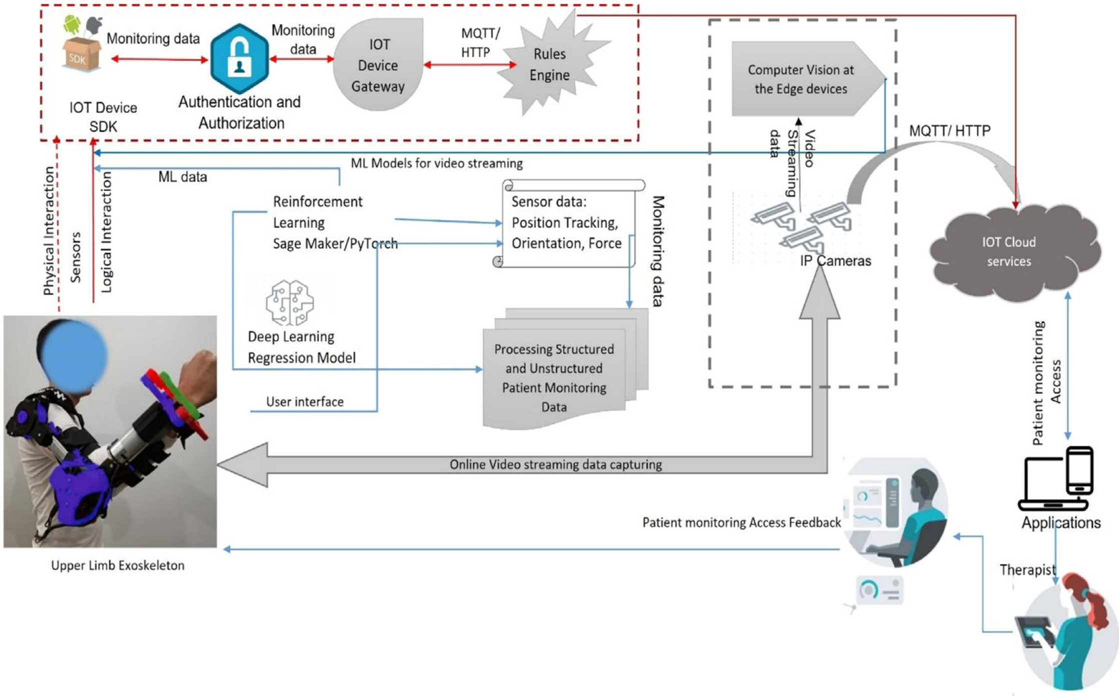

Fig. 2.1. IoRT Home Rehabilitation functionality diagram.

III. Logical Interface:

This module is developed to facilitate interaction between therapists and the robot in real time. The hardware physical interface is connected to Wi-Fi-modules, cloud services, and protocols for IoRT tractability. The authorization and ML algorithms are used to perform the analytics of the specific patient's data to provide feedback to physiotherapist for making decisions.

IV. Remote Monitoring and Intervention by Therapist:

The remote monitoring is achieved through the application software on a therapist's side which also enables intervention altering treatment tasks when required. This module allows therapist to provide oral instructions and arrange a prescribed exercises to a patient. The computer vision may incorporate the extended reality by combining the real and the virtual environments. This will give an enhanced clinic-like experience to both actors, improving the patient-machine-therapist interactions generated by IoRT and wearable devices.

The various functions of the proposed IoRT system are illustrated in Fig. 2.1, constituting sensor data acquisition and signal processing unit, IoRT hardware modelling and ML based architecture, visual servoing using network-synchronized cameras and remote monitoring and intervention by therapist. These main components of the IoRT framework together with ML based approach to solve the inverse kinematics of the developed robotic orthosis are described in detail in the following subsections.

Sensor data acquisition and signal processing

While the primary use of the wearable upper-limb robot is in providing the rehabilitation treatment to the stroke survivors, it can also be used as a measurement device evaluating patients' capabilities and health parameters through various sensors and encoders mounted on the robot. The proposed robot consists of an LM35 body temperature sensor, displacement encoders, and an electrical power metre to estimate the torque on motor's output shaft. These sensors are used to obtain data during robot motions which gives important (but unstructured) treatment-related data from the subjects.

The data acquisition DAQ system with its components is shown in Fig. 2.2. Analogue signals retrieved from the sensors are converted to digital signals using the signal conditioning circuit. Multiplexer (MUX) helps in putting together multiple analogue sensor outputs which is later passed through an analog to Digital Converter (ADC) for further analysis on a digital computer using an appropriate analysis software, such as the data acquisition toolbox in Matlab®. Presently, the robot employs joint position encoders to monitor the upper-limb activity. However, other kinds of medical data in the form of EMG signals, force sensors, images, audio, previous medical records, etc. can also be processed. Wireless communication protocols are used for embedding IoRT feature. Sensor data are amplified appropriately and are subjected to level shifting and calibration after noise filtering.

