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Design and development of humanoid robotic arm

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ABSTRACT

This paper presents the design, development, and evaluation of a 5-degrees of freedom (5-DoF) humanoid robotic arm featuring a sophisticated 5-finger gripper. The five degrees of freedom include the base, shoulder, elbow, wrist, and gripper, all controlled by MG996R servo motors to enhance grasping, positioning, flexibility, and mobility. The arm is constructed from laser-cut aluminum sheets. It effectively picks and places objects such as bottles and bags. A high-speed portable computing system is used to control robotics hand operations. A webcam is used for object detection and to acquire information about the surroundings. The system uses a convolutional neural network-based MobileNet architecture for object detection. The robotic hand is used as an assistive aid for amputees. It mimics finger movements based on detected objects. The system achieved a precision of 0.97 for bags and 0.93 for bottles, with accuracies of 96.83% and 92.42%, respectively. The system employs advanced computer vision algorithms and real-time strategies, ensuring adaptability across various tasks. It integrates advanced visual systems and improved feedback to enhance user interaction and overall usability. It addresses trade-offs between detection precision and processing time.

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1. INTRODUCTION

This paper presents the design, development, and evaluation of a 5-degrees of freedom (5-DoF) humanoid robotic arm with a sophisticated 5-finger gripper. The 5 DoFs are the base, shoulder, elbow, wrist, and gripper. These resources are controlled with servo motors, enhancing the arm's capabilities in grasping, positioning, flexibility, and mobility. Serving as the central control unit is the Raspberry Pi, directing the movements of the five servo motors through advanced algorithms to ensure seamless and precise arm operations. This robotic arm is developed for the rehabilitation of hand amputees and can be used for other industrial applications with certain modifications.

Factors affecting limb movement and grasp are analyzed by measuring joint angles using Kinect depth sensors and MediaPipe Framework [1]. This emphasized the integrated approaches for real-time challenges. To oversee the system [2], handheld input devices like joysticks, keyboards, computer mice, and touch screens are commonly employed. The constraint of limited DoF presents a hurdle, particularly when managing robots with numerous degrees of freedom, such as robotic arms. Additionally, joystick manipulation of a robotic arm necessitates non-intuitive transitions between position, orientation, and gripping control modes. Nodes [3] can control the arm, plan safe movements, and execute actions to reach initial and final positions. Neural network-based [4] learning offers accurate continuous mapping and handles multiple object shapes, enhancing object detection capabilities essential for robotic interaction in varied environments [5]. It enables continuous estimation and addresses non-linearities. The suggested strategy in [6] seeks to overcome this drawback and improve semantic representation which adopts robotic fingers with force sensors designed to hold objects for daily activities like eating and drinking were controlled using a proportional-integrated-derivative (PID) algorithm. This arm was designed for children [7]. A robotic arm for pick and place robot operation using a greedy algorithm for prioritizing the action is described [8]. Defined sequences of operation were used along with image-based object recognition for industrial applications. Decision tree-based decision is integrated with rotating the robotic arm in the trajectory defined by the sequence of operations [9]. Robotic hand grasping unseen objects is described in [10]. It implemented the pick, sense, and place strategy using adaptive techniques. A robotic arm that can grasp objects from outside is more common. The arm that holds the object from inside is implemented in [11]. Symmetrical movement for grasping is used here for holding the object with stability. Water bottle identification was carried out using the YOLOv5 algorithm with 85% accuracy of grasping the bottle by taking the path trajectory [12]. For deformable objects, grip strength is important [13] to form a stable grip without damaging the object. Point cloud scanned output is used to define the gripper coordinates to hold the object. Tactile sensor-based identification of object hardness is carried out using machine learning [14]. The Cartesian robot is trained to detect 5 hardness levels using a machine learning algorithm. Twisted strings control the robotic hand [15] and intelligent sensing-based grip is achieved. A humanoid 3D-printed hand with 5 fingers with a virtual reality-based monitoring system is implemented. Exoskeleton robots are pivotal in stroke rehabilitation, utilizing innovative inverse kinematics and robust nonlinear control approaches. These advancements enhance trajectory accuracy and ensure stability during passive therapy. Future directions involve integrating visual systems like Kinect for further refinement and effectiveness in rehabilitation protocols [16]. Bilateral haptic collaboration [17] is proposed for human-robot cooperation, featuring a CoGripper and wearable interface. Three user studies confirm efficacy, showing reduced task time and improved grasp control. The system integrates sonar sensing and vibrotactile feedback for enhanced communication. Future enhancements include automated gripper reconfiguration and improve tactile cues for user recognition. Grasping and lifting objects [18] with suitable control remains a challenge in robotics. Neurophysiology sheds light on human hand dynamics, inspiring robotic solutions. Real-time processing of tactile data poses computational hurdles. A bio-inspired approach utilizing cellular nonlinear/neural networks is proposed, enhancing robotic grasping capabilities. Successful grasps of diverse objects validate the system's efficacy. State of the art manipulators control using machine learning algorithms reviewed in [19] indicate cognitive skills development for robots. Recent studies [20] have focused on the evolution of robotic arms over the past two decades, delineating various parameters influencing their performance. These include accuracy, repeatability, kinematics, and working envelope. Commercially available arms exhibit diverse capabilities, yet research highlights gaps in optimization and suggests avenues for future algorithmic and simulation-driven enhancements. Designing [21] a three finger gripper robotic arm with low-cost components to enable various object-picking tasks is discussed. Incorporating a five-finger gripper and precise control algorithms, the prototype demonstrates effective functionality through comprehensive testing. Humanoid motion [22] planning for robotic arms integrates human arm physics and reinforcement learning, promising safer interaction for aged individuals. Robotic arm control for press, grasp, and flip operation was controlled using image inputs to a dual-arm robot [23]. Experimental results show successful implementation, enabling object manipulation via hand gestures. A pick-and-place algorithm [24] using a multirate event-triggered sliding mode controller for a robotic arm in 3D space is proposed. Control updates occur when triggering rules are violated, optimizing resource use. Validated on a human arm system, it demonstrates efficiency in object manipulation with minimum control updates. A remotely operated 6 degrees of freedom (6-DoF) robotic manipulator was designed for the swab collection of Covid patients [25]. Robotic manipulators need precise operation, and more work needs to be done to provide assistive solutions to humans.