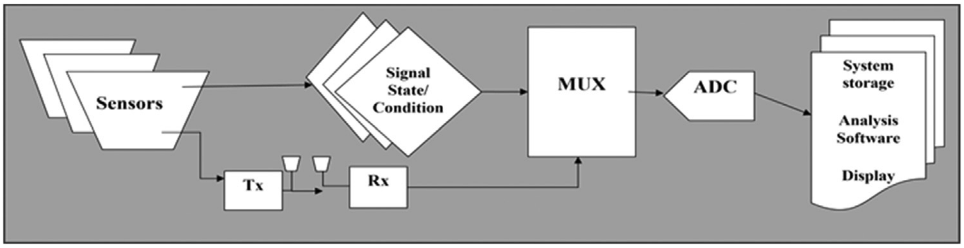

Fig. 2.2. DAQ component diagram.

Machine learning based framework

Sensor data aggregation and preliminary inferencing is carried out using reinforcement learning over the cloudlets to reduce end-to-end communication latency. Later, artificial intelligence (AI) software tools provide python programming interface between cloudlets and the cloud-based devices. This programming interface creates rules in the form of algorithms to turn the data into actionable information onto the devices. PyTorch and AWS (Amazon Web Services) SageMaker are the AI software tools which facilitate building and training of ML models. These models can be directly deployed for the present application. These AI software tools use regression-based learning, support vector machines (SVM) [30] or multiple adaptive neuro-fuzzy inference system (MANFIS) [31] to process the sensor data received from cloudlets to categorize the higher level information and further inferencing.

In the present research, MANFIS has been implemented (as explained in the next Section) to provide three joint angles from a given input end-effector position. This input is a commanded rehabilitation path obtained from the exercises prescribed by a remote therapist. This data is passed through the more efficient, highly accurate active learning and pre-labelling mechanism via pipeline pre-processed data points using deep learning on SageMaker and PyTorch platforms. At this stage, the ML models are used to establish mapping between the set of targets and the inputs. Desired angular displacements at shoulder (θ_s), elbow (θ_e), and wrist (θ_w), to achieve a given end-effector position in space, are informed by the ML models. The ML models are run through the uploaded data points in a prioritized way. Pre-labels are generated which are later used for manual labelling, reviewing, or editing. The pipeline then scales the data based on the number of sessions the patient has performed over a period of time. In other words, useful data from AI software tools is retained by the pipeline for further processing and it is scaled to optimize the overall data volume that increases with the number of sessions. Based on the data gathered in the pipeline, the patient is prescribed an appropriate mode of robot assisted treatment by the remote therapist via the Application Programming Interface (API) or User Interface (UI) accessories provided by AI software tools (Super.AI) located on the cloud.

Inverse kinematics of the robot using machine learning

The developed upper limb robotic prototype has been presented in Fig. 1.1. The human palm from wrist to fingertips is considered as the end-effector. The robot needs to be precisely controlled while it is being traversed through the necessary rehabilitation trajectories. For the human palm (end-effector) to accurately follow the commanded rehabilitation paths, two kinds of kinematic analyses, namely, forward kinematics and inverse kinematics are required. To ascertain position of the end-effector in space, we need to measure the angular displacements at shoulder, elbow, and wrist joints. Moreover, to take the end-effector at a desired location in space, we need to know the required angular displacements at the joints. Determining end-effector position from known angular displacements is termed as the forward kinematics, whereas, obtaining various angular displacements from the given end-effector position is referred as the inverse kinematics analysis. The forward kinematics solution of the robot, which is basically the pose of the end-effector in space, can be easily determined by solving kinematic equations from the known joint angles and link lengths. However, it is difficult and time consuming to perform the inverse kinematic analysis which normally doesn't yield a closed form solution and in fact, a correct unique solution needs to be found from the set of many feasible solutions [32].

In this regard, a machine learning based model can be implemented to obtain solutions of the inverse kinematics of the upper limb rehabilitation robot in a quick and precise manner. In other words, we would like to know about the required angular displacements at the shoulder, elbow, and the wrist joints so that the tip of the arm can be placed at a given position (target end-effector position). In order to develop such a model, a database is normally required for training and testing the model and obtaining optimal model parameters. In fact, solutions from the forward kinematic analysis can be used for this purpose. During the present research, a ML based model has been developed and tested to demonstrate how instructions from therapists (the commanded rehabilitation paths) about end-effector positions can be quickly and precisely translated in terms of shoulder, elbow, and wrist angles, which will be later given to the controller for further execution. In order to obtain joint angles from the information about end-effector position a multiple adaptive neuro-fuzzy inference system (MANFIS) has been developed that contains three individual fuzzy models to provide three joint angles [31]. This model takes position coordinates of the end-effector as inputs and produces three joint angles through three different ANFIS models and these outputs can be either obtained as three different outputs or as a single vector of three values.

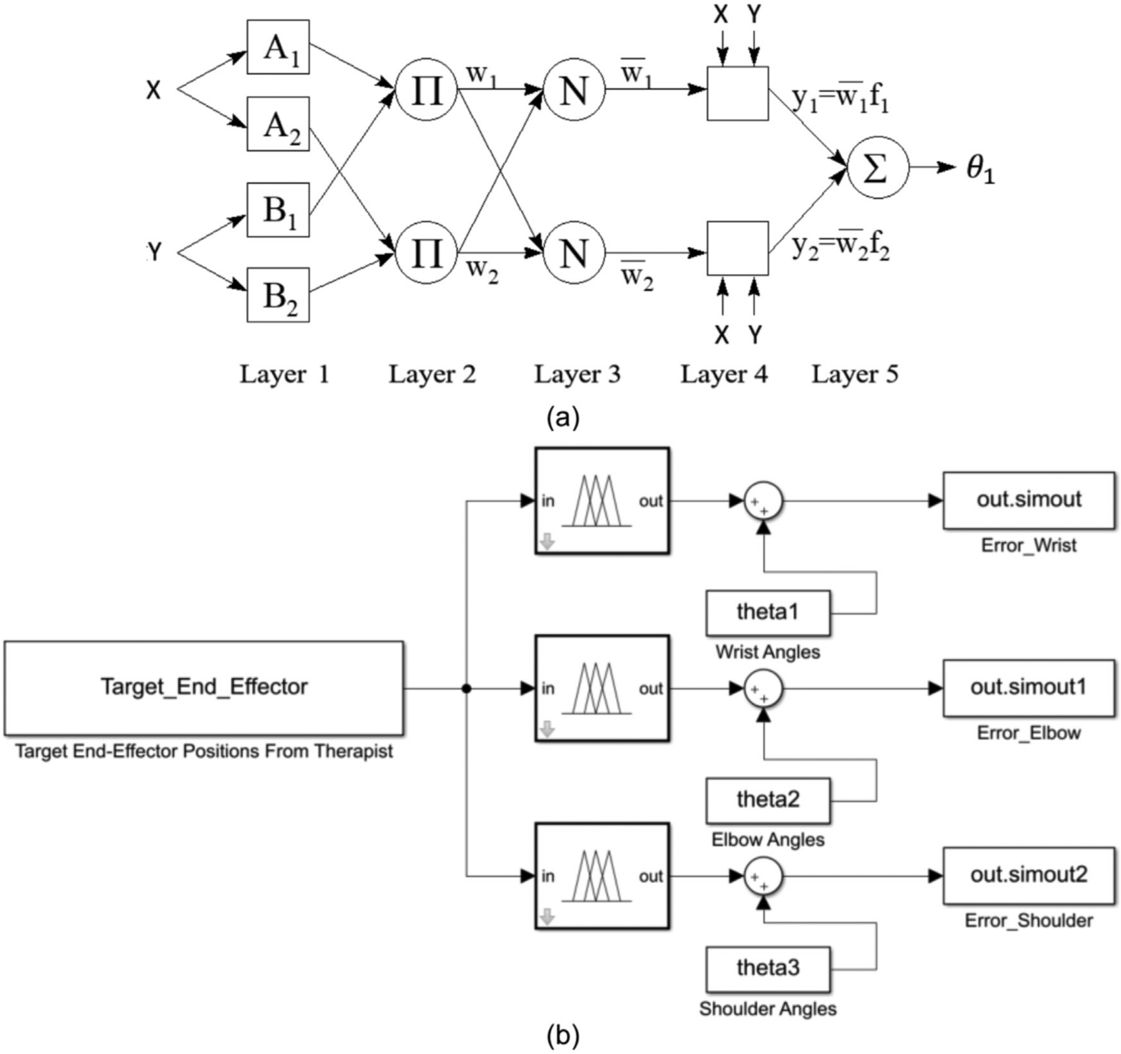

Fig. 2.3. (a) ANFIS architecture for input end-effector positions (X, Y) in sagittal plane as inputs and the joint rotations (θ_1) as outputs & (b): MANFIS-Based ML model concatenating three ANFIS models.

Three ANFIS models combined in such a way are called MANFIS (Fig. 2.3). Readers are advised to refer to [33] and the pseudo code provided here for the details of the construction, training, testing, and validating MANFIS.

Pseudo Code for ANFIS
Step 1. Generate the membership grades and define inputs as fuzzy variables.
Step 2. Generate the strength of real number inputs using the fuzzy membership functions.
Step 3. Normalize the strength values.
Step 4. Calculate output from an individual rule for given set of input values.
Step 5. Aggregate all the rule outputs from Step 4.
Step 6. Employ input-output training data to obtain the weight vector (W), using singular value decomposition (SVD) technique.

IoRT hardware modelling

The essential IoRT hardware, that is required for the robot system, contains a Raspberry PI microcontroller board which is used for implementing necessary IoRT hardware (Fig. 2.4). The IoRT hardware framework includes actuation boards for communication between motors and controllers, interface board that acts as a gateway, MQTT protocol and Long-Range low-power Wide-Area Network (LoRaWAN) used for achieving the required communication.