One of the primary limitations of current robotic arms is the challenge of robust grasping. The surface curvature of objects poses significant difficulties, necessitating integrated approaches to manage real-time grasping effectively. Additionally, the limited DoF in many robotic arms restricts precise control, particularly in arms with multiple DoFs. The control and interface mechanisms of robotic arms also present substantial limitations. Common input devices such as joysticks, keyboards, mice, and touch screens are non-intuitive for managing the position, orientation, and grip of robotic arms. Joystick manipulation, in particular, requires complex transitions between different control modes, complicating user operation and reducing efficiency. Real-time processing of tactile data and the need for computational efficiency pose significant hurdles for robotic arms. Balancing computational resources while maintaining performance is an ongoing challenge, affects the overall effectiveness of robotic systems. Current robotic systems lack intuitive interfaces for effective human-robot cooperation, making tasks such as grasping and lifting complex and inefficient. The proposed system addresses the majority of challenges. It integrates advanced visual systems and improved feedback to enhance user interaction and overall usability. It uses a lightweight MobileNet convolutional neural network (CNN) architecture, offers high accuracy and addresses trade-offs between detection precision and processing time.

2. METHOD

This work presents the design and development of an assistive robotic arm for hand amputees, with a particular focus on mimicking finger movements. Unlike a biological hand that receives instructions from the brain, this robotic arm detects objects through a computer vision system and forms the grip accordingly. The workflow of the proposed system in Figure 1 involves a sequential process starting with a camera capturing video frames. These frames are processed by the MobileNet architecture for object detection, followed by grip formation. The frames undergo normalization and resizing to a standardized 224×224-pixel format. The current system uses a camera-mounted spectacle to acquire information about the surroundings.