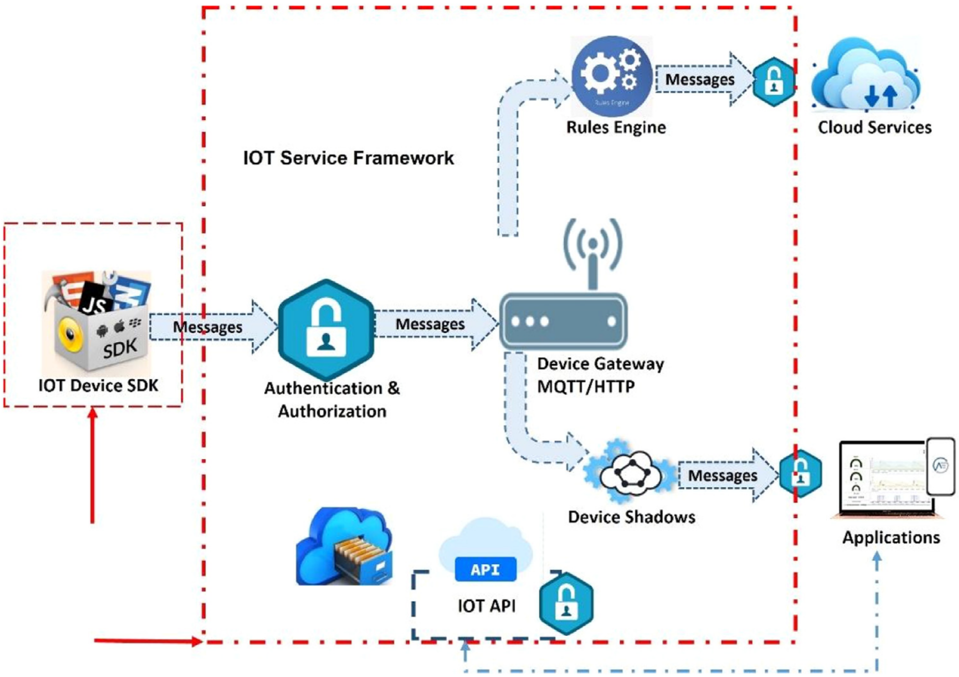

Fig. 2.4. IoT architectural diagram.

The actuation board consists of DC motors used as actuators. Their controller boards connect the upper limb robot and a digital computer through the appropriate interface board. The interface board is normally a development board such as Raspberry Pi4 for prototyping the model of IoRT consisting of several features such as Wi-Fi, Bluetooth connectivity and camera. This interface board also can connect with multiple cloud platforms over various IoRT protocols such as MQTT and LoRaWAN which are the networking protocols to connect devices to the internet and manages communication between end-node devices and network gateways. In the proposed research, the IoRT hardware interface modelling is carried out on AWS-based IoRT core provided by Amazon's cloud ecosystem that allows the required device connectivity.

The ML processed data retrieved through sensors via cloudlets is registered with IoRT Device Software Development Kit (SDK) which securely transmits messages, to and from all the IoRT devices and applications, with low latency and high throughput. Device Shadow, which is a part of the IoRT core, stores the latest state of a connected upper limb robot so it can be read or set at any time, making the device appear to the applications domain even if the device is offline due to some connectivity issues. The IoRT Core MQTT messaging IPC (Inter Process Communication) service is used to send and receive MQTT messages to and from IoRT Core. Sensors employed on the robot can publish messages to the AWS IoT Core and at the same time subscribe to topics (messages that need to be communicated) to act on MQTT messages from other sources. The developed prototype is able to interact with the connected devices owing to its capabilities of interaction to IoRT core service and cloud service provided by cloud ecosystem. The AWS IoT core services are preferred over other cloud services such as Google Cloud or Microsoft Azure due to their scalability to support billions and even trillions of messages [34].

The AWS IoT message broker component is proposed here to be implemented on MQTT which is a messaging protocol used in the 'AWS IoT' core for communication between the devices. In the proposed framework, MQTT is the broker, and the data from the sensors onboard are fetched through ML model via logical interaction to the MQTT and the regulating devices. The devices, subscribed to the service, use this information for publishing the required health monitoring data and at the same time this information can also be provided to the output devices such as sensors mounted on motor actuators which drive the robot.

Connecting with an MQTT client requires authentication with an X.509 certificate (secure protocol) and then a new set of AWS IoT-reserved MQTT topics can transfer messages between devices. It needs to set up and manage a private LoRaWAN network by connecting LoRaWAN devices and gateways to the AWS cloud, without developing or operating a LoRaWAN Network Server (LNS). The Rules engine, which is part of the authentication service, connects data from the message broker to other IoRT services for storage and additional processing. However, if the device is not always connected to internet and the applications, a device shadow service maintains state of a device in order to communicate with other devices. Subsequently when devices reconnect, they synchronize their state with that of the shadow in the device shadow service.

Visual servoing using network-synchronized cameras

The various components of the visual servoing using network-synchronized cameras are shown in Fig. 2.5. The computer vision control application tool, integrated with the ML model, processes the real time video streaming from the computer mounted

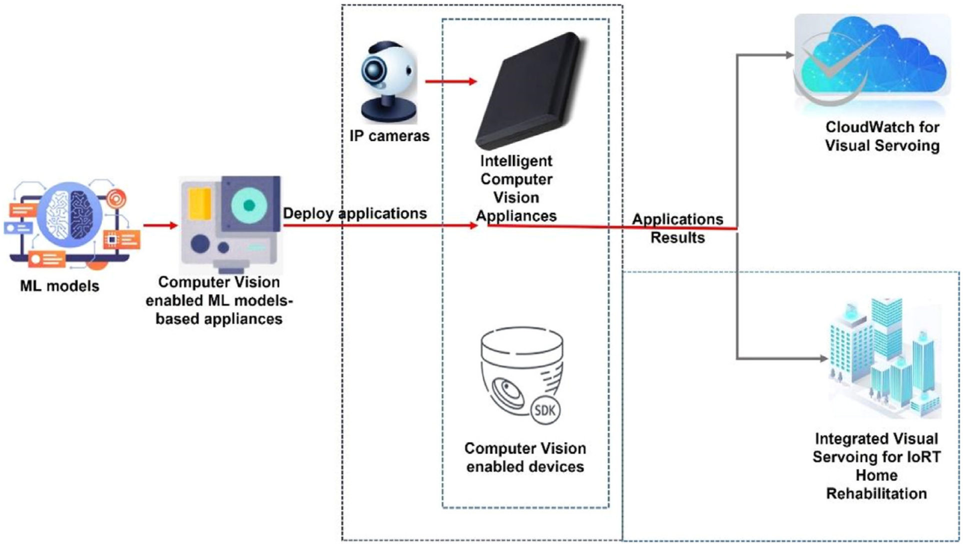

Fig. 2.5. Integrated Visual Servoing for IoRT Home Rehabilitation.

IP cameras at patient's home setting. A unique IP is provided to each of the cameras assigned to individual patients. It allows storage and processing of the video data over cloud and used at patients' home settings for updating health monitoring data. A unique IP is also used to fetch the previous history of the patient for the necessary monitoring and analysing purposes. In the present research, webcam mounted on the digital computer is used as a cloud-based IP security camera. However, a separate IP camera can be used which may be either wall mounted or placed on a tripod at the patients' home settings. With the inclusion of IP cameras and further analysis of their data it is possible to capture and recover important video instances that can be further used by the therapist for evaluation. Such video sensor data can also be utilized as feedback to the robot controller.

Remote monitoring and intervention by therapist

A specially developed User-Friendly Interface (UI) has to be used by the physical therapist (PT) where a qualified professional enters all the required settings for the home-based robotic rehabilitation according to the patient's needs. This procedure starts with entering the initial evaluation parameters to determine the functional status of the patient, such as nature of the injury, record from the previous course of care, level of function and mobility. The therapist can review the uploaded past medical history of the patient to choose the appropriate trainings at home-based setting. There are various tests that can be performed, *e.g.*, safety assessment, range of motion, tone and muscle spasticity, strength or assistive device use tests. As the main goal of the home-based rehabilitation is to recover the motor functions after stroke to perform ADL, an intermediate set of goals can be entered that will gradually lead to improvements of mobility and increased strength. The home-based treatment using a robotic device should be specific to individual's needs. A UI has to contain a library of different physical exercises for upper limb rehabilitation, according to the robotic device's capabilities, which a physical therapist can utilize to remotely supervise the patient in real-time or prescribe a home-based exercise program for patient so he or she can train them independently. The recorded data from the wearable sensors (the ranges of motion achieved in terms of the joint angles, the number of repetitions made, the forces applied by the robot, etc.), saved in a data storage, can later be analysed by PT to monitor the progress of rehabilitation and adjust the exercise program accordingly. A therapist should also be able to select a suitable training modality for robotic rehabilitation [35], *i.e.* assistive, active, passive, active-assistive, corrective, path-guidance or resistive.

The proposed IoRT framework for robotic home-based rehabilitation of upper limbs allows PT to intervene the physical exercises altering treatment tasks if required. The defined modules of IoRT framework enable the logical interface to collect the patients' data and communicate the prescribed trajectories to the robot system. The patients' treatment history data is synchronized via ML algorithms and their best performance is provided to the therapist for making decision on further treatment. For example, the wearable exoskeleton robot used in the present research sets target elbow flexion/extension based on the patient's most recent performance. The appropriate targets, prescribed for the patient to achieve, include targets for parameters such as the range of motion, end point accuracy, velocity of the flexion and extension movements, number of movement units (zero crossings of the velocity profile) and number of repetitions to be performed within a set time. Some of these parameters may not be usually available to therapists during conventional (non-robotic) assessment and supervision of exercises, such as velocity of movements and end point accuracy, so using such a robot would allow more measurable and specific targets to be set by therapists.

The developed device is essentially an upper limb robotic exoskeleton aligned with the human joints and designed to provide supportive motion to the patient. One of the movements that can be practiced assist elbow flexion/extension motion, *e.g.* unweighted or weighted bicep curls. This kind of exercise is important for upper limb rehabilitation after stroke as it helps to recover the ability to bend the arm. The elbow flexion stimulates the biceps while the extension activates the triceps muscles. The unweighted exercise are advised to regain motor control and activate neuroplasticity whereas the weighted exercises are intended to gain the strength. Another movement that can be practiced with the developed robotic orthosis is forearm pronation-supination motion. This is an important ability as it is necessary for most of the ADL. The therapist interaction consists of giving initial instructions about movements to be performed, receiving measurable data from the robot about the movements, and using that data to prescribe exercises and set measurable targets to progress the patient's ability further, and then reassess it at regular intervals. This interaction would be set within the context of usual therapeutic processes such as joint goal setting with the patient to decide on which ADL are to be achieved. The therapist would then devise appropriate movements to be practiced with the robot to help achieve these goals. The further improvements of the proposed IoRT system may include software updates with game-like exercises to increase the motivation of the patient and provide a more repetitive robotic home-based rehabilitation. Moreover, the improvements of the robot may incorporate inclusion of the modules to assist more degrees-of-freedom (DOFs) of the human upper limb and implementing different advanced control strategies, such as Assist-as-Needed (AAN) support while patients try to perform exercises on their own.