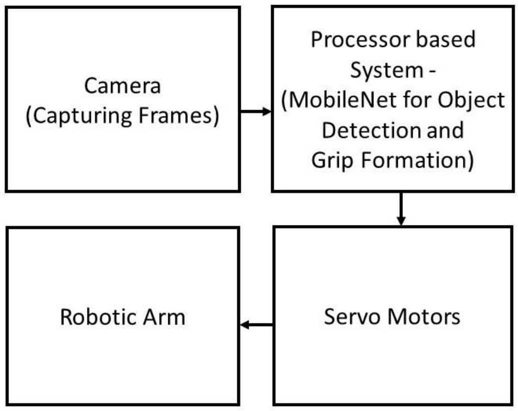

Figure 1. Humanoid robotic arm

The MobileNet CNN extracts relevant features for efficient and lightweight object recognition. Once the system recognizes an object, it uses the identified class information, such as “Bottle” or “Bag,” to trigger specific servo actions for grip formation. The servo motors then control the robotic arm to interact with the recognized objects in real-time, establishing a seamless integration between vision-based recognition and robotic manipulation. The comprehensive approach details the collection and preprocessing of the dataset as the initial phase, followed by an in-depth exploration of the system design and implementation processes.

2.1. Dataset and preprocessing

The dataset used for training the robotic arm’s computer vision system comprises 1,943 custom images sourced from various open-source datasets. These images depict bags and bottles of different colors, shapes, and sizes. The dataset is essential for training the CNN architecture, specifically MobileNet, to classify objects into two distinct categories: bags and bottles. Preprocessing steps include normalization and resizing of images to a standardized 224×224-pixel format. This optimization ensures the dataset is suitable for effective model training. The chosen CNN architecture excels at discerning patterns unique to bottles and bags, enabling accurate real-time predictions for live input images.

2.2. Mechanical design of the robotic hand

The robotic arm is crafted from high-quality aluminum sheets of 2 mm and 4 mm thickness, processed through laser cutting, and designed using SolidWorks in Figure 2. This design promises a dynamic range of applications due to its structural integrity and precision. The components undergo welding, drilling, and lathe work to ensure robust construction. The SolidWorks 3D model serves as a blueprint for seamless component integration, resulting in a balanced system where each DoF operates in harmony.

The gripper in Figure 3 features five fingers, four of which are connected with shafts. Gears are used to control the precise and synchronized movement of the fingers, enhancing the efficiency of the grip. This coordinated design ensures smooth operation and improves the overall performance of the gripper.

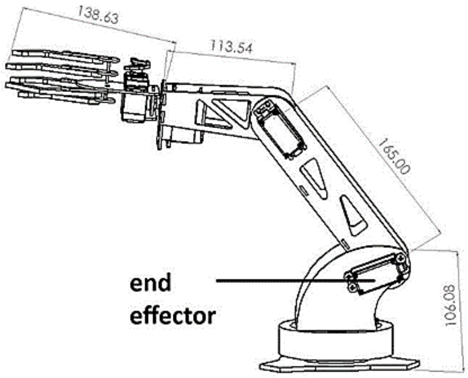

Figure 2. Robotic arm design

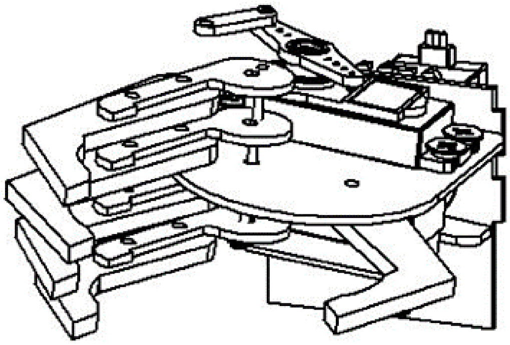

Figure 3. Gripper design

2.3. Electronic design of the robotic hand

The electronic design focuses on the control and actuation of the robotic arm. MG996R servo motors are selected based on torque requirements. The torque calculation is given in (1) and (2). Let the torque (T) in kg cm, force (F) in Newton, and distance (D) in cm. Let weight=0.5 kg and D=20 cm.

$$T = F * D \quad (1)$$

$$T_{end\ effector} = weight * distance$$
$$T = 0.5 * 20$$

$$T = 10\ kg/cm \quad (2)$$

The selected MG996R servo motor, with a torque capacity of 11 kg/cm, accommodates the placement of a 0.5 kg object at a distance of 20 cm from the robotic arm's base. This choice ensures sufficient torque for the specified load and distance requirements. The workflow of the proposed system is presented in this section as algorithm 1. It begins with capturing video frames from a specified camera using OpenCV. These frames undergo normalization and resizing to a standardized 224×224-pixel format. The resized images are processed by the MobileNet CNN to extract relevant features for efficient and lightweight object recognition.