Proposed experimental IoRT framework

Every input/output IoRT enabled device is called a 'thing' and all such 'things' are registered with AWS cloud service. In order to connect the proposed model of IoRT framework and IoT core (software framework on IoT device) to the 'thing' (such as PC and mobile), AWS cloud service is taken as AWS IoT core service. The registered Raspberry Pi4 hardware device, registered as 'thing' is shown in Fig. 3.1. After creating the 'thing' in IoT core, IoT core certificates are downloaded and copied onto the Raspberry Pi4. Later, an 'Amazon Cognito' (authentication service) is configured which allows anonymous users access with right certificates including Public Key and Private Key files. Next, policies are created and associated with generated certificates as the set of rules engines. With the steps explained above, the hardware implementation is achieved and towards the end, a python program is executed to connect IoRT core to 'things'. Subsequently, to send and receive messages, to and from AWS IoT Core, MQTT messaging IPC service is used authenticating with an X.509 certificate and Amazon Cognito.

Python program is written to publish/fetch and read messages from the connected sensors (real time sensor data) of the upper limb robot. This program also subscribes to the messages (topics) and reads them in the form of notification service to the intended application domain as demonstrated in Fig. 3.2, where subscribing the topic 'patient_monitor' and publishing it with the sensor data to the system is also illustrated.

Amazon Notification service (ANS) is connected to the application domain such as personal computers and mobile devices. It is also connected remotely to the therapist who can view and access the messages. At this stage, the therapist is able to access patients' status online while they are using the wearable robots. Cloud services are also capable of storing the real time sensor data for later offline analysis. Patients' location is accessed by Intelligent Computer Vision (CV) edge devices through IP cameras as discussed in the

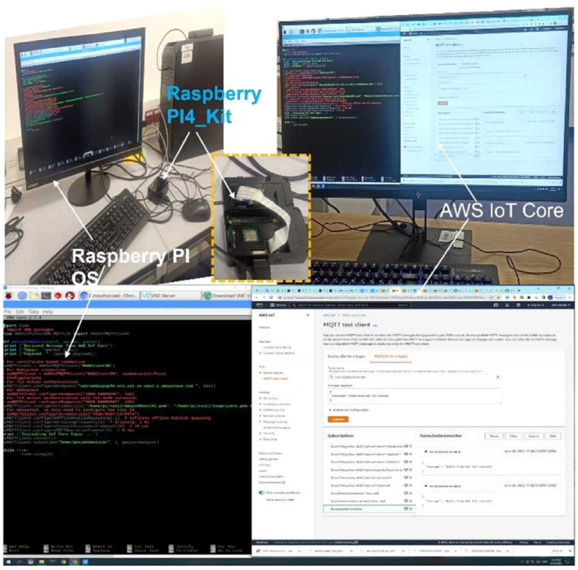

Fig. 3.1. Proposed IoRT for Home-Based Rehabilitation implemented using Raspberry Pi4.

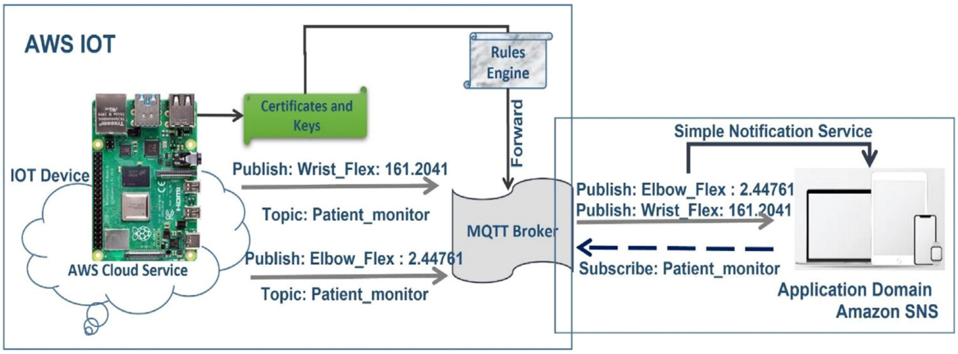

Fig. 3.2. AWS IoT Core Publish and Subscribe MQTT services.

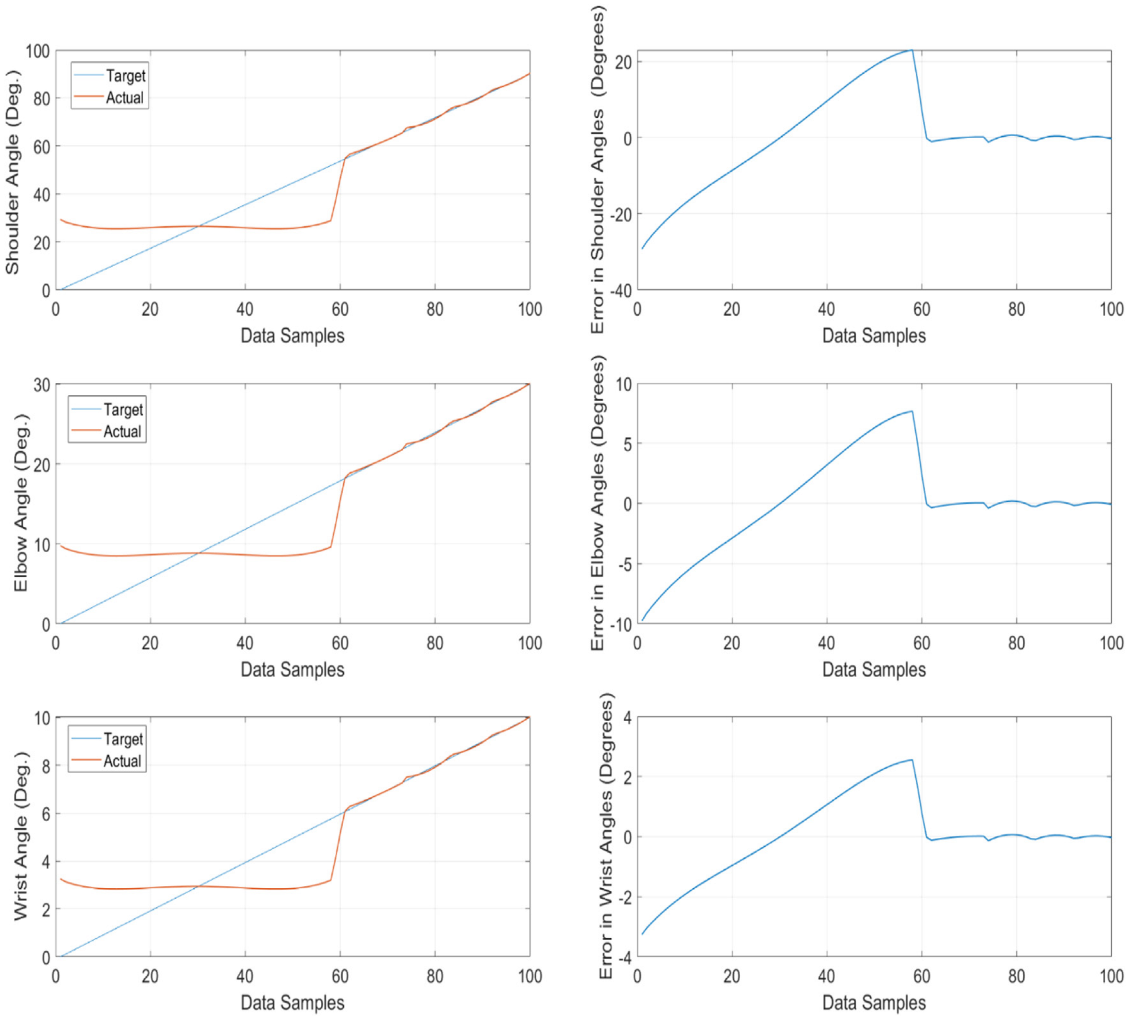

Fig. 3.3. Target and Actual Joint Angles for test data with Prediction errors (in degrees), from ML model.

previous section. These CV-enabled appliances are used to deploy and register multiple real time video streams simultaneously through a real time streaming protocol (RTSP). In the present research, the wearable robot is connected to rtsp://198.168.1.110/live/mpeg3 for observing the video stream and the IoRT module casting, while the instructions from therapist to the patient's application domain are sent via video teleconferencing.

ML based modelling for inferencing the sensor data

To test the proposed IoRT framework an inferencing of sensors' data over cloud has been implemented. First, the shoulder, elbow and the wrist joint motions of the robot are recorded, and the robot end-effector position is derived using the forward kinematics analysis from the three joint motions (shoulder, elbow, and wrist). The acquired sensor data is passed through data acquisition unit to develop an ML-based model for data inferencing. The database used for training and testing of AI model consists of robot joint motions and corresponding robot end-effector positions. Performance of the AI model developed is further assessed using RMS (root mean square) errors in target and output robot end-effector positions.

The proposed ML-based model uses deep-learning regression and support vector classification libraries of Keras (API of TensorFlow) [36], and Sci-Kit learn [37] in the python language environment for predicting a continuous-valued end-effector position attribute associated with the wearable upper limb rehabilitation robot. Sensor data was split into training and validating datasets to perform deep learning regression. The Sequential model on Keras is used to train the AI model because the proposed network consists of a linear stack of layers. ReLU (rectified linear unit) activation function is selected in this AI model and the input dimensions are kept equivalent to the number of antecedents. Requisite number of hidden layers together with one node singular output layer completes the model architecture. In order to train the model with appropriate training data, an optimizer and the loss measure are defined. While the RMS error from testing data is a loss measure, the "adam" optimizer [38] is used for a minimization algorithm in order to optimize the learning rate.

Numerical case study

To experimentally evaluate the proposed approach, three common motions were chosen as the commanded (by therapist) rehabilitation paths, namely, shoulder extension-flexion, elbow extension-flexion and wrist pronation-supination. The ranges of these motions are constrained by the robot capabilities, being $\pm 90^0$, $\pm 60^0$ and $\pm 50^0$ for shoulder, elbow and wrist, respectively. The test data includes the desired end-effector positions suggested by the therapist.