Algorithm 1. Robotic arm control
```
while true do
ret, frame=cap.read()
if not then
PRINT "Failed to grab frame"
BREAK
end if
predictions=model.predict(input_image)
predicted_class=int(predictions[0][0] > 0.5)
label=if predicted_class == 0 then "bottle"
else "bag"
end if
if predicted_class == 0 then
call bottle()
else
call bag()
end if
```

Following object detection, the system utilizes the identified class information (e.g., "Bottle" or "Bag") to trigger specific servo actions for grip formation. The script calls corresponding functions—either bottle() or bag()—to execute actions related to servo control based on the classification. This process is looped, continuously updating the displayed video frame with the predicted class and responding to detected objects in real time. The comprehensive approach ensures seamless integration between vision-based recognition and robotic manipulation, providing an assistive aid for amputees. By mimicking finger movements based on detected objects, the robotic arm demonstrates significant potential in various applications, including manufacturing, logistics, and healthcare.

3. RESULTS AND DISCUSSION

The study presents a thorough analysis of the implemented humanoid robotic arm system, enabling successful object detection and ensuing robotic manipulation. Figure 4 and Figure 5, illustrate the system's adeptness in detecting binary classes and executing precise grabbing functions. The system initiates specific grabbing functions designed for each class. This action then prompts the robotic arm to execute pick-and-place tasks in a manner that ensures the efficient and precise handling of objects within the given environment. The robotic arm (Figure 5), detects the bottle and grabs it precisely, following the elbow motor, the fingers form the desired grip to pick up the bottle. Subsequently, the wrist rotates to a specific angle, after which the fingers form the desired grip to pick up the bag.

Figure 4. Bottle detection

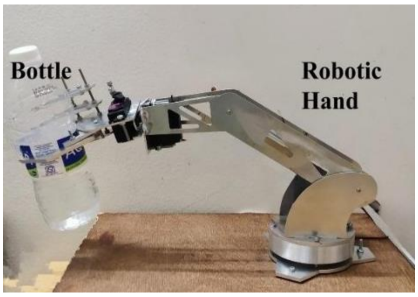

Figure 5. Grip formation

This graphical representation of the training and validation accuracy on the y-axis with respect to the number of epochs on the x-axis in Figure 6 provides a compelling narrative of the model's learning behavior. The curve illustrates a positive correlation between the number of epochs and the training accuracy, showcasing a steady increase over time. However, the validation accuracy curve exhibits an interesting trend. Initially aligning with the training accuracy, it experiences a decrease around the midway point of epochs before resuming an upward trajectory. This phenomenon suggests that the model, while excelling in learning from the training data, encounters challenges in generalization, leading to a temporary dip in performance on unseen validation data. The observed training accuracy of 98% signifies a high level of model proficiency, but the validation accuracy hovering around 93% highlights the need for further exploration into techniques for mitigating overfitting and enhancing the model's ability to generalize to new, unseen data.

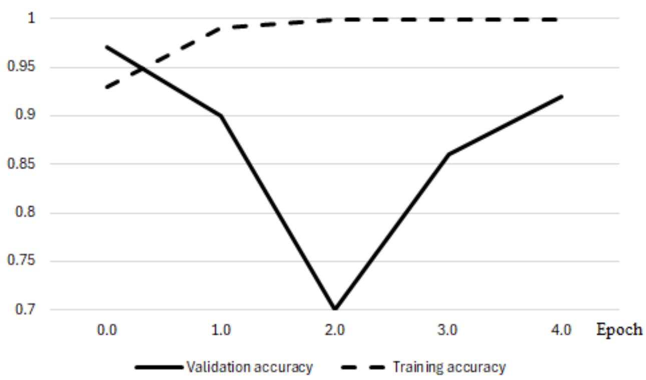

Figure 6. Training and validation accuracy

The graphical representation of the training and validation loss on the y-axis with respect to the number of epochs on the x-axis in Figure 7 reveals a noticeable pattern. Initially, the training loss demonstrates a gradual decrease as the number of epochs increases, indicative of the model learning from the training data. However, the validation loss exhibits a distinctive behavior by increasing up to the midpoint before later decreasing. This divergence suggests that, while the model is effectively learning from the training data, there may be a point where it begins overfitting and does not generalize well to unseen validation data. The increase in validation loss could be attributed to the model capturing noise or specific patterns unique to the training set, which may not necessarily apply to new data. This behavior underscores the importance of monitoring both training and validation loss to strike a balance between learning from the data and avoiding overfitting. Table 1 shows that the model was subjected to a total of 192 tests, comprising 126 instances of the 'Bag' class and 66 instances of the 'Bottle' class. Impressively, the model achieved a high overall accuracy of 95.31%, with 96.83% accuracy, 0.97 predicting 'Bag' instances, and 92.42% accuracy for 'Bottle' instances.

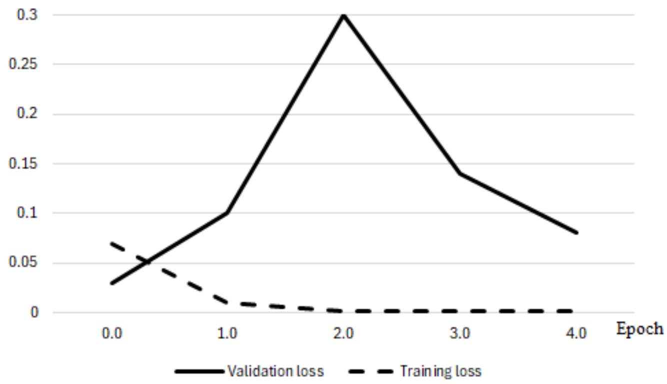

Figure 7. Training and validation loss

Table 1. Model performance

Class	Bag class instances	Bottle class instances
Tests	126	66
Correct Prediction	122	61
False Prediction	4	5
Accuracy (%)	96.83	92.42
Recall	0.91	0.89
Precision	0.97	0.93
F1 Score	0.95	0.80

The 'Bag' class, precision stands at 97%, emphasizing the model's ability to accurately identify 'Bag' instances when predicted. Additionally, a recall of 91% signifies the model's proficiency in capturing the majority of 'Bag' instances. Similarly, for the 'Bottle' class, while precision is slightly lower at 80%, the model excels with a recall of 93%. The model encountered four false predictions for the 'Bag' class, likely influenced by variations in lighting, diverse bag shapes, and occlusions in the real-world environment. Instances, where bags were partially obscured or positioned at unusual angles, could contribute to misclassifications. Similarly, in the 'Bottle' class, five false predictions may be attributed to variations in bottle shapes, sizes, and orientations, as well as challenges like label presence, translucency, and the presence of other objects. Factors such as different backgrounds and reflections could impact accurate 'Bottle' classification. Overall, these misclassifications are complex, influenced by diverse dataset conditions and real-world complexities. This involves addressing challenges by refining the dataset, augmenting training data with diverse scenarios, and exploring advanced techniques like transfer learning for improved adaptability in varied conditions. The process entails refining the dataset to enhance its quality, incorporating diverse scenarios into training data to ensure robust learning, and implementing advanced techniques, such as transfer learning, using advanced techniques like transfer learning to make the system work well in various conditions.

4. CONCLUSION

This paper presented the design, development, and evaluation of a 5-DoF humanoid robotic arm featuring a sophisticated 5-finger gripper. The system is operated by a high-speed portable computing system, utilizing a webcam for object detection and environmental awareness. The robotic hand is designed as an assistive aid for amputees, mimicking finger movements based on detected objects. Unlike a biological hand that receives instructions from the brain, this robotic arm detects objects through a computer vision system and forms the grip accordingly. The CNN-based MobileNet architecture is employed for object detection, achieving precision scores of 0.97 for bags and 0.93 for bottles, with accuracies of 96.83% and 92.42%, respectively. The results demonstrate the potential of integrating advanced computer vision algorithms and real-time strategies to develop assistive technologies. The novel approach of using computer vision to guide robotic manipulation sets a precedent for future developments in the field of assistive and industrial robotics. The high accuracy and efficiency of the system are highlighted by its performance metrics. The model's precision, recall, and F1 scores demonstrate its ability to handle diverse real-world scenarios. However, the project also identifies the complex challenges that arise in real-world situations, especially regarding misclassification. Factors such as variations in object shapes, sizes, and lighting conditions contribute to false predictions. Addressing these challenges involves refining the dataset, augmenting training data with diverse scenarios, and exploring advanced techniques like transfer learning for improved adaptability.

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