In order to implement altered end effector positions commanded by the therapist, the machine learning module converts this command to three joint angles of shoulder, elbow and wrist (θ_s, θ_e and θ_w). The target and actual joint angles for test data and the related prediction errors (in degrees) from ML model are plotted in Fig. 3.3. Prediction errors are basically the absolute differences between the target and predicted angular positions at shoulder, elbow, and wrist joints to achieve the commanded end-effector position by the therapist. As can be seen from the right-hand side of Fig. 3.3, the prediction errors are higher for the shoulder angles in comparison with elbow and wrist angles. This is due to the fact that the errors get accumulated moving from wrist to elbow and then to the shoulder joint. The means of absolute errors in predicting wrist, elbow and shoulder angles are 0.8918^0, 2.6753^0 and 8.0258^0 respectively. Furthermore, the robot link connected at the shoulder joint has larger rotational inertia and so is subjected to larger deflections compared to the links connected at elbow and wrist. These errors are observed over different ranges for the three described motions. The machine learning module was implemented on cloudlet with input data transmitted by the robot acting as an IoRT gateway.

Discussion and conclusion

A proof-of-concept prototype was developed to understand and evaluate the implementation of a potential IoRT paradigm in the robot assisted rehabilitation in home settings. The upper limb rehabilitation robot was developed that can actuate elbow flexion-extension, and wrist pronation-supination motions (Fig. 2.1) by using BLDC motors and allow other passive upper limb motions. The robot also has incremental encoders deployed on the actuators to control flexion-extension motion for shoulder (θ_S) and elbow (θ_E) in the sagittal plane, and forearm pronation-supination motions (θ_W). The IoRT framework, as described in Section 3, consists of four modules, namely, Data Acquisition, Hardware Physical Interface, Logical Interface, Remote Monitoring or Intervention by Therapist. Essential IoRT hardware consist of a Raspberry Pi microcontroller board, actuation boards, interface, and an appropriate communication protocol. The remote therapist receives higher level information that is generated by the AI tools (provided by AWS). These AI tools work with the data transmitted by the robot acting as an IoRT gateway. For instance, the therapist shall be able to know the ranges of motions that are retrieved from the robot attached to the patient's upper limb. If therapists decide to alter the locked ranges of robot motions, they can do so by sending an appropriate command through the logical Interface module of IoRT. The message received from the therapist is received by the host computer which is connected with the rehabilitation robot in home settings. Later, the interface board generates appropriate current signal to pass it to the related actuator (BLDC motors).

A novel edge intelligence framework for a bio-inspired upper limb robot has been designed based on the Internet of Robotics things (IoRT) paradigm for home-based stroke rehabilitation of upper limb impairments. Extracted sensor data from wearable robot in patients' home settings is processed using MANFIS-based machine learning models on cloudlets. Transmitting this higher-level information to the cloud is recommended to reduce end-to-end communication latency. This higher-level information that contains the machine learning model along with other important information such as correlation between sensor data and best features, is later transmitted via IoRT MQTT protocol to the cloud services. AWS cloud service further works on the information sent from the cloudlets using AI tools such as Super.AI etc. Information which is processed through AWS cloud services is later sent to the remotely connected therapist. The proposed IoRT can also be combined with visual servoing for real time video streaming through IP cameras using RTSP protocol so that therapist can monitor the sequences of exercises. The implementation of proposed IoRT for home-based rehabilitation of upper limb impairments is also shown in Fig. 3.1 whereby Raspberry Pi4 is used to interface the robot to the cloud services.

The proposed prototype is unique from previously proposed work in the literature since it also facilitates a remote therapist to intervene and manipulate the robot system at patients' home settings. It is known that the most disabling consequence of neurological damage is distal arm impairment, but mostly the recovery of proximal upper limb motor functions is studied and researched. Therefore, the upper limb rehabilitation robot developed during this study focuses on the active wrist and elbow motions while providing passive shoulder motions. The research work presented in this paper is an advancement over the prototypes studied and analysed in terms of the capabilities of the robotic system and the validation of the IoRT paradigm. As yet another distinctive feature, the proposed framework has potential of collecting image and video signals, captured through IP cameras, together with other sensor data. This important information can be processed using the intelligent edge computer vision platform on the cloud to evaluate the treatment using advanced image processing tools. The application platform proposed in this research is user friendly for both the patient as well as the therapist. During the ongoing pandemic of COVID'19 or any other such pandemic in future, this solution can help delivering treatment remotely either in real time or asynchronously.

The description of the IoRT framework and its capabilities discussed above explains that a therapist from remote locations (such as clinic or otherwise) can receive important data from the robot system through cloud. It is also explained here that the therapist is able to intervene during the ongoing treatment and alter vital parameters on the robot system in order to implement the desired changes in the robot's position and force trajectories. The message from the therapist in certain form is received by the host computer situated at the home settings. In the present case, the therapist suggest a desired end-effector position and the ML module predicts the required shoulder, elbow, and wrist angles in order to achieve the desired end-effector positions.

It is acknowledged that the proposed framework of IoRT described in this work has not yet been deployed in a controlled environment with target users. We consider that it is currently at a technology readiness level TRL3 (Technology Readiness Level), so further investigations will need to be done before conducting tests in the operational environment, *i.e.* at home-based setting with stroke patients.

CRediT author statement

Prashant K. Jamwal: Conceptualization, original draft preparation and funding acquisition; **Aibek Niyetkaliyev:** Writing – Reviewing and Editing; **Shahid Hussain:** Methodology; **Aditi Sharma:** Software Development and Analysis; **Paulette Van Vliet:** Formal analysis and writing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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